

Topics in Safety, Risk, Reliability and Quality

Sviatoslav Timashev
Anna Bushinskaya

Diagnostics and Reliability of Pipeline Systems

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Diagnostics and Reliability of Pipeline Systems

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*To my wife, Shirley Timashev, and our
grandchildren Nikita, Sophia, Stanislav,
Vladislav, Brittany, Jessica, Christina,
Caroline, and little rascal Daniel;*

—Sviatoslav Timashev

*To my parents, Nadezhda Melgunova and
Victor Bushinskiy.*

—Anna Bushinskaya

Preface

The motivation for writing book was to provide a comprehensive analysis of all aspects of integrity and safety of pipeline systems to the extent required for practical application. The book sums up ideas expressed in numerous articles penned individually and as a team by both authors, and although most of them went through double-review filters and were published in the proceedings of major international conferences and journals, they remain difficult to access. A distinctive feature of this book is its interdisciplinary approach to the solution of individual cases and of the whole imperative problem. The proposed solutions of fundamental problems have been designed, in addition to following the logic of a particular research discipline development, with specific requirements of the pipeline industry in mind. Another very important characteristic of this book is that the interdisciplinary problem discussed here has been studied as a sequence of interdependent problems from various fields of knowledge and engineering disciplines, and resolved using a task chain approach, when the solution output of the first problem is an input for the next problem, etc., until the output of the last problem produces the ultimate solution for the whole problem.

The book brings to light some of the most relevant and not yet resolved safety and integrity problems of pipeline systems, which are vital systems not only for the petroleum industry and the fuel and power sector in general, but also for any other modern industry sector.

A specific feature of all solutions in the area of new diagnostic tools for in-line inspection (ILI) development is their highly confidential nature, particularly for data analysis algorithms. Every firm carefully protects its processes, rarely disclosing what particular parameters of their technology are used as the essential variables, which is a requirement under the umbrella API 1163 (ILI Qualification Standard), and what the values are of these parameters. Published papers do not disclose the solution approach used, describing bare bone results, which cannot be verified or replicated, since there is no full description of the algorithms used in the analysis. Apart from competition and commercial secret protection, there are multiple other reasons for this situation. Without dwelling on them, we should point out that the

international API 1163 standard recommends establishing strategic partnerships between the pipeline companies and the diagnostic service providers (DSP), which, if need be, could act in concert on many issues of mutual interest.

From our long-standing experience of delivering lectures on the topic of this book to pipeline industry professionals from more than 30 countries worldwide, we are more than well aware of the certain skepticism with regard to (and even in some cases, total rejection of) the applicability of probabilistic methods when solving practical problems of pipeline systems safety and integrity management. This is due to many factors, which include existing knowledge gaps in the specialists' training and the need to change the decision makers' mentality. On the other hand, there is also insufficiently transparent presentation by researchers and scientists of the real and clear advantages offered by application of a probabilistic approach. The authors express their hope that this book will be helpful in closing this gap at least partially.

Pipeline systems (PS) are an almost ideal generalized type of a critical infrastructure computational model. In this connection, we believe that the methodological approaches outlined in the book to problem solving in the areas of diagnostics, monitoring, integrity, residual strength assessment, failure probability (reliability), maintenance, and safety of pipeline systems are of a general nature, and could be utilized for assessing other types of infrastructures.

This book, with decades of research behind it, is nevertheless, the result of a sequence of serendipity and lucky events. It started with Keith Leewis, Ph.D., (Canada/USA, Pipeline Research Council International-PRCI), who invited the first author to be a member of the API Work Group 1163, which wrote over several years, the API 1163 Standard, published in 2004, and is now the foremost desktop manual of every pipeline operator and ILI services vendor. When working in the WG 1163, the author was involved in discussions with other members of the group, comprised of top American and Canadian professionals from the pipeline transportation industry, research institutions, regulatory bodies, and academia and he learned immensely from them about the current pipeline problems (as they were seen in the West), and how they should be solved. By that time this author had a 15+ year experience of solving the same practical problems for the Soviet/Russian oil and gas pipeline industry, which has assets predominantly in West Siberia's Far North. This provided a unique opportunity to see the problem simultaneously from both sides; i.e., from a broadest possible viewpoint and to develop some innovative solutions. Members of the WG 1163 from whom the first author got the most valuable feedback include Tom Bubenik (USA), Guy Desjardins (Canada), and Bernie Selig (USA).

The second major event was when B.J. Lowe of *Clarion* (Houston, Texas) and John N. Tiratsoo of *Tiratsoo Technical* (UK, Australia) invited the first author to create for pipeline professionals intensive short courses on *Reliability based management of pipeline integrity and safety*, and *Analysis of ILI data for creating optimal integrity management plans*. By preparing and delivering these courses in the Americas and Eurasia, and receiving feedback from audiences from over 30 countries, we attained further insight into the complex socio-technological problem of pipelines operation.

Several years later, Prof. Andrew Palmer (UK, Singapore), one of the world's leading scientists in pipeline design, construction, and operation, invited the first author to participate in the research team of the Intergovernmental Panel on Climate Change (IPCC), WMO UN, to work on the problem of CO₂ capture and sequestration by means of extracting it from the atmosphere and then transporting the liquefied or compressed gas by tankers or pipelines, respectively, for depositing it on the ocean bottom, or deep in the Earth's mantle rock formations. Our work for IPCC unexpectedly won the collective Nobel Peace prize of the year 2007 (the second half of the prize went to Vice-President Al Gore).

The fourth and crowning event happened, when Prof. Adrian Gheorghe of the *Old Dominion University*, Virginia, USA, acclaimed specialist in the field of critical infrastructure theory (he coined it as *infranomics*), became acquainted with the results of many years of fundamental and applied research, obtained by the *Science & Engineering Center "Reliability and Safety of Large Systems and Machines"* Ural branch Russian Academy of Sciences on the problem of diagnostics and reliability of pipeline systems as critical infrastructures, initiated writing this monograph, which sums up the above efforts. In this regard we would like to express our sincere gratitude and acknowledgment to Prof. A. Gheorghe, who made this possible.

Although there are only two authors of the book, we thank all of our colleagues with whom numerous papers were published in peer reviewed journals and presented at most prestigious conferences in Calgary, Osaka, Rio de Janeiro, Amsterdam, Moscow, Bahrain, New York, Houston, Yekaterinburg, Krasnoyarsk, Liverpool, to name a few. Their names are cited in the list of references of this book, but it is our privilege to mention them here: Candidates of Sciences Margarita G. Malyukova (who also helped writing Chap. 7), Ludmila V. Poluyan (who lent a hand in writing Sects. 1.4, 5.3 and 8.3) Doctors of Science Alexander B. Kuzmin, Alexander N. Tyrsin and Alexander Chernyavski; Ph.D. students Zhanna V. Yurchuk, Vitaly V. Kuznetsov, Tatyana A. Makarova, Irina S. Solovyeva, Maria A. Gretsikh. In the fast changing work environment time is a very important, even crucial, asset. We are extremely grateful to Tatyana V. Govorukhina, Tatyana G. Kovalchuk, Irina G. Nikulina, and Sergey N. Shubin, who spent precious time in helping to compile the manuscript.

The authors are happy to extend their sincere and deep gratitude to Tom Morrison (Canada), Tomas Beuker (FRG, Switzerland), Francisco Caleyó (Ph.D., Mexico), Alphonso Lester, Ph.D. (both of Mexico), who graciously shared with us their vision on the ILI data analysis and interpretation, and to all professionals who provided data on defects measurements in real-life pipelines, located in three continents—Europe, Middle East, Asia, and North America—which made it possible to perform verification of the theoretical results obtained by the authors, in real-life environments. In this connection we are sincerely grateful to the late Rem I. Vyakhirev, Dr. of Sci., (CEO, JSC Gazprom, Russia), and A.D. Sedykh, Cand. Science (Chief of R&D Department, JSC Gazprom), who supported our research efforts related to reliability of gas compressor stations piping and equipment, and to the late V.N. Chepursky, Cand. Science (JSC Sibnefteprovod, Tyumen, Russia) for engaging the authors in the practical work of assessing reliability and remaining life

of oil pipelines, which operate in the permafrost of Western Siberia; Yu.V. Lisin, Dr. of Sci., (Vice-President of JSC “AK Transneft”, Russia), for inspiring a number of research tasks; E.S. Vasin, Dr. Sci. (JSC TDC “Diascan”, JSC “AK Transneft”), Candidates of Science, G.A. Zhukova, (ZAO Moscow NPO “Spectr”); V.E. Loskutov, B.E. Patramansky, S.E. Popov (all from ZAO NPO “Spetsneftegas”, Yekaterinburg), V.I. Stolypin (JSC “Gazprom Dobycha Orenburg”), as well as to ILI technology specialists Phillip Hoyt, Ph.D., USA; Martin Phillips, Ph.D., USA; Kamal Ben Amara, Ph.D. (Qatar), Mark Susich (BP, Alaska). The results obtained on the basis of statistical data made available by them have been used for successful solution of a number of applied problems in the interests of JSC Gasprom, TDC “Diascan,” ZAO NPO “Spetsneftegas,” JSC “Gazprom Dobycha Orenburg,” as well as for a number of other companies. Parts of these results have been used in this book.

The book will be useful to experts and professionals in the area of diagnostics, monitoring, maintenance, reliability, and safety of critical infrastructures, and, primarily, to decision makers—persons responsible for various types of pipeline operations. It will also be useful to diagnostic service vendors, ILI tool developers, and designers, specialists in the area of operational and environmental safety, as well as researchers, Ph.D. candidates, and graduate students majoring in respective fields. Some parts of the book are currently used as a manual by the postgraduates of the Civil Engineering Institute of the Ural Federal University.

The exciting task of writing this book was divided in the following way: Preface, Introduction, Chap. 1, Sects. 3.3, 3.4.1, 3.4.2, 3.8, 3.9 of Chap. 3, Chap. 4, Chap. 7, and Conclusions were written by the first author; the rest of the book is a result of joint effort. I feel it necessary to say that it was a pleasure to work with my co-author, Dr. Anna V. Bushinskaya, my former Ph.D. student, whom I consider highly talented and unbelievably dedicated to science. I wait with awed anticipation to see what mark she will leave in the branch of science in which she is working.

We are indebted to the Springer team Nathalie Jacobs, Cynthia Feenstra, Albert Paap, and our toughest editors, an enthusiastic, professional, and supportive team, especially, Edwin Beschler, Sharmila Rajesh, who made all efforts to make the book up to the highest standards, concise, and easily readable. We also want to thank all those specialists whose names we do not know, but nevertheless appreciate their efforts very much.

For readers’ convenience a list of abbreviations is provided in duplicate. One of the copies may be removed from the book for easy reference during reading.

Despite all our efforts to the contrary, the book may still contain some errors. The authors would be sincerely grateful to attentive readers who may point them out to us.

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About the Authors



Sviatoslav Timashev is the founder of the well-known Ural school of scientific thought “Safety of critical infrastructures and territories,” Doctor of technical sciences, Distinguished scientist of Russia, Merited Educator of the Russian Federation, Principal Scientist and Scientific Director, Science and Engineering Center “Reliability and Safety of Large Systems and Machines” Ural Branch, Russian Academy of Sciences; Professor and Director of the Research Lab and Master’s Program “Safety of Critical Infrastructures and Territories,” Ural Federal University (UrFU). Both institutions are in Yekaterinburg.

S. Timashev authored and co-authored 28 books and over 420 papers, and holds 16 patents in the field of diagnostics and monitoring systems.

He is licensed by the Russian Federal Agency for Ecological, Industrial and Nuclear Safety as the highest category expert in safety of oil and gas infrastructures. He is a specialist in stochastic stability and dynamics, diagnostics, monitoring, residual lifetime, maintenance, reliability, and safety of critical infrastructures, including pipeline systems.

S. Timashev is a member of the Russian Federation academy on quality problems, Washington Academy of Sciences Fellow; Fulbright Academy of Science and Technology member, as well as member of ASME, SRA, SARMA, MAA, and ACS. S.A. Timashev is charter member of the International Association on Structural Safety and Reliability (IASSAR) and the PIPE institute for professional pipeline engineers (UK). He is also member of the Work Group of the API 1163 Standard on in-line inspection quality. Professor S. Timashev is editorial board member of several international journals, including “Machinery Science Problems and Reliability of Machines,” “Emergency Situations and Safety Problems” (both Russia), “Structural Safety” (USA), “Pipeline Engineering” (UK), “Condition Monitoring And Diagnostic Engineering Management—COMADEM” (UK), “Journal of Risk Analysis and Crisis Reduction” (China). He also provides

international consulting services and delivers intensive short courses on “Risk Based Management of Pipeline Integrity and Safety” and on “In-Line Inspection Data Analysis for Optimizing Integrity Management Plans” for pipeline specialists and engineers of 26 countries (up to date) of Australia, Asia, Africa, Europe, North and South America.

He is also an Institutional Co-recipient (as a member of the IPCC WMO UN international team of researchers) of the Nobel Peace Prize, 2007, for developing methods and means of CO₂ sequestration from the Earth’s atmosphere and depositing it in deep rock formations and on the seabed (including the use of pipeline technology).



Anna Bushinskaya Candidate of Science, Leading research fellow of the Science and Engineering Center “Reliability and Safety of Large Systems and Machines” Ural Branch, Russian Academy of Sciences, and Associate Professor of the Ural Federal University (UrFU). Both institutions are in Yekaterinburg. She specializes in the field of statistical analysis of ILI data, integrity, reliability, residual lifetime, and predictive maintenance of pipeline systems. She is the author and co-author of one book (to date) and over 50 peer reviewed papers.

Nomenclature

AIC	Additional inspection control
AM	Adapted method
ANOVA	Analysis of variances
APR	Accident probability reduction
ASEP	Accidence sequence evaluation program
ASME	American society of mechanical engineers
BN	Bayesian network
BP	Burst (failure) pressure
BR	Building regulations
BS	building standard
CA	Corrosion allowance
CAP	Current accident probability
CCO	Critical crack opening
CCS	Corrosion control strategies
CD	Crack detection
CDF	Cumulative distribution function
CGR	Crack growth rate
CI	Critical infrastructure
CL	Confidence level
CLT	Central limit theorem
CM	Corrosion monitoring
CR	Corrosion rate
CS	Corrosion samples
DC	Decision criterion
DEM	Differential equations method
DEMC	Differential equation and Monte Carlo (method)
DM	Decision maker
DP	Design pressure
DSP	Diagnostic service providers
DV	Deterministic value
E/FTA	Event/fault tree analysis

ECP	Electrochemical protection
EMAT	Electromagnetic acoustic transducer
ER	Electrical resistance
ERP	Electric resistivity probes
EST	Engineering schools of thought
ET	Event tree
EVs	Essential variables
FD	False detection
FGE	Full group of events
FI	False identification
FND	False non-detection
FSA	Full statistical analysis
FTD	Fault tree diagram
G-C	Gram-Charlier's series
G-C-E	Gram-Charlier-Edgeworth (series or method)
GCS	Gas compressor stations
GLSM	Generalized least squares method
HE	Human errors
HF	Human factor
HIC	Hydrogen induced cracking
HPF	Hazardous production facility
IC	Implementation costs
IDP	Inherent detection probability
ILI	Inline inspection
IMPs	Integrity management plans
IPOD	Inherent probability of detection
IPS	Integral score parameter
ISM	Important sampling method
LPR	Linear polarization resistance
LSF	Limit state function
LSM	Least square method
MC	Monte Carlo (method)
MEs	Measurement errors
MFL	Magnetic flux leakage
MI	Measurement instruments
MLE	Maximum-likelihood estimation
MMSES	Man-machine-structures-environment system
MPs	Main pipelines
MS	Measurement system
MSOP	Maximum safe operating pressure
NDE	Non-destructive quantitative evaluation
NDT	Non-destructive control technique
NNLS	Nonnegative least squares (method)
OP	Operating pressure
OPS	Oil pumping stations

OSD	Operating-stress design
PBMP	Pure birth Markov process
PDMP	Pure death Markov process
PIG	Pipeline inspection gage
PILIT	Perfect ILI tool
POD	Probability of detection
POF	Probability of failure
PPTS	Pipeline performance tracking system
PS	Pipeline system
QHRA	Quantitative human reliability analysis
R&R	Repeatability and reproducibility (measurement system)
RBI	Risk-based inspection
RDs	Regulatory documents
RF	Random function
RL	Regression line
ROC	Receiver operating characteristic
RVs	Random variables
S/F	Success/failure
SA	Sensitivity analysis
SC	Stress corrosion
SCC	Stress corrosion cracking
SDE	System of differential equations
SDs	Standard deviations
SF	Safety factor
SIF	Stress intensity factor
SIs	Strategic infrastructures
SLS	Surface of limit states
SMOP	Safe maximum operating pressure
SSS	Stress-strain state
THERP	Technique of human error rate prediction
TI	True identification
TMFL	Transverse magnetic flux leakage
TPD	Third-party damage
TS	Tensile strength
UPAP	Ultimate permissible (desirable) accident probability
UT	Ultrasound type/technique
VA	Variance analysis
VF	Variation factor
VI	Verification instrument
VIC	Visual inspection control
WC	Weight contribution
WLC	Weight loss coupons
WM	Wall thickness measurement
YS	Yield strength

Chapter 1

Introduction

Modern society sustainability technologies focusing on ensuring modern competitive production are supported by systems consisting of software, communications, machines, instruments, tools, and structures which, in combination, form infrastructure systems, distributed across a certain territory. The most important infrastructural facilities are called critical infrastructure (CI), and the most critical of them—strategic infrastructures (SIs).

One of the most common CI elements is pipeline systems. These include, first of all, the infield and main oil-, product-, and gas-pipelines, as well as gas distribution lines; pipelines of nuclear and cogeneration power plants; pipeline systems of ships and aircraft control systems. An important role is also played by water mains, steam pipelines, pipelines transporting CO_2 , ore and coal pulp, etc. PS form the core of all developed countries economies. Their safe functioning is a guarantee of stable operation of critical systems, of which they are an integral indispensable element (Fig. 1.1).

Support of the safe and fault-free operation of PS is a matter of national concern [1]. Many of them have a strategic importance, since they are an element of national energy security and serve as an important instrument for the protection of the interests of any country in the international arena. The problem of safe operation of such systems draws growing attention of researchers, industry specialists, and government officials, particularly in connection with each major accident with heavy consequences—loss of life, severe environmental damage, loss of assets, or damage to the nation's prestige. From the point of view of system engineering, structural mechanics, reliability theory, an operations manager and an owner, main PS are large distributed systems. From the point of view of mechanics, the linear part of main PS, as well as a significant part of oil pumping and gas compressor stations equipment—are thin-walled cylindrical shells with imperfections, characterized by geometric and physical nonlinearity.



Fig. 1.1 Pipelines—basic component of the oil processing plants CI

In terms of reliability theory main pipelines (MPs) are large stochastically non-linear man-machine renewable systems, often with structural, functional and time redundancy, and noneconomic responsibility. From an operations manager's or an owner's position MP is a sophisticated geotechnical high-hazard consequence facility (critical infrastructure) consisting of a large number of smaller objects distributed over a large territory and functioning jointly and continuously in order to generate profit.

Solutions of safety problems for this type of facilities require a systemic interdisciplinary approach involving implementation of dedicated engineering design projects and the use of fundamental and applied research results and a comprehensive summing up of the global experience of design, construction organizations, and MP operators. A scientific base for practical MP safety implementation is the general theory and methods of risk and operational safety assessment, and the theory of reliability of large-scale renewable systems.

The main reason of the PS degradation is the destruction of pipe walls as a result of corrosion, erosion, fatigue damage accumulation, static and shock load, frost upheaval, ice load, turbulent water flows, etc. However, a distinctive feature of such systems degradation is the appearance and development of a multitude of actively growing defects of various nature and origin, each of which constitutes a potential hazard for pipe integrity. Loss of integrity results in the loss of pipeline content: water, steam, helium, coolant (e.g., lithium or sodium in the nuclear power plant's coolant recirculation systems), natural gas, oil, kerosene, gasoline, etc. This also often leads to loss of human life and material damage which may amount to several dozens or more millions of US dollars.

The notion of *integrity* has become one of the core concepts in the problem of the residual lifetime and safety of sophisticated engineering systems with containers (pipelines, high-pressure vessels, etc.) in their structure. A distinctive feature of integrity as a limit state is the fact that it is based on geometric ratios and parameters—wall thickness and pipe diameter, defect dimensions (depth, length, width, area, and volume), as well as the rate of their change in time under the effect of various external factors.

When solving reliability and residual lifetime problems of such systems, methods of accurate sizing of all pipeline geometric parameters are of paramount importance. These measurements must, as a rule, be performed without interruption of operation of the hazardous production facilities (HPF). For this purpose various monitoring and discrete nondestructive inspection and testing techniques are used.

Pipe wall defects are normally identified in the process of technical diagnostics with the use of various measurement instruments (MIs). Information obtained from the MI inevitably contains constant (systemic) and random measurement errors (MEs), which may significantly distort the real picture of the state of the system. *Random error* is an error which is changing (in value and/or sign) from one measurement to another. These errors are related to lack of accuracy of the instrument or to the measured object's irregularities, as well as to the specific nature of the measured value itself. *Systemic error* is an error which is changing in time in accordance with a certain regularity (a special case is a constant which does not change in time). Systemic errors are related to the instruments' errors (wrong scale, calibration, etc.). In cases when the MI shows overstated defect values, this results in overstating of the real pipeline problems, which in its turn, results in significant economic costs increase because of unjustified scope and time of defects repair and maintenance. Underestimating defects size may potentially lead to pipeline failure and major environmental and economic losses.

Thus, the consistency of a defect severity assessment is determined primarily by the accuracy of the correctly detected and identified defects' parameters. The best way to determine these sizes is taking into consideration the ME value for each particular instrument, which it demonstrates in a specific pipeline. The current rapid development of ILI techniques (due to legislative regulations on mandatory pipelines inspection, using external and in-line inspection techniques), is not accompanied by a sufficient development of a research-backed methodology for the analysis of results obtained using of this technology. In particular, there is no research-based methodology for the in-line magnetic defectoscopes or external laser gauges for *assessing the roughness* of the inner surface of the pipe wall. Hence, many results cannot be interpreted unambiguously, and leave open the question of quantification of the residual life and integrity of recently inspected facilities.

In this connection the issue of verification of each measurement tool ME used on a particular facility for assessing its condition becomes essentially important. Knowledge of the ME, as demonstrated by the MI in field conditions, allows taking them into account and obtaining the best possible assessments of the defects parameters. This is the straightforward way to achieve reliable assessments of residual strength,

reliability, and remaining life of a PS, as well as to determine optimal periodicity of their inspection and/or maintenance.

The adequate assessment of PS safety requires a capability for determining realistic probability of its failure (reliability) and residual life as a function of time. Currently, pipeline design is done, as a rule, using deterministic linear mechanics of thin-wall cylindrical shells. Deterministic criteria do not allow full evaluation of the PS probability of failure, since they do not take into account the random nature of pipeline geometry (thickness, diameter, and possible dent sizes), pipe material (yield and ultimate strength), load, (changes of operating pressure, various external loads and impacts), presence of a significant number of growing in time defects of various nature, and uncertainty of their dimensions due to the presence of inherent ME of the pipeline inspection process. To address this problem, it is necessary to use probabilistic methods, which allow obtaining adequate evaluation of failure probability (reliability) of PS. This problem requires a systemic research, an attempt of which has been made in this book.

For systems with multiple defects a classic approach of structural reliability theory—system representation in the form of connected in series elements (defective cross sections)—is poorly applicable in real life. According to this approach, the probability of faultless operation of the whole system equals to the product probabilities of faultless operation of all its elements. Reliability index of such a system proved to be significantly lower than the respective probability indexes of individual elements.

The number of defects in real-life PS may be quite significant and the formal use of the classic structural theory approach to the problem of PS reliability assessment leads to implausible results which differ significantly from the real picture of the phenomenon. The main reason for this is the fact that not all defects of the system contribute to the probability of failure (POF) given the *fixed time horizon* of integrity prognosis. However, in a classic POF calculation they all participate and have a significant effect on the obtained value. In addition this approach does not take into account the fact that PS is a renewable system, moreover, a system equipped with a smart protection subsystem.

The main problem of protecting pipelines' integrity and safe operation is related to the need of adequate prognosis of their future technical condition necessary for calculating the remaining life before the onset of a warning, critical, or limit state.

According to the *predictive maintenance principle* [2] for the potentially dangerous assets and structures, to which category all kinds of pipelines belong, the category of "conditional limit states" may cover conditions, realization of which does not necessarily require termination of the assets' use or their retirement. Only true limit states result in physical accidents and disasters, or the need of immediate cessation of operation (or conducting immediate maintenance). The so-called "warning" and "critical" failures do not lead to accidents, since they are conditional and are introduced for various engineering purposes in order to fixate the moment of occurrence of some characteristic states of a facility, which "trigger" certain control actions (diagnostics, repair, operating pressure relief, etc.) necessary for maintaining and keeping the system in the operation mode. These states serve as "levels"

which are optimized in a multilevel problem of failure control policy [2]. Various probability parameters and (or) physical (geometric) system characteristics must be selected as the warning and the critical failure parameters. Implementation of this approach requires the ability to calculate, with a reasonable accuracy, the time of occurrence of these types of conditional failures. Thus, the development of predictive maintenance methodology and its components is quite relevant.

In view of the above, there is a need in developing new approaches to evaluation of the POF (reliability) and residual life of a PS, which would in greater detail reflect their physical essence and allow determination of the optimal time periods for PS diagnostics and maintenance.

All these factors predetermined the content of this book, which provides original answers and solutions to the problems and tasks listed above. The content and sequence of chapters follows the logic of a design decision-making process and optimal operation of such a critical infrastructure as a pipeline system.

Chapter 2 gives an overview of existing methods of assessing PS' integrity as it degrades in time, and formulates the research problems. It contains a description of a holistic approach to integrity problem of a PS with heterogeneous defects. Failure causes and limit states of pipelines, analysis of results of their inspection, the existing corrosion wear models, methods of RL and reliability of such PS are studied. Analysis of a reliability level set forth in different national and international design codes for the design of main PL is provided. Entropy approach to assessing the degree of PL degradation from different impacts is outlined. The chapter contains description of maintenance principles and actions required to maintain strength, stability, and reliability of pipelines operation within the limits established by the design codes and the applicable regulatory documents. Hereinafter we will refer to this set of actions as "maintenance." The chapter also gives an outline of the PS stress corrosion cracking (SCC) type degradation, assessment of its state, and safety under the effect of SCC.

Chapter 3 sums up the accumulated global experience and provides a brief historical overview of the creation and development of smart ILI technologies, and gives a description of various inspection methods: magnetic, ultrasound, electromagnetic, eddy current, as well as the potential for their development. ILI stages are described in accordance with the current national and international regulatory documents (RDs).

Chapter 4 offers, apparently, the first of its kind, a holistic consistent statistical analysis of the ILI quality assessment problem. It provides a detailed description of full statistical analysis (FSA) of ILI data developed by the authors. A methodology for determining the minimum number of defects parameters measurements, which ensures a valid statistical analysis of the ILI data, is provided. A methodology is formulated for improving defects size measurement accuracy, relying on both the laboratory and field measurements. Basics of stochastic measurement theory, as applied to ILI, are presented. Quality metrics of in-line inspection tools are formulated, methods for improving accuracy of ILI measurements, and an analysis of the API 1163 international standard are described [3]. The chapter provides a description of a calibration method, which allows evaluation of *the true values of the measured defects parameters*. The authors proposed a methodology for accuracy assessment of *each run on each particular pipe* based

on regression and entropy analysis methods. The chapter provides results of numerous verification cases of the adequacy of proposed measurement mode, based on the statistical Monte Carlo method. Criteria of rejection of the employed MI and (or) ILI results are described. Analysis of reproducibility and repeatability is provided of measurements taking into account the contribution into the ME of both the MI, and qualification of the diagnosticians. Three approaches are described to assessing the possible number of missed defects of various sizes on the basis of both the purely statistical approach, and the Bayesian reevaluation of the true defects number, using results of one or two successive ILIs. A method of stochastic clustering of the “metal loss” type defects is introduced. In fact, this chapter can be considered as a full description of the current state of the problem with regard to in-line inspection theory, and is of encyclopedic nature.

Chapter 5 deals with the human factor. Different types are given of classification of human errors (HE) of their quantification. Sources of HE in the current ILI technology are described. A method of optimizing the selection of means for achieving the needed level of pipeline safety or minimizing expenditures on safety is described and implemented for two real-life cases.

Chapter 6 contains a description of PL reliability evaluation methods: the Monte Carlo (MC) method; the Gram-Charlier–Edgeworth (G-C-E) series method (with its adequacy verification) and the needed computer time for their implementation; recommendations on the selection of probability characteristics of PS parameters, defects, and load as random variables (RVs). A special section of the chapter is devoted to assessing the level of reliability empirically embedded into the national and international pipeline design codes. This chapter also provides an example of POF sensitivity to the random nature of parameters involved in the assessment algorithms.

Chapter 7 contains descriptions of several developed Markov models for describing degradation processes: (1) a model of numerous corrosion defects growth as a pure birth Markov process (PBMP); (2) a degradation model of a single defective PL section, as well as of the whole PS with a multitude of corrosion defects in the form of pure death Markov processes (PDMP). Verification of adequacy of these models has been performed. Based on the Markov processes authors proposed an approach for the gamma-percentile evaluation of PL strength, assessment of its remaining life RL, algorithm for calculating its POF, and a methodology for optimization of the maintenance/repair work scheduling.

The focus of Chap. 8 is the methodology of calculating the probability characteristics of crack propagation under the effect of a combination of random static internal pressure and cyclical loads and various types of corrosion effects—general corrosion and stress corrosion cracking for one or a multitude of longitudinal cracks. It provides solutions for the above problems using the Monte Carlo importance sampling method. It also deals with updating pipeline segment reliability assessment method under the SCC conditions according to the latest inspection results, using Bayesian network theory, which allows taking into consideration new information about pipeline condition for cases when its segments are connected in series and in parallel.

Chapter 9 provides a detailed description of PS predictive maintenance methodology on the basis of the multilevel integrity management policy under various

failure criteria [2]. The methodology is based on assessing the time of occurrence of warning, critical, and limit states of pipelines. This allows ranking these states by the time of occurrence. The remaining life of a pipeline is then determined in accordance with a national standard, which is based on the partial reliability coefficients and the international pipeline design codes (based on a unified safety coefficient). Prediction of a future pipeline state is based on projected values of the pipe wall defect size values which grow in time. The input values of defects parameters are taken from the ILI results, processed according to the procedures outlined in Chap. 4. For each pipeline failure state a time of its occurrence has been determined. Knowledge of these times allows minimizing pipeline maintenance costs, without endangering its safety or integrity. Examples are provided of practical application of the proposed methodology for drafting maintenance programs and action plans for assuring strength, stability, and reliability of real-life pipelines in accordance with design codes and operational standards. Practical application of the proposed maintenance approach allows, in the authors' opinion, performing timely reconstruction and upgrading of the most critical sections of operating pipeline systems with minimal expenditures.

The monograph presents results of successful application of the proposed methodology on a number of real-life pipelines operating in Europe, Asia, and North America.

We proceed to a description of the above results.

References

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Chapter 2

Methods of Assessing Integrity of Pipeline Systems with Different Types of Defects

The following leading scientists have made significant contributions to the development of a theoretical base of integrity and probability of failure (reliability) assessment of pipeline systems: A.A. Aladinsky, M. Ahammed, J.A. Beaver, A. Bhatia, V.V. Bolotin, A. Bubenik, F. Caleyo, A.O. Chernyavsky, O.F. Chernyavsky, J. Collins, A.S. Copner, G. Desjardins, A.M. Edwards, A. Francis, A.G. Gumerov, P. Hopkins, O.M. Ivantsov, C.E. Jaske, J. Keifner, V.V. Kharionovsky, V.I. Kharitonov, H.O. Madsen, S. Mahadevan, G.P. Marsh, R.G. Mannapov, N.A. Makhutov, B.I. Miroshnichenko, V.V. Moskvichev, T. Morrison, G.Kh. Murzakhanov, M. Nassim, S.V. Nefedov, A.D. Palmer, M. Philips, J.N.K. Rao, D.H. Richardson, P.R. Stephens, V.N. Syzrantsev, W.A. Thompson Jr., S.A. Timashev, E.S. Vasin, P. Vieth, R. Worthingham, J. Zhou et al.

Consider the current state of the problems outlined in the Introduction.

2.1 Causes of Pipeline Failures

One of the main reasons for reduced strength capacity and destruction of pipelines is the appearance of local pipeline wall defects during its manufacture, construction, and operation [1–26].

Out of all defects of pipeline systems the corrosion defects proportion-wise are the most significant. Thus, over the period of 1999–2001 the percentage distribution of all failures in the Unified Gas Supply System looks as follows [20]:

- external corrosion—41.2 (including stress corrosion cracking—39.8);
- construction and assembly defects—17.6 (including weld defects—9.8);
- mechanical damage—8.8;

- defects of pipes and connecting pieces—14.7;
- natural disasters—4.9;
- noncompliance with operational rules and standards—1.0;
- internal corrosion and erosion—2.9;
- other causes—9.8.

All types of local pipe wall defects occurring in pipelines have been defined and classified in [20, 22, 27–37] and numerous other works.

According to the VNIIGAZ data all pipeline defects fall into three classes [29, 30]:

- pipeline axis deviation from the design position;
- cross section shape irregularity;
- local pipe wall defects.

Defects of the linear part of a product pipeline are classified for maintenance purposes into five groups of parameters [29, 30]:

- by the nature of causes (metallurgical, welding, mechanical, corrosion);
- in association with a particular technological process (defects of steel sheets, pipe manufacturing, third-party damage);
- defects location (parent metal, plant weld, girth weld, weld thermal effect zone, lower pipe element, upper pipe element);
- location of defect inside the pipe wall or weld (surface, inner, through-defects);
- defects configuration (pitting, linear, large area).

VNIIST classifies main pipeline failures' causes into four groups [20]:

1. failures caused by pipe elements, check, and control valves;
2. construction defects;
3. violation of operation standards;
4. soil corrosion caused by research and design mistakes, use of low-quality materials, construction stage defects, violation of mode, and standards of operation.

According to [38], defects may be visible, hidden, as well as critical, significant and insignificant.

Analysis of literature on the subject allows stating that the most common types of defects identified during pipeline systems inspection are pipe wall surface defects, predominantly of the corrosion damage nature. There is no unified methodological approach to pipeline failure classification. In addition, analysis of consequences of operating pipeline failures and existing failure classifiers prove the relevance of using the stochastic approach when studying corrosion processes, as it adequately accounts for the multifactor nature of these phenomena when prognosing PS failure probability.

2.2 Pipelines Limit States

In the general case, the following limit states are considered for structural elements of the main pipelines linear part [12, 20, 21, 39, 40]:

- depletion of strength under a force impact (static and fatigue strength);
- loss of general (longitudinal) or local stability under compressive strain;
- depletion of pipe material plasticity;
- reaching the ultimate permissible lateral (in the vertical or horizontal plane) displacement by a structural element;
- pipeline rupture as a result of wall thinning, caused by corrosion and (or) inner surface erosion;
- integrity loss as a result of local deformations (local corrosion, defect opening, random mechanical impacts);
- extended fracture caused by crack(s) propagation;
- underwater and aboveground pipelines movement under the dynamic impact of water or air pressure;
- avalanche-type buckling of a deep-water pipeline under the water column pressure, etc.

Analysis of pipelines operation over many years [30, 41–44] demonstrates that their linear segments predominantly fail in two modes: leak and burst [45, 46]. Both limit states are considered in this book.

A *leak* is a disruption of a pipeline integrity due to appearance of micro-holes which manifest themselves by a limited leakage rate (up to several liters per minute).

Burst, destruction, or guillotine-type rupture is the pipeline destruction across its cross section up to a complete rupture. This type of failure is the most dangerous and often causes severe ecological and economic consequences.

Actual pipeline reliability assessment requires taking into consideration all the aforementioned types of limit states. This book presents pipeline reliability assessment problems under the simultaneous effect of two factors—various types of active corrosion and operating pressure.

2.3 Analysis of In-Line Inspections (ILI) Results

The degradation processes occurring in a PS (corrosion, erosion, cracks propagation, etc.) lead to the appearance of various physical and geometrical defects, which affect the general characteristics of system operability. In this connection, it becomes necessary to know the sizes of these defects, and how they change in time. This is done by regular ILI during which the defect parameters are registered (depth, length, width, angle position relative to the pipeline axis, etc.).

The main task of technical PS diagnostics is timely assessment of pipeline technical condition due to change of operational regimen, interaction with the environment,

and accumulation of all kinds of defects. Inspection results serve as the basis for assessing pipeline residual life, and selecting the most efficient type of maintenance.

Information obtained during an inspection consists of data on the pipeline material metallurgical anomalies, other types of defects, their location, orientation along the longitudinal axis and across the pipe circumference (perimeter), as well as their dimensions (length, depth, width). This information inevitably contains some constant and random inherent built-in measurement errors (ME), since it is physically impossible to create measurement tools free of any measurement errors. These ME may significantly distort the real state of the studied system.

Studying a PS integrity and its *fitness-for-purpose*, it is necessary to take into account these ME while using ILI results. Conclusions made on the basis of these “contaminated” data about the state of a technological system and the required integrity and reliability protection actions may prove to be inadequate and (or) late. This, in its turn, may result in incidents, accidents, and disasters with huge material damage and loss of life/limb.

Because of ME, the diagnostics methods per se are not capable of producing true values of the measured parameters. The results of defects parameters measurements are just an approximate evaluation of the true values. The following factors affect the control reliability:

- physical limitations of the measurement tool;
- quality and integrity of the instrument being used;
- state of the objects surface in the control zone;
- conditions of control;
- time of control;
- visual acuity and physical condition of the inspector/diagnostician;
- qualification and the psycho-physiological condition of the inspector.

Currently, a sufficiently developed general theory of measurements and their statistical analysis are as follows [43, 47–61]:

- the general theory of measurements and their statistical analysis;
- the theory of measurement tools and calibration testing;
- scientifically justified set of ILI quality metrics, as applied to thin-walled cylindrical pipelines (see Chap.4).

The level of application of this theory in practice of sizing defects in various purpose pipelines is quite insufficient.

The consequences of such situation are accidents on critical pipeline systems. For instance, it is well known that the accident on the USA nuclear facility “*Three Mile Island*” was caused by a defective steam pipeline burst, which was diagnosed shortly before the accident as faultless. Consequent verification of qualification level of the certified personnel which carried out the inspection of the failed steam pipelines by the United States Nuclear Regulatory Commission *NUREG* in accordance with the so-called round robin test (inter-laboratory verification of MI and measurement results performed by different inspectors) demonstrated an unacceptable accuracy spread between measurements of the same defects performed by one and the same

tool from one specialist to another, and from one group of inspectors to another, notwithstanding their legally identical qualification certification levels [62].

ILI inspection is not yet capable of providing ultimate solution to all the problems of safe PS operation. Statistics of real incidents on pipelines demonstrate that many accidents occur early on, or right after the “successful” inspection completion. This may be explained by the fact that even the state-of-the-art in-line (external) measurement tools often incorrectly detect (identify) or underestimate (overestimate) the sizes of the defect parameters. Analysis of accidents on the USA oil pipelines, which occurred soon after a successful inspection (within 3–12 months), performed by the US Department of Transportation in 2005, demonstrated that causes of these disasters were [63, 64]: omission of serious defects (51 %), underestimation of the defects sizes (32.4 %), and wrong identification (16.6 %). As a result, the potential danger of discovered defects severity is not always adequately recognized.

Hence, it is obvious that, when assessing severity of a defect, the consistency of this assessment depends on the accuracy of determining the values of its parameters. In this connection, the following should be provided by inspection vendors about the results of a specific PS: (1) probability of detecting defects; (2) probability of correct identification of the detected defects; and (3) accuracy of measurement of the defects parameters, or the ME of the used measurement tools.

Most common measurement instruments (MI) used in ILI of oil pipelines are magnetic tools. In modern high-resolution HRMFL tools the ME tolerance (with regard to measuring the depth of the “metal loss” type defects) normally corresponds to about 10 % wt of the pipe wall thickness at 80 % confidence interval (CI). For MFL tools with super high resolution, the ME equals 5 % wt at 80 % CI. In case of ultrasound type (UT) tools with high and super high resolution, the defect depth measurements demonstrate tolerance of 1.0 and 0.5 mm, respectively, at 95 % CI.

ILI accuracy is established by means of verification, i.e., by additional control (another, independent measurement). Currently, in practice only a small part of detected defects is subjected to verification. This procedure may involve the use of different tools: laser, UT, visual control, wall thickness, as well as welder universal template, etc. While comparing results of the original inspection and verification, it can be seen that, practically in all cases, the results of inspection, in addition to random ME, contain also constant (average and multiplicative) errors, which, to make calculations simpler, usually are neglected [65].

Existing approaches to inspection quality assessment are mostly based on mathematical models, which describe measurements as containing only random errors and neglecting systemic errors (the average and the multiplicative MI bias). Figure 2.1¹ shows the ratio of the depth of the verified corrosion defects to the depth of the same defects measured by the ILI tool. From Fig. 2.1 it is obvious that the true size of defects depth was severely underestimated: by half, on average ($\lambda_{cp} = 2$). From this it follows that for correct sizing of corrosion defects, it is necessary to take

¹Figure 2.1 is taken from the Proceedings of the OOO VNIIGAS Conference “Innovative potential of young scientists and specialists of OOO VNIIGAS,” 2015, vol. 1, p. 242.

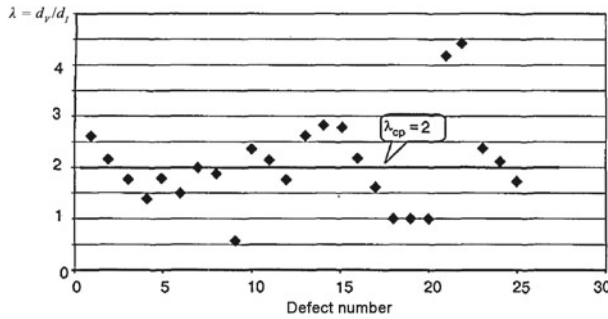


Fig. 2.1 Ratio of corrosion defects depth d_v , measured by local methods (verification) to the defects depth d_l , measured by ILI tool (russian gas pipeline “Urengoi–Surgut–Chelyabinsk–2”)

into account both systematic and random errors. This is possible only when using mathematical measurement models which account for both types of MEs.

For compensation of the MEs, which inevitably occur during any inspection, most of the standards and industry guidelines use certain permanent values (called tolerance). For instance, the “*Gasprom*” Standard [41] recommends, for ME compensation, adding 1 mm to the depth of each defect. In the industry standard [66] the defect parameters (depth, length, width) are multiplied by a correction coefficient, depending on defect type and the mathematical model of the used measurement tool. Apparently, these tolerances were assigned according to the results of statistical analysis of measurement obtained in laboratory conditions, or on the basis of statistical accuracy of the instrument. In reality, this tolerance (MI accuracy) changes each time when one and the same MI is used in different pipes, and when it is repaired or modified. If we were to add, according to [41], $c = 1$ mm to each measurement obtained during ILI inspection, then in case of overstating by the ILI tool of the defects depth, it would make them even deeper. This would have a negative effect, when assessing the pipeline state and result in premature and costly repairs.

In fact, the rate of depth growth a_d (assuming its linear) would not change, if corrected by adding tolerance to its value:

$$\frac{(d_L + c) - (d_P + c)}{t_L - t_P} = \frac{d_L - d_P}{t_L - t_P} = a_d,$$

where d_L , d_P are, correspondingly, the defect depth according to the latest and the second last inspection, respectively; $t_L - t_P$ is the time interval between inspections.

Indeed, already when using the simple criterion of the critical, “leak,” state of defect (defect depth equals 80 % of the pipe wall thickness wt), obtain

$$d(t) = d_L + c + a_d t,$$

$$t_{res} = \frac{0.8wt - d_L - c}{a_d} = \frac{wt - d_L}{a_d} - \frac{c}{a_d}.$$

Thus, the defect residual life according to the “leak” criterion t_{res} is reduced by c/a_d . According to the same “Gazprom” Standard [41], based on generalizing results of diagnostics of a set of pipelines transporting corrosive substances, it was found that after 15 years of their operation, the corrosion rate on the pipe inner surface reaches 0.253 mm/year, and on the outer surface CR is 0.206 mm/year, at a confidence probability of 90%. In other words, if 1 mm is added to the depth of each defect, the external defects residual life according to the “leak” criterion will be reduced by almost 5 years, and the residual life of internal defects will be 4 years shorter. When conducting calculations, the verification instrument (VI) is often considered as absolutely accurate and, on this basis, an assessment of the second measuring tool accuracy (presumed less accurate) is made. Assuming ideal VI (MEs are equal to zero) may result in that any MEs of VI can be attributed to the used ILI tool, which will lead to unjustified worsening of its quality assessment. This has to be taken into account when evaluating quality of the diagnostician or of an early diagnosis.

Thus, it should be acknowledged that existing methods of analyzing ILI results for obtaining estimates of the true values of detected defects sizes are insufficiently substantiated. Therefore, the degree of potential danger of defects is not always determined correctly, and may lead to contradictory results. This does not allow obtaining consistent estimates of integrity and probability of failure (reliability) of inspected objects.

In the past, the quality of used ILI tool was not subjected to detailed analysis. At present, important work is carried out to inter-calibrate the inspection tools being used, so as to obtain generalized characteristics of their operation in real-life conditions [64, 67–70]. The problem of optimal means and methods for detecting defects in pipelines is discussed in [65]. In a number of articles [49, 51, 52, 71] the current level of ILI accuracy is comprehensively reviewed. In [72, 73] one of the authors of this book suggested and substantiated a set of seven basic metrics of ILI tools quality (for details see Sect. 4.3). On their basis, it is possible to make more accurate estimates of POF, residual strength, and remaining life of pipelines, as well as assign optimal time of their next diagnostics.

Another problem consists in that the results of any ILI do not give the true number of actual defects. The set of defects detected by the used ILI tool contains, as a rule, a subset of false defects. This can have a serious negative impact on the accuracy of pipeline reliability assessment. Moreover, according to the full stochastic classification of pipe defects, based on the results of inspections (proposed, as far as we know, in 2002 [5]), the set of each type of defects, found in the ILI data, can be divided into four groups, namely true (correctly detected) defects, false (phantom) detects, falsely undetected (missed) defects, and correctly undetected defects (areas without defects). The first three of these four subsets are of the greatest interest because they directly affect the reliability of pipelines. However, even in the API Standard 1163 [74]

the probability of nondetection of defects was excluded from direct examination. Currently, among pipeline diagnosticians there exists a growing recognition that all three groups of defects—the true (correct detection), falsely detected, and falsely undetected defects—should be taken into account when evaluating pipeline POF [5]. Moreover, these three subsets of each type of defects, if known, allow estimating the actual number of each type of defects in the pipeline, through a certain correction procedure. One of the most effective methods for correcting probabilistic assessment of pipeline physical parameters is developed based on the Bayesian approach. It finds wide application in various fields of science and technology [1–4, 6, 75].

In this book, the authors propose methods of updating the true number of defects in a pipeline after ILI and subsequent verification of the ILI results by a second, independent, measurement tool.

2.4 Analysis of Existing Corrosion Degradation Models of Pipeline Systems

Corrosion is a spontaneous destruction process of metals as a result of environmental (including atmospheric) exposure, accompanied by energy release and diffusion of matter (entropy increase). The rate of corrosion is expressed via change of the material mass, depth of corroded pipe surface, formation of pittings, amount of corrosion products, change of pipe material tensile strength, yield strength, or its deformation.

By the early 1980s, a sufficiently full classification of corrosion models was developed [20]. As a result of studies [58, 60, 76–93], the following quantitative models were developed:

- empirical dependencies for assessing metal corrosion losses, taking into account up to four random parameters;
- random multiparameter corrosion regression models;
- mathematical multiparameter models with a large number of correction coefficients based on statistical representation of corrosion kinetics, without accounting for the duration of the corrosion process;
- models describing corrosion of metals (in different aggressive environments), using nomograms and table coefficients;
- cybernetic models with inner feedback in a corrosion pair, which permits prognosis of the corrosion process flow;
- specifically tailored mathematical models (for describing atmospheric corrosion, of aluminum, underground corrosion of steel in various types of soil, sea corrosion, etc.);
- mathematical models built on the basis of data about actual corrosion metal losses.

A large number of corrosion studies were conducted in the 1980s, based on laws of electrodynamics [20], and methods of electrochemical corrosion calculation were being developed [94].

Currently, a large number of mathematical models are available for describing the kinetics of steel corrosion process based on experimental data. These models could be grouped into five categories [20, 22, 76–78, 84, 87, 92, 93, 95–101]:

- models taking explicitly into account time, aggressive environment properties, metal properties, etc.;
- specifically tailored environmental corrosion models (atmospheric corrosion of different grades of steel, aluminum and aluminum alloys, sea corrosion of various materials, etc.);
- probabilistic models, developed using information from a limited number of tests, which may be extended on the whole general sample set, including analogs, which well correspond to the experimental data by certain criteria;
- models based on the study of actual corrosion metal losses for a specific case. Adequacy of these models to real-life processes depends on the available volume of experimental results;
- models, describing the corrosion process by certain types of functions [73, 76, 84, 92, 102–105].

Vast majority of these studies consider each defect separately. Using this approach for assessing pipeline segment reliability may produce misleading results. To correctly address this problem, it is necessary to consider simultaneously behavior of the whole set of defects on a given pipeline segment.

This book offers an overview of probabilistic methods used for describing corrosion of the whole set of defects detected on a given pipeline segment described as a Markov pure birth process. Using this approach in combination with random value models of other pipeline parameters allows calculating the conditional POF of a PS according to the leak criterion under the joint effect of operating pressure and active growth of pipe wall corrosion defects.

2.5 Analysis of Residual Strength of Main Pipelines Segments with Localized Corrosion Defects

One of the main reasons for PS destruction is decrease of their strength capacity due to the development of local defects in pipe wall. Most of these types of accidents occur due to surface-type defects. The term *surface-type defect of either external or internal pipe surfaces* refers to the following types of damages:

- corrosion caverns (general, spot, pit, rill corrosion, etc.);
- erosion wall thinning (due to the abrasive impact of small solid particles on the inner pipe wall surface, present in the transport flow);
- mechanical damage (dents, scuffing, nicks, etc.) inflicted during pipeline excavation;
- cracks (SCC, high-, and low-cycle fatigue cracks).

In addition to surface defects, technological defects (lamination, cracks, rolling laps, different metallurgical anomalies of pipe material, etc.) also may be dangerous, as well as various weld defects. Defects can also be classified as (1) longitudinal and (2) circumferential. In longitudinal defects their size along the pipeline axis is greater than their size across the pipe perimeter; it is vice versa for the circumferential defects. Residual strength assessment of the defective pipe segment depends both on the defect type and on its orientation relative to the pipeline axis. Classical deterministic methods of strength analysis [8, 21, 39, 106–111] are not suitable for obtaining a full solution of this problem. Assessment of pipeline structural reliability under this approach is performed on the basis of solving a deterministic strength problem, applied as a rule, to the most vulnerable defective pipe section [20]. In this case, the following strength analysis sequence is being used:

- detect most loaded pipeline system segments;
- determine forces and moments acting on the segments boundaries;
- study the stress–strain state (SSS) of linear pipeline segments using the girder- or strut-type finite elements, taking into account the already known force factors;
- conduct more comprehensive SSS analysis of the most critical segments, using shell-type and 3D-type finite elements;
- analyze the bearing capacity of the vulnerable pipeline segments using strength and destruction criteria.

On the one hand, in strength analysis advanced solid body mechanics methods and criteria are used, which adequately reflect fracture processes. On the other hand, to compensate for the random character of the loading, manufacturing, and operation errors, different safety factors are introduced, which, as a rule, are set in accordance with the pipelines design and operation experience. This resulted in certain discordance in the existing codes and methodologies when accounting for various factors, which affect structure weight and strength [20]. To eliminate this discordance it is necessary to account for the random nature of a multitude of factors, which contribute to pipeline structure operation and determine the random character of its loading and the level of stress and strain state under different operation modes.

Currently, the most internationally recognized methodology for assessing the residual strength of longitudinally oriented surface (external or internal) corrosion defects is the code developed by the American Society of Mechanical Engineers (ASME). The initial code, ASME B31G, was adopted as the US national standard [112] and, in simplified form, as the national standard of Canada [113]. Subsequently, the modification of this standard was developed, which is called B31Gmod [114]. In addition to the codes B31G and B31Gmod widely used methodologies are DNV [115], Battelle [116], and Shell-92 [117]. These methodologies are also used (with some modifications) for designing water mains, subsea pipelines, hydraulic systems of nuclear power plants NPP, ships, and aircrafts, as well as pulp transportation pipelines. Design of some specific PS is also based on codes [114, 115].

All the above practical methodologies [112, 114–117] are based both on theory and extensive experiment, conducted on real scale pipes. Their essence [118] is in that the design estimate of the burst (failure) pressure for pipeline defective cross

section is derived using formulas obtained from linear relationships of the theory of strength of materials, by introducing into them some empirical factors, which account for the physical nonlinearity of pipe material. Such factors, obtained from analysis of a large number of pipe segments, subjected to field tests, include the following:

- Folias factor—a coefficient, which connects defect parameters with pipe geometry;
- Flow stress, which is the stress required to create plastic strain in the pipe metal (effective yield strength). It accounts for the effect of metal strengthening under load.

For calculating the residual strength of a pipeline segment with longitudinally oriented defect, the B31G, B31Gmod, Shell92, and DNV codes use the semi-empirical criterion of plastic fracture equation in the form [119]

$$\sigma_h = \sigma_f \frac{A_0 - A}{A_0 - AM^{-1}} = \sigma_f \frac{1 - \frac{d}{wt}}{1 - \frac{d}{wt.M}}, \quad (2.1)$$

where σ_h are the hoop fracture stresses of pipeline segment with a single defect; σ_f are the yield stresses; $A_0 = l \cdot wt$ is the initial area of the longitudinal cross section of the damaged pipe segment, where l is the maximum length of the defect along the pipe axis, wt is the pipe wall thickness, $A = ld$ is the area of defect in the longitudinal cross section of the defective pipe segment, where d is the maximal defect depth; M is the Folias factor.

Criterion (2.1) describes the fracture stresses of a pipe under internal pressure caused by a longitudinally oriented defect. This criterion is based on the fracture of thin-walled cylindrical shells with a surface crack.

In high-pressure vessels (vessels, pipelines, etc.) an axial crack may develop. Hoop stresses acting across this crack and created by the pressure inside the pipeline are calculated by the Gadolin–Barlow formula [120, 121]:

$$\sigma_h = \frac{PD}{2wt}, \quad (2.2)$$

where P is the pipeline pressure and D is the pipeline outer diameter. For aboveground pipelines $P = P_{int}$, for underground pipelines— $P = P_{int} - P_{ext}$, where P_{int} is the inner pressure in a pipeline; P_{ext} is the external pipeline pressure; $P_{int} > P_{ext}$.

Crack propagation or destruction will occur when its opening (growth of the distance between crack faces) reaches a critical value (CCO). CCO is the critical crack opening at its tip, which is a plastic deformation parameter at the crack tip. According to Dugdale [122] (this is the most suitable scheme for pressure vessels and pipelines), the CCO is calculated by the formula [123]

$$CCO = \frac{8\sigma_f^2 l}{\pi E} \ln \left[\sec \left(\frac{\pi \sigma}{2\sigma_f} \right) \right], \quad (2.3)$$

where E is the elastic modulus, which characterizes the material resistance to tensile (compression) stress under elastic strain; l is the crack half length; and σ_f is the rupture stress.

Stress intensity factor K_I (SIF) is related to CCO by the formula

$$CCO = \frac{K_I^2}{E\sigma_f}. \quad (2.4)$$

SIF is the stress singularity measure around the crack tip used for describing stress fields near the crack tip.

Substituting σ with $M_h\sigma_h$, from Eqs. (2.3) and (2.4) obtain that SIF is calculated by the following formula [123]:

$$K_I^2 = \frac{8\sigma_f^2 l}{\pi} \ln \left[\sec \left(\frac{\pi M_h \sigma_h}{2\sigma_f} \right) \right], \quad (2.5)$$

where M_h is the stress intensity growth factor.

Factor M_h accounts for the experimentally observed fact of crack faces buckling outward under pressure.

It may be expected that fracture will take place at $K_I = K_{Ic}$, where K_{Ic} is the fracture toughness of the material, which describes the material ability to resist the beginning of crack movement and propagation under mechanical and other types of impact.

Using the formula (2.5), it may be shown that at high values of $\frac{K_I^2 \pi}{8\sigma_f^2 l}$ the value of expression $\frac{M_h \sigma_h}{\sigma_f}$ approaches unity [123]. In these cases, destruction is independent of fracture toughness, and the fracture criterion takes the form [123]

$$\sigma_h = \sigma_f M_h = \sigma_f \frac{1 - \frac{d}{wt}}{1 - \frac{d}{wt \cdot M}}. \quad (2.6)$$

where M is the Folias factor.

According to this criterion, fracture occurs when the general yield occurs, or a bit later [123]. The general yield means that the body acquires the property of unlimited plastic deformation, i.e., deformations increase significantly without any increase of external loading.

Relatively recently (2000) on the basis of studies conducted in the Battelle Institute, of the fracture mechanism for actual pipes, the PCORRC (Battelle) methodology was developed [116]. Under this methodology, for high resilience pipe steels, unlike in expression (2.1), the equation for determining the hoop stresses, arising as a result of a defective pipeline segment destruction, has the form

$$\sigma_h = \sigma_f \left(1 - \frac{d}{wt} M \right). \quad (2.7)$$

When assessing the influence of other loads on the hoop and axial stresses, e.g., high temperatures, soil movement, or seismic activity, their detailed modeling is required. In these cases it is advisable to use the finite element method [124–127].

Substituting into the formula (2.6) the expression for hoop stress (2.2), it is possible to determine the failure pressure of a defective pipeline segment at time t :

$$P_f(t) = \frac{2wt \cdot \sigma_f}{D} \frac{\left(1 - \frac{d(t)}{wt}\right)}{\left(1 - \frac{d(t)}{wt \cdot M(t)}\right)}. \quad (2.8)$$

The expression (2.8) for evaluating failure pressures in each of the codes (B31G, B31Gmod, Shell92, or DNV) is different, depending on the expressions used for the Folias factor M , flow stress σ_f , and on how geometric shape of the defect is approximated. For the PCORRC code the expression for failure pressures is obtained from (2.7) taking into account (2.2).

Expressions for calculating the Folias factors were obtained by analyzing hydrostatic testing results of a large number of main pipelines with corrosion defects [118].

According to [120], all methods are classified as the SMYS-based and the UTS-based, where SMYS and UTS are specified minimum yield strength and ultimate tensile strength of the pipe material, respectively. UTS-based methods use the ultimate tensile strength of pipe material to define destruction of the pipeline defective cross section.

The described above codes can be applied only to a single cross section of the pipeline containing a longitudinally oriented, flat bottom surface defect of the corrosion/erosion type. The methodologies are based on the assumption that the defective pipe segment failure occurs as a result of plastic fracture [120].

We consider each methodology in detail.

B31G code [112]. In this methodology a surface defect in the longitudinal (axial) section of a defective pipe segment is approximated by a parabolic form (see Fig. 2.2) and the effective defect area (highlighted in gray) in this section is calculated as $\frac{2}{3}d \cdot l$.

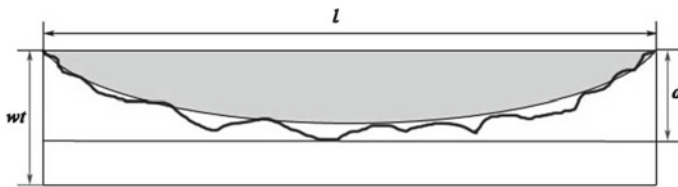


Fig. 2.2 Parabolic approximation of the surface defect in the pipeline longitudinal cross section, according to B31G code

The Folias factor is calculated by the formula

$$M_1(t) = \sqrt{1 + 0.893 \frac{l^2(t)}{D \cdot wt}}. \quad (2.9)$$

The flow stress $\sigma_f = 1.1SMYS$.

The formula for failure pressure of a pipeline segment with a surface longitudinally oriented corrosion/erosion type defect has the form

$$P_f(t) = \frac{2wt \cdot 1.1SMYS}{D} \cdot \frac{\left(1 - \frac{2}{3} \frac{d(t)}{wt}\right)}{\left(1 - \frac{2}{3} \frac{d(t)}{wt \cdot M_1(t)}\right)}. \quad (2.10)$$

Maximal admissible length of defect with depth $d(t)$ is calculated by the formula

$$l_{\max}(t) = 1.12B(t) \sqrt{D \cdot wt},$$

where parameter $B(t)$ equals

$$B(t) = \sqrt{\left(\frac{d(t)/wt}{1.1d(t)/wt - 0.15}\right)^2 - 1}.$$

Formula (2.10) applies to defects which length $l \leq 4.48\sqrt{D \cdot wt}$. For longer defects ($l > 4.48\sqrt{D \cdot wt}$) the fracture pressure is determined by the formula

$$P_f(t) = \frac{2wt \cdot 1.1SMYS}{D} \cdot \left(1 - \frac{d(t)}{wt}\right). \quad (2.11)$$

The code is applicable only to pipes, which material class is below the X56 API 5L standard [128] (i.e., SMYS and UTS are less than, respectively, 386 and 489 MPa). The defects depth must be within the (10–80 %) range of pipe wall thickness.

This code should be applied only to

- a single cross section of the pipeline containing a longitudinally oriented, flat bottom surface defect of the corrosion/erosion type;
- pipes, which material class is below the X56 API 5L standard [128] (i.e., SMYS and UTS are less than, respectively, 386 and 489 MPa);
- defects which depth is within the 10–80 % range of pipe wall thickness.

B31Gmod code [114]. Modification of B31G code consists in the change of expressions for flow stress, Folias factor, and the estimated parabolic form of defect (factor $2/3$ in formula 2.10) is replaced with an arbitrary one. For this purpose a correction factor of 0.85 is introduced.

The Folias factor is calculated by the formula

$$M_2 = \begin{cases} \sqrt{1 + \frac{62.75 \cdot 10^{-2} l^2(t)}{D \cdot wt} - \frac{33.75 \cdot 10^{-4} l^4(t)}{(D \cdot wt)^2}}, & \frac{l^2(t)}{D \cdot wt} \leq 50, \\ \frac{3.20 \cdot 10^{-2} l^2(t)}{D \cdot wt} + 3.3, & \frac{l^2(t)}{D \cdot wt} > 50. \end{cases} \quad (2.12)$$

The flow stress $\sigma_s = SMYS + 68.95 \text{ MPa} (10 \text{ ksi})$.

Failure pressure for a pipeline segment with a longitudinally oriented defect of the corrosion/erosion type is calculated by the formula

$$P_f(t) = \frac{2wt(SMYS + 68.95 \text{ MPa})}{D} \frac{\left(1 - \frac{0.85d(t)}{wt}\right)}{\left(1 - \frac{0.85d(t)}{wt \cdot M_2(t)}\right)}. \quad (2.13)$$

This criterion uses a more accurate expression for the Folias factor than the code B31G, and is less conservative [120].

The restrictions of this code as compared to applicability of the B31G code have one difference: the defects depth can reach 85 % of pipe wall thickness.

DNV code [115]. Unlike the B31G and B31Gmod codes, the DNV methodology takes into account other loading conditions, including the compressive axial loads. This code is a result of a joint industrial project of “Det Norske Veritas” (Norway) and “BG Technology” (Canada). These companies have created a vast database of real-life pipe samples subjected to rupture tests, with a single corrosion defect and several interacting corrosion defects of irregular shape. Alongside with these experimental data, a large number of three-dimensional nonlinear finite element pipe models were built, which were subsequently verified with experimental data, the results of which have been used for developing this criterion [120].

In this approach the defect is approximated by a rectangular form (Fig. 2.3) and the area of surface damage in the axial pipeline cross section is calculated as $d \cdot l$.

The Folias factor is calculated by the formula

$$M_3(t) = \sqrt{1 + 0.31 \frac{l^2(t)}{D \cdot wt}}. \quad (2.14)$$

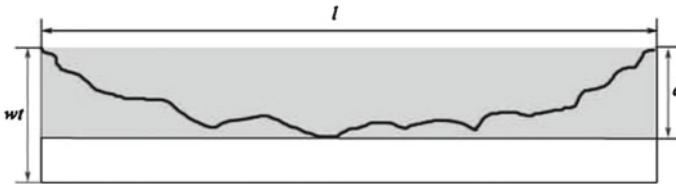


Fig. 2.3 Rectangular shape approximation of a surface defect in the longitudinal cross section of the pipeline, according to DNV methodology

The flow stress is equal to UTS.

A formula for failure pressure of a pipeline segment with longitudinally oriented surface defect of the corrosion/erosion type has the form

$$P_f(t) = \frac{2wt \cdot UTS}{D - wt} \frac{\left(1 - \frac{d(t)}{wt}\right)}{\left(1 - \frac{d(t)}{wt \cdot M_3(t)}\right)}. \quad (2.15)$$

This code should be applied only to

- single cross section of the pipeline containing a longitudinally oriented, flat bottom surface defect of the corrosion/erosion type;
- defects which depth is less than 85 % of pipe wall thickness.

Shell92 code [117]. As in the case of DNV code, the defect is approximated by a rectangular form (see Fig. 2.3).

The Folias factor is calculated by the formula

$$M_4(t) = \sqrt{1 + 0.805 \frac{l^2(t)}{D \cdot wt}}. \quad (2.16)$$

The flow stress in this code is equal to $0.9UTS$.

A formula for failure pressure calculation of a pipeline segment with a surface longitudinally oriented defect of the corrosion/erosion type has the form

$$P_f(t) = \frac{2wt \cdot 0.9UTS}{D} \frac{\left(1 - \frac{d(t)}{wt}\right)}{\left(1 - \frac{d(t)}{wt \cdot M_4(t)}\right)}. \quad (2.17)$$

This code should be applied only to

- single cross section of the pipeline containing a longitudinally oriented, flat bottom surface defect of the corrosion/erosion type;
- defects which depth is less than 85 % of pipe wall thickness.

PCORRC (Battelle) code [116]. PCORRC methodology was developed on the basis of studying the mechanism of destruction of pipes, material of which has improved or high fracture toughness, and on the high-precision modeling of the finite element pipe models performed at the “Battelle” Institute [129]. According to field test results of a large number of actual pipe segments, the destruction mechanism for defective pipeline segment depends on the pipe material fracture toughness. These tests also showed [120] that only pipes made out of steel with improved or high fracture toughness fail a result of plastic fracture. In determining the Folias factor the effect of increased stress concentration and steel hardening in the plastic deformation zone at the start of the defect failure process was taken into account.

According to PCORRC, the failure pressure for a pipeline segment with a longitudinally oriented defect of the corrosion/erosion type is calculated by the formula

$$P_f(t) = \frac{2wt \cdot UTS}{D} \cdot \left(1 - \frac{d(t)}{wt} M_5(t)\right), \quad (2.18)$$

where the Folias factor is calculated by the formula

$$M_5(t) = 1 - \exp \left[-0.16 \frac{l(t)}{\sqrt{\frac{D}{2} (wt - d(t))}} \right]. \quad (2.19)$$

This code should be applied only to

- a single cross section of the pipeline containing a longitudinally oriented, flat bottom surface defect of the corrosion/erosion type;
- pipelines, which operate at temperatures exceeding the temperature of pipe material ductile–brittle transition, and for pipe material with the impact energy of Charpy 61 J and above [116].

2.6 Assessment of Pipeline Systems Reliability

A lot of attention is being paid worldwide to the problem of improving pipeline systems structural and operational reliabilities [17, 20, 21, 28, 43, 106, 130–148].

All methods of reliability assessment of thin-walled cylindrical shell systems (pipelines) may be classified as methods based on the RVs theory and the theory of various types of random functions (RF) or fields. Methods based on RV theory are more common. These, in their turn, may be broken down into methods, which reduce the plethora of probability density functions PDFs, used to describe the random parameters, to the Gaussian normal law, and to methods which operate directly with non-Gaussian PDFs. The former methods go back historically to the works of Freudenthal, N.S. Streletskyand, and A.R. Rzhantsyn.

A universal, but practically unrealizable, straight forward method for solving high dimensionality reliability problems is the method of direct n-fold integration of a n-dimensional joint PDF of parameters, which describe the condition of a structure, over an admissible domain in the space of the design parameters. Even for a relatively small value of n and irregular complex shape of the admissible region, the computational complexity of integration becomes insurmountable.

Formulation of reliability problems based on theory of RF is more correct than the quasi-static (based on RV theory). However, its solution requires knowledge of the correlation functions or spectral density functions of the loading process, by which the structure condition parameters are described, and its capacity is calculated.

The *mainstream approach* to structural reliability problems using the RV theory started after the well-known work of A. Freudenthal [149] when all the random “input” parameters of the problem were normalized, using specific mathematical methods. This normalization is done by transforming all non-Gaussian PDFs into “equivalent”

Gaussian PDFs using various mathematical transformations which, obviously, add some unknown errors into the final result. At the same time, physical interpretation of the problem becomes difficult and its transparency is lost immediately. The next step in solving this problem is constructing the limit state surface (SLS) in the space of multidimensional normalized parameters, which in itself is a nontrivial mathematical problem. SLS may be a linear or nonlinear multidimensional surface. In the latter case it is linearized. Then the minimum distance from the origin of coordinates to the limit state surface is found which, in its turn, requires application of various, quite complex optimization procedures. If the number of the problems parameters is larger than three, the problem becomes hard to visualize and, in addition, requires multiple solutions, to make sure that a global, not local, minimum was found. This minimal distance from the origin to SLS would be the system reliability factor, and is expressed in a number of standards. The linearized reliability assessment algorithm received an abbreviation FORM (First-order reliability method), FOSM (First-order second moment), and the nonlinear algorithm is known as SORM (Second-order reliability method). From the description of this approach, it can be seen that it uses sophisticated mathematical methods with unverified accuracy of results, which is hard to visualize. It should also be noted that up to now no methods existed which would, theoretically, give absolutely correct POF assessments.

A practical method of reliability assessment should have the following traits: it should allow accounting for a large number (>5) of RVs in the nonlinear limit state equation, be physically transparent, algorithmically relatively simple and reasonably fast, and produce verifiable and defensible results. In this context, the FORM methods are not suitable as they do not account for the nonlinearity of the limit state function and give only rough reliability estimates. The SORM methods do account for the nonlinearity, but are quite algorithmically complex, especially when a large number of RVs have to be taken into consideration, and physically not transparent, because they involve a sequence of complex mathematical procedures, each of which takes the problem farther away from physical reality. The results are also hard to verify, because the algorithm involves an optimization procedure which seeks the minimal distance of the design point from the origin in a multidimensional nonlinear space. The problem may have several minima and it is not clear, whether the optimization procedure found the actual "*minimum minimorum*" [150]. For real-life cases this method is also very computer time consuming and not quite fit for producing mass calculations.

In this context, research along the way using direct identical transformations of the actual PDF, which reflect real essence of this or that parameter [2, 5, 10, 20, 22, 151], became an alternative to the above method.

It should be noted, however, that the maturity of both described approaches is yet insufficient for confident practical assessment of the complex systems reliability. A reason for this is the lack of methods, algorithms, and programs which would allow direct accounting for a large number of random parameters ($>6-7$), which is a must for obtaining accurate reliability and probability of failure assessments of real-life large-scale mechanical systems.

The second approach to pipelines reliability assessment based on the RF theory employed representation of a force impact on a pipe in the form of differentiable stationary (homogeneous) Gaussian functions of time (V.V. Bolotin, B.P. Makarov, V.P. Chirkov, G.Kh. Murkhazanov et al.) which, however, inadequately describe the actual impact on the pipe with the exception of, probably, operating pressure fluctuations. Use of this load and impact representation requires availability of a significant volume of input information, which may be obtained only on the basis of continuous monitoring of the structure. The contemporary state of the problem is characterized by the deficit of statistical data about load parameters changing in time. In addition, this kind of representation of loads does not permit evaluation of the probability of exceeding low levels of loads, which is necessary for solving the reliability problem under a combination of vector loads applied to a pipe. At the same time the problem about combination of loads is the basic one.

In [144] a method to solve this kind of problem is proposed, by representing loads as Markov processes of birth and death (discrete states, continuous time), and diffusion Markov processes. This kind of description allows getting an ultimate solution of the problem of combination of loads on a designed mechanical system in the space of loads and impacts.

Pipeline material properties (tensile strength and yield strength of both the main pipe material and the weld) have been long time recognized as random values. Processing of a large volume of statistical data on steels, produced by metallurgical plants worldwide, demonstrates that the distributions of the said parameters are very well described by a normal law [20]. In practice, normal distribution is the most commonly used. This is explained primarily by the fact that it is the simplest and most convenient distribution allowing using in calculations the table values of normal PDF and its integral.

This book presents an updated version of the well-known method of reliability assessment based on expansion of the limit state distribution function in Gram–Charlier–Edgeworth series, as applied to a defective pipeline segment with defects. It is normalized in a way that the expansion is a genuine PDF, and has the ability to account for the nonlinearity of the limit state function (LSF) and for avoiding negative probability values in the tail areas of non-Gaussian distributions (which sometimes takes place).

This allows accounting for any required number of LSF moments and for the majority of cases. The proposed method accounts for the random nature of pipeline parameters, defects, and loads. G–C–E expansion is built on the first four LSF distribution moments. For the initial data (pipe parameters, defects size, load, and mechanical properties of material) various PDFs are used: uniform, normal, logarithmically normal, exponential, Weibull or Rayleigh, which allow satisfactory description of, practically, any statistical data encountered in practice.

As was mentioned before, one of the main causes of pipeline systems failure is the existence of a large number of actively growing defects of various types. A classic approach of structural reliability theory—representation of a system in the form of connected in series elements [10] (defective cross sections)—is poorly applicable in real life. When this calculation approach is used, the probability of

faultless operation of the whole system equals to the product of faultless operation probabilities of all its elements. Reliability parameters of this type of system are lower than the respective parameters of its elements, and with the growth of the number of elements (defects) there is a dramatic decrease of the system reliability. If the number of elements m of the system is significant, it becomes practically impossible to build a system with the required (high) reliability factor. For instance, if m is significant, it becomes practically impossible to build a system with the required (high) reliability factor. For instance, at $m = 10^3$ and assuming each element reliability $P_0 = 0.9999$ (probability of failure equals 10^{-4}), reliability of the whole system would equal $P = 0.9999^{1000} \approx 0.91$, then the whole system POF equals $0.089 > 10^{-4}$. Hence, the average life time of such a system is 103 times shorter than the average life time of each element. The main cause of this is that in the chain model all defects are involved in the POF calculation and essentially influence its value. But, in distributed pipeline systems not all the defects present are capable of creating an input into its POF.

To account for this circumstance it was suggested to take into consideration only “significant” defects which can actually affect the system reliability. At the same time there are no recommendations on to how to select the “significant” defects. Practically, to select from the entire set of defects, those which possess this quality, it is necessary to perform fairly complex calculations.

In this book PS degradation—decrease of its residual strength (failure pressure) is described by a nonhomogeneous Markov pure death process, and corrosion defects growth—by a Markov pure birth process, both with a discrete number of states and continuous time. This allowed studying joint behavior of a large number of actively growing defects in a pipeline as in a *distributed system* and eliminating the deficiency of the classic structural reliability theory approach.

Description of corrosion defects growth detected in a pipeline segment, and the degradation (residual strength decrease) of this segment by Markov pure birth and pure death processes, respectively, allowed determining the conditional probabilities of its failure by the leak and the burst criteria under combined action of operating pressure and active growth of the pipe wall defects. This approach makes it possible to calculate the optimal time for the next inspection or maintenance of a defective pipe segment.

An approach to mechanical systems reliability assessment using the random processes theory based on representing loads as Markov processes of birth and death (discrete states, continuous time) and diffusion Markov processes (continuous states, continuous time) was proposed in 1978–1979 by S.A. Timashev [144] and applied for assessing reliability of frames and shell systems under a combination of random loads.

Markov chains are used in [152] for describing cumulative damage in the form of fatigue cracks and wear in structures and its elements, using the so-called B-models. In [153] and [119] the theory of Markov models was applied to assess the state of high-pressure pipelines. In [153] the growth of corrosion pittings is considered as a Markov chain. In [119] a Markov chain in the form of the Yule model was chosen for consideration because it is the simplest model, which operates with only one transition intensity.

However, Markov processes (with a discrete number of states and continuous time) are more universal and adequately describe the true state of thin-walled pipeline systems. Markov processes are described by systems of differential equations and do not depend on the nature of objects and their physical properties. In this sense, they are universal and are widely and successfully used in various fields of science and technology: nuclear physics, biology, astronomy, queueing theory, reliability theory, etc. [10, 144, 152, 154–157]. Unlike Markov chains, they permit assessment of the probability of finding the system in each of the states and the intensity of transition from one state to another at any time.

Examination of literature shows [158–161] that there are no studies on the construction of such Markov models as a pure birth (death) Markov process which describes the degradation of the bearing capacity of a distributed system with a finite set of discrete defects. In order to use these processes, the transition probabilities must not depend on the past, and the sojourn time for a process to be in any particular state should be exponentially distributed. Multiple empirical studies show [158–161] that both conditions take place in most types of technical systems, including pipelines. Assessment of reliability of such systems usually is based on an exponential distribution of pipeline defective cross sections uptime, and does not depend on the previous time of safe operation.

2.7 Reliability Level Embedded in Pipeline Design Codes

Two main principles are currently used for structural design: the operating-stress design method and the limit state method. The operating-stress design (OSD) method [162] is based on the rule that the dimensions of structural elements are defined subject to the condition that the operating stresses in them should not exceed allowable stresses, understood as a certain portion of the material tensile strength limit. The ratio of tensile strength to allowable stress is called a safety factor. The assigned values of this factor did not have sufficient scientific background. In addition, the allowable stresses themselves make sense only when assuming proportionality between the active load and stresses right up to destruction, which, as is known, takes place only on rare occasions [162]. In pipeline design codes [112, 114–117] the OSD method is used [43].

The Russian code [163, 164] prescribes that pipeline design be done using the limit state method [5, 43, 162, 165]. The limit state method is a modern method for designing civil engineering structures, which belongs to the group of semi-probability methods, since it relies on statistical methods for justification of the selected codified safety factors using quantiles of a certain level. A distinctive feature of the limit state method as compared to the operating-stress design method, apart from its universality, is the introduction of several limit states, which limit operation of the structure, and a new system of design factors (overload, homogeneity, and operation conditions), instead of a single safety factor [162].

Three types of limit states are distinguished:

1. *bearing capacity limit state* (strength and stability of structures, material fatigue), upon reaching of which the structure or its element loses ability to further resist the external impact, or accumulates such residual deformation, which makes its further operation impossible;
2. *excessive deformations limit state* of structures under static and dynamic loads, upon reaching of which a structure, otherwise maintaining strength and stability, is not able to continue to operate safely, due to appearance of excessive deformations or vibrations;
3. *crack formation or crack opening limit state*. Upon appearance and opening of cracks in a structure (which maintains its strength and stability) to the extent, which makes its further operation impossible/impractical, due to loss of the required tightness/integrity, danger of corrosion, or the lining damage.

The root idea and the final goal of structural design using the limit state method is obtaining sufficient guarantees that over the period of the structure operation none of the inadmissible limit states will occur, either for the structure as a whole or for its individual elements.

The ability of reaching any of the structure limit states depends on many factors, the most important of which are the following:

- external loads and impacts;
- quality and mechanical properties of structure materials;
- general conditions of manufacturing, operating the structure, etc.

The main pipelines limit state design method was originally developed by the “VNIIST” team of research engineers *I.P. Petrov, A.G. Kamerstein, V.S. Turkin*, et al. Main pipelines design codes [164] are based on this methodology. The essence of the method is consideration of such a stress and strain state of a pipeline which makes its further operation impossible.

According to [164], the pipeline-bearing capacity is characterized by the ultimate tensile strength of pipe metal. To ensure safe pipeline operation, when defining the value of the design strength, several partial reliability factors are introduced: reliability factor for pipe material, reliability factor for pipe operation conditions, and safety factor which takes into account the pipeline purpose of existence.

In [164] the first limit state is written in the form of an equation in which the tensile hoop and tensile axial longitudinal stresses are equaled to the design pipe material strength. For the case of tensile/compressive stress state the equivalent stresses are equal to the design strength.

To limit plastic deformations in the pipeline, the second limit state is provided. This state is expressed via stresses in the most stressed point of the pipe section, which are defined from all characteristic loads and impacts (taking into account their combinations). A criterion of reaching the second limit state is the condition under which the hoop and tensile axial stresses, or the equivalent stresses, are equal to the pipe metal yield strength. Standard [164] does not account for the presence of various

types of defects in operating pipelines, and all calculations are performed for ideal pipes without defects

Industry guidelines and companies' standards [30, 41, 166–168], which have, in fact, only status of recommendations, are just interpretations and some modifications of the method [114]. In these standards certain safety factors were changed, or additional ones introduced, as a reflection of pipelines construction and operation specifics. A comparative analysis of main pipelines design methods according to codes of different countries is provided in [162].

From the moment of the first introduction of codes [112, 114–117], in the early 1980s and to this day, their development was and still is focused exclusively on experimental updating of their empirical parameters and factors. However, the underlying basis of all “modified” design formulas is the criterion of plastic fracture (2.1) and the formula (2.2), which expresses the dependence of hoop stress in a linear elastic thin-walled cylindrical shell of ideal shape on the inner pressure [120, 121].

Deterministic methods for calculating residual strength of pipeline segments [112, 114–117] do not account for the random nature of pipeline geometry (wall thickness, diameter, and possible dent sizes), properties of the pipe material (yield and ultimate strength), loads and impacts (changes of operating pressure), the presence of a significant number of stochastically growing in time defects of various natures, and uncertainty of their dimensions because of the ME made during pipeline inspection. The main purpose of these methods is to provide a design tool which would be as simple as possible and require minimum amount of input data for calculation.

To compensate for the random nature of loading, pipeline geometry, material properties, as well as errors during construction, and operation of pipelines, the developers of various semi-empirical methodologies introduce large safety coefficients. In the course of practical application of these methods, this (often excessive) conservatism becomes obvious, when they lead to severely underestimated failure pressure values, which, in their own right, lead to over rejection of defective pipeline segments, significant reconstruction-related material costs, and a substantial decrease of the pipeline transportation capacity. However, this conservatism of methods [112, 114] does not make them less used. JSC “*Gasprom*,” while using [30, 41, 168, 169], in order to account for national specifics, on the contrary, introduced additional safety factors into the design expressions of method [114].

Comparison of calculation results obtained for the modified criteria [114], with the actual field tests data gleaned from pipelines with corrosion defects, indicates that the methodology [114] is excessively conservative. This was repeatedly noted by specialists involved in the operation of commercial PS and employing method [114] (and the like) for assessing residual strength of the defective segments.

Thus, comparison of the hydro-testing data of 92 corrosion affected segments of the “*TNG*” (Argentina) with the results of calculations using modified criteria [114] shows that the experimental burst pressure values, in practically all cases, were 1.3–1.7 times higher than the estimated ones [118]. According to the data of JSC “*Orenburg Gasprom*” [170], analysis of failed pipes damaged by corrosion demonstrated that the actual burst pressure was, on average, 1.2–1.5 times higher than the design pressure calculated using the modified criteria [114].

Thus the deterministic criteria do not account for many factors contributing to the PS POF probability of failure (reliability) value. To eliminate this problem it is necessary to use probabilistic models, which account for the random nature of their parameters and loading.

However, in this case another problem appears. The regulatory documents used in various industries and countries for the highly critical structures, including oil pipelines, establish quite low admissible failure probability (emergency situations) values: for accident with disastrous consequences— 10^{-6} , for major (critical) accidents— 10^{-4} – 10^{-6} . When the probability of failure is low, it is necessary to evaluate the real reliability level which is embedded in the PS design methods. The calculated in such a way probabilities may be interpreted as some analogs of safety factors initially built into the design methodology, and more informative than the strength factor in a deterministic formulation.

It is also important to know how sensitive are the design codes for pipelines with defects to the random nature of certain parameters covered by these methodologies. Such parameters are pipeline geometry parameters (web thickness and diameter), properties of the pipe material (yield and ultimate strength), loading (operating pressure), and the defect parameters (depth and length). This type of analysis allows understanding which of the parameters of a pipeline system with defects are the most critical for its reliability. The reliability embedded into the design of a pipeline with a single defect was studied in [171].

2.8 Entropy of Degrading Pipeline Systems

Any information about a physical/engineering system (machine, apparatus, structure, or infrastructure) is complex and usually contains sets of different types of data about the object. If monitoring and/or diagnostics of such a system is conducted, its operator receives, continuously or intermittently, reports on its current condition. The data being received would be meaningful only if the current state of the system is not known in advance. This is the case for engineering systems, which are subjected to different forces and influences of random nature, and are comprised of materials which change their physical properties over time in a stochastic manner. Therefore, its physical state is randomly changing over time.

Consider an engineering system (say, a pipeline), which is continuously monitored, and the information about the current state of the system and its elements and components is fed to a decision maker (DM). Obviously, the utility of the gleaned information is more valuable for the DM, the greater is the uncertainty of the current system state. Here a natural question arises: What does “more” or “less” of uncertainty degree mean, and how it can be measured?

In physics and the probability theory a specific measure of uncertainty is used, namely the *entropy* [108, 153, 172–177].

Entropy (from ancient Greek “turn,” “transformation”) in science in general is a measure of disorder of a system consisting of numerous elements. Entropy is one of

the most important concepts of physics. The word “entropy” was first used in 1864 by Rudolf Clausius in his book “Abhandlungen Fiber die Warmetheorie” (“Works on the Theory of Heat”) as a notation of the quantity that characterizes the process of converting thermal energy into mechanical energy.

In 1877 Ludwig Boltzmann established a relationship between entropy and probability of the system being in a particular state. Later, this relationship was utilized in the Max Planck formula (postulate). Albert Einstein called it the Boltzmann’s principle, and with it the statistical mechanics began. Boltzmann’s principle allowed going beyond the equilibrium of thermodynamics and statistical physics, into other areas of science, including information theory.

Shannon continued and developed the principles of Boltzmann statistical thermodynamics and in his works used entropy as an index of uncertainty in information theory [176, 178], assuming that an increment of information equals the lost uncertainty value. Therefore, the amount of acquired information may be measured by the quantity of lost uncertainty, i.e., entropy.

Shannon’s definition of entropy was related to the notion of thermodynamic entropy. There is a relationship between the thermodynamics and the information entropy—a profound similarity of mathematical tools of these two fields up to complete identity of formulas (e.g., for discrete random values entropy). Application of the information entropy concept in various fields of knowledge and technology proved to be quite effective.

The research potential of entropy concept is far from being exhausted by the existing applications. In perspective, the entropy approach may be taken up by a new scientific research discipline—synergetics, which focuses on the study of the regularities of the formation and disintegration of space-time structures in systems of various types: physical, chemical, biological, economical, social, etc. [174].

In [179] a problem of using entropy for studying large structural systems is discussed. However, so far there are practically no studies on the quantitative use of the concept of entropy for analyzing processes of degradation of machines, equipment, and structures.

This book describes an example of practical application of the entropy concept as an integral index of structural damage of structures, with pipelines chosen as a meaningful example. This approach may be used for the study of other structures’ and machines’ behavior.

2.9 Prediction of Fracture and Assessment of Pipelines State Subjected to SCC

A significant part of worldwide main gas pipelines is located in the waterlogged soil environment. This contributes to stress corrosion cracking which is a serious problem for the gas industry [180–183]. worldwide. SCC-type defects are characterized by the presence of spots, consisting of hundreds of surface longitudinal cracks, which

may merge, forming extended surface defects [180, 183]. A typical defect length to depth ratio of a SC crack is 50–200 [184]. An environment responsible for SCC is most often a carbonate–bicarbonate solution [180].

Identification and characterization of corrosion damage areas is performed with the use of various nondestructive control methods. If, as a result of inspection, a SCC-type defect is detected, it is necessary to evaluate its effect on the remaining life of a pipeline in order to define priority actions required to maintain its integrity (continue operation, conduct repair, or replacement of a defective segment) [184].

Surface defect depth is usually approximated by a semi-ellipse. In the case when there is a series of defect depth sizes along its length, the corresponding (effective) defect area is determined in the longitudinal cross section of the pipeline. The worst defect is approximated by an equivalent semi-ellipse [60, 184]. In the absence of these data the maximum depth and length of a defect are considered. Frequent pipeline failures under the SCC conditions give evidence of the need to develop a failure model, which may be used for assessing safety and integrity of pipelines operation.

The main scheme of prognosis and assessment of pipelines state under SCC conditions has been discussed in [184, 185]. The following main stages are identified:

- determine geometric parameters of a corrosion defect (its initial size);
- select the failure criterion;
- conduct prognosis of the defect critical size, which will cause pipe failure;
- calculate the remaining life of a pipeline segment by accounting for the stress corrosion defect growth.

In this book, a solution is described of evaluating remaining life of a pipe segment with longitudinally oriented external stress corrosion crack, subjected to cyclical load impact. An algorithm is proposed to assess the remaining life of a pipeline with SCC-type cracks by the crack growth criterion, using nonlinear failure mechanics. Examples are provided of calculations for a main pipeline segment with a single (maximal) and multiple SCC-type cracks, taking into account their interaction. Application of the more efficient (as compared to the statistical testing Monte Carlo method) adaptive important sampling method for assessing reliability of pipelines with SCC-type cracks is demonstrated, including an algorithm for updating reliability of a pipeline segment under the SCC conditions for three different outcomes of the segment inspection.

An updating algorithm is proposed, which employs a Bayesian network for assessing pipeline reliability and the distribution characteristics of its random parameters, taking into account new information (received as a result of inspection) of pipe condition and its individual segments. Cases of series and parallel connections of pipe segments are studied.

2.10 Predictive Maintenance of Pipeline Systems with Defects

Maintenance is a combination of organizational and technical actions taken for maintaining operability and integrity of a pipeline (as an element of a complex system) in the process of its operation, including monitoring of its state, risk management, etc.

The main principles of critical systems maintenance aimed at ensuring their safety and integrity are described in [144, 186–188].

According to the proactive maintenance principle for potentially hazardous assets and structures, including pipelines, the category of “conditional limit states” may cover conditions, realization of which does not necessarily require cessation of their operation/use for intended purpose or their decommissioning. The so-called “warning” and “critical” failures do not lead to accidents, since they are conditional failures, and are introduced out of various engineering considerations, only to fixate the moment of occurrence of some specific states of an object, which “trigger” certain maintenance actions, necessary for keeping the system in operational condition (e.g., diagnostics, repair, operating pressure relief, etc.). When reaching these states, the operability of a structure is not compromised. However, future operation of the object may involve a significant increase of the risk of real failure occurrence.

These states serve as the “levels,” which trigger some actions, aimed at renewal of the object, or at preserving the current condition of the asset. These levels are then optimized by solving the problem of multilevel policy control of infrastructure failure probability. Defining the time of occurrence of these conditional failures is the key for ensuring safety and integrity of PS operation.

Significant attention is being paid to the problem of calculating PS remaining life before a critical or limit state occurred [4, 10, 108, 145, 169].

The remaining life is a *conditional random time* of transition of a pipeline segment from the current state into a critical or limit state. RL is a random value, since it is dependent on many random parameters, and is based on a multitude of constraints and rules introduced into the operational characteristics of a pipeline.

Knowledge of the remaining time till the occurrence of a certain warning, critical, or limit state allows optimization of PS maintenance and repair costs, without creating unjustified risks for its integrity, and making informed management decisions about selection of a critical or limit state criterion to be used in a particular situation.

Analysis of industry standards, as well as literature on the subject, revealed that in practice in a majority of cases the RL assessment is based on two deterministic failure criteria: “leak” and “rupture,” and the shortest remaining life time is selected. Time of reaching the critical state by a “leak” criterion is defined as the time required for a defect under the estimated corrosion rate to reach the depth of 60, 70, or 80 % of the pipe wall thickness (depending on the code used). Semi-empirical codes [112], B31Gmod [114], Shell92 [117], DNV [115], and PCORRC [116] are used, as a rule, for evaluating residual strength (burst pressure).

Obviously, when assessing the pipeline RL, possible types of conditional failures must be taken into account, which would allow predicting, with sufficient accuracy, full evolution of the PS state, up to the moment of its physical failure.

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Chapter 3

Basics of ILI of Pipelines

3.1 A Brief History of Creation and the Current State of Art of Smart ILI Technology

In-line inspection tools are used for one or more of the following reasons:

- pipeline cleaning;
- change of the transported product (batching);
- scheduled or unscheduled (e.g., in case of pipeline movement as a result of accident) inspection (diagnostics) of the pipeline state.

Historically, the very first ILI tools were simple cleaning scrapers in the form of solid rawhide balls. They appeared in the nineteenth century when it became necessary to clean the first in the history of pipeline industry oil pipeline built in Pennsylvania (USA), clogged in the process of operation. They became known as “pigs” because when such scraper traveled underground; people heard a sound resembling a pig’s squeal, which was a result of friction of the scraper against the pipe wall. And even though the superstitious Mexicans hearing this sound referred to it as “diabolo” (devil in Spanish) it was the original name that stuck. There is another explanation of the name as an abbreviation of expression *Pipeline Inspection Gauge*, which means a “sensor (gauge) for pipeline inspection.” In the course of time when the ILI tool functions became more sophisticated they were nicknamed “intelligent pig,” i.e., intelligent in-line inspection gauge (tool).

The first attempts of collecting information about a pipeline condition/state with the help of ILI tool go back to 1959, when an American firm, *T.D. Williamson*, began using a borehole geometry tool (caliper) for detecting dents in a pipe wall, and “*Pan-American Petroleum*” developed a tool based on registration of a magnetic flux leakage (MFL) induced in a pipe as a result of its magnetization, under the name “*Cooley Tool*.” *Tuboscope Co.* developed a tool that could detect defects in down-hole casings and the pipeline companies were asking for a pipeline version of the tool. Simultaneously, Shell Oil Research was developing a technique for detecting pittings

in down-hole casings which worked on the remote field eddy current principle, which became known under the name “*MacLean Tool*.” In 1962, *Tuboscope* obtained a license for the *MacLean tool* and started developing an intelligent pig on its basis. However, its tests failed, as the tool could not detect known pits even in test spools [1].

Tuboscope then approached *Pan-American Petroleum* and purchased the *Cooley Tool* patent, on the basis of which it developed the first ILI MFL tool, known today as the “*Linalog*.” The first commercial job for the *Linalog* tool was for *Shell* in 1965. At that time the tool had only four sensors and could inspect only the bottom 90° of the pipeline. Nor did it have a distance measuring wheel (odometer) which would measure a distance passed by a tool inside the pipe. Location of the pig was identified by placing permanent magnets directly on the pipe for which purpose it had to be excavated. The moment of the pig’s passing was detected by a coil on the drive unit of the pig.

From the early beginnings and to this day all intelligent pig developments were driven by the request of pipeline companies or a country, across the territory of which a new pipeline was laid [1].

Thus, in the early 1970s, intelligent pigs were first used in pipelines for detecting corrosion and deformation. In those days, one of the conditions for the Trans-Alaska oil pipeline construction was the requirement of the United States Department of the Interior (Federal Agency in charge of primary pipeline construction supervision) to develop a pipeline deformation monitoring system. This requirement was included as one of the terms into the contract for land allocation for the pipeline, because of possible sagging of hot pipes in the permafrost area containing a significant amount of unstable ice in the melting conditions. Under this contract an in-line tool for detecting pipe curvature was developed under the name “*Superpig*,” which was a three-segment ILI tool 4.27 m long and weighing 2,250 kg. The central sensor section had 16 wheels contacting with the pipe via spring arms. Pipe curvature was detected by the difference between the distances passed by the wheels. Several pig runs were made, but its use was stopped after the tool stuck in a valve cavity and had to be extracted in parts.

At the same time pipeline companies approached *Tuboscope* asking to deliver a tool that could inspect the full 360° circumference of the pipe. In response to this request *Tuboscope* developed in 1966 a prototype of such tool for a 10 in. (254 mm) diameter pipe. Next year, in 1967 a 24 in. (601 mm) diameter tool was undergoing test loop trials.

Early inspection pigs were delivering to pipeline operators data that enabled them to target their maintenance more effectively. At that time printed circuit boards were relatively unsophisticated, and rare earth magnets were not yet available. The indications recorded by the pigs were transferred from the on-board data recorders to a roll of ultraviolet-sensitive paper. The findings were displayed as blips on a trace and often did not give an indication unless the metal loss was great. They gave the PS operators some, not quite reliable information about the location of detective pipeline segments where they should dig.

In the 1970s, *British Gas* invited all inspection companies to test their equipment at a test loop, built for that very purpose. All the tools that were tested were low-resolution tools and would only give a “low—medium—severe” indication of any

feature found in the pipeline, which did not allow engineers to make a quantitative assessment of the defects' severity. After that, *British Gas* decided it should develop its own high-resolution pigs. The project started in 1974. First a 24 in. (601 mm) diameter, 12-channel analog prototype tool was built. Its testing did not satisfy the company, and it started developing high-accuracy high-resolution pigs with high sensor density (ten sensors per every pipe inch diameter) and high sampling frequency (each 3.3 mm of pig travel). The high volume of data generated could not be recorded onto analog tape; therefore a move to a new digital technology of recording, transfer, and storage of data was needed. The first runs with 60-channel digital recorders and data registration on 25 mm tape at 4–8 mm/s frequency were a difficult task, since the recorders themselves had to be precision built and meticulously maintained [2].

At this time, when the high-resolution technology was in its infancy, the costs associated with design and construction of intelligent pigs were sky high and the focus was on ensuring the pigs produced accurate and consistent repeatable results. This was essential if the data gathered, and the subsequent reports generated were to be used with confidence when calculating residual strength of pipelines with defects, and making fitness-for-purpose and integrity assessments.

By the 1980s the first intelligent ILI tools were built, which were successfully used by the *British Gas* network of pipelines. Once the ILI tools reached this stage of development, the next stage was to develop and refine the defects sizing algorithms. Magnetic pigs could not directly measure the defects parameters; they could only calculate their sizes by registering the disturbances, caused by a defect in the magnetic field around the ILI tool sensor(s). After that, using sophisticated software (including neuron net algorithms) assessment was performed of the metal loss percentage and defect sizing.

In 1984 in Germany the “*Pipetronics*” company was established, which developed the first intelligent pig based on the well-established by that time ultrasound technique and with an array of UT probes on its board. Unlike the MFL, the UT was capable of taking direct measurements of the defects parameters and pipe wall thickness, earning the reputation of a more accurate tool than the MFL tools. However, the UT tool needs a liquid medium to transmit the signal from the UT sensor to the inspected object. UT tool was convenient for use in oil pipelines, but for using in gas pipelines it had to be placed within a liquid slug, which made using this type of inspection significantly more expensive.

Further development of the in-line inspection technology continued in the direction of improving all components of the ILI tool: more accurate detection of the type and number of defects, their location and sizes. Standard MFL type ILI tools were capable of detecting both general and local pipe wall corrosion, down to small diameter pittings. However, they were practically incapable of detecting axial narrow corrosion defects in plant welds and the SCC type cracks (which are particularly dangerous for gas pipelines). To solve this problem, ILI tools using circumferential magnetic flux leakage technique were developed. This type of tool had some limited success, usually only in areas where the cracking was relatively severe. That is why ultrasonic tools have been developed, which used a technique, whereby ultrasound waves were fired into the pipe wall steel at an angle, to propagate them full circle

around the pipe. These tools have proved to be very successful in detecting longitudinal cracks, but were still limited in usage, as they still needed a liquid medium to operate in.

In 1974, at the UK *Harwell Atomic Energy Research Establishment* an UT tool was developed, which did not require a liquid medium. It also worked on the principle of firing the ultrasound wave into the pipe wall, but used for this an angled UT probe, which was carried inside a liquid-filled wheel with a polyurethane tyre, traveling along the pipe. The system was known as the “*Elastic Wave*.” These pigs were notoriously difficult to maintain and expensive to run [2].

The latest development in the quest to address this problem is the so-called electromagnetic acoustic transducer (EMAT). Though this technology is quite new, most major inspection companies are already offering EMAT type tools for pipeline inspection.

The advancements of the electronics technology were followed by a rapid growth in computing power and miniaturization of the data storage devices, with simultaneous exponential growth of their capacity. The cost of a digital recorder system capable to store up to several thousand gigabytes of data is no longer \$US 100,000 per unit, but fell down to only several hundreds of US dollars today. Similarly, though the data processing systems are still custom designed and built, they no longer cost around \$US 1 million, as before. This has enabled a large number of small companies without huge financial means, to enter the market, offering pipeline Operators a choice of new various purpose ILI tools.

Alongside the ongoing development of computer and electronic technologies, the ILI tools have also improved significantly in terms of accuracy and detection capability of such anomalies as cracks. Today’s market offers a wide range of tools which accuracy and reliability vary, depending on a particular tool, pipeline condition, and type of defects to be inspected.

Another, very important innovation area is the development of more advanced software for ILI data analysis. Instead of paper reports, inspection companies now offer software which allows pipeline engineers to digitally process the data obtained during inspection. Today quality of the report is becoming one of the most crucial parts of the inspection contract, since it is, after all, the end product for which the client is paying.

Most of the recent innovations in the ILI area are focused on solutions for “*unpiggable*” pipelines, i.e., pipelines which cannot be inspected by standard ILI tools. This type of “unpiggable” pipelines may operate at high pressures, or have segments with tight bend radii, varying diameters along the their length, have only one point of entry (for example, as for a tanker loading line), lack of launch and receive traps, etc. Solutions for this type of pipelines inspection include robotic tractor units, tethered and autonomous, with ability to control the speed of their travel inside the pipe. The inspection modules employ a variety of technologies: magnetic, MFL, or remote eddy current, ultrasound (time of flight or transverse), and even visual, using cameras and laser light sources. It is reported that for the piggable pipelines ultrahigh accuracy magnetic tools are developed using the subminiature triaxe Hall sensors,

manufactured using latest achievements of nanotechnology, which allows placing up to 1080 plus sensors around the tool perimeter (high-density sensor assembly).

Currently following companies are the major global ILI service providers (listed in the order of their respective weight): “*Rosen*,” “*BJ Services Company*,” “*GE-PII*,” “*T.D. Williamson*” (MFL and EMAT tools, calipers), “*NDT Systems & Services*” (UT technique), “*Applus NDT & Inspection*” (laser outer pipe surface scanning).

3.2 ILI Tools

The main goal of PS control and inspection is the assessment and prediction of its technical condition using comprehensive monitoring to ensure safe and reliable pipeline operation.

The pipeline industry employs for inspection purposes both destructive and non-destructive types of control. Destructive types of control include sample tests for assessing mechanical properties of pipe material, and hydrotests of individual pipes or pipeline segments for assessing their overall strength and leak-tightness parameters. The destructive types of control are performed, as a rule, during commissioning the pipeline and when investigating accidents.

The nondestructive types of control allow inspecting structure’s quality without compromising its operability, and are used for detecting such defects as material discontinuity; geometry imperfections; or for assessing physical and chemical properties of pipe materials. This type of control is based on obtaining data in the form of electrical, light, sound, and other types of signals about the quality of objects being inspected, when they interact with physical fields (electrical, magnetic, acoustic, etc.).

PS inspection during its operation is performed by special type high accuracy measurement tools, which utilize one of the nondestructive ND control methods, and are designed for detecting, locating and sizing defects, measuring pipeline geometry and its specific parameters. Such instruments are:

- magnetic tools;
- ultrasound tools;
- eddy current (electromagnetic) tools;
- electromagnetic–acoustic tools;
- calipers (caliper tools).

Pipeline defects are a potential hazard to its integrity, since they may cause leak or rupture type accidents. Therefore, the ability to detect and assess the sizes of various defects (anomalies) of pipe walls at the earliest possible stages of their development and propagation (while they are still in the stable growth phase) is very important for ensuring safe operation of PS.

In-line inspection tools allow detection of such pipe defects as dents, flattenings, wrinkles, general inner diameter changes, ovality, and the like deviations from design sizes, as well as pipe wall defects, related to corrosion and erosion, change of their thickness, laminations, cracks, etc.

Currently, ILI is a standard procedure of collecting data about a pipeline, needed for assessing its integrity and fitness-for-purpose. Main task of ILI is providing accurate information about the length, width, depth, orientation, and location of pipeline defects. The validity of measurements directly depends on correct choice of tools and their accuracy. The ILI tools have their respective strengths and weaknesses. This should be taken into consideration when selecting of a particular MI for assessing defects parameters.

Depending on the type of pipe wall damage, various ILI tools are used for inspection. In general, metal loss defects caused by internal or external corrosion may be detected by MFL or UT inspection pigs. Cracks and laminations may be detected with varying degrees of confidence by magnetic, ultrasound, or eddy current tools. Such mechanical defects as dents, scuffing and warpings may be detected by caliper pigs, MFL or UT tools. Movement of the pipe centerline is best detected by inertial navigation units additionally fitted onto the ILI tool. Control over deformations and the stress state of individual pipeline segments under complex operational conditions (e.g., in case of sagging and upheaval in permafrost, at water crossings, in regions with high seismic activity, etc.) can be done using acoustic emission method and extensometry.

We now discuss briefly the main ILI tools. Historically, two techniques of nondestructive control used for ILI became predominant—the magnetic and the ultrasound technologies. Each has its own specifics and spheres of application.

Magnetic tools. The principle of a magnetic tool operation is based on registering the magnetic flux leakage, which originates in the location of a pipe wall defect, as a result of its magnetization. As the MFL tool travels along the pipeline, it creates, by its constant magnets, a strong magnetic field inside the pipe wall. The sensors, located between the magnet poles, register the magnetic field changes, and measure its values. The magnetic flux leakage is registered by the flux field Hall detectors. They are installed on elastic holders, which can move relative to the tool body, thus following the actual pipeline geometry. The sensors scan the inner surface of a pipeline, and their readings are converted into electric signals, registered by the ILI tool. The principle of MFL registration in a pipeline is shown in Fig. 3.1.

Three types of sensors are used in magnetic pigs. Most common are the so-called type I sensors, which serve for detecting pipeline parameters and detection of “metal loss” and “girth weld anomaly” type defects. The sensors are electromagnetic coils. In pipes with constant (nominal) wall thickness magnetic flux leakage outside the pipe surface does not occur and the sensors do not register any signals. In a defect zone the constant magnetic flux induced by the MFL tool magnets is distorted and the sensor reacts to a magnetic flux leakage, which allows measuring the size and shape of the discovered defect.

Type II sensors placed in a weak, local magnetic field (which penetrates only the surface layer of metal) are used for detecting pipe surface areas (internal or external) which contain the defect. The principle of their operation is similar to type I sensors.

Type III sensors are used for measuring the absolute magnetic flux values on the inner surface of a pipeline. Their readings are used for calculating pipe wall thickness. These sensors also utilize the Hall effect.

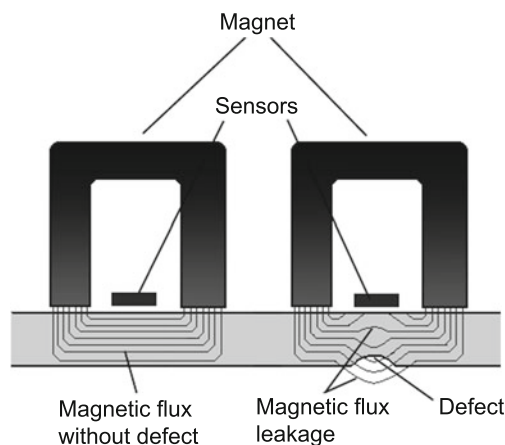


Fig. 3.1 The principle of magnetic flux leakage registration

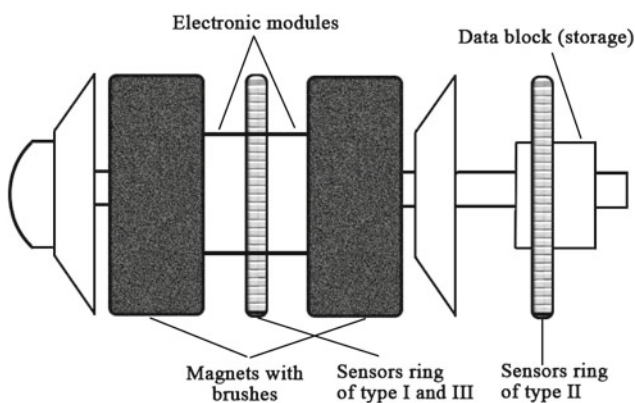


Fig. 3.2 Principal schematic of a MFL ILI tool

The principal diagram of a magnetic tool is shown in Fig. 3.2. Magnetization of the pipeline wall to full saturation is achieved by powerful magnets located on the ILI tool front section. The magnetic flux closure on the pipe wall is achieved via flexible magnetic conduits made, as a rule, in the form of steel brushes. The first sensor ring, located between the magnet's poles, is formed by type I and type III sensors. Most of them are high-resolution type I sensors. The last ILI tool section is centered at the pipe's center with the help of brushes (magnetic conduits) and the supporting wheels, located on the tool perimeter and pressed to pipe wall with springs. In front of and behind this section there are sealing rings made out of wear-resistant polyurethane. These sealing rings in addition to participating in ILI tool center alignment and ensuring the required leak-tightness also create the necessary pressure drop which propels the tool in the direction of liquid or gas flow. In the

second section of a MFL tool contains a type II sensors ring. This section contains the data collection and processing system and batteries.

Referencing of the defects location to particular points of the pipeline route is done with the help of markers. A MFL tool has an on-board data registration system, which includes a real-time meter. The on-board time of a ILI tool is set before each run and is synchronized with the reference points system tools—the magloggers. A maglogger is an above ground portable tool placed in advance at reference points of the pipeline route. The magloggers react to a pig's magnetic field and register the time of its passage of this particular point. This is needed for future geo-referencing of the in-line inspection data. After completion of a pig run, the information from magloggers is copied on a computer and the location of the defects is determined.

Modern high resolution MFL tools are capable of detecting both metal loss defects and defects in welds, but, as a rule, do not detect axial narrow corrosion defects (cracks, corrosion, nicks). For such defects detection the transverse MFL (TMFL) pigs have been developed. These tools use superhigh-resolution sensors. A distinctive feature of the TMFL is that their magnetic flux is oriented perpendicular to a longitudinally oriented defect (Fig. 3.3). Examples of MFL and TMFL magnetic pigs are shown in Fig. 3.4.

High and superhigh-resolution magnetic tools are capable of detecting following pipeline defects and anomalies:

- geometrical defects (including those, which are adjacent to welds, or are in them);
- geometrical defects in combination with metal loss;
- metal loss (pitting-type and continuous);

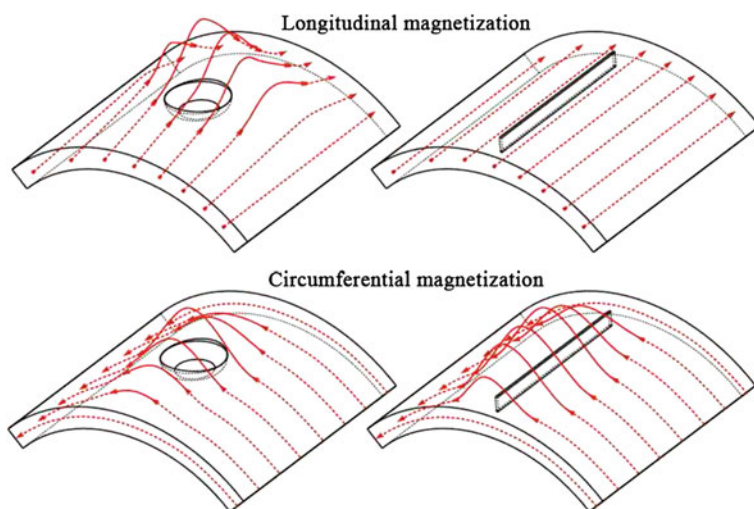


Fig. 3.3 Principal schematic of the longitudinal and transverse magnetization of pipe wall (image taken from the website: <http://www.spetsneftegaz.ru>)



Fig. 3.4 Magnetic tools (image taken from the website: <http://www.spetsneftegaz.ru>) **a** MFL tool. **b** TMFL tool

- nicks, scratches, scuffing (transversely oriented—by a MFL tool, lengthwise oriented—by a TMFL);
- cracks in the pipe body or in a weld (laterally oriented—by a MFL tool, longitudinally oriented—by a TMFL tool);
- laminations which manifest themselves on the inside or the outside pipe wall surface;
- girth weld defects;
- girth weld shift;
- metallurgical defects;
- changes in the nominal wall thickness;
- pipeline valves and fittings (including tees, wyes, latches, bends, anodes, linear compensation inserts, external pipe supports, points of the ferromagnetic type cathodic protection);
- inadmissible maintenance and repair methods of structures.

Restricted capability of the magnetic tools to saturate the pipe wall with a magnetic field sets a constraint on the maximum wall thickness which could be effectively diagnosed by MFL tools. The inspection results may also be influenced by the pipe material properties and their fluctuations along the pipe length.

Tables 3.1, 3.2 and 3.3 [1] show typical capabilities of ILI MFL tools for detecting and sizing defects.

Ultrasound tools. A physical basis of the UT nondestructive control technique (NDT) is the ability of the ultrasound wave to reflect from interfaces of media with different specific acoustic resistances. Ultrasound waves are generated by special sensors. The most common type of sensors used in UT pigs is the so-called piezoelectric sensor, which converts due to piezoelectric effect, the electric oscillations

Table 3.1 Specifications of typical magnetic tools when sizing corrosion defects

Parameter	Standard resolution	High resolution
Minimum detectable defect depth	20 % <i>wt</i>	10 % <i>wt</i>
At 80 % confidence interval		
Accuracy of defect depth measurement (tolerance)	$\pm 15\%$ <i>wt</i>	$\pm 10\%$ <i>wt</i>
Accuracy of defect length measurement	± 13 mm	± 10 mm
Measurement accuracy of defect location along the pipe axis	± 0.1 m	± 0.1 m
Measurement accuracy of defect circumferential location	$\pm 30^\circ$	$\pm 5^\circ$

Notation *wt* is the pipe wall thickness

Table 3.2 Capability of MFL tools to detect different types of defects

Parameter	Standard resolution	High resolution	Ultra high resolution
Pitting corrosion	Good	Excellent	Excellent
General corrosion	Excellent	Excellent	Excellent
Mechanical damage	Poor	Satisfactory	Satisfactory

Notation Excellent—95 %, good—85 %, satisfactory—70 %, poor—<70 %

Table 3.3 Typical magnetic tools capability to measure different types of defects

Parameter	Standard resolution	High resolution	Ultra high resolution
Pitting corrosion	Poor	Good	Good
General corrosion	Satisfactory	Good	Good
Mechanical damage	Poorly	Poor	Poor

Notation Good— $\pm 20\%$ at 80 % confidence interval, satisfactory—depending on the defect depth

into the acoustic ones and vice versa. The sensors (converters) are placed on a flexible holder, which ensures a fixed distance (standoff) between their emitting surface and the inner surface of a pipeline. The ultrasound sensors operate according to the immersion principle, which requires that the space between the sensor and the pipe surface to be filled with a liquid medium (water, oil, oil products). Hence, most of the UT pigs may operate only in the presence of liquid medium in a pipeline.

Depending on the type of defects the ultrasound sensors are mounted in a pig's holder either perpendicular or at a certain angle to the pipeline surface. This predetermined existence of two types of UT pigs: WM—wall thickness measurement tool and CD—Crack Detection tool.

The UT WM type tool operation is based on measuring the passage time of the ultrasonic signal reflected from the inner and the outer pipe wall. Figure 3.5 shows the principle of this type of UT pig operation while measuring the local pipe wall thickness. This technique may also be used for detecting and sizing of the “metal loss” type defects.

Review the operating principle of these tools. Ultrasound sensors are mounted on holders perpendicular to the pipe wall. When the sensor generates an ultrasound signal,

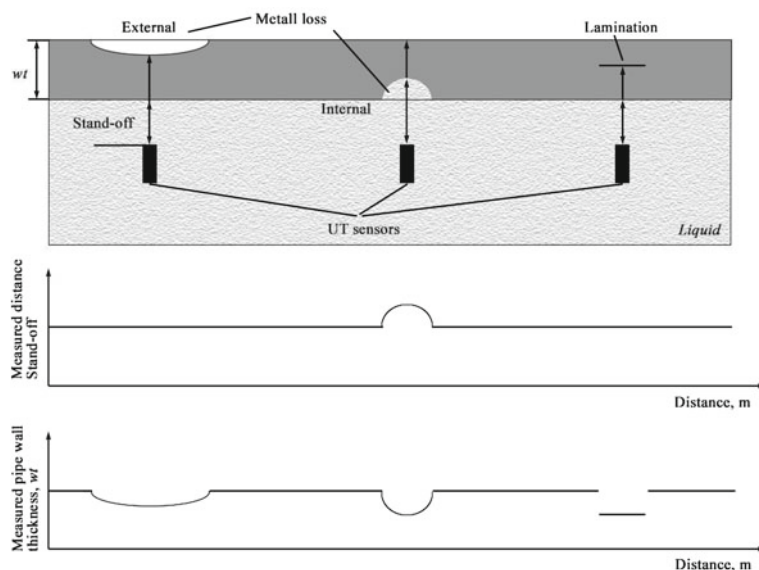


Fig. 3.5 Operating principle of the UT WM tool

it is reflected first from the inner and then from the outer wall of the pipe. Reflected signals are registered by an ultrasound sensor. Hence, the ultrasound sensors operate in an echo-pulse mode, i.e., they are simultaneously transmitters (generators) and receivers of acoustic waves (receive the echo-signals reflected from the defects). The time interval between the sent and the first reflected signal (at a known speed of ultrasound propagation in a specific liquid medium) is converted into a distance from the sensor to the inner surface of a pipe wall (standoff). The time interval between the first and the second reflected signals is converted into a pipe wall thickness. A lag between the time of transmission and receipt of a reflected signal is achieved by pulsating sensor signals. In case of external corrosion the time of the signal passage inside the pipe wall decreases, which allows obtaining metal loss quantification. In case of inner corrosion the time of signal passage in the liquid medium increases. Ultrasound tools allow direct measurement of local pipeline wall thicknesses, which are used for assessing the residual strength of a defective pipe segment.

The constraints and the capabilities of typical UT WM tools are listed in Tables 3.4 and 3.5 [1].

Ultrasound WM type ILI tools are capable of detecting following defects and pipeline structural parameters [3]:

- geometrical defects (including those, which are adjacent to welds, or are in them);
- geometrical defects in combination with metal loss;
- metal loss (pitting-type and continuous);
- laminations, including those, which manifest themselves on the inside or the outside pipe wall surface;

Table 3.4 Specifications of typical UT WM tools when measuring defects parameters

Parameter	Specification (mm)
Accuracy of defect depth measurement (tolerance)	± 0.5
Measurement accuracy of pipe wall thickness and flat surface defects depth	± 0.2
Accuracy of defect length measurement	± 3.0
Minimum detectable defect depth	0.2

Table 3.5 Typical UT WM tools capability to detect different types of defects

Parameter	Standard resolution
Pitting corrosion	Satisfactory
General corrosion	Excellent
Dents	Excellent

Notation Excellent—95 %, satisfactory—70 %

- nicks, scratches, scuffing, snatching;
- girth weld shift;
- metallurgical defects;
- variations in welded pipes thickness;
- inadmissible structural elements, maintenance structures and repair methods.

An UT type pig is shown in Fig. 3.6.

Ultrasound WM type ILI tools, due to their operation mode can, as a rule, detect only the longitudinally oriented defects.

Currently, ultrasound technique is a reliable and affordable method for detecting and sizing longitudinal and transverse stress-corrosion cracks in pipe walls, including

**Fig. 3.6** UT WM tool (image taken from the website: <http://www.spetsneftgaz.ru>)

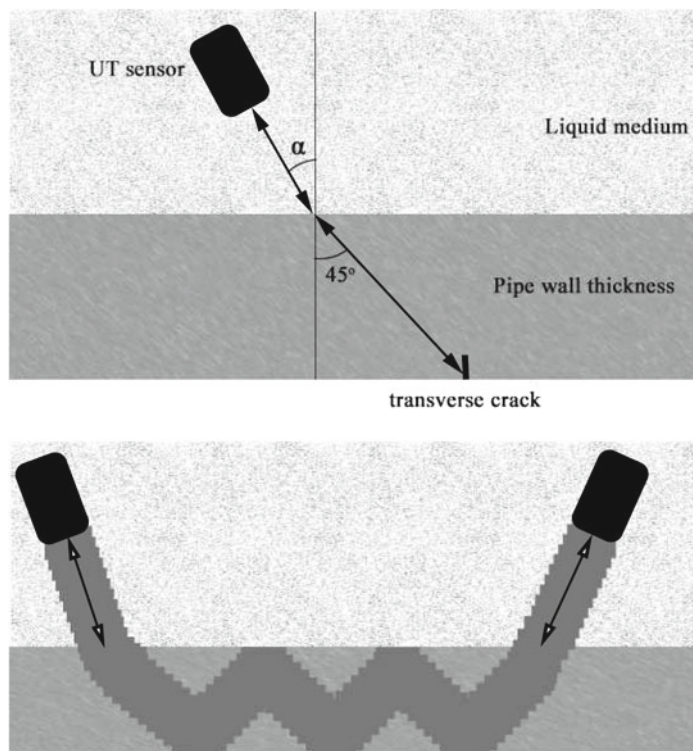


Fig. 3.7 Operating principle of UT CD tool

cracks in welds, as well as lack of fusion defects. Figure 3.7 shows the principle of operation of the CD type UT pig for cracks detection. Control of defects oriented perpendicular to a pipe wall, and defects in welds, is performed using converters mounted at an angle to the radial pipe surface. The operation principle of this type of sensors is based on registering and measuring the amplitude of signals reflected from the cracks and the time intervals between the sent impulse and the impulse reflected from the inner pipeline wall and the crack. The ultrasound wave, emitted by a sensor, enters the metal at a certain angle to the pipe surface (depending on the type of oil pumped, the entry angle varies from 15° to 21°). The sensor angle is chosen so that the ultrasound beam propagation angle inside the pipe wall is set at 45° to its surface (Fig. 3.7). Signals reflected from a crack are received by the same sensor. Capabilities of this type of UT pigs are shown in Table 3.6 [1].

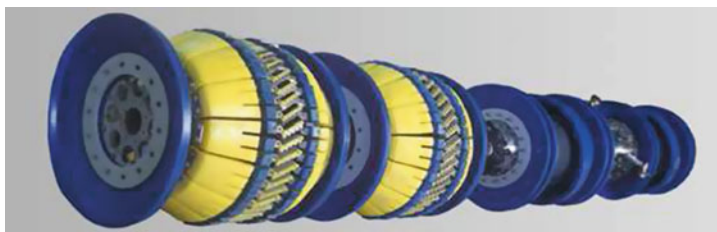
The CD type ILI UT tools can detect following defects [3]:

- geometrical defects (including those, which are adjacent to welds, or are in them);
- nicks, scratches, scuffing;
- cracks and crack-like defects;
- stress-corrosion cracking;

Table 3.6 Typical UT WM tools capability to detect different types of defects

Parameter	Standard resolution
Pitting corrosion	Excellent
General corrosion	Good
Dents	Satisfactory

Notation Excellent—95 %, good—85 %, satisfactory—70 %

**Fig. 3.8** UT CD tool (image taken from the website: <http://pss.weatherford.ru>)

- weld defects;
- transverse and axial welds displacements;
- laminations (in-wall and surfacing);
- surface defects (nonhomogeneous surfaces).

CD type pig is shown in Fig. 3.8.

Ultrasound pigs are sensitive to alien media inside the pipeline or on its walls. This is particularly related to paraffins and asphaltic resin deposits. Therefore, to successfully use ultrasound tools, it is necessary to thoroughly clean the pipeline before the pig run. Use of ultrasound inspection tools on pipes with inner lining and protected welds is inefficient, since in this case there is an additional scattering and absorption of the ultrasound signal on the inner lining, which reduces measurements accuracy. In this case MFL tools would produce better results. Magnetic fields do not scatter on the inner lining, which allows for registration of magnetic flux leakage in the presence of defects.

EMA tools. Unlike magnetic tools, the UT pigs require a liquid medium for their operation, which makes them unsuitable for inspection of gas pipelines, or pipelines transporting two-phase liquids. This problem is addressed by a relatively new and currently actively developed ILI tool, which uses piezoelectric sensors instead of the ultrasound sensors. It employs the electromagnetic–acoustic method of excitation and receiving UT oscillations, which makes it possible to perform measurements *without the liquid medium or cleaning the inspected surface via an air gap or nonconducting coating* (paint, varnish, film). This EMA method is based on applying strong alternating magnetic fields to a metal surface. Ultrasound oscillations in a metal body of the pipe are being excited and received in a contact-free mode by the EMA converters.

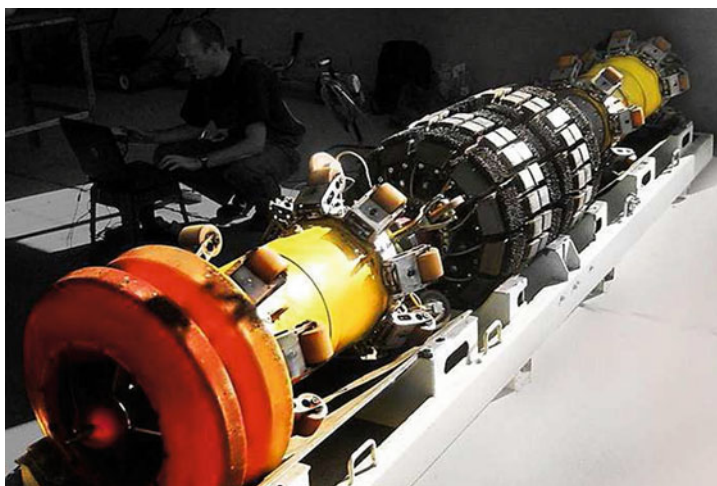


Fig. 3.9 The EMAT tool with converters (image taken from the website: <http://www.spetsneftegaz.ru>)

The principle of EMA tool operation is based on the impulse-echo method of measurement using the property of ultrasound oscillations to reflect from surfaces, which divide mediums with different acoustic resistances. Excitation of the ultrasound oscillations is generated by interaction between the eddy currents, induced on the conducting material surface by an EMA converter coil, upon receiving a current impulse of the UT frequency, and the magnetic field of this converter. The EMA converter creates a directed impulse by combining the Lorentz force and the magnetostriction effect. A surge current is passed via the induction coil which is placed in a magnetic field. As a result, certain forces are generated. At sufficiently short impulses the acoustic wave will propagate within the pipe wall limits. The receiver action is oriented in the direction, opposite to the transmitter, therefore the acoustic wave interacts with the converter and generates a measurable electric impulse. An example of the EMA type tool is shown in Fig. 3.9.

The nondestructive ultrasound inspection technique has been used for many years for various control and inspection tasks. The main advantage of this technique is the possibility to make quantitative measurements of higher accuracy. Normally, the threshold values of UT measurements of a metal loss or crack depth are set at 1 mm. The declared accuracy of the latest generation UT tools for the pipe wall thickness and the defect depth measurements is about ± 0.2 –0.5 mm.

Unlike the magnetic pigs, the UT tools are not limited by any maximum pipe wall thickness, but such limit exists for a minimum value. They cannot be used on pipelines with wall thickness less than 4 mm, or on small diameter pipes (< 150 mm). They are not very efficient either for pipes with wall thickness from 4 to 6 mm. The pipeline material has practically no effect on the UT tool operation, since the acoustic



Fig. 3.10 Combined tool of two types: MFL and UT CD (image taken from the website: <http://www.transneft.ru>)

properties of different pipe steel grades are quite similar and their effect on results of measurements performed by UT tools is negligible.

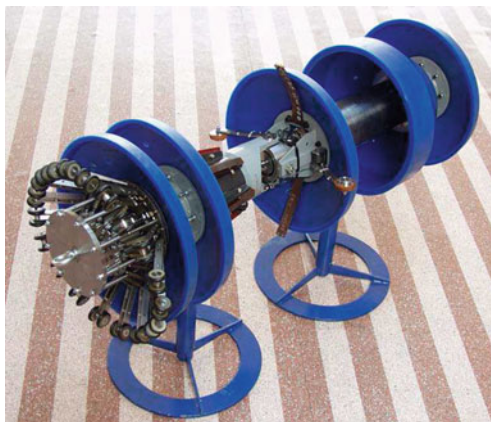
Currently exist mixed type pigs, which combine on one platform several non-destructive control techniques. For instance, a mixed type tool MFL + UT CD (Fig. 3.10) or MFL + UT WM + UT CD tool. Such tools perform complex inspections simultaneously conducting several types of inspections in one run. In addition, many ILI vendors provide customers with opportunity to customize configuration of the tool to be used (by means of modular structure options) to best meet the particular client requirements.

Eddy current tool—is a tool based on the eddy current nondestructive control methods and used for detection of pipe wall discontinuities (various type of cracks, lamination, rolling laps, voids, nonmetallic inclusions and flaws, the planes of which are not parallel to pipe surface and are positioned at an angle of over 10°).

The eddy current control principle is based on interaction between the external magnetic field and the electromagnetic field of eddy currents induced in pipe wall by a converter transmitting coil. The current in the eddy current sensor generates an electromagnetic field which excites eddy currents in the inspected pipeline. Eddy current electromagnetic field acts upon the converter coil and induces in it an electromotive force, or changes its electric resistance. The signal from the eddy current sensor goes to the electronic block of the eddy current tool and the obtained data are converted into crack size (anomaly) values. A specific feature of the eddy current control is that it can be performed without a contact between the converter and an inspection object. The gap size could be from a fraction of a millimeter to several millimeters. The converter signals are practically unaffected by moisture content, pressure, radioactivity or pipeline surface contamination factors (including presence of nonconductive substances), there is also an option to perform inspection through pipeline coating.

The eddy current control is not efficient for detecting defects in structural elements and parts:

- with electro conductive protection coatings, if the defects do not open onto the coating surface;
- with defects filled with electro conductive particles;
- with corroded surfaces.

Fig. 3.11 Caliper tool

According to RD [4], the eddy current control allows detecting cracks opening to the surface where the opening width is over 0.01 mm, depth over 0.1 mm, and length over 2 mm.

Calipers tools. Calipers (Fig. 3.11 [5]) are designed for measuring the inner pipeline cross section and allows determining of: pipeline bends radii, position of welds, backing rings, valves, and latches. It is capable of detecting such defects as dents, corrugations, section ovality. Pipeline axis deviation is registered by an inclinometer. The covered distance is measured by special measuring wheels (odometer). Referencing of the defects location to the pipeline route is done by markers.

Data obtained by a caliper run permits making a decision on the viability of performing an inspection tool run.

3.3 Code Requirements for ILI of Pipelines

To enable inspection each inspected segment of a pipeline must be equipped with launching and receiving chambers for ILI tools and cleaning devices. Launching and receiving chambers serve for reeving the ILI tool into a pipeline and starting its movement, as well as for stopping the ILI tool at the end of inspected segments and its removal from the pipeline. All ILI tools move along the pipeline by the transported liquid or gas flow.

According to the industry RD [6], in operating main oil pipeline systems following types of inspection are performed:

- in-line inspection (profilometry and defectoscopy) of pipeline linear part and cross-ings (including underwater crossings) over natural and artificial barriers;
- external inspection of the launching and receiving chambers, connecting structural elements, welded elements and repair structures, and tanks for collecting oil at the launching chambers;

Table 3.7 Schematic of diagnostics in gas pipelines

<i>Main directions of diagnostics in gas pipelines</i>			
Detection of pipe wall geometry defects and integrity	Inspection of insulation coating and electrochemical protection means	Gas leaks detection	Inspection of pipeline route condition
Inspection of pipe fittings	Inspection of pipeline structural elements	Pipeline stress and strain state assessment	Inspection of gas distribution stations
<i>Ways of gas pipeline technical diagnostics</i>			
ILI	Above ground inspection of gas pipeline crossings through roadblocks	Pipeline in -ditch inspection	Aerospace pipeline inspection
<i>Main methods of diagnostics</i>			
Magnetic, ultrasonic and other methods of detecting metal loss	Electrometry	Magnetic, ultrasonic, acoustic and other methods	Thermal, infrared, radar, laser shooting of gas pipelines
	Magnetometry	Measuring of thickness, hardness testing, methods of chemical composition and structure analysis	Laser and thermal methods for detecting gas leaks
	Radiolocation	Magnetic, acoustic, extensometric methods of stress-strain state assessment	
	Diving inspection, echo sounding, hydrolocation, etc.	Radiography of weld seams	
	Visual optical method		

- acoustic emission control of segments, linear part elements, and underwater crossings, which do not lend themselves to ILI, due to structural constraints: segments with backing rings, spiral-welded pipes, jump-over lines;
- measurement of oil pipelines depth of occurrence and definition of the design position of its structural elements;
- electrometric diagnostics of the linear part of oil pipeline.

For gas pipelines in accordance with [7], the structural schematic of diagnostics activity is shown in Table 3.7. For structural elements of the linear part of main pipelines the inspection algorithm provides for ILI (if the inspected pipeline segment is suitable for this type of inspection), while other types and methods of inspection, according to Table 3.7, are used for detecting defects, anomalies and disruptions, not detectable by ILI.

3.3.1 ILI Stages

In accordance with the industry RD [8] (for gas pipelines) and [6] (for oil pipelines), in-line inspection is performed in three large stages: preparation, performance, analysis and verification of obtained results. For each part of the main pipeline to be inspected, the pipeline Operator (client) fills in a questionnaire, which contains a list of data determined from the design, construction, and operational documentation.

Preparation for ILI. Preparing a pipeline for ILI requires performing certain organizational and technical actions to make possible tool launching and receiving, ensure its safe passage and obtaining the most accurate data about condition of the inspected pipeline segment. These actions include the following:

- cleaning pipeline from dirt, metal and foreign matter, using cleaning devices;
- determining the real minimum pipeline passage cross section by means of caliber pig run;
- elimination of short radius bends, impassable for the in-line inspection pigs, as well as places of critical narrowing of pipeline passage cross section;
- determining the necessary number and location of digging and non-digging markers, which must be placed along the pipeline route strictly over the pipe axis;
- making a list of actions required to ensure the ILI tool safe passage mode;
- establishing a communication network between the staff and the launching and receiving chambers, dispatcher, and support teams;
- planning of emergency and accident response actions;
- inspecting above ground passages and their supports and strengthening them where necessary. Pipeline route inspection for possible leakages and their elimination prior to the ILI. Inspection of pipeline valves and ensuring they are fully open, repair of defective valves.

Pipeline cleaning is performed by special cleaning devices—scrapers, which could also be used for cleaning quality control. There are several types of scraper type pigs, capable of cleaning a pipeline from paraffin-resin deposits and metallic items, as well as corrosion pockets on the inner pipe surface. Cleaning scraper pigs are shown in Fig. 3.12.

The scope of pipeline cleaning work (number of cleaning pig runs) depends on the type of product being transported and the initial cleanliness of pipeline inner surface.



Fig. 3.12 Cleaning tools (image taken from the website: <http://www.spetsneftegaz.ru>)

For oil pipelines the number of scraper runs for profilometry purposes (caliper tool runs) depends on the achieved result, where the last scraper run brings not more than 20 L of suspension, and up to 1 L of solid asphalt paraffin deposits.

After cleaning the pipeline it is necessary to determine its actual minimum passage cross section (i.e., get confirmation that the required cross section for safe passage of caliper pig is really available) by means of a caliber pig run. Caliber pigs are used for determining pipeline narrowings. Due to their ability to pass the narrowest pipeline sections (up to 65 % of their outer diameter), calibers are capable of passing through the most narrow pipeline segments without getting stuck. The measurement (calibrating) disks mounted on the caliber provide information about the presence of narrowed down pipeline segments which may cause the caliper or ILI tool stop. A successful caliber pig run does not give a 100 % guarantee of a safe caliper tool passage, since it does not give a full understanding of the quickly changing situation in a gas pipeline (change of pipeline valves position, presence of long-length or large-size debris inside the pipe, etc.).

ILI performance. After the preliminary pipeline cleaning before the ILI tool run it is necessary to perform profilometry in order to obtain information about inner pipe geometry, actual bend radii, and pipeline geometry defects. Minimum pipeline passage cross section required for the caliper tool run is 70 % of the pipeline inner diameter. Express report on caliper tool passage generated by the inspection service is issued to the pipeline operator. Using profilometry results, pipeline Operator corrects pipe geometry defects in case they reduce the pipeline cross section to less than 85 % of its outer diameter, to ensure successful ILI tool run.

Before the ILI tool run the pipe is thoroughly cleaned by means of running scraper pigs and a magnetic cleaning template piston. For oil pipelines the number of the cleaning scrapers runs depends on the achieved result, where the last run scraper brings not more than 5 L of suspension, and up to 0.5 L of solid asphalt paraffin deposits, for the purposes of UT intelligent pigs run, and not more than 1 welding electrode per 10 km of a cleaned pipeline for the purposes of magnetic pigs run. According to best practice experience all in all it requires 6–14 cleaning runs (taking into account preliminary cleaning at the first ILI stage) to provide for successful in-line inspection [3].

Pipeline segment inspection is performed in succession by several types of ILI tools according to the in-line inspection plan. For oil pipelines the following succession of ILI tools runs is normally used:

1. profilometry (1st level, caliper tool);
2. detection of corrosion, lamination, nicks, inclusions (2nd level, UT WM type tool);
3. detection of girth welds defects and corrosion defects (3rd level, MFL type tool);
4. detection of longitudinal and circumferential cracks (4th level, UT CD type tool).

For exact referencing of the detected defects during ILI tool passage, markers are installed along the pipeline route. Their layout is drafted at the stage of ILI preparation and constitutes an integral part thereof. Marker points must be placed over the pipeline axis, the distance between them should not exceed 2 km. Installation of

marker points on the pipeline crossings over rivers, channels, water bodies, railways and motor roads, in the hard-to-access areas (swamps, mountainous areas, etc.), and near production facilities is mandatory.

Analysis and verification of obtained results. After the ILI tool run the inspection provider performs an express analysis of in-line inspection results and submits a report, which should contain the following information:

- completeness and quality of the recorded information;
- availability of reference points marks (construction elements, installed markers);
- compliance of the ILI tool speed during the run with the prescribed regimen, which ensures obtaining accurate information about the technical state of the inspected gas pipeline;
- information about all dangerous defects.

The final report on the analysis of information obtained during the ILI is generated by the information processing department of the inspection service provider (ISP). Processing, interpretation and submission of inspection results are performed by qualified staff, using information analysis software systems and physical and mathematical methods of detecting, locating, identifying and sizing of the registered specifics, anomalies, defects, etc. Final report includes a full and updated information about the detected defects and construction elements of the pipeline (tees, wyes, valves), a list of detected defects, deviations from pipeline design, violations of safeguard zones and of inspected pipeline operational rules, as well as the data which ensures correct localization (for digging) of dangerous defects. The report also contains assessment of the detected defects risk level (residual strength calculation and remaining life estimates); recommendations on how to further operate the inspected PS segment, conduct its maintenance and next inspection; opinion on the advisability of additional inspection control (AIC). Assessment of the detected defects risk level is performed in accordance with the methodologies and criteria recognized by the operator.

After receiving the report the pipeline operator performs necessary maintenance of the defective segments and digging (as a preparation for ditch repair) for additional inspection and updating parameters of the dangerous defects before starting the repair. Digging by special equipment (excavator, bulldozer) is allowed, in the absence of the pipe leakage, but not closer than 0.5 m from the pipeline sideline. In case of leakage, digging is done manually without using any impact tools (i.e., pick, crowbar, or club hammer), or using only spark proof tools. Fine excavation within 0.5 m from the pipeline to its surface must be performed only manually, without any impact tools, in order to avoid its damage.

In the process of AIC (verification) following parameters are to be measured:

- the distance between the adjacent reference points in sections where digging is to be made;
- defect's parameters, as well as conformity of the actual nature of the detected defect to its description in the report;
- error in the referencing of defects around pipe perimeter and with regard to girth-welds.

For identifying and sizing of defects after the ILI and electrometry, following AIC procedures are used: visual inspection control (VIC), ultrasound inspection (ultrasound defectoscopy and wall thickness control); dye-penetrant inspection; magnetic particle control; control of physical and mechanical properties of the pipe metal, and of its chemical composition.

For inspecting pipelines in ditches following methods are used:

- VIC;
- acoustic;
- magnetic;
- optical;
- electromagnetic (eddy currents);
- electrometric;
- radiographic;
- extensometry.

VIC is performed for detecting and sizing of defects of insulation coating (holidays), outer metal surfaces of the pipeline's structural elements and welds. Insulation thickness is measured with a coating thickness gauge (magnetic, ultrasound, electromagnetic).

Acoustic control methods include:

- echo-pulse and shadow, mirror-shadow, and echo-shadow ultrasound inspection. They are used for detecting various pipeline wall defects, and both the outer and inner surface defects;
- passive acoustic emission method, used for detection of discontinuity flaws on the pipeline surface or in its wall, in welds, and structural elements. This method is used for detecting developing fatigue and stress-corrosion cracks, lack of fusion, offset edges, undercuts, laminations, slag inclusions, gas leakage, etc.;
- ultrasonic wall thickness tools, which are used for measuring actual pipeline wall thickness. Based on the results of these measurements it is determined whether, the pipeline wall thickness is within the standard range, and the corrosion or erosion wear rate is estimated.

Magnetic types of control include:

- magnetic powder method;
- magnetographic method;
- magnetic ferritic probe method;
- induction method;
- magnetic memory metal method;
- noncontact magneto metric diagnostics.

Magnetic powder defectoscopy is used for detecting both local and distributed surface and subsurface defects. Magnetic ferritic probe, magnetographic and induction control methods are used for indicating defects in a magnetized object of control, including indication of defects in welds. Metal magnetic memory method registers magnetic anomalies in an inspected object. Noncontact magnetometric diagnostics is

performed for detecting the most stressed and prone to damage zones of the pipeline linear part. The purpose of the noncontact magnetometric diagnostics is the detection of defects in the parent metal and welds, as well as the general stressed state of the pipeline.

The optical method is used for detection of various types of surface defects: cracks, mechanical and corrosion damage, protective coating discontinuity, and leakage. The radiographic method is used for inspecting pipeline welds, for detecting metallurgical pipe wall defects, welding defects, and corrosion type defects. Extensometry is used for the assessment of pipeline SSS.

Metal hardness measurement is performed in accordance with state standards. Its results are used for indirect measurement of actual mechanical properties of pipe metal and welds.

Determining of the pipe metal chemical composition is performed to confirm steel grade and establishing its conformity to specification data. Determining pipe steel chemical composition and its grade is performed on pipelines by express methods using chemical composition analyzers, or additionally, by stationary laboratory equipment on samples of metal cut out from pipe body.

Electrometric method (electrometry) is used for assessment condition of the insulation coating state: its resistance, discontinuities (holidays), change of physical and mechanical properties. The scope and content of electrometric inspection work includes:

- inspection of pipeline corrosion condition;
- inspection of pipeline insulation state;
- assessment of efficiency of insulating joints;
- assessment of technical condition of electrochemical protection (ECP) means;
- assessment of ECP efficiency.

In the process of corrosion state assessment the PL segments with out-of-spec protection potential level are detected and the total downtime of the ECP tools is measured; specific electric soil resistivity at the pipeline depth is measured; presence of stray direct current sources and places with maximum corrosion hazard are identified; in the presence of other alternating-current sources the corrosion hazard is assessed; the PL segments are classified with regard to corrosion hazard; places with the highest corrosion hazard are identified for digging; VIC of the insulation condition and the pipe metal is performed in ditches; the pipeline corrosion rate at existing level of the protection potential is assessed.

The estimated specific electric soil resistivity is the parameter which defines soil conductivity level to identify pipeline segments with high soil corrosion activity, and for designing the cathode and galvanic protection. Specific soil resistivity measurement is performed by the 4-pin Wenner method.

The scope of the insulation coating inspection includes the following:

- VIC of pipe insulation;
- detection of pipeline insulation holidays;
- determining the insulation resistance via SCP parameters within the coverage area of each ECP unit on the inspected pipeline segment.

VIC of pipe insulation is performed in ditches. The disadvantage of this method is the subjective assessment of insulation quality.

Detection of through faults (holidays) in pipeline coating is performed by the J. Pearson survey method. The essence of the method is that an acoustic frequency generator of about 1,000 Hz is connected with one pole to an underground pipeline, and with another—to the ground. The direction of the impressed current in coated pipelines, as it flows out of the pipeline, identifies the exit points of damaged insulation and creates an increase of the ground potential, which can be gauged by a two-probe unit. This survey is performed by special tools—holiday seekers.

More accurate detection of faults in the protective insulation coating may be achieved by measuring the direct current gradient on the ground surface above the pipe axis (the DCVG—direct current voltage gradient method). When a direct current is applied to a pipeline the potential gradient (electric potential differential) on the ground is created, due to the current flow from the anode base to bare steel exposed in holidays. Pipeline segments with insufficient protection are determined by the results of measuring “ground—pipe” potentials using control and measuring units.

A typical plan of conducting ILI consists of following sequence of operations [8]:

1. Preparation of the ILI tool for a run in a depot;
2. Transportation of ILI equipment to the site;
3. Unloading and preparation of the ILI tools;
4. Conducting run of a cleaning scraper;
5. Conducting a caliber pig run;
6. Pipeline route mark up for markers placement;
7. Caliper pig run;
8. Express processing of data obtained as a result of inspection;
9. Control caliper pig run;
10. Express processing of data and generation of express analysis results;
11. Cleaning scraper run;
12. Magnetic cleaning piston-template run;
13. Pipeline route mark up for markers placement;
14. Intelligent ILI tool run;
15. Copying of information to magnetic media;
16. Verification of the recorded information;
17. Express processing of data;
18. Magnetic cleaning piston-template run;
19. Control run of the intelligent ILI tool;
20. Copying of received information to magnetic media;
21. Verification of the recorded information;
22. Express processing of data and generation of analysis results;
23. Preparing equipment for dispatch;
24. Return equipment to depot;
25. Data processing, final report generation.

3.3.2 Periodicity of ILI

According to RD [6], the types and periodicity of oil pipelines inspection are shown in Table 3.8.

For gas pipelines the inspection priority is set in accordance with the expected probability of failure of the pipe linear segment during operation. The ILI periodicity for the purpose of detecting corrosion and stress-corrosion defects is determined from dependencies obtained on the basis of statistical analysis of the ILI data and the defects depth growth projections. For more detailed description of these techniques see RD [7].

Table 3.8 Types, scope, sequence and timing of technical diagnostics of main oil pipelines

Types of diagnostic		Time of performance of initial diagnostic	Frequency of diagnostic
ILI		Not later than 3 years from the date of commissioning	Not less than once in 6 years
ED	Chambers of launching and receiving of ILI tool	Not later than 3 years from the date of commissioning	Once in 10 years
	Connecting and structural parts, welded elements, repair constructions	Not later than 3 years from the date of commissioning	Once in 10 years
	Tanks collecting oil from the launching and receiving chambers	Not later than 10 years from the date of commissioning	Once in 10 years
	AEC of non-piggable pipeline sections	Not later than 3 years from the date of commissioning	Not less than once in 6 years
	Measuring of pipeline occurrence depth	Not later than 5 years from the date of commissioning	Once in 10 years
	Electrometry	Not later than 3 years from the date of commissioning	Once in 5 years in sections with highly corrosive activity
			Once in 10 years in other sections
			Once in 3 years, if the cathodic protection zone is less than 3 km long

Notation ED—external diagnostics; AEC—acoustic emission control

3.3.3 International ILI Quality Standards

Review some aspects of the USA ILI quality standard API 1163 (2005) [9], which was developed by a work group of leading specialists from the USA, Canada, and Russia (S.A. Timashev). The work group included representatives of major oil and gas pipeline operators, inspection service providers, consulting firms, academies and universities. This standard was developed with the practical application in mind and implies joint responsibility of the inspection service provider and the pipeline operator for the final ILI outcome.

As was described above, the ILI consists of three stages: preparation, implementation and verification of the obtained results. These stages, in accordance with API 1163 [9], are shown in Fig. 3.13.

For the purpose of pipeline efficient diagnostics it is recommended that the staff and equipment employed in the process of ILI and data analysis were certified in accordance with API 1163 and the accompanying documents: ANSI/ASNT ILI-PQ-2010 [10] (first edition was published in 2005), intended for the attestation and certification of ILI staff, and the NACE Standard RP0102-2002 [11], containing practical recommendations as to how perform pipeline ILI. These three standards combined contain all requirements to ILI performance, including personnel qualification, inspection tools, and the methods for analysis of the obtained results.

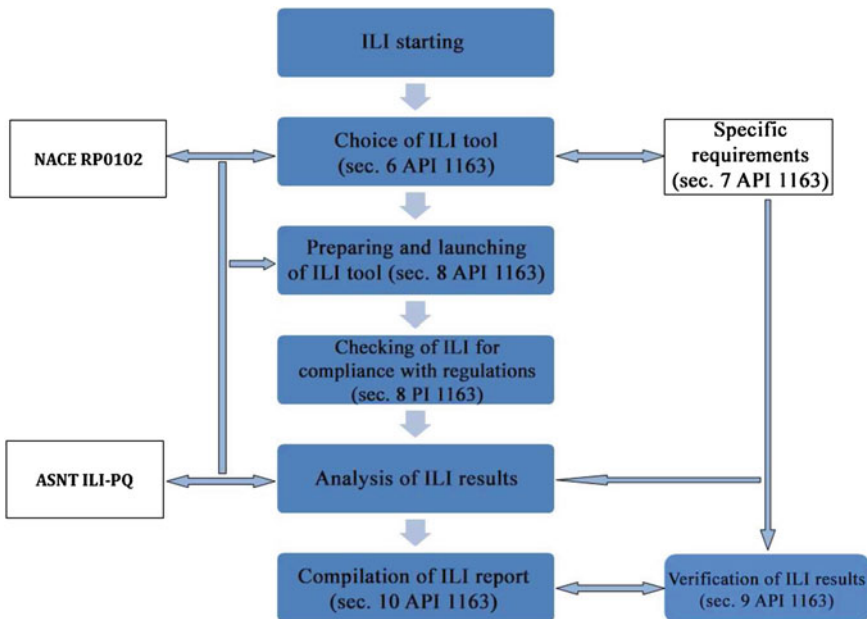


Fig. 3.13 ILI diagram according to the API 1163 Standard [9]

Such ILI tool specification parameters as detection probability and identification probability (see Sect. 4.3 of Chap. 4), as well as ME of the ILI tool, when sizing the detected defects dimensions, must be clearly stated in the text of inspection services contract. In the subsequent data verification process the used tools specification data must also be checked for compliance with the contract terms.

Since ILI is a part of any approved by the pipeline Operator Integrity Management Program (IMP), it is necessary to check in advance that ILI meets its goals and purposes. A number of useful recommendations on this issue are available in API 1160 [12] and ASME B31.8S [13].

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Chapter 4

Methods of ILI Results Analysis

This chapter contains a systemic description of the methodology for integrated holistic analysis of statistical data obtained as a result of pipeline inspection for the purpose of their practical applications when ensuring safety and integrity of pipelines. To begin with, we introduce some definitions.

The diagnostics of the technical state of the linear part of a PS is performed with the use of in-line diagnostic tools—defectoscopes. Hereinafter, unless expressly stated otherwise, they will be referred to as the ILI tools.

After completion of the ILI a small percentage of detected defects is verified, i.e., a second set of measurements is performed with another, as a rule, more accurate instrument.

The *results* of measurements represent an approximate evaluation of the true values of defect parameters.

The *true values* are the values ideally describing the object's properties. They are considered an absolute truth and therefore are immeasurable; they may only be evaluated with a certain degree of accuracy.

A *measurement error* is an unknown random value. All MI have inherent ME, since there could be no ME-free measurement instruments.

According to the character of their manifestation, measurement errors may be classified as follows: (1) *random errors*, which are changing (in value and/or sign) from one measurement to another. These errors are related to imperfections of the tool, the operator, or the measured object, as well as to specific features of the measured value itself; (2) *systemic errors*, which are changing in time in accordance with a certain regularity (a special case is a constant error). Systemic errors are related to instrument errors (wrong scale, calibration, etc.); and (3) *rough error* (a miss or an outlier), resulting from an operator's negligence or undetected malfunctioning of the tool. This book analyzes random and systemic errors of measurement tools.

4.1 Introduction to ILI Result Analysis

4.1.1 *General Characteristic of the ILI Tool as a Measurement System*

In recent years, MFL ILI tools have been transformed from purely inspection tools to relatively accurate measuring instruments. The principal differences of measurements conducted by ILI tools as compared to measurement tools used in manufacturing industries (automotive, metal processing and such) are as follows:

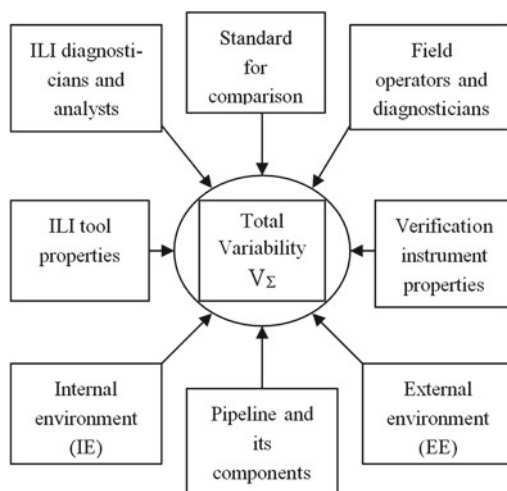
- The object of measurement (pipeline) is in a complex, constantly changing internal environment (pipe wall metal magnetic anisotropy, pressure, temperature, corrosion, debris, speed surges, etc.), and external environment (surrounding soil, corrosion, third-party intervention, etc.);
- An ILI tool is wearing out during a single run, some of its critical components can fail during inspection with no opportunity for replacement;
- The pig run parameters are not stabilized (pipe internal wall cleanliness, pig velocity, magnetic/UT field, sensors stand-off are continuously changing during the inspection);
- It is impossible to make a second measurement of the same pipe conditions; and
- It is hard to create a standard of comparison for ILI measurements due to inaccurate field measurements, human factors, and type of sensors, signal acquisition, processing algorithm, and data recording.

All the above demands creating a measurement technology which allows characterization of pipe defects, with accounting for the ILI specifics. The basics of such technology are outlined below.

The measurement process is influenced by systematic and random sources of variability. In order to control and minimize this variability, it is necessary to define all meaningful potential sources of such variability. The main sources of variability of pipeline defect parameter measurements and their interrelation with given measurement technology are given in Fig. 4.1.

Every measurement has an intrinsic indispensable error. This error, in its own right, consists of many components, as shown in Fig. 4.1. It is necessary to be able to extract each component separately and to conduct sensitivity analysis, which would permit ranking all sources of variability, and to understand what should be done to minimize the MEs. This is usually done by the ANOVA (ANalysis Of VARIances) methodology. One of the key components of the ANOVA methodology is the indispensable and unavoidable “iron” rule of statistics which dictates that, in order to extract from the total variance a partial variance, the experiments should be conducted in a way that provides freezing of all the sources of variance, except the one that is being extracted. In the case of ILI technology this rule implies that for objective assessment of reliability of ILI results it is necessary to plan and perform verification measurements on the same object. Without adhering to this iron rule it

Fig. 4.1 Main sources of variability of pipeline defect parameter measurements



is very easy to produce results that would be, using M. Twain’s classification, considered worse than “damn lies.” Unfortunately, current wording of the API 1163 [1] does not enforce this issue.

4.1.2 Why Adjust the Raw MFL ILI Readings?

It is hard to overstate the value of correct sizing of defects, because they are the key element in correctly assessing residual strength and life, POF/reliability, and risk of on- and off-shore pipelines. Hence, no rational (to say nothing about optimal) integrity management plans (IMPs) are possible without having correct, consistent defect sizes. Therefore, it is essential for the ILI readings to be as accurate as possible. This is particularly so for cases which involve corrosion issues, when several ILI readings separated in time have to be considered. The accuracy of sizing defects is directly dependent on the *essential variables* (EVs) of the ILI technology. The values of these EVs during the whole ILI run should be in the optimal region, so as to make minimal MEs. According to API 1163 [1] the EVs are ILI tool characteristics (and analysis steps) which are essential for achieving desired results, in our case—obtain accurate sizes of defect parameters. Vendors are obliged to document in their specs on ILI tool all the EVs, because there are relationships (expressed by expert assessments, formulas, or algorithms, and developed in-house) between physical characteristics of an ILI tool and its accuracy. Among such “physical” EVs are ILI tool velocity (which is a random function of the logdistance), level of pipe wall magnetization during ILI (which depends on pipe wall material magnetic properties, magnets size, form, strength, and number), and sensor lift-off (which is a function of pipeline cleanliness at each point of its logdistance, and the overall design of the

ILI tool and technology of ILI). The above calibration relationships permit making adjustments of the raw data, which are routinely made by vendors when delivering results of an ILI. Unfortunately, this part of ILI technology is rarely published and/or discussed in public, because it is considered proprietary. The operators and consulting companies, in their turn, add to or replace the adjustments, made by vendors, by their own adjustments, when assessing the residual strength and POF of pipelines. This technology is also not well known by people other than operators or consultants, by the same reason. It should be noted that adjustments are done automatically for vast majority of the defects. But for large defects and defects outside the specifications this is done manually. Hence, the ILI technology clearly involves three human (which could be, at times, irrational) sources of MES: field diagnosticians, in-house defect analyzers, and professionals who perform adjusting of the defect sizes. It also should be noted that now, with sophisticated methods of ILI data analysis available, in any litigation cases that involve pipeline loss of containment, it would be necessary for the operator or vendor to prove in court that they used the best practices of defect size assessment which exist on the market, if they do not want to become bankrupt [2].

The main goal of ILI is (according to the seven basic ILI quality metrics (see Sect. 4.3)) to correctly detect, locate, and identify all types of defects present in the pipeline and to size them in a fashion which allows statistical assessment of their true sizes. If achieved, the last fact opens wide the door to meaningful usage of the most sophisticated methods of structural mechanics (which were developed spending, worldwide, billions of \$\$\$, but not used yet to its fullest in the pipeline industry) and obtaining most accurate values possible of pipeline residual strength, probability of failure, and residual life time. This, in its turn, permits using the predictive maintenance technology in pipeline operation, introducing optimal inspections and repair logistics, and maximizing the long-term utility of the asset (in our case, the pipeline system). This book describes the (developed by the authors) methodology of a holistic innovative approach to ILI data generation and data management, which dramatically increases ILI inspection capabilities. This methodology to a large extent decreases existing uncertainties, minimizes scatter of input parameters and, thereby, makes predictions based on ILI data less conservative. As a result, all this permits generating safe solutions and avoiding dangerous errors in predictions which involve assessment of pipeline inspection frequency and safety margin.

According to API 1163, the ILI measurement results are characterized by three parameters of statistical nature: *tolerance*, *certainty*, and the *confidence level*. *Tolerance* is the range with which anomalies' dimension or characteristic is sized. *Certainty* is the probability that a reported anomaly characteristic is within a stated tolerance. *Confidence level* (CL) is a statistical term used to describe the mathematical certainty with which a statement is made. CL indicates the confidence with which the tolerance and certainty levels are satisfied. Consider separately each of the parameters.

Accuracy of any ILI tool is characterized by the tolerance of the measurements for a given certainty, which are found via its ME. It is assumed that any measurement of the defect parameter made using an ILI tool is, with probability p , inside the limits $\pm k \cdot wt$, where k is a portion of pipe web thickness wt . For instance, for HR ILI tools

the tolerance for the defect depth is $\pm 10\%$ *wt* ($k = 0.1$) with probability $p = 0.8$ (80% confidence interval). This can be expressed as

$$P(|X - \mu| \leq k \cdot wt) = 1 - \alpha = p,$$

where X is the error of a single measurement of the defect depth; μ is the mathematical expectation of the ME; $\alpha = 1 - p$ is a confidence level; p is the certainty according to API 1163 [1]; and $k \cdot wt$ is the statistical accuracy (tolerance, according to API 1163 [1]).

Usually, it is assumed that MEs are normally distributed with zero mathematical expectation. In this case the graphical interpretation of the ME distribution for different values of certainty p has the form as given in Fig. 4.2.

The random value ME is inside the symmetrical, as related to the origin, interval $[-k \cdot wt; k \cdot wt]$, with probability $p = 1 - \alpha$. For instance, $p = 0.8$, then 80% of all MEs will be inside the interval $[-k \cdot wt; k \cdot wt]$. Hence, total area of the tails is equal to α . The interval is symmetric; therefore, area of each tail is equal to $\alpha/2$. According to the properties of the normal PDF,

$$P(-k \cdot wt < X < k \cdot wt) = 1 - \alpha = 2\Phi\left(\frac{k \cdot wt}{\sigma}\right) - 1, \quad (4.1)$$

where $\Phi(x)$ is the standard normal cumulative distribution function (CDF).

From formula (4.1) it follows that the tolerance for the ILI tool is calculated according to the formula

$$k \cdot wt = z_{1-\alpha/2}\sigma, \quad (4.2)$$

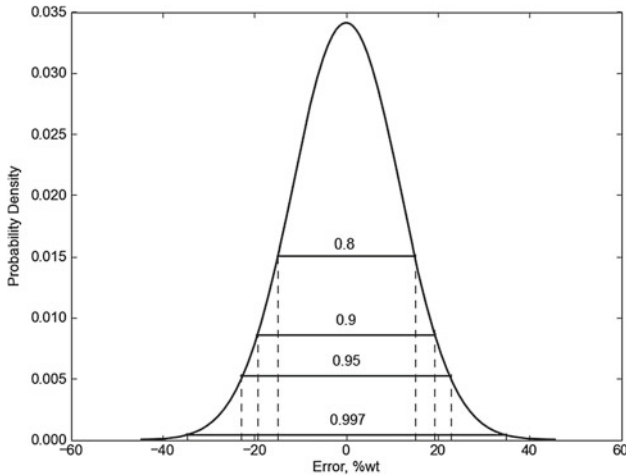


Fig. 4.2 Error bands for different certainties for the case when the PDF of ME is normal

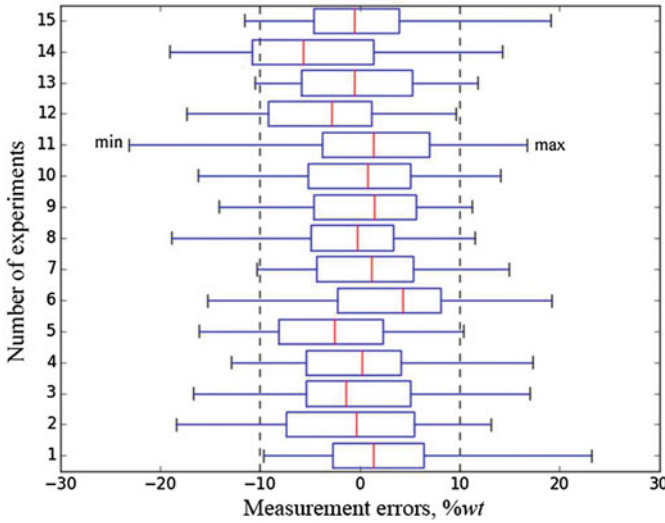


Fig. 4.3 Graphical interpretation of the *confidence level*

where $z_{1-\alpha/2}$ is the quantile of the standard normal distribution of level $1 - \alpha/2$.

Hence, with known ILI tool tolerance (from Eq. (4.2)) it is possible to define the SD of tool MEs.

The meaning of the confidence level is in that, when $CL = 95\%$, *certainty* = 80% and *tolerance* = 10% wt then in 95% of the time of conducting ILI, 80% of the MEs will be within the boundaries $\pm 10\%$ wt. Visualization of this fact is given in Fig. 4.3. This figure reflects results of 15 computer simulated ILIs. In each of the virtual 30 ILI MEs were made. In Fig. 4.3 the rectangle represents a sample of MEs. The red vertical lines are sample medians (50% level quantile), the boundaries of the rectangles are the 10% and the 90% sample quantile. The length of the rectangle embodies 80% of all the MEs. Horizontal lines represent the scatter of the MEs. From Fig. 4.3 it can be seen that in one of the 15 sets of virtual ILIs the left boundary of the rectangle is out of the 10% wt limit.

4.1.3 Types of Defect Size Adjustments

Over the years, the world pipeline industry developed several Engineering Schools of Thought (EST) regarding defect sizing (see, for instance, [3–6]). One of the EST is presented in the API 1163 document [1]. It utilizes the “Unit” curve concept (which is equivalent to accepting no bias in both ILI and verification instrument readings, no MEs in the VI readings, and normal distribution of the ILI MEs). The other, most commonly used types of adjustment can be formalized as follows:

$$\text{“Unit” curve (No bias admitted);} \quad (4.3)$$

$$d_V = d_{tr} \ (\sigma_V \equiv 0); \quad (4.4)$$

$$d_{adj} = d_I \cdot k; \quad (4.5)$$

$$d_{adj} = d_I + k\sigma_{\varepsilon I}; \quad (4.6)$$

$$\sigma_{adj} = k\sigma_{\varepsilon I}; \quad (4.7)$$

$$\sigma_{adj} = \sigma_{\varepsilon I} + \Delta_{adj}; \quad (4.8)$$

$$d_{adj} = \varphi(d_I, d_V, \sigma_{\varepsilon I}, \sigma_{\varepsilon V}); \quad (4.9)$$

$$d_{adj} = d_I + \sqrt{tol_I^2 + tol_V^2}; \quad (4.10)$$

$$\text{Probability of exceedance method.} \quad (4.11)$$

Here d_I , d_V are correspondingly the ILI tool and the VI measurements; $\sigma_{\varepsilon I}$, $\sigma_{\varepsilon V}$ are correspondingly the standard deviations (SDs) of the ILI tool and the VI measurement errors; tol_I , tol_V are correspondingly the tolerances for the ILI tool and the VI measurements; d_{adj} , σ_{adj} , Δ_{adj} are correspondingly the adjusted ILI tool reading, adjusted SD and the adjusting safety margin; and k ($k > 1$) is a multiplicative safety coefficient.

We proceed to the description of each approach defined above. The expression (4.3) surmises that both measurement instruments (ILI tool and VI) are free of any MEs.

The expression (4.4) means that the VI measurements do not contain MEs, i.e., VI is “ideal.” Actually, this can never happen. The assumption that VI is ideal may lead to assigning de facto its MEs to the ILI tool, which will lead to an unjustified low assessment of its quality. This is especially important to account for when assessing possibilities of an ILI tool or of a candidate diagnostician. Hence, it is necessary to assess the MEs of each instrument separately.

The simplest types of adjustments are presented by formulas (4.5) and (4.6). They amount to multiplying the ILI readings (“raw” ILI data) by a coefficient, which is more than unity. Sometimes, this type of adjustment is applied to the SD of ILI readings; see expressions (4.7) and (4.8). In Eq. (4.8) the term is a safety margin added to the SD. In general, the adjusted ILI reading is a function of the readings of both ILI and VI instruments, and of the SDs of the MEs of both tools (4.9). The explicit expression which accounts for this is given by Eq. (4.10), and Figs. 4.2 and 4.4. According to them, the tolerance for the ILI readings is taken at the certainty (in API 1163 wording) of 80 % (recently, some companies started to prefer 90 %). Under the 80 % certainty the tolerance for the ILI tool would be $\pm 1.28 \cdot \sigma_{\varepsilon I}$ (see Eq. (4.2)). For the 90 % certainty the tolerance is $\pm 1.65 \cdot \sigma_{\varepsilon I}$.

The probability of exceedance approach per se (Eq. (4.11)) is a staple model in structural reliability theory, where it is widely used in conjunction with the random function theory. When applied to the problem being discussed in this chapter, the main problem is how to construct the PDF for the ME of the ILI tool and whether to select the level of exceedance as a deterministic or a random value.

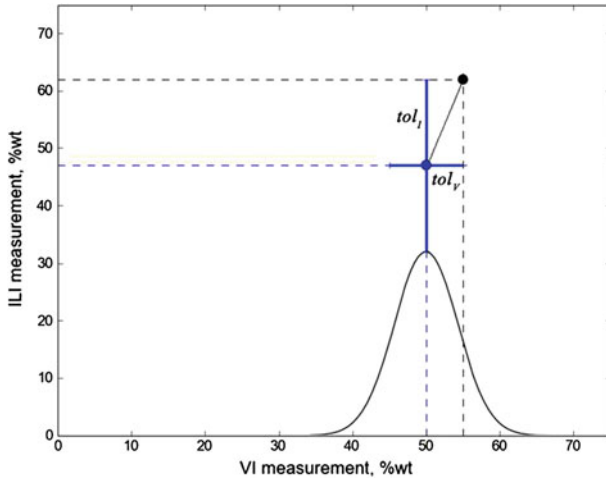


Fig. 4.4 Design (adjusted) point taking into account the tolerances of both tools

4.2 Assessment of the Minimal Required Number of Measurements for Consistent Statistical Analysis of ILI Results

To evaluate the accuracy of ILI measurements the verification of a *sufficient number* of defects must be a mandatory element of each inspection run. This paragraph gives an outline of evaluation techniques used to define the minimum required number of detected defects for performing a valid statistical analysis of the ILI results. These techniques may also be used for evaluation of the minimum number of defects necessary for performing a valid verification.

4.2.1 Approach Based on the Central Limit Theorem

In mathematical statistics it is proven that the law of large numbers and the central limit theorem (CLT) are applicable in practice with a sufficient accuracy, given the sample size over 30. According to the CLT, the sampling mean is normally distributed given the sample size over 30, regardless of the type of the original population distribution.

Consider a sample of size $n > 30$ of identically distributed random values x_i . Under the given confidence probability $p = 1 - \alpha$ determine the confidence interval for mathematical expectation μ , for evaluation of which the arithmetic mean $m = \sum_{i=1}^n x_i / n$ is used.

The PDF for the assessments of mathematical expectation distribution is close to normal, since the distribution of the sum of independent random values with finite variance is asymptotically normal. The expression for the confidence probability will have the form

$$P(|m - \mu| \leq \varepsilon) = 1 - \alpha, \quad (4.12)$$

where ε is the statistical accuracy and $\alpha = 1 - p$ is the confidence level.

Normal law has two parameters—mathematical expectation m and variance. As RV x_i are distributed identically with variance σ^2 , and m equals the arithmetic mean of the identically distributed random values, its variance will be

$$D(m) = D\left(\frac{\sum_{i=1}^n x_i}{n}\right) = \frac{\sum_{i=1}^n D(x_i)}{n^2} = \frac{n\sigma^2}{n^2} = \frac{\sigma^2}{n}.$$

In expression (4.12) introduce the standardized variables:

$$P\left(\frac{|m - \mu|}{\sqrt{\sigma^2/n}} \leq \frac{\varepsilon}{\sqrt{\sigma^2/n}}\right) = 1 - \alpha.$$

For a standardized RV $z = \frac{m - \mu}{\sqrt{\sigma^2/n}}$, the probability

$$\begin{aligned} P\left(|z| \leq \frac{\varepsilon}{\sqrt{\sigma^2/n}}\right) &= \Phi\left(\frac{\varepsilon}{\sqrt{\sigma^2/n}}\right) - \Phi\left(-\frac{\varepsilon}{\sqrt{\sigma^2/n}}\right) \\ &= 2\Phi\left(\frac{\varepsilon}{\sqrt{\sigma^2/n}}\right) - 1 = 1 - \alpha. \end{aligned}$$

From this formula it follows that the expression $\varepsilon/\sqrt{\sigma^2/n}$ is a level $1 - \alpha/2$ order quantile $u_{1-\alpha/2}$ of standard normal distribution:

$$\frac{n\varepsilon^2}{\sigma^2} = u_{1-\alpha/2}^2.$$

Then the required sample size for obtaining the evaluation of mathematical expectation with given reliability and required accuracy (error) is calculated as

$$n = \left[\frac{u_{1-\alpha/2}^2 \sigma^2}{\varepsilon^2} \right], \quad (4.13)$$

obtained under the assumption that the size of the sample is sufficiently large, i.e., $n \geq 30$.

Thus the minimum number of defects required for consistent statistical analysis equals 30.

4.2.2 Approach Based on the Binomial Distribution

This approach is used when the true value of variance σ^2 is unknown. Assume that k is the number of “successes” in a sequence of n tests, and has a binomial distribution with “success” probability p , and conditions, $0,05 < p < 0,95$, $np > 4$, and $n(1-p) > 4$, are met. Then, from the local de Moivre–Laplace theorem (a corollary from the CLT) it follows that the statistical accuracy ε is calculated by the formula

$$\varepsilon = u_{1-\alpha/2} \sqrt{\frac{p(1-p)}{n}}.$$

Hence, the required sample size for obtaining a given accuracy ε equals

$$n = p(1-p) \left[\frac{u_{1-\alpha/2}}{\varepsilon} \right]^2.$$

Since value $p(1-p)$ is limited from above, $p(1-p) < \frac{1}{4}$, it is possible to obtain a more conservative and robust evaluation of sample size:

$$n = \frac{1}{4} \left[\frac{u_{1-\alpha/2}}{\varepsilon} \right]^2.$$

At $\varepsilon = 0.1$ (meaning sampling frequency of “successful” measurements does not deviate from its true value more than 10%) the dependence of sample size on the value of probability $p = 100(1-\alpha)\%$ at different values of the confidence level α is shown in Fig. 4.5. It is seen that for a “success” probability $p = 80\%$, which is normally used for evaluation of quality of measurements of the defects, the minimal size of the sample equals 41 defects.

4.2.3 Approach Based on the χ^2 Distribution

Represent via s^2 the unbiased sample variance of random normally distributed values x_i , $i = 1, \dots, n$, and let σ^2 be the true (but unknown) value of their variance.

According to the Fisher theorem for normal samples, the value $Y = \frac{(n-1)s^2}{\sigma^2}$ will have the χ^2 distribution with $(n-1)$ degrees of freedom. Let k_1 and k_2 be positive numbers which are the solutions of equations

$$\begin{aligned} P_1 = F(k_1) &= P\{Y < k_1\} = \frac{\alpha}{2}, \\ P_2 = F(k_2) &= P\{Y < k_2\} = 1 - \frac{\alpha}{2}, \end{aligned} \quad (4.14)$$

where F is the χ^2 -distribution function.

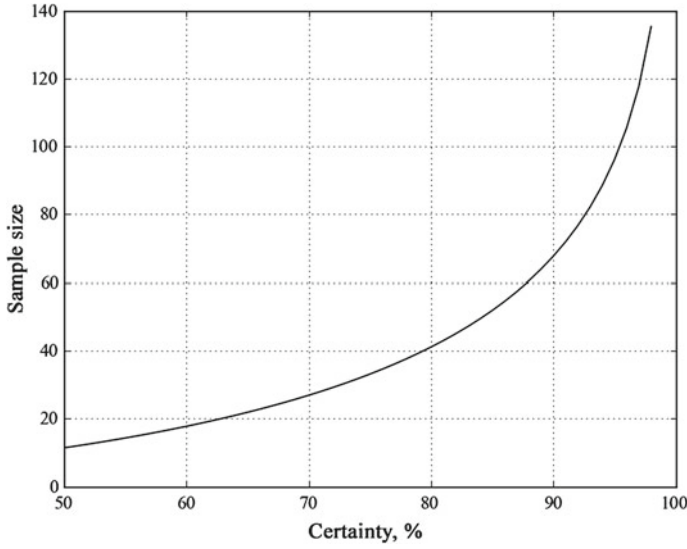


Fig. 4.5 Dependence of the sample size from certainty (binomial distribution is used)

Then, according to its properties

$$F(k_1 < Y < k_2) = P_2 - P_1 = 1 - \frac{\alpha}{2} - \frac{\alpha}{2} = 1 - \alpha = p.$$

On the basis of Eq. (4.14), at known sample size n , the confidence levels α of k_1 and k_2 are quantiles of the χ^2 distribution.

Consider an expression for evaluation of the confidence interval, *covering* the unknown mean-square deviation σ with reliability $p = 1 - \alpha$:

$$P\{|\sigma - s| < \varepsilon\} = 1 - \alpha,$$

where s is the unbiased sample standard deviation.

Represent the inequality $s - \varepsilon < \sigma < s + \varepsilon$ from the latter expression in equivalent form:

$$s \left(1 - \frac{\varepsilon}{s}\right) < \sigma < s \left(1 + \frac{\varepsilon}{s}\right). \quad (4.15)$$

Denote $\varepsilon/s = u$. Since the statistical accuracy of ε is rather low, then $0 < u < 1$. Rewrite Eq. (4.15) in the form

$$\frac{1}{s(1+u)} < \frac{1}{\sigma} < \frac{1}{s(1-u)}.$$

Multiply this equation by $s\sqrt{n-1}$ and square it:

$$\frac{n-1}{(1+u)^2} < \frac{s^2(n-1)}{\sigma} < \frac{n-1}{(1-u)^2}.$$

As the random value $\frac{s^2(n-1)}{\sigma}$ has χ^2 distribution with $(n-1)$ degrees of freedom, the right and the left values of the last inequality may be found using the values of k_1 and k_2 :

$$k_1 = \frac{n-1}{(1+u)^2},$$

$$k_2 = \frac{n-1}{(1-u)^2}.$$

Express $(n-1)$ from the first and the second equations and equalize the obtained expressions:

$$k_1(1+u)^2 = k_2(1-u)^2.$$

Bearing in mind that k_1, k_2 are quintiles of order $\frac{\alpha}{2}, 1 - \frac{\alpha}{2}$ (or, in the terms of confidence probability, of level $\frac{1-p}{2}, \frac{1+p}{2}$) correspondingly, obtain, from the previous expression

$$\chi_{\frac{1-p}{2}, n-1}^2 (1+u)^2 - \chi_{\frac{1+p}{2}, n-1}^2 (1-u)^2 = 0, \quad (4.16)$$

where $\chi_{\frac{1-p}{2}, n-1}^2, \chi_{\frac{1+p}{2}, n-1}^2$ are the χ^2 distribution quantiles with $(n-1)$ degrees of freedom of level $\frac{1-p}{2}, \frac{1+p}{2}$ correspondingly.

Parameter u may be interpreted as statistical accuracy. Indeed, from (4.15) it follows that $s(1-u) < \sigma < s(1+u)$. Then, provided the deviation of s from σ does not exceed 10% we obtain $u = 0.1$.

Thus, in order to determine the minimum sample size for a given certainty p , and accuracy u , Eq. (4.16) must be solved numerically for n .

The dependence of the sample size on the value of probability p at $u = 0.1$ is shown in Fig. 4.6, from where it becomes obvious that for $p = 80\%$ at least 83 measurements are required.

The approaches reviewed above represent various statistically valid methods for evaluation of the minimal sample size. The smallest admissible sample size was obtained using the CLT ($n \geq 30$). The binomial distribution requires a larger number of measurements: $n \geq 41$. In the case when χ^2 distribution is used, the number of measurements must be at least 83. It is apparent that the increase of the number of measurements improves reliability of the statistical analysis results.

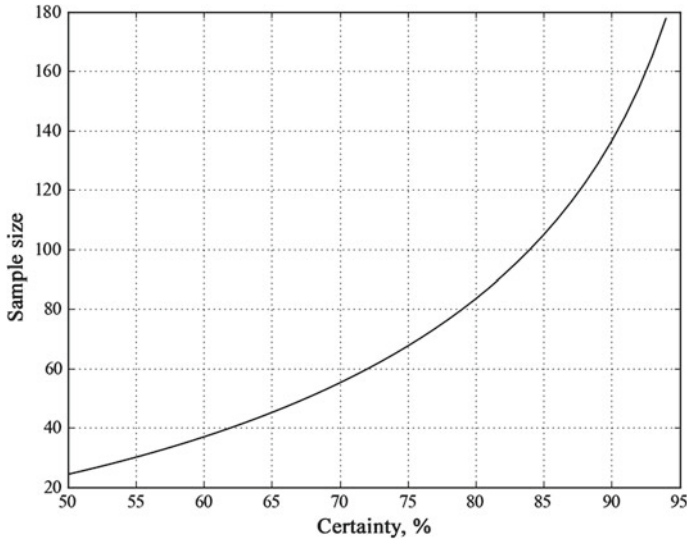


Fig. 4.6 Dependence of the sample size from certainty (the χ^2 -distribution was used)

4.3 ILI Tools Quality Metrics

4.3.1 *Practical Elements of Stochastic Theory of Measurements as Applied to the ILI*

Non-destructive quantitative evaluation of pipeline defects involves measurement of complex parameters (depth d , length l , width w , volume v) with inherent variations in both measurement process and the pipeline geometry.

Although every measurement during ILI is intrinsically stochastic and contains multiple kinds of errors that accumulate when detecting and recognizing defect images and then sizing them, it is possible to show that the following simple generalized additive measurement still holds true:

$$y(t) = \lambda(t) + \xi(t),$$

where $y(t)$ is the measured value of a defect parameter (e.g., crack length), obtained by a specific method and inspection means; λ is a RV, which can have only two values: $\lambda_0 = 0$, when there is no actual defect and $\lambda_1 = 1$, when the defect is actually present, with known prior probabilities $P_0(\lambda_0)$ and $P_1(\lambda_1)$ accordingly; $P_0(\lambda_0) + P_1(\lambda_1) = 1$; x is the constant true but unknown value of the defect parameter, for which only the interval of possible values is known with some accuracy (for instance, for pipe wall crack depth it would be the wall thickness $[0, wt]$); $\xi(t)$ is a realization

of a random process $\{\xi(t)\}$, which describes the measurement errors with known probability density function PDF $W(\xi, t)$:

$$W(\xi, t) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\xi^2(t)/2\sigma_\xi^2\right],$$

with average $E\{\xi(t)\} = 0$ and variance σ_ξ^2 .

Having the measurement $y(t)$ of the defect parameter, it is necessary to make a decision on whether the defect is absent (λ_0) or present (λ_1) with respect to the parameter being measured. Any decision made will always be escorted by the following events and their probabilities:

- conditional probability of a false detection of defect (or false call) $P_{FD}(\lambda = 1 | \lambda = 0)$, when a decision is made that a defect is present, while in reality it is nonexistent;
- conditional probability of a false non-detection of defect $P_{FND}(\lambda = 0 | \lambda = 1)$, when a decision is made that there is no defect, while in reality it exists;
- conditional probability of true detection $P_{TD}(\lambda = 1 | \lambda = 1)$, when a decision is made that a defect is present, and in reality it exists; and
- conditional probability of a true non-detection of defect $P_{TND}(\lambda = 0 | \lambda = 0)$, when a decision is made that no defect is present, and in reality there is no defect.

The above four probability functions, which form a full group of events (FGE), will be, in general, specific for each ILI tool. Moreover, they may change during the ILI process, because of wear of the sensors, change in velocity of the instrument during inspection as it travels along the pipe, and unavoidable lift-offs of the sensors during the ILI, due to geometric irregularities of the pipeline cross section and possible presence of debris. Thus, the processes of detection, acquisition (registration), and measurement (sizing) of the defect parameters contain inherent bias, which may result in erroneous detection and sizing of defect parameters. Moreover, statistical relations derived from results of laboratory experiments will not be identical to the same relations, obtained in the field.

Until recently, these four outcomes were treated inconsistently in the non-destructive quantitative evaluation (NDE). Only the probability of a true positive (the so-called probability of detection (POD)), and later on, its counterpart, the probability of false detection is utilized in the API 1163 Standard [7], but inconsistently calculated [8]. The way the experiments were conducted and subsequent calculations did not account for the above outcomes as a FGE. This leads to the *situation*, where the sum of $(P_{TD} + P_{FD})$ alone could amount to more than a unity [8], which is impossible.

Independent of any chosen decision-making criteria, the above conditional probabilities will always comprise a full group:

$$P_{FD} + P_{FND} + P_{TD} + P_{TND} = 1. \quad (4.17)$$

Thus the probability of a wrong decision is

$$P_{WD} = P_{FD} + P_{FND} \quad (4.18)$$

and the probability of a right decision is

$$P_{RD} = P_{TD} + P_{TND} = 1 - P_{WD}. \quad (4.19)$$

The probabilities (4.17)–(4.19) are the basic characteristics of defect detection, by which different types of detectors are to be compared.

Taking into account the economic consequences to which lead false detection (FD) and the non-detection (FND) of defects (losses caused by wrong decisions), the Bayes detection criterion was chosen, which minimizes expenditures of false detection C_{FD} and false non-detection C_{FND} . The decision-making threshold is defined as the solution of the problem of minimizing the sum of total costs $C_{FD} + C_{FND}$. The full algorithm of synthesizing the continuous optimal detector is described in [9].

Using this approach, it is possible to

- independently analyze the data that can be found in published literature devoted to measurement accuracy; and
- create correct plans of laboratory and field experiments that yield the needed probability functions: P_{TD} , P_{FD} , P_{TND} , and P_{FND} .

4.3.2 Quality Metrics of ILI Instruments

Since ILI tools started measuring defect sizes, they *de facto* became measurement instruments. Due to several objective factors (see section “ILI essentials...”) they as yet do not follow the worldwide standards established in the high accuracy and precision measurement instruments industry. According to these standards, every instrument (in our case each ILI tool) has to have in its manual a set of baseline specifications that consistently and quantitatively describe the quality (precision) of the instrument throughout its lifetime.

The ultimate goals of any ILI are:

- detecting all types of defects;
- interpreting correctly all found images of defects;
- locating the discovered defects:
 - along the longitudinal pipeline axis (logdistance);
 - along the pipeline circumference (angle Θ);

- 3D sizing of the defects:

- depth d ;
- length l ; and
- width w .

All in all, there are seven goals: one for detecting and one for interpreting, two for locating, and three for 3D sizing of the defect. These goals have to be achieved for each type of defects.

Due to intensive wear during each pig run these baseline specifications must be updated after each pig run and tool repair.

To the best of the authors' knowledge, a consistent methodology for evaluating the technical and economic benefits of diagnostics based on ILI can be constructed using the results presented below.

Through implementation of the above theory and diagnostic algorithms in the frame of condition-based monitoring one expects to obtain some technical and economic benefits. A measure of the magnitude of these benefits can be calculated using ILI tools performance metrics that are associated with the full set of probabilities of defect detection, identification, location (log distance and clock position), and sizing, along with cost issues. These metrics should be consistent, repeatable, easily understood, and obtainable through already existing ILI technology and practice. They also should provide means to accurately prognose the pipeline remnant life.

It is obvious that the detection ability of different ILI tools (hardware + software) affects the total ownership cost of implementing a particular ILI technology.

Performance of any high-resolution ILI tool can be defined by parameters indicated in Fig. 4.7, where P_{TI} is the probability of true (correct) identification of a detected defect and P_{FI} is the probability of false (irregular) identification of defect. It can be seen, that in order to assess the benefits of ILI, one should weigh the benefits achieved through accurate detection, location, identification, and sizing of pipeline defects against the cost associated with false location, false detection, false non-detection and poor sizing of defects, licensing and resource requirements of operating the ILI tool, and implementing specific diagnostic techniques.

Because of the intrinsic stochastic nature of ILI measurements, it is natural to use probabilistic parameters to define all the ILI tool performance metrics.

The current trend in ILI is to create multipurpose tools, which would in one survey detect and measure as many types of defects as possible. Such modern tools should have separate performance metrics for each type of anomaly and defect they are able to detect. This separation of performance metrics and statistics for each type of defect is necessary for understanding the true capabilities of the ILI tool in consideration as related to each defect type. As a last comment on the performance metrics, it should be noted that the requirements for the performance metrics naturally flow out from the goals of the ILI. Moving from the goals backward to the ILI tool requirements, it is easy to outline and construct the performance metrics.

We now proceed to derive the above-mentioned ILI tool performance metrics. As it was outlined earlier, performance of ILI detection and diagnostic algorithms are to be

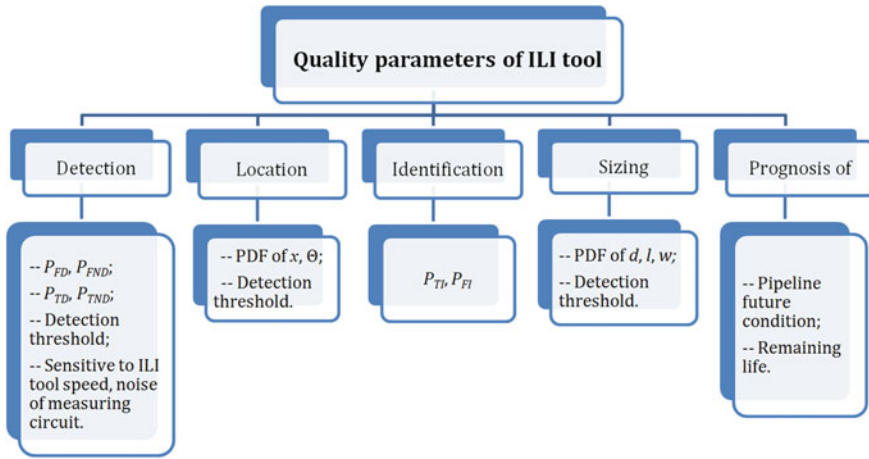


Fig. 4.7 ILI technology performance metrics (for each type of defect)

measured by some Performance Metrics (PM's) as it is done in high-precision measurement instrument industry and machinery diagnostics. They can be arranged into five categories (detection, location, identification, sizing, and prognosis, as shown in Fig. 4.7).

Detection performance metric measures the ability of the ILI tool to correctly find the actual existing pipeline anomalies of all types.

Identification performance metric measures the ability of the ILI tool to accurately identify the type of discovered detects, according to the classification adopted by the industry.

Location performance metrics measure the ability of the ILI tool to accurately assess the coordinates (distance, angle position) of the discovered defects in the pipeline section (s, θ).

Sizing performance metrics measure the level of precision and accuracy when assessing the sizes of the discovered 3D defects (d, l, w).

Prognosis performance metric measures the ability of the prognosis algorithms to accurately forecast the future condition of the pipeline section, using the defect sizes as inputs. The conditionality of this metric is due to that it, by necessity, uses different algorithms for predicting residual life, depending on the type of external forces and influences.

For instance, for assessing fatigue reliability and residual life of a pipeline with crack-type defects there exists the S–N curves method, the classical linear and non-linear elastic plastic theory of strength (fracture), as well as the J -integral approach. These methods explicitly use the crack size which permits implementation of the ILI results in corresponding calculations. Hence, in order to avoid rough calculation errors and get enhanced assessments of pipeline residual life it is necessary to provide maximum possible and, at the same time, economically justified accuracy of defect sizing during their diagnostics.

The first four groups of metrics are necessary and sufficient to cover all the seven goals of ILI. Because of this, they are called the basic set of *performance metrics*.

Now introduce an entirely new concept—the notion of the perfect ILI tool (PILIT). The perfect tool is a virtual tool that has the following basic set of performance metrics for any given type of defects:

$$\begin{aligned}
 M_D &= P_{TD} + P_{TND} = 1, (P_{FD} = 0, P_{FND} = 0), \\
 M_I &= P_{TI} = 1, (P_{FI} = 0), \\
 M_s &= \delta(\eta_s), \\
 M_\Theta &= \delta_0(\eta_\Theta), \\
 M_d &= \delta_d(\eta_d), \\
 M_l &= \delta_l(\eta_l), \\
 M_w &= \delta_w(\eta_w),
 \end{aligned}$$

where $\eta_s, \eta_\Theta, \eta_d, \eta_l, \eta_w$ are the corresponding sensitivity thresholds (their description given below); and $\delta(\dots)$ is the delta function.

An ILI tool with the above set of performance metrics is called perfect (ideal), because these metrics cannot be beaten (improved). The perfect or ultimate tool therefore is an excellent and natural benchmark.

In general, the overall performance of an ILI tool should be judged separately by each of the above parameters. But it is also possible to construe an integral performance metric, which is a weighted sum of the basic set of performance metrics. Considering all basic metrics equivaluable, assign them an equal to unity weight. In this case the total score for the perfect ILI tool, which is able to detect simultaneously N types of different defects (anomalies), will be

$$S_t = 7N.$$

It is possible to prioritize the basic metrics according to their usefulness as related to a specific case in consideration. Scores from the individual performance metrics can then be combined, according to the hierarchy, to produce summary scores for each category of defects, and for overall performance. In the latter case the total score will take the following form:

$$S_t = N \sum_{i=1}^7 M_i w_i,$$

where M_i is the i -th basic performance metric and w_i is the corresponding weight of the i -th metric (description of how to assign the weights is given below).

The ability of the ILI tool to detect and correctly size anomalies (defects) is measured as a function of the defect sizes and is the ultimate size requirement for pipeline condition monitoring and for the ILI tool to be useful in making efficient maintenance actions in a timely manner.

The *Detection Performance Metric* for any ILI tool is exhaustively defined by the full set of probabilities: P_{TD} , P_{TND} , P_{FD} , and P_{FND} . Varying inspection operating conditions and/or noise (due to variations in ILI tool speed, sensor wear, debris, etc.) may cause fluctuation in the above full set of detection probabilities.

The overall success function of an ILI tool as related to a given i -th type of defect then can be defined as

$$S_i(x) = P_{TD_i}(x) + P_{TND_i}(x),$$

as the sum of true positive and true negative, where x is the corresponding defect size. Omitting the $P_{TND}(x)$ will lead to underestimating of the success function.

The overall failure function to detect an i th type of defect by the ILI tool then will be

$$F_i(x) = P_{FD_i}(x) + P_{FND_i}(x),$$

as the sum of false positive and false negative.

The overall detection metric score represents the area under the success function. Conversely, the overall non-detection metric score is the area under the failure function. Success function is a random function of the size and type of defect. In general, the success function will vary for different ILI tools and pipeline sections. It is possible to assign some specified confidence level to the success function, using relevant statistics.

Location performance metrics measure in probabilistic terms the accuracy of locating the actual coordinates of the discovered defects. Any pipeline defect (anomaly) can be pinpointed using only two coordinates: by the coordinates along the pipeline longitudinal axis, and by the angle Θ (clock position) on the pipeline circumference.

The *identification (characterization) performance metric* carries many traits of the detection performance metrics. But there are differences. Consider the general case when the ILI tool is capable of identifying M types of features (defects, anomalies), which have been already detected. Assume that we are trying to construct a specific identification performance metric for an i th type of defect. During identification there could be only two outcomes: true identification (TI) and false identification (FI). The false identification in its turn can be, theoretically, of the kind when the i th type of defect is misinterpreted as one of the $(M - 1)$ remaining types of defect. If the number of actual defects of the i th type is N_i and the ILI tool correctly recognizes n_i defects out of N_i , then the specific probability (frequency) of true identification P_{TI_i} of the i -th type of defects is defined as

$$P_{TI_i} \sim n_i/N_i, \quad (4.20)$$

and the probability of false identification P_{FI_i} :

$$P_{FI_i} \sim (N_i - n_i)/N_i,$$

and, of course

$$P_{TI_i} + P_{FI_i} = 1.$$

All the false identification cases can be divided into groups, depending on what misinterpretations were committed. In general, in the frame of the above reasoning, there can be $(M - 1)$ such groups. The consequences of each kind of misinterpretations would be different. Some of the consequences may be negligible; other may be more serious than if the defect would be interpreted correctly. One can also write

$$P_{FI} = \frac{m_i}{N_i} + \dots + \frac{m_{M-1}}{N_i} = P_{FI_i} + \dots + P_{FI_{K-1}} = 1 - \frac{n_i}{N_i},$$

where $m_i, \dots, m_{M-1}$ are the numbers of misinterpretations in the relevant categories of defect types and P_{FI_i} are the probabilities of specific misinterpretations.

The probabilities P_{TI} (P_{TI_i}) and P_{FI} (P_{FI_i}) can be used as the identification performance metric. The closer is P_{TI} to unity, the higher is the quality of the ILI tool. As it can be seen, in some extravaganza cases $P_{TI} = 0$ and $P_{FI} = 1$ [8].

Example 4.3.1 Consider a real-life pipeline with a 1420 mm diameter and pipe wall thickness $wt = 15.9$ mm. During the ILI 1369 defects were discovered of the stress corrosion type with depths ranging from 1 to 73 % wt . The histogram of the defect depths is shown in Fig. 4.8.

Probability of correct identification, calculated according to the formula (4.20) depending on defect sizes is shown in Fig. 4.9, according to which the ILI tool gives

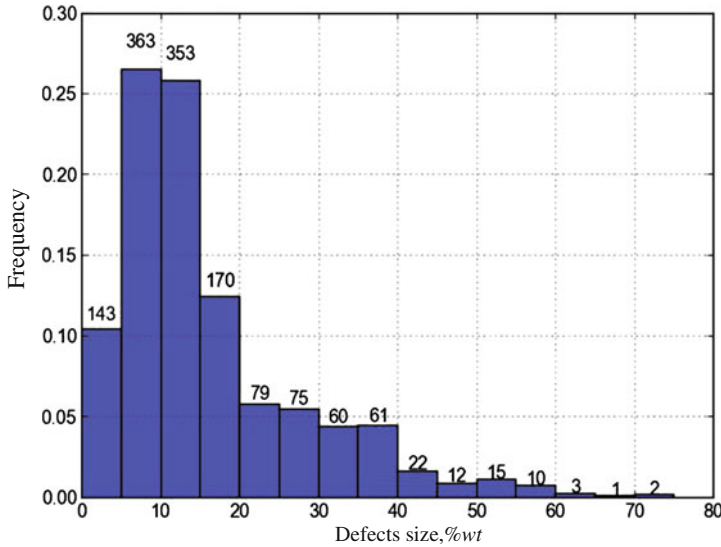


Fig. 4.8 Histogram of the sizes of discovered defects

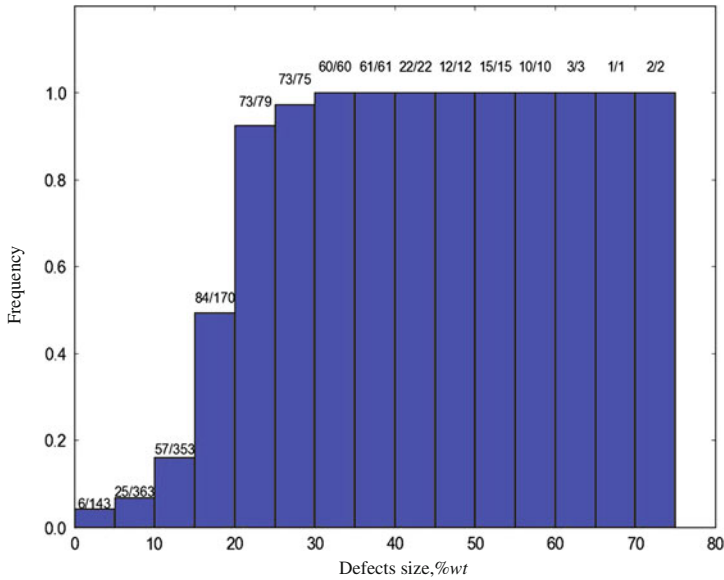


Fig. 4.9 Probability of correct identification of defects

a 100 % correct identification of defects in the inspected pipeline when the defects are deeper than 30 % of pipe web thickness.

Assume the difference between the actual and reported coordinate s (log distance) as Δs and the same difference for Θ as $\Delta\Theta$ (Fig. 4.10). The angular (clock position) difference is counted from the vertical axis of the pipe cross section. Both of them are RVs. During the verification process (digging ditches) these errors are found. Constructing and smoothing their histograms we arrive at their PDF's with known averages and variance.

Now the *location metrics for an i th type of defect* can be established as a 0.997 (3σ) quantile of distribution of RV Δs and $\Delta\Theta$ accordingly:

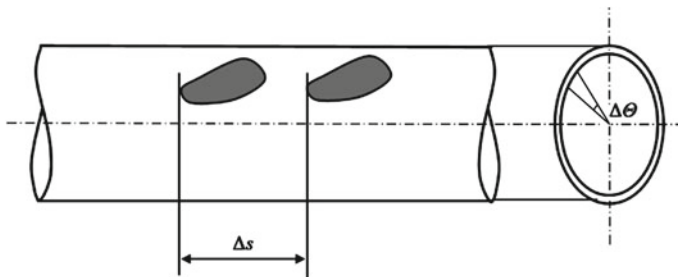


Fig. 4.10 Discrepancies between the actual and reported log distance (Δs) and the clock position ($\Delta\Theta$) of a defect

$$M_{i,\Delta s} = q_{0.997}(\Delta s), \text{ (m) },$$

$$M_{i,\Delta \theta} = q_{0.997}(\Delta \theta), \text{ deg. (min).}$$

The sizing accuracy of an ILI tool is calculated by comparing the depth, length, and width of all types of defects discovered by the ILI, with the same parameters, measured by another, more accurate instrument (usually considered errorless) during field excavations (verification).

Denote measurements performed on an i th type of defect by an ILI tool as d_i , l_i , w_i and by measurements performed during excavations as d_v , l_v , w_v . Assuming that the second measurements are precise, we may calculate the measurement errors as $\Delta d = d_v - d_i$, $\Delta l = l_v - l_i$, $\Delta w = w_v - w_i$.

In the general case, for constructing the sizing accuracy performance metrics, joint PDF should be constructed: (d_i, d_v) , (l_i, l_v) and (w_i, w_v) .

The *accuracy performance metrics for an i th type of defect depth* can be established as a 0.997 quantile of PDF (Δd) :

$$M_{i,\Delta d} = q_{0.997}(\Delta d), \text{ (mm) }.$$

The choice of the quantile order is not formalized. It is conditioned by economic considerations, level of ILI technology, and agreements between the pipeline companies and the DSP.

Conversely, the *accuracy performance metric for i th type of defect length and width*

$$M_{i,\Delta l} = q_{0.997}(\Delta l), \text{ (mm) }.$$

$$M_{i,\Delta w} = q_{0.997}(\Delta w), \text{ (mm) }.$$

The seven basic performance metrics derived above can be divided into two groups. The *performance identification and detection metrics* (that are associated with P_{TD} , P_{FD} , P_{TND} , P_{FND} , P_{TI} , and P_{FI}) are initially probabilistic and therefore are dimensionless. The other five PMs deal with measurement errors of defect parameters. The dimensions of these errors are linear and angular. In order to make them also dimensionless, divide each measurement error by the sensitivity threshold of the corresponding sensor, measurement channel, or technology utilized in the ILI tool to measure the particular parameter of the defect anomaly. Usually, the sensitivity threshold (physically, the resolution of the physical principle utilized in the measurement channel of the ILI sensor) is equal to a unit (increment) value on the corresponding scale. For instance, the increment scale value of a UT tool, in the best case, could be from 0.5 to 1.0 mm, when measuring defect depth, and 10 mm, when measuring defect length. When measuring defect width (and clock position) it would be half the distance between two adjacent (circumferentially) sensors (see Table 4.1). When measuring the log distance the sensitivity threshold is a derivative of the technology (ies) used. A topical value of the threshold when using GPS technology could

Table 4.1 Basic set of performance metrics (PMs) for one type of defects and one specific ILI tool

ILI tool	$M_{i,D}$	P_{FD_i}	P_{FND_i}	$M_{i,l}$	P_{FI_i}	$M_{s,i}$	$M_{i,\Delta\theta}$	$M_{i,\Delta d}$	$M_{i,\Delta l}$	$M_{i,\Delta w}$
PILIT	1.0	0.0	0.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0
Specific MFL tool	0.89	0.06	0.05	0.872	0.128	250	5	200	50	32.5
Absolute scale unit value	—	—	—	—	—	2 cm	1 min	1 mm	10 mm	10 mm

be somewhere around 20 mm. In general, the sensitivity thresholds reflect the level of the ILI tool precision under consideration. It is important, therefore, to have a description of what thresholds were used during the procedure of making the PM's dimensionless.

The basic set of PM's for one type of defects and one type of ILI tool is shown in Table 4.1. For comparison the basic metrics of the perfect ILI tool are also given. This table should be supplemented by curves (or corresponding histograms) for P_{TD} , P_{TND} , P_{FD} , P_{FND} as well as with PDFs or histograms for Δs , $\Delta\theta$, Δd , Δl , Δw and their joint PDFs or histograms $\{d_i, d_v\}$, $\{l_i, l_v\}$, $\{w_i, w_v\}$, which are used when calculating the parameters in Table 4.1.

The sensitivity thresholds for the above performance metrics were denoted earlier as η_s , η_θ , η_d , η_l , η_w . Accounting for this, we have

$$\begin{aligned}
 \Delta\Theta_i &= \Delta\tilde{\Theta}_i/\eta_\Theta; \\
 \Delta s_i &= \Delta\tilde{s}_i/\eta_s; \\
 \Delta d_i &= \Delta\tilde{d}_i/\eta_d; \\
 \Delta l_i &= \Delta\tilde{l}_i/\eta_l; \\
 \Delta w_i &= \Delta\tilde{w}_i/\eta_w.
 \end{aligned}$$

In these formulas physical values of corresponding MEs of defect parameters are denoted by a tilde.

Now, all the seven basic PMs can be fused in one parameter integral performance score that will characterize the overall ILI tool performance quality as related to the i th type of defects. The fusion process consists of the calibration and the convolution processes. During calibration the weight of each specific metric is defined, depending on its importance in each particular case. Selection of the weight can be performed by the Provider and/or by the Operator using their previously accumulated expertise. The convolution of each metrics into one is achieved by the integral performance score $ISP_i()$ for a given ILI tool, as related to a specific (j th) type of pipeline defect:

$$ISP_i = \frac{w_{i,1}M_{i,1} + w_{i,2}M_{i,2} + \cdots + w_{i,j}M_{i,j} + \cdots + w_{i,n}M_{i,n}}{\sum_{j=1}^n w_{i,j}},$$

where $M_{i,j}$ are the relevant metric scores that are chosen to be representative for the particular case; n is the number of metrics; and $w_{i,j}$ are the assigned weights.

It is also possible to use the Euclid rule of convolution which gives

$$ISP_i = \sqrt{\sum_{j=1}^n M_{i,j}^2}.$$

Finally, for an ILI tool that is capable of detecting N types of different defects (anomalies) the total value of its quality (integral quality index) will, obviously, be

$$TPQ_{\Sigma} = \sum_{i=1}^N ISP_i.$$

Now all different kinds of ILI tools can be compared, using the basic performance metrics and the total quality index.

4.3.3 Additional Quality Metrics of ILI Tools

In this section some additional quality metrics are considered, which permit an in-depth assessment of the ILI quality.

The *detection sensitivity metric for an i th type of defects* measures the difference between the success functions of the ILI under two operations conditions (preferably on the same or similar pipeline section):

$$M_{i,ds} = \sqrt{\int_0^{\infty} (S_{i,1}(x) - S_{i,2}(x))^2 dx},$$

where $S_{i,1}(x)$, $S_{i,2}(x)$ are correspondingly the success functions for the first and second operating conditions relative to an i -type of defects.

The *false call probability metric for an i th type of defects* is

$$M_{i,fd} = \int_0^{\infty} P_{FD_i}(x) dx.$$

The *false non-detection metric for an i th type of defects* is defined as

$$M_{i, \text{fnd}} = \int_0^{\infty} P_{\text{FND}_i}(x) dx.$$

The *robustness metrics of the diagnostics algorithms* as related to results of diagnostics of the i th type of defects, which are contaminated by electronic noise of different nature (vibration and acceleration of the ILI tool during its run, sensor lift-off, etc.), has the form

$$M_{i, \text{ns}} = \sqrt{\int_0^{\infty} [F_{i,2}(x) - F_{i,1}(x)]^2 dx},$$

where $F_{i,1}$, $F_{i,2}$ are correspondingly the ILI tool failure functions for two conditions of its operation, as related to an i th type of defects.

4.3.4 Quality Metrics of Pipeline Residual Lifetime Prognosis

As was shown earlier the ultimate goal of ILI is to produce as precise as possible measurements of all discovered defects in the form that permits consistent and accurate assessment of the remaining life of the inspected pipeline. It is, therefore, expedient to have a suitable instrument for assessing the quality of the prognostication algorithms which uses the ILI measurements. The role of this instrument can be played by the *prognosis performance metric* M_{pp} . This metric is constructed in the following way.

Assume that the results of ILI are in the form of $PDF(d)$, $PDF(l)$, $PDF(w)$, and pipeline Operator chose one of the acknowledged deterministic design codes for defining pipeline residual life and a probabilistic method for assessing its PDF.

In order to construct the M_{pp} it is necessary to also have some experimental or observation data about the actual remaining life of the pipeline, which allows constructing its PDF.

The PDF of the difference between observed and analytical remaining life now can be expressed as

$$PDF(\Delta RL) = PDF_1(RL) * PDF_2(RL),$$

where $*$ is the convolution operator and $PDF_1(RL)$, $PDF_2(RL)$ are, correspondingly, the PDFs of the observed and the analytical values of the remaining life.

Then the *prognosis performance metric* will take the form

$$M_{pp} = q_{0.997}(\Delta RL) .$$

The smaller is this quantile, the better is the forecasting algorithm and the ILI measurement performance (the quality of other components of the algorithm is not considered here).

4.3.5 Efficacy Metrics of ILI Instruments

The integral effectiveness of ILI tool can now be assessed in terms of achieving the ultimate inspection/diagnostics goal using *efficacy metrics* (Fig.4.11). In general, the efficacy metrics utilizes many of the same metrics as in the case of performance metrics. But they can be combined and calibrated differently, depending on the concrete application of the ILI tool. Such metrics of the ILI tool as its acquisition cost (or implementation cost), robustness, and resource requirements are unique to the overall effectiveness of the ILI tool. Acquisition and implementation costs of the diagnostic ILI tool have a significant impact on ILI tool cost effectiveness.

In the context of the discussed problem, robustness is understood as stability of ILI tool operation under conditions, when it receives substantial disturbances from its environment. The cost of ILI tool (or service) purchase metric measures financial efforts needed for acquiring the gadget or the service.

The *implementation cost metric*. This metric measures the annual (or per 1000 km of pigged pipeline) cost incurred to keep the ILI tool operable. These costs include

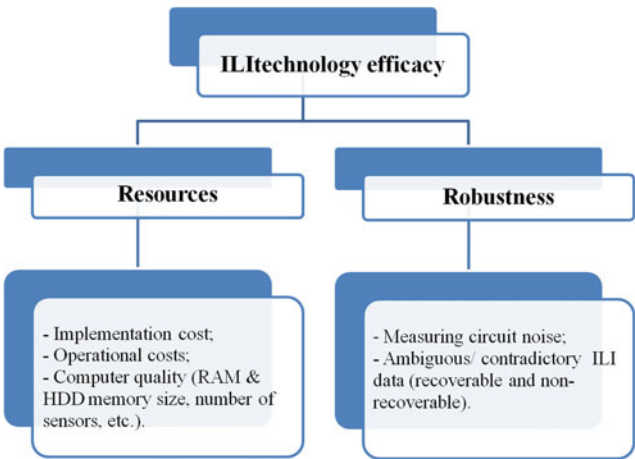


Fig. 4.11 ILI technology efficacy metrics

costs associated with the pigging proper, with computer processing and retrieval of the raw data, field and laboratory testing of the ILI tool, its repair and maintenance, transportation to and from the inspection site, etc.

A metric that takes into account the computational requirements to produce an assessment of the defects in a pipeline section is called the *computer resource metric*. This metric computes a score based on the generalized CPU time to run the ILI tool and deciphering process (on work stations).

The ILI tool *complexity metric* measures its complexity in terms of the number of sensors and number of lines of code which diagnoses and sizes the discovered defects.

Summarizing, pipeline Operator has the following benefits from ILI through accurate detection, location, identification, and sizing: (1) benefits (savings) realized by correctly detecting all types of critical defects prior pipeline burst or leak, and (2) benefits of correct accurate 3D sizing of the detected defects (correct failure prediction).

Once the leak/rupture occurred and oil spilled, most of the costs of mitigating the impact of accident are outside of the operator's control. The above costs can be classified as:

- direct costs for response, clean-up, reporting to regulator, management time, loss of revenue;
- costs to analyze the incident, evaluate whether correcting procedures are needed;
- additional expenditures on fines, penalties, legal liabilities; and
- bad will and damage to company's reputation, which could impede its operator for an incalculable amount of time.

Preventing leaks/ruptures is equivalent to the avoidance of these possible expenditures.

At the same time the very same ILI requires certain resources for implementing and/or operating the ILI tool(s). Simultaneously with benefits, the ILI incurs losses due to false calls, no detection of dangerous defects, misidentification of defects, and mislocation of defects. The difference between the benefits and costs is the actual measure of the ILI tool effectiveness in a given successful inspection.

This inspection typically will discover multiple defects which can be classified by the level of their danger, depending on their sizes (i.e., depth): (1) small, not dangerous; (2) reportable defects, which at present are not dangerous, but may become dangerous in the near future; and (3) dangerous defects, which should be repaired immediately. The ranges of the defect depths are shown in Fig. 4.12, where x_0 is the physical threshold value of defect size; x_r is the minimal reportable size of defect; and x_d is the minimal size of a dangerous defect.



Fig. 4.12 Calibration of discovered defects depending on their size

This classification of defects can also be performed, using some pipeline strength code (B31G [10], B31Gmod [11], DNV [12] et al.), depending on the values of the safety factors.

The number of discovered dangerous defects provides information about the volume of prevented leaks/ruptures and their possible consequences, and allows conducting optimal monitoring of the condition of the whole pipeline system.

The first approximation of the effectiveness of ILI (as related to one type of pipeline defects) can be obtained as the difference between the benefits b_i of ILI implementation and possible losses c_i in the absence of ILI. Net profit from the use of ILI is equal to

$$ILI_{NV} = \sum b_i - \sum c_i.$$

The current methods of defect detection, identification, location, and sizing of defects need improvement, because they do not provide for proper assessing efficiency of the ILI tool and qualification of the diagnostician.

In order to increase safety of pipeline systems it is worthwhile to develop state and industry diagnostics quality standards for each type of ILI tool using the above metrics. The basic algorithms used when calculating the core specifications of ILI tools should be presented in each tender for conducting in-line inspections. This would allow the consumer to assess the utility function of the ILI tool or the service.

Developing and implementing the ILI tool metrics requires well-documented sets of data on pipeline defects. These sets of data are gathered by the Provider of diagnostic services and the pipeline Operator during ILI, field and lab tests of ILI tool, and should be used for creating the next generation of ILI technology using ILI quality metrics, adapting them if needed, to the current level of ILI technology. This would enhance the ILI quality in two ways:

- the pipeline operators would be able to compare and select the ILI tool that best fits their particular needs; and
- the ILI tool developers would be able to use the metric-based evaluation process to assess and improve their diagnostic algorithms, which are associated with detecting, identifying, and sizing of all types of defects.

The market of inspection services and its customers will both win if the described above approach, which already exists in the measurement instruments industry, will be adopted in the pipeline transportation industry. This will allow providing each ILI tool with a specification which will contain its quality metrics and track their changes after each repair and reconfiguration over its life cycle. This will enhance its accuracy, precision, reproducibility, and repeatability (see Sect. 4.7 of this Chap. 4).

Increasing accuracy of the tool after each run requires conducting additional independent measurements in ditches. These verification measurements have their own errors and confidence intervals, which should be accounted for when assessing the overall accuracy of the ILI tool.

In this context it seems worthwhile to conduct, on a purely volunteer basis, a comparative comprehensive and representative quality analysis of ILI tools of different

manufactures, using metrics, such as described above, as it was done many years ago by *British Gas* (see Chap. 3) using data provided by willing Vendors and Operators.

4.4 Method of Increasing Authenticity of ILI Measurements

This section describes the methodology for improving authenticity of the ILI results [13]. The description of the methodology is done for the case of defect depth and is based on performance of several (at least two) independent measurements of the absolute depth of each “metal loss” type defect and the thickness of the undamaged pipe wall. This allows, unlike the known normative methods, to evaluate measurement errors contributed by each particular MI when inspecting each particular pipeline, thus improving accuracy of the defect depth measurements.

One of the main current ILI problems is the insufficient amount of knowledge about the defects (their number, identification, location, and size). This problem requires assessment of the degree of pipeline damage, predicting its degradation and ensuring, on that basis, its safe operation. The proposed below methodology improves the certainty of measurement results of actively growing defects of “metal loss” type, due to application of more accurate algorithms of processing measurement results.

4.4.1 Analysis of Existing Methods of ILI

The most often used approach to the ILI results analysis is based on measurements of the defect parameters. It is outlined in the ILI quality standard API 1163 [1], in accordance with which the single direct (with the help of UT) or indirect (using magnetic technique) measurements are made of the absolute depth of defects $\hat{d}$ and the absolute wall thickness $\hat{wt}$ depending on what type of intelligent pig is used—the UT or the MFL. The confidence intervals for the relative depth d/wt of each defect are considered to be symmetrical and are calculated according to the formula

$$\left(\frac{\hat{d}}{\hat{wt}} - \Delta_{d/wt}^*; \frac{\hat{d}}{\hat{wt}} + \Delta_{d/wt}^* \right), \quad (4.21)$$

where $\Delta_{d/wt}^*$ is the ultimate error of the relative defect depth determination (quantile of level p), equal to

$$\Delta_{d/wt}^* = u_p \frac{d}{wt} \sqrt{\left(\frac{\sigma_d}{\hat{d}} \right)^2 + \left(\frac{\sigma_{wt}}{\hat{wt}} \right)^2}, \quad (4.22)$$

where u_p is the level p quantile of standard normal law; $p = (1 + \gamma)/2$; γ is the given authenticity level; $\hat{d}$ is the measured or calculated absolute defect depth; $\hat{wt}$ is the measured total (full) wall thickness; σ_d is the standard deviation of measurement error of the absolute depth d ; and σ_{wt} is the standard deviation of ME of the total (full) wall thickness wt .

According to [1], the standard deviations σ_d and σ_{wt} are set a priori, on the basis of statistical data accumulated earlier in laboratory conditions during the diagnostic tool calibration, or by processing “suitable” statistical information, obtained using this or similar ILI tool on “similar” pipelines. Here it is important to emphasize that these deviations are not determined by direct measurements performed on the inspected pipeline, as it is prescribed by the iron law of statistics. The Standard [1] does not contain scientific justification for the transfer of statistical characteristics, derived in laboratory conditions or another pipeline condition, or from another tool, to the ILI tool in consideration, which is operating under unique specific conditions of the inspected pipeline.

Further, the right boundary of the CI is determined (4.21) as

$$\tau = \frac{\hat{d}}{\hat{wt}} + \Delta_{d/wt}^*, \quad (4.23)$$

which is compared with the ultimate permissible value (according to existing rules and pipeline operation codes) for the relative defect depth D . If $\tau > D$, then, with reliability γ , this defect is considered to be exceeding the maximum allowed value.

The critical disadvantage of the method described in [1] is the insufficient certainty of the defect depth measurements, due to the replacement of the direct evaluation of σ_d and σ_{wt} , based on current experimental data obtained with a specific in-line inspection tool on a given pipeline, by standards determined a priori through measurements made earlier, under other uncontrolled conditions, on other pipelines, and using other ILI tools.

Moreover, in the described method formula (4.21) for evaluation of the CI of the relative defect depth is inaccurate and needs to be clarified. To prove this statement [13], consider formula (4.22) for determining the ultimate permissible error of the relative defect depth. It is known that the true values of the absolute depth d and the total wall width wt , with the given authenticity level γ , lie respectively within the following CI:

$$\begin{aligned} \hat{d} - \Delta_d < d < \hat{d} + \Delta_d, \\ \hat{wt} - \Delta_{wt} < wt < \hat{wt} + \Delta_{wt}, \end{aligned} \quad (4.24)$$

where Δ_d , Δ_{wt} are, with probability γ , the ultimate permissible values of error, when determining d and wt , and equal $\Delta_d = u_p \sigma_d$, $\Delta_{wt} = u_p \sigma_{wt}$.

Assuming that $\hat{wt} > \sigma_{wt}$ and $\hat{d} > \sigma_d$, and taking into account (4.24), determine that the true value of relative depth d/wt lies within the CI

$$\left(\frac{\hat{d} - \Delta_d}{\hat{wt} + \Delta_{wt}}; \frac{\hat{d} + \Delta_d}{\hat{wt} - \Delta_{wt}} \right), \quad (4.25)$$

i.e., CI (4.25), unlike statement (4.21), is asymmetric.

Now transform the right boundary of CI (4.25):

$$\left(\frac{\hat{d} + \Delta_d}{\hat{wt} - \Delta_{wt}} = \frac{\hat{d}}{\hat{wt}} + \frac{\hat{d}\Delta_{wt} + \hat{wt}\Delta_d}{\hat{wt}(\hat{wt} - \Delta_{wt})} = \frac{\hat{d}}{\hat{wt}} + \frac{u_p(\hat{d}\Delta_{wt} + \hat{wt}\Delta_d)}{\hat{wt}(\hat{wt} - u_p\sigma_{wt})} \right).$$

This expression allows writing the ultimate permissible error of the relative defect depth determination as

$$\Delta_{d/wt} = \frac{u_p(\hat{d}\Delta_{wt} + \hat{wt}\Delta_d)}{\hat{wt}(\hat{wt} - u_p\sigma_{wt})}. \quad (4.26)$$

Comparing (4.22) and (4.26), it could be seen that $\Delta_{d/t} \neq \Delta_{d/t}^*$, where the difference could be both to the larger, or to the smaller side. Therefore, while using [1] the calculation formula (4.23) should be replaced by

$$\tau = \frac{\hat{d}}{\hat{wt}} + \Delta_{d/wt}.$$

The reviewed shortcomings of the method result in its incomplete validity/authenticity. Moreover, the postulated measurement accuracy may prove to be:

1. higher than the actual. This leads to a situation when the maximum allowed values of the relative defect depth D will lie to the left of the actual value of D_2 (as shown schematically in Fig.4.13). As a result, the defect size may be overstated, and require larger scope of expensive field excavations and verification measurements; and
2. lower than the actual. In this case the maximum allowed value of the relative defect depth D will lie to the right of the actual value of D_1 (see Fig.4.13), leading to possible missing of significant defects and, correspondingly, to higher risk of pipeline accidents.

A consequence of the above is, in some cases, the impossibility to fully automate processing of the ILI results and the higher dependence on the qualification of ILI operators, who are responsible for detecting, identifying, and sizing of the relatively large and potentially dangerous (quickly growing) defects, using the in-line measurement data.

An alternative approach to ILI is based on simultaneous measurement of the pipe defect sizes using several measurement tools, which operate using different physical principles. In [14] one such approach is described. It consists of detecting defects using simultaneously the UT technique, the MFL method, and the magnetic-optic technique, and then comparing results of all the three sets of measurements. The

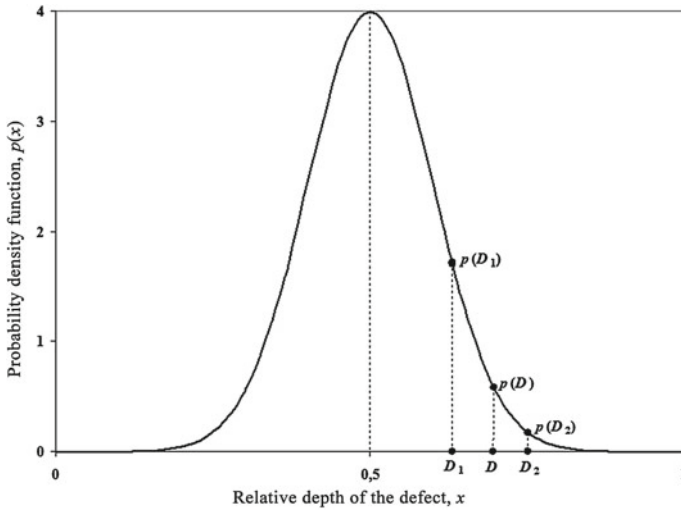


Fig. 4.13 Probability density function of the relative depth of defects

shortcomings of this approach and the method in general are the complexity and the low operational efficiency of diagnostics (due to the need to harmonize several measurement techniques). There is also the low validity of the defect measurement, due to the lack of control of the measurement accuracy (in the same way as in the first method).

4.4.2 Possible Ways of Increasing Validity of ILI Tool Measurements

As was shown above, the main reason for in some cases insufficient validity of ILI is the fact that the defect sizing is based on the use of prior information about the accuracy of the used ILI tools (in the form of numerical estimates of the standards σ_d and σ_{wt}), obtained in *statistically uncontrolled environment*, which, as a rule, differs significantly from the actual conditions of the conducted in-line inspection. Since the measurement conditions in a particular pipeline in most cases dramatically differ from the conditions in which the assigned standards were obtained, the actual measurement accuracy may differ significantly from assigned accuracy. This problem may be solved by assessing the measurement errors *directly and every time when inspecting each particular pipeline*. In order to achieve this it is necessary to perform, during each run, several *independent* measurements of the absolute depth of each defect and the thickness of the *undamaged* pipe wall around it.

Based on these results, it is possible to determine the standard deviation of measurement error, and also improve accuracy of the parameter evaluation by averaging

results of several measurements. Taking independent measurements of the absolute depth of each defect and the undamaged pipe wall thickness may be performed by mounting on the ILI tool two independent defect depth measurement systems, and two sets of sensors for measuring the pipe wall thickness.

Variance of measurements performed with any MI always consists of two components—variance of the true values of the measured parameter (defect depth or pipe wall thickness) and variance of the respective error. Moreover, the variance of measurement error for a given measurement instrument under the given conditions may be obtained as a difference between the variance of the instrument's measurements and the variance of the true values of the defect parameter. Describe the method of analysis of ILI results on the simplest case of taking two independent measurements of a defect depth.

For an arbitrary i th defect,

$$\begin{aligned} x_{1i} &= d_i + \varepsilon_{1i}, \\ x_{2i} &= d_i + \varepsilon_{2i}, \end{aligned} \quad (4.27)$$

where x_{1i} and x_{2i} are the results of the first and the second measurements of the i -th defect, taken by different instruments; d_i is the true value of the i -th defect; and ε_{1i} and ε_{2i} are the mutually independent random measurement errors of the first and the second measurement of the i -th defect with zero mathematical expectation (i.e., no systemic measurement errors present).

Consider two possible cases.

Measurement errors are independent of each other and to the true values of the measured defect parameter. In this case the covariance between the results of the first and the second sets of measurements is equal to the variance of the true depth of defects

$$\text{cov}(x_1, x_2) = \sigma_{d0}^2.$$

Assume that the actual sizes of the defect depth and errors of measurement results are independent random values. Then

$$\begin{aligned} \sigma_{x1}^2 &= \sigma_{d0}^2 + \sigma_{\varepsilon1}^2, \\ \sigma_{x2}^2 &= \sigma_{d0}^2 + \sigma_{\varepsilon2}^2. \end{aligned}$$

Hence, the error variances of the first and the second sets of measurements will be

$$\begin{aligned} \sigma_{\varepsilon1}^2 &= \sigma_{x1}^2 - \sigma_{d0}^2 = \sigma_{x1}^2 - \text{cov}(x_1, x_2), \\ \sigma_{\varepsilon2}^2 &= \sigma_{x2}^2 - \sigma_{d0}^2 = \sigma_{x2}^2 - \text{cov}(x_1, x_2). \end{aligned}$$

To reduce the random error, average the results of all pairs of measurements:

$$x_i = \frac{x_{1i} + x_{2i}}{2}, \quad \varepsilon_i = \frac{\varepsilon_{1i} + \varepsilon_{2i}}{2}.$$

As a result, taking into account the independence of random errors ε_{1i} and ε_{2i} , determine the variance σ_ε^2 , and standard deviation σ_ε , of the defect depth ME:

$$\sigma_\varepsilon^2 = \frac{\sigma_{\varepsilon 1}^2 + \sigma_{\varepsilon 2}^2}{4},$$

$$\sigma_\varepsilon = \sqrt{\sigma_\varepsilon^2}.$$

Similarly, using results of paired measurements (y_{1i} , y_{2i}) of the pipe wall thickness

$$y_{1i} = wt_{1i} + \xi_{1i},$$

$$y_{2i} = wt_{2i} + \xi_{2i}$$

obtain average values y_i , variance σ_ξ^2 , and standard deviation σ_ξ of the pipe wall thickness ME wt . Note that in this case the condition of independence of ε_i and ξ_i ME is not mandatory.

We introduce the following definitions: $\hat{d}_i = x_i$, $\hat{w}t_i = y_i$, $\sigma_d = \sigma_\varepsilon$, and $\sigma_{wt} = \sigma_\xi$.

Then, for a sample size n there are n pairs of defects and wall thickness measurements:

$$(x_{1i}, x_{2i}), (y_{1i}, y_{2i}), i = 1, 2, \dots, n.$$

Therefore, the calculation formulas will acquire the form

$$cov(x_1, x_2) = \sigma_{d0}^2 = \frac{1}{n-1} \left[\sum_{i=1}^n x_{1i}x_{2i} - \frac{1}{n} \left(\sum_{i=1}^n x_{1i} \right) \left(\sum_{i=1}^n x_{2i} \right) \right];$$

$$\sigma_{x1}^2 = \frac{1}{n-1} \left[\sum_{i=1}^n x_{1i}^2 - \frac{1}{n} \left(\sum_{i=1}^n x_{1i} \right)^2 \right];$$

$$\sigma_{x2}^2 = \frac{1}{n-1} \left[\sum_{i=1}^n x_{2i}^2 - \frac{1}{n} \left(\sum_{i=1}^n x_{2i} \right)^2 \right];$$

$$cov(y_1, y_2) = \sigma_{t0}^2 = \frac{1}{n-1} \left[\sum_{i=1}^n y_{1i}y_{2i} - \frac{1}{n} \left(\sum_{i=1}^n y_{1i} \right) \left(\sum_{i=1}^n y_{2i} \right) \right];$$

$$\sigma_{y1}^2 = \frac{1}{n-1} \left[\sum_{i=1}^n y_{1i}^2 - \frac{1}{n} \left(\sum_{i=1}^n y_{1i} \right)^2 \right];$$

$$\sigma_{y2}^2 = \frac{1}{n-1} \left[\sum_{i=1}^n y_{2i}^2 - \frac{1}{n} \left(\sum_{i=1}^n y_{2i} \right)^2 \right];$$

$$\sigma_{\varepsilon 1}^2 = \sigma_{x1}^2 - cov(x_1, x_2), \quad \sigma_{\varepsilon 2}^2 = \sigma_{x2}^2 - cov(x_1, x_2);$$

$$\begin{aligned}\sigma_d &= \sigma_\varepsilon = \sqrt{\frac{\sigma_{\varepsilon 1}^2 + \sigma_{\varepsilon 2}^2}{4}}, \\ \sigma_{\xi 1}^2 &= \sigma_{y 1}^2 - \text{cov}(y_1, y_2), \quad \sigma_{\xi 2}^2 = \sigma_{y 2}^2 - \text{cov}(y_1, y_2); \\ \sigma_{wt} &= \sigma_\xi = \sqrt{\frac{\sigma_{\xi 1}^2 + \sigma_{\xi 2}^2}{4}},\end{aligned}$$

where σ_d is the mean-square deviation (standard) of measurement error of the absolute depth d ; σ_{wt} is the standard ME of the full wall thickness wt ; and (x_{1i}, x_{2i}) , (y_{1i}, y_{2i}) , $i = 1, 2, \dots, n$ are pairs of measurements of the defect size and wall thickness.

Now we introduce the following symbols: $\hat{d}$ is the measured or calculated absolute depth of defect and $\hat{wt}$ is the measured full wall thickness. Then, using formula (4.21) determine the more accurate boundaries of the confidence interval CI of the relative defect depths, as compared to [1]. The upper CI boundary (4.23) is compared with the maximum allowed (according to codes) value of the relative defect depth D , which was set *a priori*. If $\tau > D$, then the confidence interval covers the maximum allowed relative defect depth value. Therefore, with given reliability γ , this defect exceeds the maximum allowed value. This means that the measurement is considered to be valid.

Measurement errors correlate with each other, but are independent of true values of the measured defect parameter. In this case several paired measurements of the virgin (without defects) wall thickness are made in a local area of pipe without defects, using the same measurement tools, which will be further used to measure the defect depth and the wall thickness. For a wall thickness in a local area without defects the model of two related measurements made with two measurement tools will be

$$\begin{aligned}v_1 &= t + \eta_1, \\ v_2 &= t + \eta_2,\end{aligned}\tag{4.28}$$

where v_1 and v_2 are the results of the first and the second virgin wall thickness measurements; t is the true value of wall thickness (a deterministic but unknown value); and η_1 and η_2 are correlated with each other random errors of the first and the second wall thickness measurements in a local area without defects, with zero mathematical expectation.

Based on m pairs of results of these measurements, the paired correlation factor ρ is determined for the ILI tool measurement errors:

$$\rho = \rho(v_1, v_2) = \rho(\eta_1, \eta_2) = \frac{\text{cov}(v_1, v_2)}{\sigma_{v1}\sigma_{v2}},\tag{4.29}$$

where $\text{cov}(v_1, v_2)$ is covariation between the first and the second wall thickness measurements in a local area without defects; σ_{v1}^2 is the variance of the first wall

thickness measurement in a local area without defects; and $\sigma_{v_2}^2$ is the variance of the second wall thickness measurement in a local area without defects:

$$\begin{aligned} cov(v_1, v_2) &= \frac{1}{m-1} \left[\sum_{j=1}^m v_{1j} v_{2j} - \frac{1}{m} \left(\sum_{j=1}^m v_{1j} \right) \left(\sum_{j=1}^m v_{2j} \right) \right], \\ \sigma_{v_1}^2 &= \frac{1}{m-1} \left[\sum_{j=1}^m v_{1j}^2 - \frac{1}{m} \left(\sum_{j=1}^m v_{1j} \right)^2 \right], \\ \sigma_{v_2}^2 &= \frac{1}{m-1} \left[\sum_{j=1}^m v_{2j}^2 - \frac{1}{m} \left(\sum_{j=1}^m v_{2j} \right)^2 \right]. \end{aligned}$$

Using the obtained correlation factor, the standard deviations of defect depth and wall thickness measurement error are determined.

This is achieved by means of conducting n paired measurements $(x_{1i}, x_{2i}, y_{1i}, y_{2i})$ $i = 1, 2, \dots, n$ of defect depth and wall thickness in an area next to a defect.

For an arbitrary defect there is a model (4.27) of two related measurements, where ε_1 and ε_2 are random defect depth measurement errors of the first and the second sensors with zero mathematical expectation (no systemic measurement errors) and a paired correlation factor equal ρ .

In this case, taking into account (4.29) and the aforementioned assumption $\rho(\varepsilon_1, \varepsilon_2) = \rho(\eta_1, \eta_2) = \rho$, following equations will be true

$$\sigma_{x_1}^2 = \sigma_{d0}^2 + \sigma_{\varepsilon_1}^2, \quad (4.30)$$

$$\sigma_{x_2}^2 = \sigma_{d0}^2 + \sigma_{\varepsilon_2}^2, \quad (4.31)$$

$$\sigma_{d0}^2 = cov(x_1, x_2) - cov(\varepsilon_1, \varepsilon_2) = cov(x_1, x_2) - \rho \sigma_{\varepsilon_1} \sigma_{\varepsilon_2}, \quad (4.32)$$

where

$$\begin{aligned} cov(x_1, x_2) &= \sigma_{d0}^2 = \frac{1}{n-1} \left[\sum_{i=1}^n x_{1i} x_{2i} - \frac{1}{n} \left(\sum_{i=1}^n x_{1i} \right) \left(\sum_{i=1}^n x_{2i} \right) \right], \\ \sigma_{x_1}^2 &= \frac{1}{n-1} \left[\sum_{i=1}^n x_{1i}^2 - \frac{1}{n} \left(\sum_{i=1}^n x_{1i} \right)^2 \right], \\ \sigma_{x_2}^2 &= \frac{1}{n-1} \left[\sum_{i=1}^n x_{2i}^2 - \frac{1}{n} \left(\sum_{i=1}^n x_{2i} \right)^2 \right]. \end{aligned}$$

We derived a system of Eqs. (4.30)–(4.32) with three unknown values σ_{d0}^2 , $\sigma_{\varepsilon_1}^2$, $\sigma_{\varepsilon_2}^2$. From Eqs. (4.30) and (4.31) we obtain

$$\begin{aligned}\sigma_{\varepsilon 1}^2 &= \sigma_{x1}^2 - \sigma_{d0}^2, \\ \sigma_{\varepsilon 2}^2 &= \sigma_{x2}^2 - \sigma_{d0}^2.\end{aligned}\tag{4.33}$$

Substituting these equations into (4.32), we derive

$$\text{cov}(x_1, x_2) - \sigma_{d0}^2 = \rho \sqrt{(\sigma_{x1}^2 - \sigma_{d0}^2)(\sigma_{x2}^2 - \sigma_{d0}^2)}.$$

From this it follows that

$$\begin{aligned}&\rho^2 \sigma_{x1}^2 \sigma_{x2}^2 - \rho^2 \sigma_{d0}^2 \sigma_{x2}^2 - \rho^2 \sigma_{d0}^2 \sigma_{x1}^2 + \rho^2 \sigma_{d0}^4 - \text{cov}^2(x_1, x_2) \\ &+ 2\text{cov}(x_1, x_2) \sigma_{d0}^2 - \sigma_{d0}^4 = 0 \\ &\sigma_{d0}^4 (\rho^2 - 1) + \sigma_{d0}^2 (2\text{cov}(x_1, x_2) - \rho^2 (\sigma_{x2}^2 + \sigma_{x1}^2)) \\ &+ (\rho^2 \sigma_{x1}^2 \sigma_{x2}^2 - \text{cov}^2(x_1, x_2)) = 0.\end{aligned}$$

We have obtained a quadratic equation in respect of σ_{d0}^2 ,

$$a_d \sigma_{d0}^4 + b_d \sigma_{d0}^2 + c_d = 0,\tag{4.34}$$

where $a_d = \rho^2 - 1$, $b_d = 2\text{cov}(x_1, x_2) - \rho^2(\sigma_{x1}^2 + \sigma_{x2}^2)$, $c_d = \rho^2 \sigma_{x1}^2 \sigma_{x2}^2 - \text{cov}^2(x_1, x_2)$.

A discriminant $D_d = b_d^2 - 4a_d c_d$ of Eq. (4.34) $D_d > 0$ at $\rho \neq 0$ and $D_d = 0$ at $\rho = 0$, i.e., always has roots. Case $\rho = 0$ corresponds to uncorrelated measurement errors ε_1 and ε_2 .

Equation (4.34) has two solutions $\frac{-b_d \pm \sqrt{D_d}}{2a_d}$. Take as the σ_{d0}^2 value the admissible solution, i.e.,

$$\sigma_{d0}^2 = \frac{-b_d + \sqrt{D_d}}{2a_d}.$$

A second solution $\sigma_{d0}^2 = \frac{-b_d - \sqrt{D_d}}{2a_d}$ is inadmissible, since variance cannot be negative.

Substituting the obtained value of the defect depth variance σ_{d0}^2 into (4.33), we find the measurement error variances $\sigma_{\varepsilon 1}^2, \sigma_{\varepsilon 2}^2$.

In order to decrease the random error, average the results of all defect depth measurement pairs $(x_{1i}, x_{2i}), i = 1, 2, \dots, n$:

$$x_i = \frac{x_{1i} + x_{2i}}{2},$$

As a result, taking into account the dependencies of random errors ε_{1i} and ε_{2i} the variance σ_d^2 and standard deviation σ_d of defect depth MEs are determined by the formulas

$$\sigma_d^2 = \frac{1}{4} (\sigma_{\varepsilon 1}^2 + \sigma_{\varepsilon 2}^2 + 2\rho\sigma_{\varepsilon 1}\sigma_{\varepsilon 2}), \quad \sigma_d = \sqrt{\sigma_d^2} = \frac{1}{2} \sqrt{\sigma_{\varepsilon 1}^2 + \sigma_{\varepsilon 2}^2 + 2\sigma_{\varepsilon 1}\sigma_{\varepsilon 2}\rho}.$$

Similarly, for virgin wall thickness around the defect we have a model of two uncorrelated measurements, made with two measurement tools,

$$\begin{aligned} y_1 &= t + \xi_1, \\ y_2 &= t + \xi_2, \end{aligned} \quad (4.35)$$

where y_1 and y_2 are the results of the first and the second wall thickness measurements; t is the true value of wall thickness; ξ_1 and ξ_2 are random errors of wall thickness measurements of the first and the second sensors with zero mathematical expectation, and a paired correlation factor equal ρ .

Following the approach similar to the one used for the defect depth measurements, determine the variance σ_t^2 , and the standard deviation σ_t of wall thickness ME in close proximity to the defect by the formulas

$$\sigma_t^2 = \frac{1}{4} (\sigma_{\xi_1}^2 + \sigma_{\xi_2}^2 + 2\rho\sigma_{\xi_1}\sigma_{\xi_2}), \quad \sigma_t = \sqrt{\sigma_t^2} = \frac{1}{2} \sqrt{\sigma_{\xi_1}^2 + \sigma_{\xi_2}^2 + 2\rho\sigma_{\xi_1}\sigma_{\xi_2}}. \quad (4.36)$$

As in the previous case, using formula (4.21) the confidence intervals are determined for each defect depth measurement. The derived confidence intervals for the relative defect depth are compared with the maximum allowed value of the relative defect depth.

4.4.3 Analysis of Obtained Results

We now perform a comparative analysis of the known [1] and the proposed above methodologies.

For the sake of simplification (without loss of generality) assume that the accuracy of all independent measurements of defect depth and wall thickness is equal.

Example 4.4.1 Consider first the ultimate error of the relative defect depth value (4.22). Denote as $\Delta_{d/wt}^{*0}$, $\Delta_{d/wt}^{*1}$, respectively, the ultimate errors of the relative defect depth assessments according to methodology [1] and the proposed above algorithm, given availability of k independent measurements. Study the best case for methodology [1], when the true values of error variances of defect depth and wall thickness measurements are known. Then the mathematical expectation of the ratio $\Delta_{d/wt}^{*0}/\Delta_{d/wt}^{*1}$ equals

$$M \left[\frac{\Delta_{d/wt}^{*0}}{\Delta_{d/wt}^{*1}} \right] = \frac{u_p \sqrt{\left(\frac{\sigma_d}{d}\right)^2 + \left(\frac{\sigma_{wt}}{d}\right)^2} \frac{d}{wt}}{u_p \sqrt{\frac{1}{k} \left(\frac{\sigma_d}{d}\right)^2 + \frac{1}{k} \left(\frac{\sigma_{wt}}{d}\right)^2} \frac{d}{wt}} = \sqrt{k},$$

i.e., the proposed methodology offers $\sqrt{k}$ times higher accuracy, and the relative defect depth assessment obtained with the use of this method is closer to the true value.

Even if the true values of ME variances of the absolute depth of defects and wall thickness are not known, the proposed methodology still produces results of the same accuracy. But, at the same time, the methodology [1] demonstrates the above artificial expansion or narrowing of the CI (4.21), which leads to lower validity of performed diagnostics.

In order to illustrate the obtained estimates, statistical analysis of ILI results using the described above algorithm is provided. The required input data (absolute defect depth, wall thickness, and their ME values are given in mm) were modeled (Table 4.2) using the following parameters:

- sample size $n = 30$;
- number of sample realizations $m = 1000$;
- number of independent measurements of each defect $k = 2$;
- reliability level $\gamma = 0.9545$ with $u_p = 2$;
- absolute defect depth, wall thickness, and their ME values are taken in mm;
- MEs of defect depth have normal distribution $N(0; 0.64)$ with zero mathematical expectation and variance $\sigma_{\varepsilon_1}^2 = \sigma_{\varepsilon_2}^2 = 0.64$;
- MEs of wall thickness have normal distribution $N(0; 0.36)$ with zero mathematical expectation and variance $\sigma_{\xi_1}^2 = \sigma_{\xi_2}^2 = 0.36$;
- wall thickness has normal distribution $N(12; 0.25)$ with mathematical expectation 12 mm and variance 0.25; and
- four types of PDFs of defect depths were considered: (a) normal distribution $N(4; 1)$ with mathematical expectation 4 mm and variance 1 mm²; (b) lognormal distribution $LN(1.2613; 0.5)$ with mathematical expectation 4 mm and variance 4.5445; (c) exponential distribution $E(0, 25)$ with mathematical expectation 4 mm and variance 16 mm²; and (d) Rayleigh distribution $R(3, 196)$ with mathematical expectation 4 mm and variance 4.3719 mm².

From Table 4.2 it is seen that all estimates $\Delta_{d/wt}^{*0}/\Delta_{d/wt}^{*1}$ are close to the theoretical value $\sqrt{2} = 1.414$. Lower accuracy for the lognormal and the exponential distributions of the defect depth is the consequence of a heavier right-hand “tail” of these distributions.

Now consider the updated ultimate error of the relative defect depth value (4.26). Denote as $\Delta_{d/wt}^0, \Delta_{d/wt}^1$ the ultimate errors of the relative defect depth value, using

Table 4.2 The results of statistical modeling

Distribution of defect depths	$\Delta_{d/wt}^{*0}$	$\Delta_{d/wt}^{*1}$	$\Delta_{d/wt}^{*0}/\Delta_{d/wt}^{*1}$
$N(4; 1)$	0.1365	0.0968	1.410
$LN(1.2613; 0.5)$	0.1423	0.1024	1.389
$P(0, 25)$	0.1372	0.0981	1.397
$R(3, 196)$	0.1388	0.0983	1.413

methodology [1] and, according to the proposed above method, assume that k independent measurements are available for both methods. Assume that true values of the absolute defect depth and wall thickness ME variances are known. The mathematical expectation of expression $\Delta_{d/wt}^0/\Delta_{d/wt}^1$ then equals

$$M \left[\frac{\Delta_{d/wt}^0}{\Delta_{d/wt}^1} \right] = \frac{\frac{u_p(d\sigma_{wt} + wt\sigma_d)}{wt(wt - u_p\sigma_{wt})}}{\frac{u_p\left(d\frac{\sigma_{wt}}{\sqrt{k}} + wt\frac{\sigma_d}{\sqrt{k}}\right)}{wt\left(wt - u_p\frac{\sigma_{wt}}{\sqrt{k}}\right)}} = \frac{wt(\sqrt{k} - 1)}{wt - u_p\sigma_{wt}} + 1 > \sqrt{k},$$

i.e., the proposed methodology offers $\sqrt{k}$ times higher accuracy.

Example 4.4.2 Evaluate adequacy of the described above methodology for assessing the standard deviations of defect parameters MEs and CIs by computer modeling of the measurement process using random number generator.

Consider a virtual pipeline made out of grade 20 steel with nominal pipe wall thickness $wt = 9$ mm. Measurement modeling is done by pairs for defect depths according to the mathematical model (4.27), for pipe wall thickness according to model (4.28). Modeling parameters are given in Table 4.3.

The standard deviation of the sensors ME was calculated based on the assumption that the defect depth measurement tolerance with 80 % reliability equals $\pm 10\%$ wt . For simplicity it is assumed that the accuracy of all sensors is identical.

According to metallurgical standards, for this steel grade the ultimate deviation of pipe wall thickness is $+0.6$ and -0.8 mm. Considering that pipe wall thickness as a normally distributed random value, and using the three sigma rule and the stated above ultimate deviation, it is possible to determine its mathematical expectation and standard deviation. For the 9 mm pipe wall thickness the average is $(9.6 + 8.2)/2 = 8.9$ mm, and the standard deviation is $-(9.6 - 8.2)/2/3 = 0.23$ mm.

The true sizes of a defect d_i are modeled by two-parameter Weibull distribution. Distribution parameters a and b are calculated by numerical solution of the following system of equations:

Table 4.3 Input data for modeling measurements

Input data	Symbol	Distribution law	Mathematical expectation, mm	Standard deviation, mm
True values of defect depths	d	Weibull	$0.4 wt = 3.60$	$0.15 wt = 1.35$
Pipe wall thickness near the defect	wt	Normal	8.90	0.23
MEs of the first sensor	ε_1	Normal	0.00	$0.1 wt/1.28 = 0.70$
MEs of the second sensor	ε_2	Normal	0.00	$0.1 wt/1.28 = 0.70$

$$\begin{cases} M = a\Gamma\left(1 + \frac{1}{b}\right); \\ D = a^2\left(\Gamma\left(1 + \frac{2}{b}\right) - \Gamma^2\left(1 + \frac{1}{b}\right)\right), \end{cases}$$

where M and D are the mathematical expectation and the measurement variance, respectively; and $\Gamma(x)$ is the gamma function.

Uncorrelated measurement errors. For checking reliability of the proposed methodology perform $N = 1000$ experiments with 30 measurements in each. For the obtained assessments of standard deviation of the defect depth and the wall thickness MEs determine the sample statistical characteristics (the average and the standard deviation). Compare obtained estimates with their true values. The results are shown in Figs. 4.14 and 4.15.

The average standard deviation of the defect depth ME is 0.69 mm (true value 0.70 mm), and the average standard deviation of the pipe wall thickness ME is 0.70 mm (true value 0.70 mm). In both cases the standard deviation of assessments did not exceed 13.2 % of their average.

Consider now a more general case of ME correlation.

Measurement errors correlate with each other. For simplicity consider, as previously, the case when all sensors have one and the same variance. In this case, generation of a correlated ME with the given correlation factor ρ is done as follows. ME of the first sensor ε_1 is generated according to the normal law with zero mathematical expectation and standard deviation σ_{ε_1} . ME of the second sensor ε_2 is related to ME of the first sensor ε_1 by the formula

$$\varepsilon_2 = \rho\varepsilon_1 + \sqrt{1 - \rho^2}\xi, \quad (4.37)$$

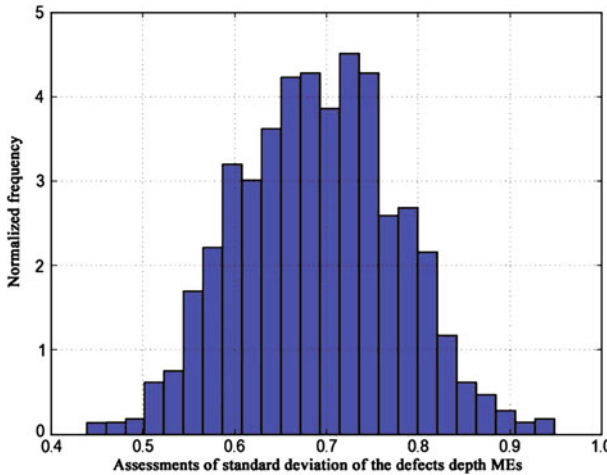


Fig. 4.14 Histogram of the standard deviation of the defect depth ME assessment (assessment average 0.69 mm, standard deviation of assessments 0.09 mm)

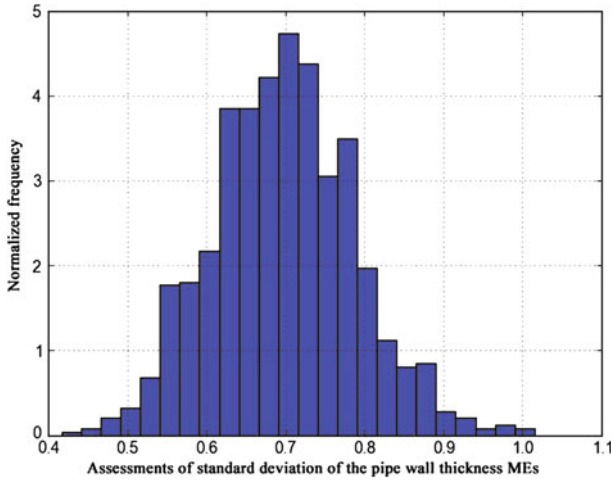


Fig. 4.15 Histogram of the standard deviation of the pipe wall thickness ME (assessment average 0.70 mm, standard deviation of assessments 0.09 mm)

where ξ value is generated by normal law with zero mathematical expectation and SD $\sigma_{\varepsilon 2} = \sigma_{\varepsilon 1}$.

All other RVs are modeled according to the parameters of Table 4.3.

1. *Assessment of the correlation coefficient on the basis of measurements of the undamaged pipe wall thickness.* Modeling of the intact pipe wall thickness measurement is performed using mathematical model (4.28). Perform $N = 1000$ realizations (each with 30 measurements), for a correlation coefficient ρ of undamaged pipe wall thickness, $\rho = 0.1, 0.2, 0.3, \dots, 0.9$. For the obtained correlation coefficient determine their sample average and standard deviation. The obtained results are shown in Table 4.4 and Figs. 4.16, 4.17.

Table 4.4 Sample statistical characteristics of correlation coefficient (number of realizations $N = 1000$)

True value of correlation coefficient	Sample assessments of correlation coefficient	
	Mean	Standard deviation
0.10	0.09	0.18
0.20	0.19	0.17
0.30	0.31	0.17
0.40	0.40	0.16
0.50	0.50	0.14
0.60	0.60	0.12
0.70	0.69	0.10
0.80	0.79	0.08
0.90	0.90	0.04

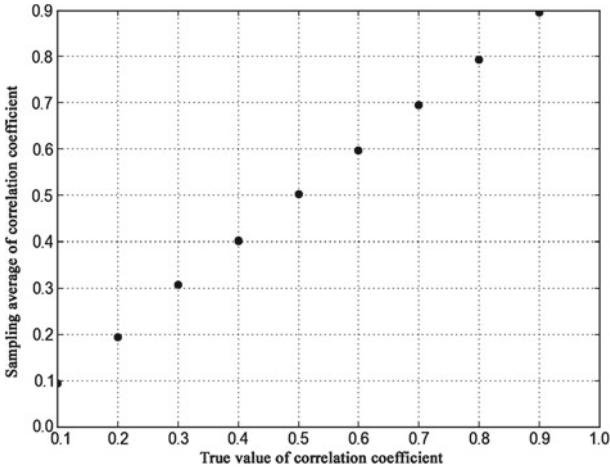


Fig. 4.16 Sampling average of correlation factor assessments

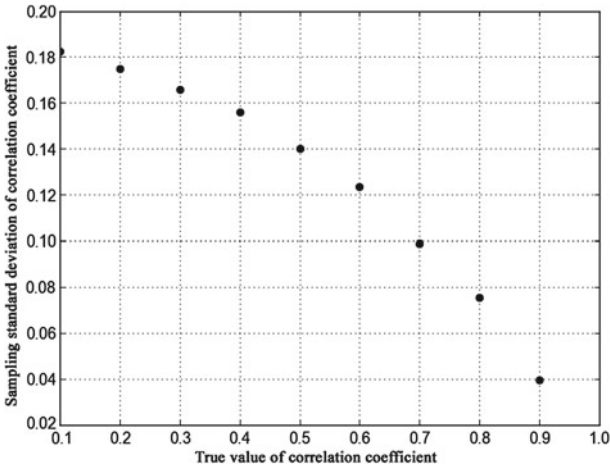


Fig. 4.17 Sample standard deviation of correlation coefficient assessments

From Fig. 4.16 and Table 4.4 it is clear that the assessments practically coincide with their true values. According to Fig. 4.17, standard deviation of assessments decreases linearly with growth of the correlation factor true value. *Practically, identical results were obtained also for a much smaller number of experiments ($N = 30$).*

2. *Assessment of the defect depth ME variance.* Modeling of the defect depth measurements is based on mathematical model (4.27), where the second sensor ME

is modeled by formula (4.37). Conduct $N = 1000$ experiments with various values of $\rho = 0.1, 0.2, 0.3, \dots, 0.9$. Based on 30 measurement samples of undamaged pipe wall thickness, assess the correlation coefficient, and use it to assess the defect depth ME variance. The results of calculations are shown in Figs. 4.18, 4.19 and 4.20 and in Tables 4.5, 4.6 and 4.7.

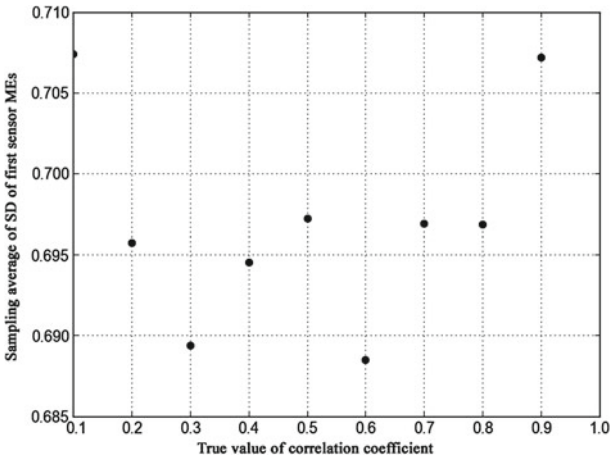


Fig. 4.18 Sample average of the first sensor standard deviation of the defect depth ME assessment, as a function of the true value of the correlation coefficient (true standard deviation value 0.70 mm)

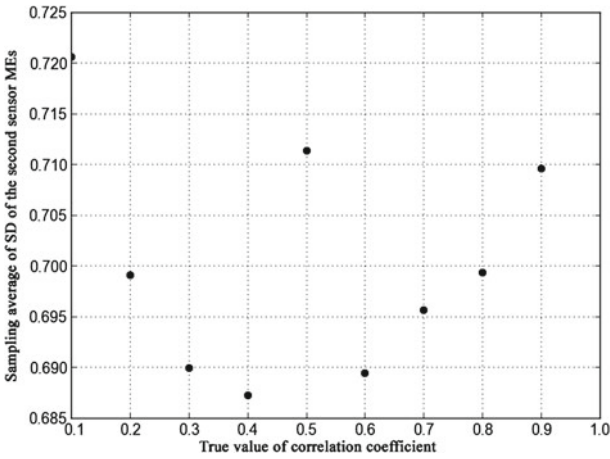


Fig. 4.19 Sample average of the second sensor standard deviation of the defect depth ME, as a function of the correlation coefficient true value (true standard deviation value 0.70 mm)

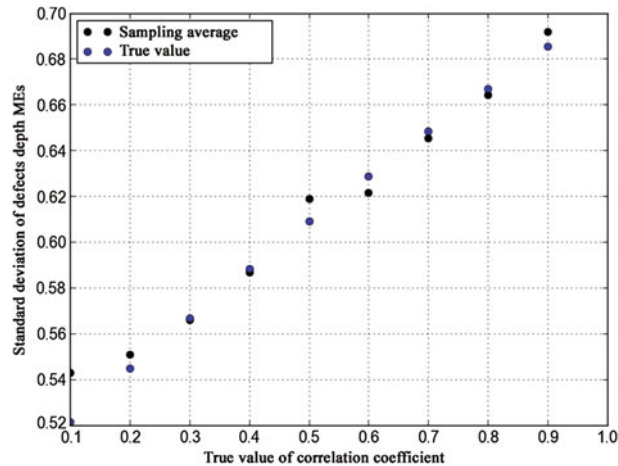


Fig. 4.20 Sample average of assessment and true values of standard deviation of the defect depth ME depending of the variance factor

Table 4.5 Sample statistical characteristics of the first sensor standard deviation of the defect depth MEs, depending on the variance factor true value (true standard deviation value 0.70 mm)

True value of correlation coefficient	Sample Assessments	
	Mean	Standard deviation
0.10	0.71	0.20
0.20	0.70	0.19
0.30	0.69	0.19
0.40	0.69	0.19
0.50	0.70	0.19
0.60	0.69	0.18
0.70	0.70	0.18
0.80	0.70	0.18
0.90	0.71	0.17

Table 4.6 Sample statistical characteristics of the second sensor standard deviation of the defect depth ME, as a function of the true value of variance factor (true standard deviation value 0.70 mm)

True value of correlation coefficient	Sample Assessments	
	Mean	Standard deviation
0.10	0.72	0.19
0.20	0.70	0.19
0.30	0.69	0.19
0.40	0.69	0.18
0.50	0.71	0.19
0.60	0.69	0.17
0.70	0.70	0.18
0.80	0.70	0.17
0.90	0.71	0.16

Table 4.7 Sample statistical characteristics of assessments of standard deviation of the defect depth MEs, as a function of the variance factor true value

True value of correlation coefficient	True value	Sample Assessments	
		Mean	Standard deviation
0.10	0.52	0.54	0.11
0.20	0.54	0.55	0.12
0.30	0.57	0.57	0.13
0.40	0.59	0.59	0.14
0.50	0.61	0.62	0.15
0.60	0.63	0.62	0.15
0.70	0.65	0.65	0.16
0.80	0.67	0.66	0.16
0.90	0.69	0.69	0.16

According to the obtained results all assessments, on average, coincided with their true values. True value from Table 4.7 was calculated by formula (4.36). From Table 4.7 it is clear that the sample average almost always coincided with the true value, and the standard deviation of assessments was insignificant.

Thus, the proposed methodology is adequate and allows improving reliability of in-line diagnostics, due to the higher accuracy of the defect depth measurement.

Example 4.4.3 Consider application of the methodology on a specific example of modeled measurements. Generate $n = 30$ measurements of virgin pipe wall thickness according to mathematical model (4.28) with correlation coefficient $\rho = 0.7$. In Table 4.8 the generated measurements are given. Based on these measurements assess the correlation coefficient ρ . The obtained ρ value is 0.71.

Further, generate $n = 30$ defect depth measurements, according to model (4.27), and pipe wall thickness near the defect, according to model (4.28), where the second sensor ME is modeled by formula (4.37). Modeling parameters are shown in Table 4.3. The obtained measurements are shown in Table 4.8.

Evaluate the ME standard deviation for the obtained measurements. The assessments are for the defect depth—0.67; and for pipe wall thickness—0.60. The true value of this standard deviation is 0.64.

At the final stage, a confidence interval is determined for each measurement, according to formula (4.21). Assume the reliability γ equals to 0.9. The obtained results are shown in Table 4.9.

Table 4.8 The generated measurements of defect-free pipe wall thickness, defect depths, and pipe wall thickness near defect

Measurements of defect-free pipe wall thickness		Measurements of defect depths		Measurements of pipe wall thickness near defect	
First sensor	Second sensor	First sensor	Second sensor	First sensor	Second sensor
9.66	9.99	5.27	5.51	8.95	8.72
9.31	10.21	2.62	3.11	9.52	9.34
7.96	7.62	1.72	2.05	8.94	8.48
8.56	9.14	5.13	4.68	9.63	10.11
9.13	9.41	3.09	3.79	9.06	9.06
8.34	9.47	3.54	2.80	9.02	8.21
9.91	9.96	2.12	2.18	8.43	8.40
8.91	8.95	5.09	5.26	10.00	9.66
9.29	9.08	6.50	6.34	8.99	9.03
9.96	9.02	1.76	2.27	7.42	8.28
8.89	9.47	3.45	2.91	8.21	9.06
9.16	9.02	3.06	3.34	9.39	9.93
9.56	10.18	4.74	4.85	8.57	8.24
8.64	9.04	3.67	3.65	7.77	8.76
9.14	9.33	3.60	3.63	9.37	9.40
8.65	8.00	3.66	4.35	10.27	10.79
8.60	8.64	2.51	1.43	8.92	8.83
9.34	8.75	2.81	2.78	7.33	7.64
8.26	8.48	2.61	1.99	6.82	8.02
9.15	9.48	3.77	3.73	8.85	8.76
10.33	9.23	2.44	3.42	8.67	8.71
9.07	8.40	1.95	1.68	9.70	10.19
8.68	7.69	0.39	0.29	8.91	8.01
9.06	9.04	3.74	3.08	9.30	8.79
11.13	10.93	3.17	3.44	9.57	9.47
9.46	8.63	4.24	4.29	9.11	8.80
8.32	7.97	1.37	2.22	9.51	9.82
8.80	9.01	1.20	1.30	9.55	9.03
8.71	8.85	4.19	4.93	8.60	8.23
8.47	8.19	1.80	2.52	8.52	8.58

Table 4.9 Absolute and relative defect depths and the confidence intervals for the relative defect depth

Defect depth		Confidence interval for the relative defect depth	
Absolute	Relative	Lower boundary	Upper boundary
5.39	0.61	0.48	0.74
2.86	0.30	0.19	0.41
1.88	0.22	0.10	0.33
4.90	0.50	0.38	0.61
3.44	0.38	0.26	0.50
3.17	0.37	0.24	0.49
2.15	0.26	0.13	0.38
5.17	0.53	0.41	0.64
6.42	0.71	0.58	0.85
2.02	0.26	0.13	0.39
3.18	0.37	0.25	0.49
3.20	0.33	0.22	0.44
4.80	0.57	0.43	0.71
3.66	0.44	0.31	0.57
3.61	0.39	0.27	0.50
4.00	0.38	0.28	0.48
1.97	0.22	0.11	0.34
2.80	0.37	0.23	0.52
2.30	0.31	0.17	0.45
3.75	0.43	0.30	0.55
2.93	0.34	0.22	0.46
1.82	0.18	0.08	0.28
0.34	0.04	0.00	0.16
3.41	0.38	0.26	0.49
3.31	0.35	0.24	0.46
4.27	0.48	0.35	0.60
1.79	0.19	0.08	0.29
1.25	0.13	0.03	0.24
4.56	0.54	0.41	0.68
2.16	0.25	0.13	0.37

4.5 Full Statistical Analysis Method of ILI Results

This paragraph describes a methodology for full statistical analysis of ILI results considering a more general practical case, when the ILI tool measurements contain not only random ME, but also the systemic ones (constant and multiplicative bias). The methodology consists of the *actual ILI tool accuracy assessment* technique used

in the process of a specific pipeline inspection, and the calibration technique of all (*verified and unverified*) ILI tool measurements for the purpose of obtaining more accurate values of the measured defect parameters.

Consider the most common practical case when the ILI tool possesses both random and systemic MEs, and the verification tool only random ME. The mathematical model of measurements in this case will have the form

$$\begin{aligned} p_I &= \alpha + \beta p_{tr} + \varepsilon_I; \\ p_V &= p_{tr} + \varepsilon_V, \end{aligned} \quad (4.38)$$

where p_{tr} is the true (unmeasurable) value of the parameter to be measured; p_I is the ILI tool reading; p_V is the VI reading; α, β are, respectively, the intercept and the slope of the regression line (RL) of the ILI tool, related to constant systemic measurement errors: α is the average bias, β is the multiplicative bias; ε_I is the random measurement error of ILI tool; and ε_V is the random measurement error of the VI.

According to measurement model (4.38), the MI accuracy will be determined by statistical characteristics of measurement errors $\varepsilon_I, \varepsilon_V$, in particular, only by their variances $\sigma_{\varepsilon_I}^2, \sigma_{\varepsilon_V}^2$, since the mathematical expectation of ME equals zero.

The methodology consists of the subsequently solving the following subproblems:

- assessment of measurement model parameters (4.38) (constant ILI tool measurement bias);
- assessment of the ILI tool and VI MEs variance;
- assessment of the true sizes of *verified* defects; and
- assessment of the calibration line parameters, using which it is possible to obtain more accurate values of the *unverified* ILI tool measurements.

This technique is based on variance and regression analysis. It consists in comparing the diagnostics results with the verification data, *limited* in scope. Its final goal is calibration of the diagnostics results for obtaining a more accurate assessment of the true values of the defect parameters. The technique provides capability for:

1. Assessment of the actual accuracy of the implemented ILI tool in real-life conditions of its operation.
2. Improving accuracy of all (*verified and unverified*) measurements of defect sizes based on joint analysis of the diagnostics results and the limited in scope verification. This leads to a significant savings of funds and labor.

Assessments of the true sizes of the defect parameters obtained using this method allow performing more accurate calculations of probability of failure POF (reliability), residual strength, and the remaining life of PS, and optimize their predictive/preventive maintenance schedules.

4.5.1 Prerequisites of Using the Method

Successful application of the proposed technique described in detail below requires the following conditions to be met:

- measurements are made by two independent tools, one measurement by each tool;
- measurement errors ε_I , ε_V are normally distributed with zero mathematical expectation and variance $\sigma_{\varepsilon_I}^2$, $\sigma_{\varepsilon_V}^2$, respectively;
- MEs ε_I , ε_V are independent of each other and the true values p_{tr} of the measured parameter;
- scope of the field verification measurements on a pipeline must be sufficient for establishing a reliable set of statistical data for each type of defect. Method of assessing the minimum acceptable number of verification measurements is described in Sect. 4.6. They must be available from all ranges of parameter sizes: small, average, and large. Otherwise, assessments obtained with the help of the proposed technique will be applicable only to the defect sizes which fall within the given range.
- scatter of measurements between the two compared MI (ILI tool and VI) must be below 10 %. This scatter is calculated using the RMSD (Root-mean-square deviation) of measurements made with one tool from the measurements made with another tool:

$$RMSD = \sqrt{\sum_{i=1}^n \frac{(p_{Ii} - p_{Vi})^2}{n}},$$

where n is the number of verified measurements and p_{Ii} and p_{Vi} are the measurements of defect parameter sizes, which were set as percentage of the pipe wall thickness. Otherwise, the ILI tool (when compared against the VI) will produce insufficiently accurate readings and the results of its measurements will have to be rejected [1, 15]; and

- the correlation between the ILI tool and the VI measurements is linear.

4.5.2 Assessment of the Constant Bias of the ILI Tool Measurements

Method of moments. For assessing the average and the multiplicative bias of the ILI tool measurements, which are included in the measurement model (4.38), it is necessary to build a scatter diagram of the verified measurements and determine the RL parameters of the ILI tool and the VI measurements. In this case the VI measurements are assumed to be the independent variable (regressor).

In this case the problem of assessing the regression line parameters is non-trivial, since the independent variables of the measurement regression model (4.38) contain

“inherent” errors (stochastic regressors). The stochastic regressors are the cause of correlation of the independent variable p_V with the measurement errors:

$$p_I = \alpha + \beta p_V + (\varepsilon_I - \beta \varepsilon_V) = \alpha + \beta p_V + \varepsilon^*.$$

Hence, the covariance of independent variable p_V and errors ε^* equals

$$COV(p_V, \varepsilon^*) = -\beta \sigma_{\varepsilon_V}^2 \neq 0.$$

Therefore, the use of the classic least square method (LSM) becomes impossible because the assessment by LSM will be, in general, biased and inconsistent [16]:

$$\lim \hat{\beta} \xrightarrow{P} \beta + \frac{COV[p_V, \varepsilon^*]}{D[p_V]} = \beta - \frac{\beta \sigma_{\varepsilon_V}^2}{\sigma_{ir}^2 + \sigma_{\varepsilon_V}^2} = \frac{\beta \sigma_{ir}^2}{\sigma_{ir}^2 + \sigma_{\varepsilon_V}^2} < \beta,$$

i.e., the LSM assessment of parameter β is biased toward zero. In this expression $D[p_V]$ is the variance of VI measurements and σ_{ir}^2 is the variance of the true values of defect parameters.

Provided that the VI ME $\sigma_{\varepsilon_V}^2$ is known in advance, the consistent assessments of parameters α , β of the measurement model (4.38) have the form [17]:

$$\begin{aligned} \hat{\beta} &= \frac{s_{IV}}{s_V^2 - \sigma_{\varepsilon_V}^2}, \quad s_V^2 > \sigma_{\varepsilon_V}^2, \\ \hat{\alpha} &= \bar{p}_I - \hat{\beta} \cdot \bar{p}_V, \end{aligned} \quad (4.39)$$

where $\bar{p}_I$, $\bar{p}_V$ are the sample averages of the ILI tool and VI measurements, respectively; s_I^2 is the unbiased sample variance of the ILI tool measurements; s_V^2 is the unbiased sample variance of the VI measurements; and s_{IV} is the ILI tool and the VI measurement covariance, determined by the formulas

$$\begin{aligned} s_I^2 &= \frac{1}{n-1} \left(\sum_{i=1}^n p_{Ii}^2 - \frac{1}{n} \left(\sum_{i=1}^n p_{Ii} \right)^2 \right), \\ s_V^2 &= \frac{1}{n-1} \left(\sum_{i=1}^n p_{Vi}^2 - \frac{1}{n} \left(\sum_{i=1}^n p_{Vi} \right)^2 \right), \\ s_{IV} &= \frac{1}{n-1} \left[\sum_{i=1}^n p_{Ii} p_{Vi} - \frac{1}{n} \left(\sum_{i=1}^n p_{Ii} \right) \left(\sum_{i=1}^n p_{Vi} \right) \right]. \end{aligned} \quad (4.40)$$

In the denominator of the first expression (4.39) there is an additive $\sigma_{\varepsilon_V}^2$, which in the typical regressive model is assumed to be zero. Thus, the assessment (4.39) of the RL slope β contains a bias (in other words, the slope is calibrated) toward zero.

The degree of calibration is set by expression $k = \frac{\sigma_{tr}^2}{\sigma_{\varepsilon V}^2}$, i.e., by the ratio of the true value of defect parameter variance to the ME variance of the measured values.

The formula for assessing parameter β from (4.39) may be easily derived by the method of moments, according to which the theoretical and empirical moments of the distribution are set equal.

According to model (4.38), because of independence of the RV p_{tr} and ε_V , the RV p_V has mathematical expectation μ and variance:

$$\sigma_V^2 = \sigma_{tr}^2 + \sigma_{\varepsilon V}^2.$$

Setting equal the sample second central moments and their theoretical values, we have

$$s_V^2 = \sigma_{tr}^2 + \sigma_{\varepsilon V}^2, \quad (4.41)$$

where s_V^2 is the unbiased sample variance of the VI measurements, determined by formula (4.40).

Prove that assessment of the true values of defect parameter variance equals the sample covariance, divided by the parameter β :

$$\hat{\sigma}_{tr}^2 = \frac{s_{IV}}{\hat{\beta}}. \quad (4.42)$$

Consider the difference:

$$p = p_I - p_V = \alpha + (\beta - 1)p_{tr} + (\varepsilon_I - \varepsilon_V).$$

Obviously, due to independence of p and $\varepsilon_I, \varepsilon_V$, the RV p is distributed with a variance equal:

$$\sigma_p^2 = (\beta - 1)^2 \sigma_{tr}^2 + \sigma_{\varepsilon I}^2 + \sigma_{\varepsilon V}^2.$$

Then

$$S = \sigma_{\varepsilon I}^2 + \sigma_{\varepsilon V}^2 = \sigma_p^2 - (\beta - 1)^2 \sigma_{tr}^2. \quad (4.43)$$

Demonstrate that the unbiased sample variance RV p equals $s_p^2 = s_I^2 + s_V^2 - 2s_{IV}$:

$$\begin{aligned} s_p &= \frac{1}{n-1} \left(\sum_{i=1}^n (p_{Ii} - p_{Vi})^2 - \frac{1}{n} \left(\sum_{i=1}^n (p_{Ii} - p_{Vi}) \right)^2 \right) \\ &= \frac{1}{n-1} \left(\sum_{i=1}^n (p_{Ii}^2 - 2p_{Ii}p_{Vi} + p_{Vi}^2) - \frac{1}{n} \left(\sum_{i=1}^n (p_{Ii} - p_{Vi}) \right)^2 \right) \\ &= \frac{1}{n-1} \left(\sum_{i=1}^n p_{Ii}^2 - 2 \sum_{i=1}^n p_{Ii}p_{Vi} + \sum_{i=1}^n p_{Vi}^2 - \frac{1}{n} \left(\sum_{i=1}^n p_{Ii} - \sum_{i=1}^n p_{Vi} \right)^2 \right) \end{aligned}$$

$$\begin{aligned}
&= \frac{1}{n-1} \left(\sum_{i=1}^n p_{li}^2 - 2 \sum_{i=1}^n p_{li} p_{vi} + \sum_{i=1}^n p_{vi}^2 \right. \\
&\quad \left. - \frac{1}{n} \left(\left(\sum_{i=1}^n p_{li} \right)^2 - 2 \left(\sum_{i=1}^n p_{li} \right) \left(\sum_{i=1}^n p_{vi} \right) + \left(\sum_{i=1}^n p_{vi} \right)^2 \right) \right) \\
&= \frac{1}{n-1} \left(\sum_{i=1}^n p_{li}^2 - \frac{1}{n} \left(\sum_{i=1}^n p_{li} \right)^2 + \sum_{i=1}^n p_{vi}^2 - \frac{1}{n} \left(\sum_{i=1}^n p_{vi} \right)^2 \right. \\
&\quad \left. - 2 \left[\sum_{i=1}^n p_{li} p_{vi} - \frac{1}{n} \left(\sum_{i=1}^n p_{li} \right) \left(\sum_{i=1}^n p_{vi} \right) \right] \right) = s_I^2 + s_V^2 - 2s_{IV}.
\end{aligned}$$

Then, considering that s_p is the unbiased assessment of the theoretical variance σ_p^2 , from (4.43), we derive

$$S = \sigma_{\varepsilon I}^2 + \sigma_{\varepsilon V}^2 = s_I^2 + s_V^2 - 2s_{IV} - (\beta - 1)^2 \sigma_{tr}^2.$$

Since $s_I^2 = \beta^2 \sigma_{tr}^2 + \sigma_{\varepsilon I}^2$, $s_V^2 = \sigma_{tr}^2 + \sigma_{\varepsilon V}^2$, then

$$\begin{aligned}
S &= \sigma_{\varepsilon I}^2 + \sigma_{\varepsilon V}^2 = s_I^2 - \beta^2 \sigma_{tr}^2 + s_V^2 - \sigma_{tr}^2 \\
&= s_I^2 + s_V^2 - 2s_{IV} - (\beta - 1)^2 \sigma_{tr}^2.
\end{aligned}$$

From the previous expression we have

$$2s_{IV} = (\beta^2 + 1) \sigma_{tr}^2 - (\beta - 1)^2 \sigma_{tr}^2 = 2\beta \sigma_{tr}^2 \Rightarrow s_{IV} = \beta \sigma_{tr}^2.$$

Finally, from (4.41), taking into account (4.42), we derive formulas (4.39).

Entropy approach [18]. To assess the parameter β of measurement model (4.38) introduce a random value η , depending on its assessment $\hat{\beta}$:

$$\begin{aligned}
\eta &= \eta(\hat{\beta}) = p_I - \hat{\beta} p_V = \alpha + \beta p_{tr} + \varepsilon_I - \hat{\beta}(p_{tr} + \varepsilon_V) \\
&= \alpha + (\beta - \hat{\beta}) p_{tr} + \varepsilon_I - \hat{\beta} \varepsilon_V,
\end{aligned}$$

where $\hat{\beta}$ is some nonrandom number.

From the information point of view, the random value of η has a principal specific feature. Namely, for all $\hat{\beta} \neq \beta$, the RV η consists of a linear combination of three RVs: X , ε_I and ε_V , but at the desired point $\hat{\beta} = \beta$ is a sum of only two RVs: ε_I and ε_V . This means that in point $\hat{\beta} = \beta$ value η demonstrates the least uncertainty. A measure of uncertainty is entropy [19]. The described phenomenon may also be explained on the basis of the central limit theorem. It is known that at a fixed mathematical expectation and variance the largest uncertainty (entropy) has the normally distributed RV [20]. Adding one more error (random value) according to the CLT will increase the

proximity of the summary error distribution to the normal law, i.e., will make the RV, using the theory of information terminology, more uncertain. Therefore, the problem of assessing $\hat{\beta}$ is reduced to minimization of entropy of the standardized (with zero average and unity variance) RV η . The algorithm for solving this problem consists of the following.

1. Assume a set of measurement pairs (p_{li}, p_{vi}) , $(i = 1, \dots, n)$.
2. Define a set of possible values of $\hat{\beta}$, $\hat{\beta} \in B$. For example, performing a proportional discretization with a given step (chosen in accordance with the required solution accuracy) of range B .
3. For each $\hat{\beta} \in B$ obtain a set of assessments $\{r_i(\hat{\beta})\}$:

$$r_i(\hat{\beta}) = p_{li} - \hat{\beta}p_{vi}, \quad (i = 1, \dots, n).$$

4. Standardize this set, i.e.,

$$\hat{r}_i(\hat{\beta}) = \frac{r_i(\hat{\beta}) - \bar{r}(\hat{\beta})}{s(\hat{\beta})},$$

where $\bar{r}(\hat{\beta})$ and $s(\hat{\beta})$ are the average and standard deviation of the set of assessments $\{r_i(\hat{\beta})\}$.

5. Solve the problem of minimizing the entropy of the set of assessments $\{r_i(\hat{\beta})\}$:

$$\hat{\beta}^* = \arg \min_{\hat{\beta} \in B} H(\hat{\beta}), \quad (4.44)$$

where entropy is calculated by formula [19]:

$$H = - \sum_k P_k \ln P_k,$$

summation is performed over all intervals $\hat{r}_i(\hat{\beta})$.

6. Calculate factor α by the formula

$$\hat{\alpha} = \bar{p}_I - \hat{\beta}^* \bar{p}_V.$$

Assessment of multivariate regression parameters using the entropy approach is described in [18].

Example 4.5.1 The algorithm is utilized on the basis of a number of experiments for various distribution laws of RVs and MEs.

Assume that the sample size $n = 1200$; number of experiments $M = 10,000$; random errors $\xi \sim N(0; 1^2)$, $\varepsilon \sim N(0; 0.8^2)$; and regression coefficients $\alpha = 0.5$, $\beta = 1.05$. Assume for parameter $\hat{\beta}$ discretization step of 0.005.

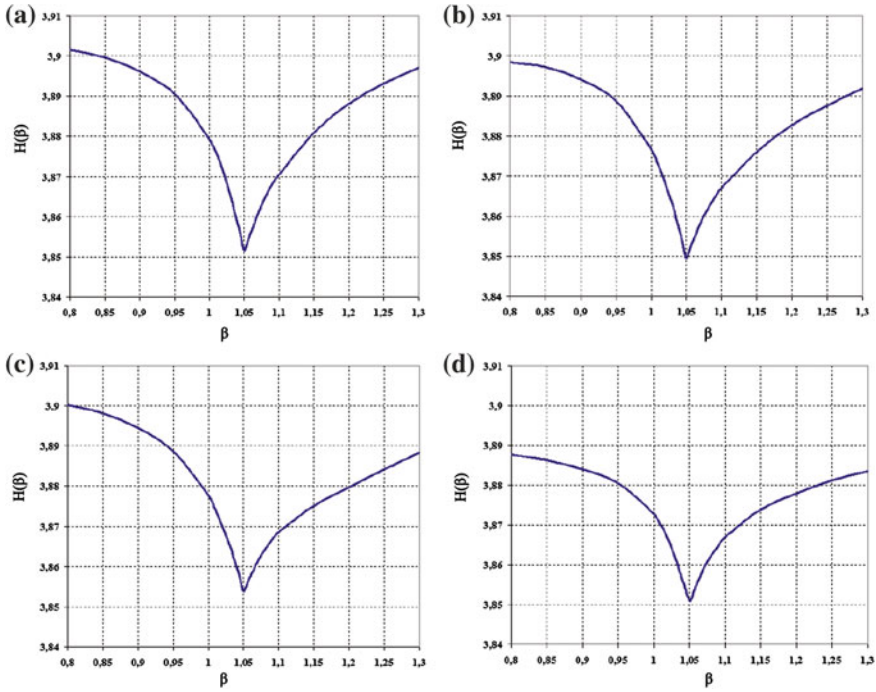


Fig. 4.21 Entropy dependencies on parameter $\hat{\beta}$: **a** case 1; **b** case 2; **c** case 3; **d** case 4

Consider four types of distribution of the random variable X :

1. X is distributed according to normal law $N(5.5; 1.5^2)$, i.e., it has mathematical expectation $M[X] = 5.5$ and variance $D[X] = 2.25$.

2. X is distributed according to lognormal law with parameters 1 and 0.5, then $M[X] = 3.0802$, $D[X] = 2.6948$.

3. X is exponentially distributed with parameter 0.75, then $M[X] = 1.3333$, $D[X] = 1.7778$.

4. X distribution has the Rayleigh distribution pattern with parameter 2, then $M[X] = 2.5066$, $D[X] = 1.7168$.

Entropy dependencies on parameter $\hat{\beta}$ are represented in Fig. 4.21. It is clear that they are practically insensitive to the type of X distribution. In all four cases the minimum entropy lies in the desired point $\hat{\beta}^* = \beta = 1.05$. However, $\hat{\alpha}^* = \alpha = 0.5$.

4.5.3 Assessment of the ILI Instrument Accuracy

Case when the ILI tool measurements do not contain multiplicative bias. For this case, when in the measurement model (4.38) $\beta = 1$, the method of assessing the

error variances ε_I , ε_V was proposed by Grubbs [21]. According to his approach, the variance of the measurements, obtained using a arbitrary MI, consists of two parts:

- variance of the true values of the measured parameter (i.e., defect depths); and
- variance of the ME of the used measurement instrument.

The sample assessment of the *covariation* between two MIs is a *non-biased assessment of the true sizes of defects*. Then, the assessment of the ME variance of each MI can be evaluated as the difference between the sample variance of measurements of the MI being assessed, and the sample assessment of the covariation of the measurements:

$$\begin{aligned}\hat{\sigma}_{tr}^2 &= s_{IV}; \\ \hat{\sigma}_{\varepsilon V}^2 &= s_V^2 - s_{IV};\end{aligned}\tag{4.45}$$

$$\hat{\sigma}_{\varepsilon I}^2 = s_I^2 - s_{IV}.\tag{4.46}$$

In the case when one of the assessments (4.45), (4.46) turns out to be negative, Thompson [22] suggested to use the following assessments (on the premise, that $\hat{\sigma}_{\varepsilon I}^2$ is negative):

$$\begin{aligned}\hat{\sigma}_{tr}^2 &= s_I^2; \\ \hat{\sigma}_{\varepsilon V}^2 &= s_I^2 + s_V^2 - 2s_{IV}; \\ \hat{\sigma}_{\varepsilon I}^2 &= 0.\end{aligned}$$

In other words, if the variance assessment is negative, it is assumed to be equal to zero. For the case when $\hat{\sigma}_{\varepsilon V}^2$ is negative, the same lines of argument are used.

Generalized case. The Grubbs method may be modified and summarized for the case, when the ILI tool measurements contain both average and multiplicative bias.

According to the measurement model (4.38), because of independence of p_{tr} and ε_I , ε_V , the RVs p_V and p_I will have variances:

$$\begin{aligned}\sigma_I^2 &= \beta^2 \sigma_{tr}^2 + \sigma_{\varepsilon I}^2, \\ \sigma_V^2 &= \sigma_{tr}^2 + \sigma_{\varepsilon V}^2,\end{aligned}\tag{4.47}$$

where σ_{tr}^2 is the true value of the defect parameter p_{tr} variance.

Considering that the unbiased sample variances of ILI tool and VI measurements s_I^2 , s_V^2 , determined by formulas (4.40), are the unbiased assessments of theoretical variances σ_I^2 , σ_V^2 , respectively, the assessment of ILI tool ME and the assessment of the defect parameters' true value variances may be found from (4.47) by the formulas

$$\begin{aligned}\hat{\sigma}_{\varepsilon V}^2 &= s_V^2 - \frac{s_{IV}}{\hat{\beta}}, \\ \hat{\sigma}_{\varepsilon I}^2 &= s_I^2 - \hat{\beta} s_{IV},\end{aligned}\tag{4.48}$$

where $\hat{\beta}$ is the assessment of the RL slope determined using one of the approaches described in Sect. 4.5.2.

In a number of real-life cases, the assessments obtained with the use of formulas (4.48) were *negative*. This occurs when, and only when [23],

$$s_I^2 (s_V^2 - \sigma_{\varepsilon V}^2) - s_{IV}^2 \leq 0. \quad (4.49)$$

In practice assessments of the ME variance (4.48) may take negative values. In such cases it is possible to use the method developed by Jaech [24], according to which

$$\begin{aligned} \hat{\sigma}_{\varepsilon V}^2 &= \frac{SI_0}{I}; \\ \hat{\sigma}_{\varepsilon I}^2 &= S - \hat{\sigma}_{\varepsilon V}^2; \\ S &= \frac{n-1}{n} (s_I^2 + s_V^2 - 2s_{IV}); \\ I_0 &= \int_0^1 x \cdot f(x) dx; \\ I_1 &= \int_0^1 f(x) dx; \\ f(x) &= [s_I^2(1-x)^2 + x^2 s_V^2 + 2x(1-x)s_{IV}]^{-n/2}. \end{aligned} \quad (4.50)$$

Formulas (4.50) are used when the ILI tool measurements do not contain multiplicative bias. If $\beta \neq 1$ the Jaech method has to be modified in the following way: Zero in on the expression for covariation and modify formulas for S and $f(x)$. Now consider the sum of MEs variations, using formulas (4.48)

$$\begin{aligned} S &= \hat{\sigma}_{\varepsilon V}^2 + \hat{\sigma}_{\varepsilon I}^2 = s_V^2 - \frac{s_{IV}}{\hat{\beta}} + s_I^2 - \hat{\beta}s_{IV} \\ &= s_V^2 + s_I^2 - s_{IV} \left(\frac{1}{\hat{\beta}} + \hat{\beta} \right) \\ &= s_V^2 + s_I^2 - s_{IV} \left(\frac{1 + \hat{\beta}^2}{\hat{\beta}} \right). \end{aligned} \quad (4.51)$$

The sum of S and function $f(x)$ is interconnected; hence, the expression for $f(x)$ can be written as follows:

$$f(x) = \left[\frac{n}{n-1} Sx^2 + 2x(s_{IV} - s_V^2) + s_V^2 \right]^{-n/2}. \quad (4.52)$$

Then, taking into consideration formula (4.51), expression (4.52) takes the following form:

Table 4.10 Initial data for simulated defect depths

Parameters of the distribution of the true defect depths	Parameters of the distribution of the ILI tool MEs	Parameters of the distribution of the VI MEs
PDF: Normal	PDF: Normal	PDF: Normal
Mean, mm: 6	Mean, mm: 3	Mean, mm: 0
SD, mm: 1.5	SD, mm: 1.5	SD, mm: 0.3
Number of measurements: 30		

$$f(x) = \left[s_V^2(1-x)^2 + s_I^2x^2 + s_{IV}x \left(2 - x \frac{1+\beta^2}{\beta} \right) \right]^{-n/2}. \quad (4.53)$$

Therefore, when $\beta \neq 1$, in formulas (4.50) expression (4.51) is used, instead of S , and expression (4.53), instead of $f(x)$. Other equations of the Jaech method remain unchanged.

It should be noted that in reality the sample covariation s_{IV} may also be negative. This happens only in the case when small values of one tool measurements are related to the large values of the other measurement tool. This is a sign to reject one of the tools as unsuitable for use.

Example 4.5.2 Initial data for simulating measurements of defect depth was obtained using (4.38) which has $\alpha = 0$, $\beta = 1$, and the Monte Carlo simulation method, with the following parameters (see Table 4.10):

Conduct an experiment, which consists in modeling $N = 10,000$ sets of pairs of measurements of defect depths using the distribution parameters given in Table 4.10. Applying the Grubbs method (or the modified Grubbs method) to each set of measurements, we obtain in most cases that the assessments of the MEs variances are negative (see Fig. 4.22). Application in this case of the Jaech method or its modification allows us to obtain only positive values of the MEs variance (see Fig. 4.23).

4.5.4 Method of Increasing the Measurement Accuracy (Calibration) of Defect Parameters

Consider the method of assessing the true sizes of defects. Rewrite the measurement model (4.38) in matrix form:

$$\begin{pmatrix} p_I - \alpha \\ p_V \end{pmatrix} = \begin{pmatrix} \beta \\ 1 \end{pmatrix} p_{tr} + \begin{pmatrix} \varepsilon_I \\ \varepsilon_V \end{pmatrix}.$$

Denote

$$Y = \begin{pmatrix} p_I - \alpha \\ p_V \end{pmatrix}, \quad X = \begin{pmatrix} \beta \\ 1 \end{pmatrix}, \quad E = \begin{pmatrix} \varepsilon_I \\ \varepsilon_V \end{pmatrix}.$$

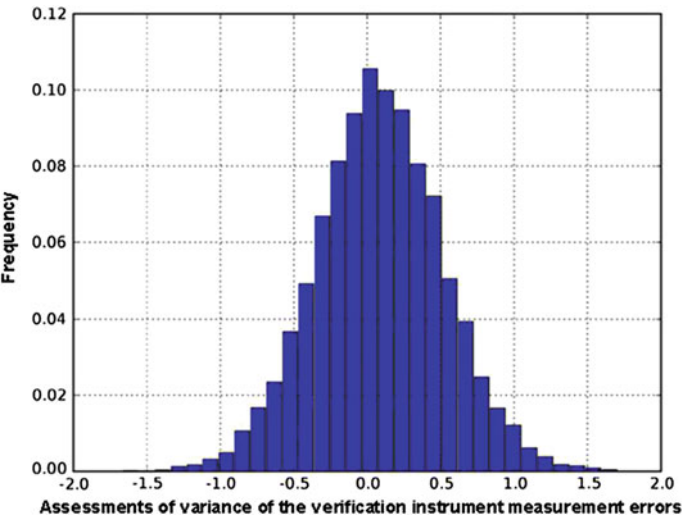


Fig. 4.22 Assessments of the VI MEs variances obtained using the Grubbs method

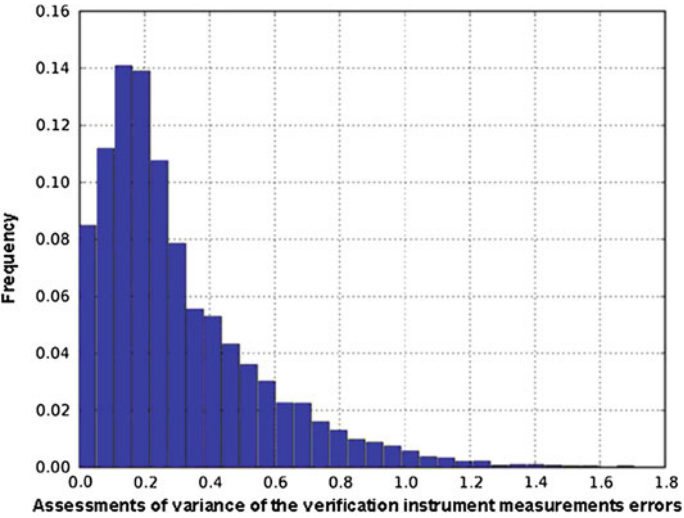


Fig. 4.23 Assessments of the VI MEs variances obtained using the Jaech method

Then, the measurement model (4.44) can be rewritten as

$$Y = p_{tr}X + E. \quad (4.54)$$

Expression (4.54) is a generalized linear regression model, where p_{tr} is the unknown parameter (true value of the verified defect parameter).

According to the Aitken theorem [16], the best (effective) unbiased assessment of the unknown parameter p_{tr} of model (4.54) is the assessment obtained using the *generalized least squares method* (GLSM).

In this case variation of the assessment of the true verified defect parameter is calculated by formula [16]:

$$V(\hat{p}_{tr}) = [X^T C_{\varepsilon\varepsilon}^{-1} X]^{-1}, \quad (4.55)$$

where $C_{\varepsilon\varepsilon}$ is the ME covariation matrix ($\varepsilon_I, \varepsilon_V$):

$$C_{\varepsilon\varepsilon} = \begin{pmatrix} \hat{\sigma}_{\varepsilon I}^2 & 0 \\ 0 & \hat{\sigma}_{\varepsilon V}^2 \end{pmatrix}.$$

Express from the second equation of the measurement model (4.38) the value of the true size of the defect parameter $p_{tr} = p_V - \varepsilon_V$ and substitute this expression into the first equation of model (4.38):

$$p_I = \alpha + \beta p_V + (\varepsilon_I - \beta \varepsilon_V) = \alpha + \beta p_V + r. \quad (4.56)$$

Errors r in Eq. (4.56) are similar to the deviations of the classic paired regression, but are correlated with the independent variable p_V .

After multiplying the matrices in the generalized model (4.54), constructed using the GLSM, and collecting similar terms, write the expression for assessing the true value of the verified defect parameter, in the form

$$\hat{p}_{tr} = a_1 (p_I - \hat{\alpha}) + a_2 p_V. \quad (4.57)$$

Since assessment $\hat{p}_{tr}$ is an unbiased assessment of p_{tr} , the conditional mathematical expectation $\hat{p}_{tr}$ at a fixed value of p_{tr} will have the form

$$E(\hat{p}_{tr} | p_{tr}) = p_{tr}. \quad (4.58)$$

As the residuals r themselves are a linear combination of $(p_I - \alpha)$ and p_V , the expression (4.57) may be written in the form

$$\hat{p}_{tr} = c_1 p_V + c_2 r. \quad (4.59)$$

From condition (4.58) and condition $E(r) = 0$ it follows that in formula (4.59) $c_1 = 1$. Then assessment of the true size of the verified defect parameter shall assume the form

$$\hat{p}_{tr} = p_V + c_2 r, \quad (4.60)$$

where $c_2 = f(\hat{\beta}, \hat{\sigma}_{\varepsilon_I}^2, \hat{\sigma}_{\varepsilon_V}^2)$ is a function of the (1) assessment of parameter $\hat{\beta}$, calculated by one of the approaches described in Sect. 4.5.2; (2) assessment of ILI tool ME variance $\hat{\sigma}_{\varepsilon_I}^2$, calculated by formula (4.48); and (3) assessment of VI ME variance $\hat{\sigma}_{\varepsilon_V}^2$, calculated by formula (4.48). This function is determined from the assessment of the unknown parameter p_{tr} with GLSM.

The final goal of this method is calibration of the raw ILI tool measurements, i.e., defining the calibration line parameters, with the help of which it is possible to adjust the defect parameter values of all other, *unverified* ILI tool measurements. If the calibrating experiment is performed on a sample of size n , then the adjusted defect parameter value for the $(n + i)$ th unverified measurement p_I^{n+i} is determined from equation

$$\hat{p}_{tr}^{n+i} = \hat{\xi} + \hat{\gamma} p_I^{n+i}, \quad (4.61)$$

where $\hat{\xi}$, $\hat{\gamma}$ are the calibration line parameters.

These parameters are assessed by means of equations

$$\begin{aligned} \hat{\gamma} &= \begin{cases} \frac{(s_V^2 + \hat{\sigma}_V^2) s_{IV} + 2(n-1)^{-1} s_{IV} \hat{\sigma}_V^2}{s_{IV} + (n-1)^{-1} |C_{IV}|}, & \hat{\lambda} > 1.0, \\ s_{IV} / s_I^2, & \hat{\lambda} \leq 1.0, \end{cases} \\ \hat{\xi} &= \bar{p}_V - \hat{\gamma} \bar{p}_I, \end{aligned} \quad (4.62)$$

where value $\hat{\lambda}$ is the root of equation

$$\left| C_{IV} - \hat{\lambda} \begin{pmatrix} 0 & 0 \\ 0 & \hat{\sigma}_{\varepsilon_V}^2 \end{pmatrix} \right| = 0.$$

In this expression C_{IV} is covariation matrix of measurements (p_I, p_V) ; sign $|\dots|$ means a determinant.

Variation of the parameter $\hat{\gamma}$ assessment equals

$$V(\hat{\gamma}) = \frac{[(m_V + \hat{\sigma}_V^2) s_{bb} + \hat{\sigma}_V^2] \hat{\gamma}^2}{m_V (n-1)},$$

and parameters included in this expression are calculated by the formulas

$$s_{bb} = \frac{\sum_{i=1}^n [(p_{Vi} - \bar{p}_V) - \hat{\gamma} (p_{Li} - \bar{p}_L)]^2}{(n-2)},$$

$$m_V = \begin{cases} s_V^2 - \hat{\sigma}_V^2, \hat{\lambda} > 1, \\ s_I^2 / s_{IV}^2, \hat{\lambda} \leq 1. \end{cases}$$

In this case the variance of assessment (4.61) or the variance of the predicted error value is calculated by the formula

$$V(\hat{p}_{tr}^{n+1}) = (n-1)^{-1} s_{bb} + V(\hat{\gamma}) \left[(p_I^{n+1} - \bar{p}_I)^2 - \hat{\sigma}_I^2 \right] + \hat{\gamma}^2 \hat{\sigma}_I^2. \quad (4.63)$$

Example 4.5.3 Consider a virtual pipeline with wall thickness of 11 mm. Based on the input data defined in Tables 4.11 and 4.12, according to measurement model (4.38) 120 ILI tool measurements of the defect depth were modeled. For 30 measurements of that number verification measurements were modeled. On their basis assessments of the constant ILI tool measurement bias were obtained (see Table 4.13), and then the ILI tool accuracy was assessed (see Table 4.14). At the final stage assessments of true values of the modeled defect depths were obtained using formula (4.60) for the 30 verified measurements, and by formula (4.61) assessments of the true values of other 90 unverified measurements were made.

Table 4.11 Deterministic values required for modeling ILI tool and VI measurements

Parameters	Symbol, dimension	Value
Pipe wall thickness	wt , mm	11
Average bias of ILI tool measurements	α , mm	-0.5
Multiplicative bias of ILI tool measurements	β	0.9
Overall number of measurements	N , pcs	120
Number of verified measurements	n , pcs	30
MFL tool tolerance, according to its specification	t_I , % wt	± 10
Ultrasonic tool tolerance, according to its specification	t_V , mm	± 0.5

Table 4.12 Input data required for ILI tool and VI measurement modeling

Parameter	Symbol	Distribution law	Mathematical expectation, mm	Standard deviation, mm
True value of defect depth	d_{tr}	Normal, Lognormal, Weibull	5.000	1.650 (0.15 wt)
ILI tool ME	ε_I	Normal	0	0.859
VI ME	ε_V	Normal	0	0.255

Table 4.13 Comparative table of the true values of the constant bias of ILI tool measurements and their assessments

Constant bias of ILI tool measurements	α , mm	β
True values	0.500	0.900
True sizes of defect depths (normal distribution)	−0.588	0.887
True sizes of defect depths (lognormal distribution)	−0.581	0.905
True sizes of defect depths (Weibull distribution)	−0.548	0.868

Table 4.14 Comparative table of the true values of ILI tool ME variance and its assessment

ILI tool ME variance	$\sigma_{\varepsilon_I}^2$, mm ²
True values	0.739
True sizes of defect depths (normal distribution)	0.706
True sizes of defect depths (lognormal distribution)	0.736
True sizes of defect depths (Weibull distribution)	0.723

The variance of MI ME from Table 4.12 was determined using the tools characteristics given in Table 4.11, as follows: the ILI tool tolerance t_I , according to its characteristics, as demonstrated when measuring the defect depth with 80 % validity, is $\pm 10\%$ wt. Thus, taking into account that the MEs are normally distributed, the standard (mean-square deviation) of ILI tool ME, when measuring the defect depth is $0.1wt/1.28 = 0.859$ mm. The ILI tool tolerance t_V , according to its characteristics as demonstrated when measuring the defect depth with 95 % validity is ± 0.5 mm, and the standard deviation of the VI ME is $0.5/1.96 = 0.255$ mm.

According to Tables 4.13 and 4.14 the assessments of the measurement model parameters (ILI tool measurement bias) are close to their true values (maximum error for parameter α −17.6 %, for β −3.6 %) and assessments of the ILI tool ME agreed well with their true values (maximum error is −0.033 mm² (−4.5 %)).

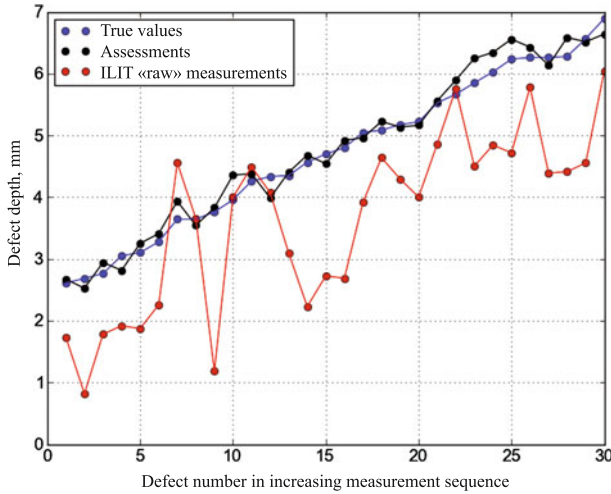


Fig. 4.24 True values of the verified defect depth, their assessments, and the “raw” ILI tool measurements (true defect depth sizes are normally distributed)

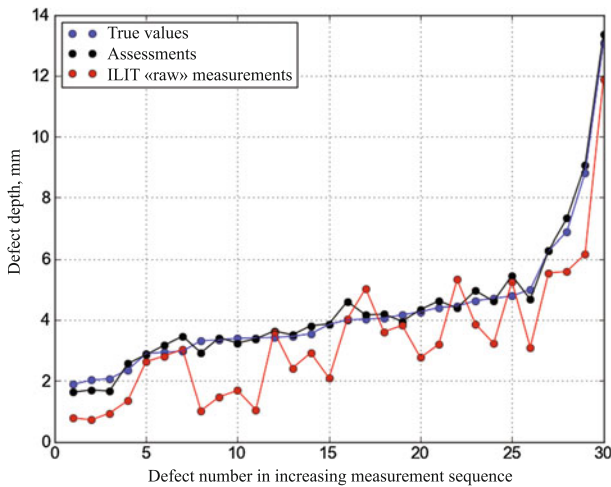


Fig. 4.25 True values of the verified defect depth, their assessments, and the “raw” ILI tool measurements (true defect depth sizes are lognormally distributed)

In Figs. 4.24, 4.25 and 4.26 the true values of 30 verified defect depths are presented, as well as their assessments and the “raw” (uncalibrated) ILI tool measurements. It is obvious that unlike the ILI tool measurements the defect depth assessments are closer to their true values, regardless of the type of distribution of the true defect depth sizes.

Table 4.15 shows assessments of the calibrating line parameters calculated by formulas (4.62). In Figs. 4.27, 4.28 and 4.29 the true values of the other 90 unverified

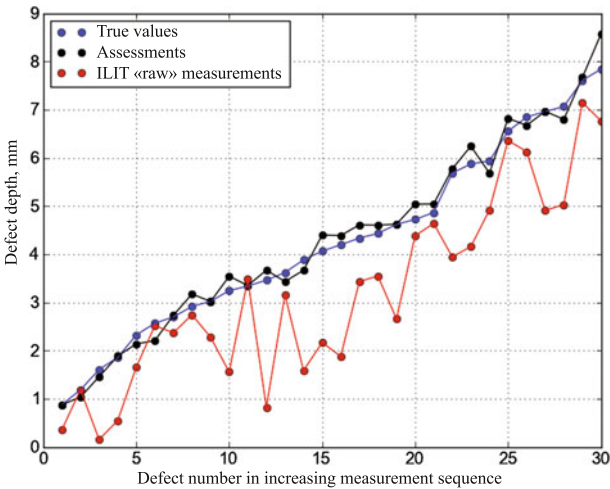


Fig. 4.26 True values of the verified defect depth, their assessments, and the “raw” ILI tool measurements (Weibull law true defect depth size distribution)

Table 4.15 Calibration line parameter assessments

Parameters of calibration line	$\hat{\xi}$, mm	$\hat{\gamma}$
The true sizes of defect depths (normal distribution)	0.736	1.106
The true sizes of defect depths (lognormal distribution)	0.663	1.099
The true sizes of defect depths (Weibull distribution)	0.660	1.143

defect depths are presented, as well as their assessments and the “raw” (uncalibrated) ILI tool measurements. Assessments of the true defect depth values were obtained based on the calibration line parameters from Table 4.15. According to Figs. 4.24, 4.25, 4.26, 4.27, 4.28 and 4.29, in all cases assessments of the true defect depth sizes were closer to their true values than the “raw” ILI tool measurements.

4.5.5 Validation of the Implemented Measurement Model

In order to check adequacy of the measurement model (4.38) the solutions obtained using this model are checked for such statistical analysis errors as lack of variance homogeneity, the presence of data outliers, nonnormality of residues (model errors) distribution, and error dependencies. In this context, for this purpose residues $\hat{r}$ between the ILI tool measurements and the respective values obtained from the regression model are calculated:

$$\hat{r} = p_I - \hat{\alpha} - \hat{\beta}p_V. \tag{4.64}$$

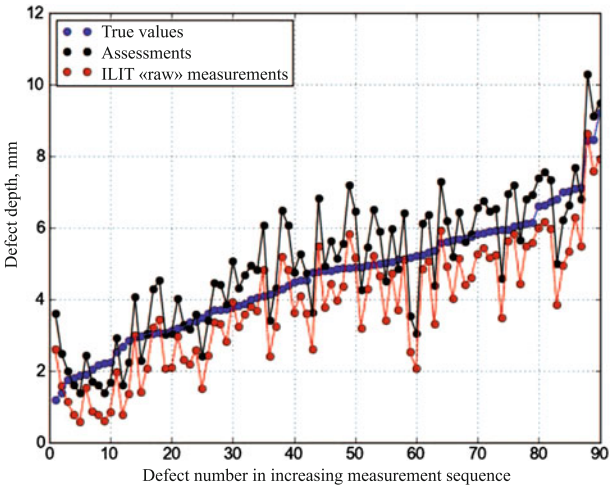


Fig. 4.27 True values of the unverified defect depth, their assessments, and the “raw” ILI tool measurements (true defect depth sizes are normally distributed)

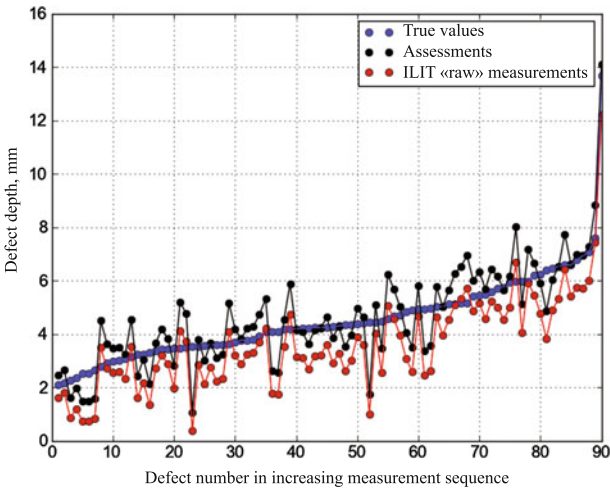


Fig. 4.28 True values of the unverified defect depth, their assessments, and the “raw” ILI tool measurements (true defect depth sizes are lognormally distributed)

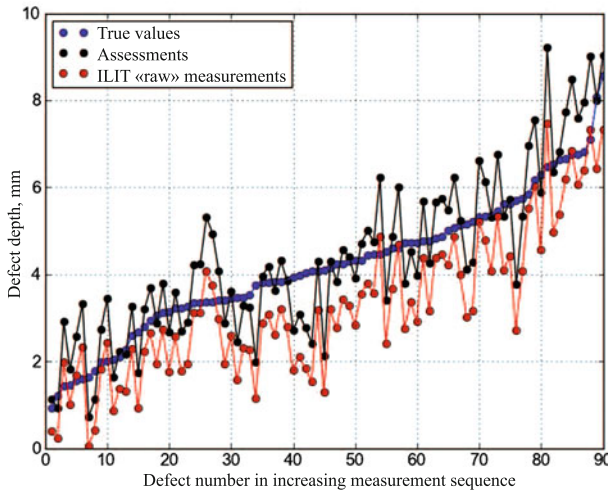


Fig. 4.29 True values of the unverified defect depth, their assessments, and the “raw” ILI tool measurements (Weibull law true defect depth size distribution)

When checking homogeneity of the residue variance, the error assessments $\hat{r}$ are plotted together with the corresponding values of the measurements p_V . The purpose of this analysis for heteroskedasticity (nonhomogeneity of the residue variance) is to determine factors, which affect the change of variance, the number of measurements, or the value of one of the attributes. The presence of heteroskedasticity may often be clearly visible from the correlation field, e.g., the residue variance is growing with the growth of p_V ; residue variance reaches its maximum value at average values of variable p_V and decreases at the minimum (maximum) values of p_V ; the maximum residue variance at low values of p_V etc. The presence of heteroskedasticity may also be identified with the help of the Spearman rank correlation test and tests of Rark, Glejser, and White et al. [16, 25].

The error normalcy is analyzed, e.g., with the help of the Shapiro–Wilk or Frosini tests, or other methods for verification of normality of the distribution [25]. The outliers of the data sequence $\hat{r}$ are identified, e.g., using the Hoaglin–Iglewicz test, or other methods [25]. Independence of the sequence of $\hat{r}$ values may be checked by the Durbin–Watson serial correlation coefficient, or other methods [25].

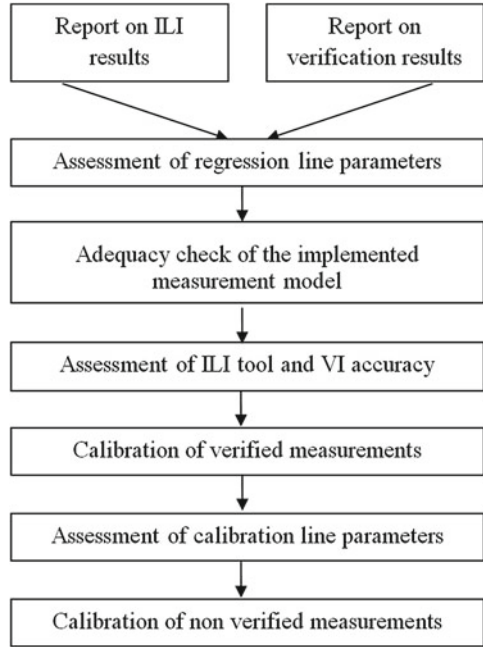
4.5.6 Statistical Analysis Algorithm of the ILI Results

The general algorithm of the method described above is shown in Fig. 4.30.

Consider application of the algorithm in a real-life case.

Example 4.5.4 Table 4.16 (Block 1) presents input data for analysis: $n = 37$ verified measurements of the defect depths of a “metal loss” type and $N = 10$ unverified

Fig. 4.30 Block diagram of the algorithm of statistical analysis of the pipeline system diagnostics results



measurements. Verification of the ILI tool measurements was done with the use of an ultrasound tool. According to its specifications, the ME for the defect depth measurement at the 95 % confidence level is $\pm 0,5$ mm. Hence, the ILI tool ME standard deviation is $\sigma_{\varepsilon V} = \frac{0.5}{1.96} = 0.255$ mm, and the VI ME variance equals $\sigma_{\varepsilon V}^2 = 0.065$.

Block 2. In order to assess parameters of the mathematical measurement model it is necessary to calculate sample mathematical expectations of the ILI tool and the VI measurements, their unbiased sample variance, and the measurement covariance using formulas (4.40):

$$\bar{p}_I = 1.821; \bar{p}_V = 2.289; s_I^2 = 0.610; s_V^2 = 1.018; s_{IV} = 0.546.$$

Now check further applicability of the algorithm by formula (4.49):

$$0.610 (1.018 - 0.055) - 0.546^2 = 0.229 > 0.$$

Assessments of the ME variance, and the true defect depth size variance, obtained using the above methodology, are positive; hence, further calculations are legitimate.

Table 4.16 Initial data: ILI tool and VI measurements

#	ILI tool measurements	VI measurements
1	2.0	1.0
2	1.5	2.0
3	1.0	2.0
4	0.7	1.0
5	2.3	2.5
6	1.6	1.5
7	2.0	2.5
8	2.3	3.0
9	2.2	3.5
10	2.2	1.4
11	2.6	2.5
12	0.8	2.0
13	2.4	2.0
14	1.2	1.6
15	1.2	1.8
16	2.1	2.5
17	0.7	2.0
18	0.8	2.0
19	0.8	2.5
20	1.9	3.5
21	1.6	2.5
22	2.2	3.2
23	2.4	2.4
24	2.9	4.5
25	2.6	4.9
26	1.1	1.0
27	1.4	1.4
28	2.2	2.0
29	2.6	3.1
30	3.5	3.8
31	1.9	1.2
32	0.7	0.7
33	0.8	1.0
34	3.0	3.2
35	3.1	3.2
36	2.2	2.8
37	0.9	1.0
38	1.1	–

(continued)

Table 4.16 (continued)

#	ILI tool measurements	VI measurements
39	1.5	–
40	1.7	–
41	1.6	–
42	2.3	–
43	1.9	–
44	2.2	–
45	2.3	–
46	2.8	–
47	2.9	–

Measurement model parameter assessments are found by formulas (4.39):

$$\begin{aligned}\widehat{\beta} &= \frac{0.546}{1.018-0.065} = 0.573, \\ \widehat{\alpha} &= 1.821 - 2.289 \cdot 0.573 = 0.509.\end{aligned}$$

Figure4.31 shows the scatter diagram of the ILI tool and the VI measurements and the determined RL.

Block 3. Prior to further calculation check adequacy of the employed model. To do this calculate residues r , represented in Fig.4.32 using formula (4.64).

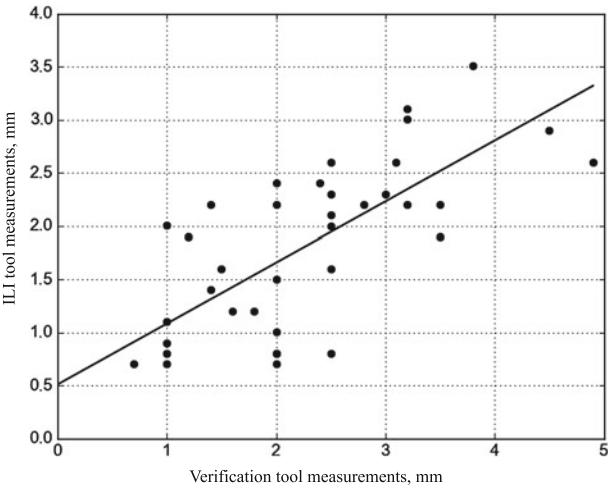


Fig. 4.31 The scatter diagram “ILI tool measurements vs VI measurements” and the regression line

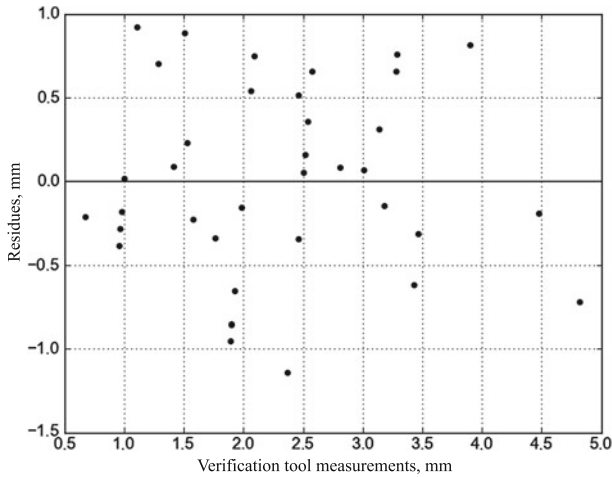


Fig. 4.32 Residuals between the ILI tool measurements and the corresponding values obtained from regression model

At this stage of the analysis using the Frosini test [25] with confidence probability 0.99, it was established that the residues are distributed normally. The Hoaglin–Iglewicz test [25] demonstrated, with the confidence probability 0.99, that there were no data outliers in the residue set. Using the Spearman rank correlation test [25] the hypothesis of absence of residue heteroskedasticity was made, which was not rejected at 0.99 confidence probability. Independence in the sequence of $\hat{r}$ values was checked with the help of the Durbin–Watson serial correlation coefficient [25].

Thus, the used model is adequate, which allows us *to continue the analysis*.

Block 4. Assess the ILI tool ME and the true defect depth sizes variance by formulas (4.48):

$$\begin{aligned}\hat{\sigma}_{tr}^2 &= 1.018 - 0.065 = 0.953, \\ \hat{\sigma}_{\varepsilon I}^2 &= 0.610 - 0.573^2 \cdot 0.953 = 0.297.\end{aligned}$$

Block 5. True values of the verified defects are assessed by formula (4.60). Using formula (4.55) calculate the variance of these assessments (variance of the error of predicted true values of the verified defect depth). The results of the calculations are shown in Fig. 4.33 and summed up in Table 4.17. Thus, assessment of the true size of each verified defect depth will be distributed relative to its true value with variance equal to 0.06 mm^2 .

Judging by Fig. 4.33, an ILI tool may underestimate the defect depth sizes, which is a serious threat, since the assessment of the potential risk in a pipeline segment, performed on the basis of “raw” ILI tool measurements, will not allow obtaining adequate assessment of the real condition of the pipeline, which may lead to an accident with grave consequences.

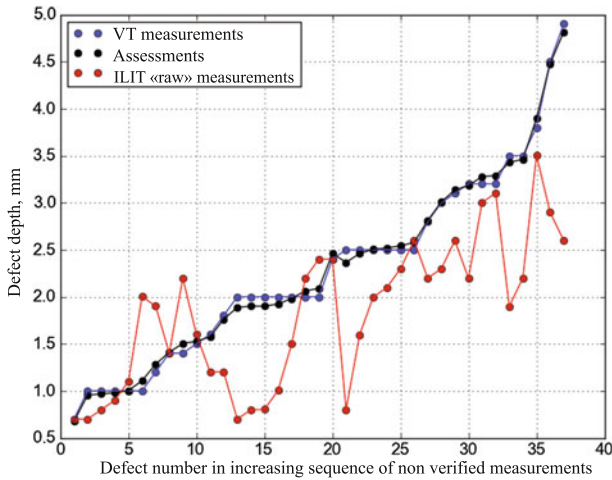


Fig. 4.33 Assessment of the true size of verified defect depth, the VI measurements, and the “raw” ILI tool measurements

Block 6. Assess the calibrating line parameters by formula (4.62):

$$\hat{\gamma} = 1.699, \hat{\xi} = -0.805.$$

Block 7. Assess true values of the unverified defects by formula (4.61). Using formula (4.63) calculate variance of these assessments (variance of the error of predicted true values of the unverified defect depth). The results of calculations are shown in Fig. 4.34 and in Table 4.17.

From Fig. 4.34 it may be seen that a small part of the defects (shallow metal losses) was overstated by the ILI tool, and values of the deeper defects were, on the contrary, understated, which is dangerous. Therefore, in the process of assessing unverified defects, calibration of shallow defect depth measurements was more pronounced than for the deeper and the more dangerous ones.

4.5.7 Some Results of Application of the FSA Method to Modeled Measurements

Example 4.5.5 Some of the results of computer testing of the method are shown in Fig. 4.35, showing the case when the ILI tool is under reporting.

A very important question is how the accuracy of the VI affects assessments of the true values of the unverified defects. Figure 4.36 illustrates the answer. The best approximation is obtained, obviously, when the VI (with no bias) precision is better than the accuracy of the ILI tool. But even when the VI has less accuracy than the ILI tool, the approximation of the true (unknown) values of the unverified defects is better than the ILI tool readings (Fig. 4.36).

Table 4.17 ILI tool and VI measurements and their updated values

#	ILI tool measurements, mm	VI measurements, mm	Assessment of the true defect depth, mm	Variance of the prognosis error, mm ²
1	2.00	1.00	1.11	0.06
2	1.50	2.00	1.98	0.06
3	1.00	2.00	1.92	0.06
4	0.70	1.00	0.96	0.06
5	2.30	2.50	2.54	0.06
6	1.60	1.50	1.53	0.06
7	2.00	2.50	2.51	0.06
8	2.30	3.00	3.01	0.06
9	2.20	3.50	3.46	0.06
10	2.20	1.40	1.50	0.06
11	2.60	2.50	2.58	0.06
12	0.80	2.00	1.90	0.06
13	2.40	2.00	2.09	0.06
14	1.20	1.60	1.57	0.06
15	1.20	1.80	1.76	0.06
16	2.10	2.50	2.52	0.06
17	0.70	2.00	1.89	0.06
18	0.80	2.00	1.90	0.06
19	0.80	2.50	2.37	0.06
20	1.90	3.50	3.43	0.06
21	1.60	2.50	2.46	0.06
22	2.20	3.20	3.18	0.06
23	2.40	2.40	2.46	0.06
24	2.90	4.50	4.48	0.06
25	2.60	4.90	4.82	0.06
26	1.10	1.00	1.00	0.06
27	1.40	1.40	1.41	0.06
28	2.20	2.00	2.06	0.06
29	2.60	3.10	3.14	0.06
30	3.50	3.80	3.90	0.06
31	1.90	1.20	1.28	0.06
32	0.70	0.70	0.68	0.06
33	0.80	1.00	0.97	0.06
34	3.00	3.20	3.28	0.06
35	3.10	3.20	3.29	0.06
36	2.20	2.80	2.81	0.06
37	0.90	1.00	0.98	0.06

(continued)

Table 4.17 (continued)

#	ILI tool measurements, mm	VI measurements, mm	Assessment of the true defect depth, mm	Variance of the prognosis error, mm ²
38	1.10	–	1.06	0.90
39	1.50	–	1.74	0.87
40	1.70	–	2.08	0.86
41	1.60	–	1.91	0.86
42	2.30	–	3.10	0.88
43	1.90	–	2.43	0.86
44	2.20	–	2.93	0.87
45	2.30	–	3.10	0.88
46	2.79	–	3.94	0.94
47	2.90	–	4.12	0.96

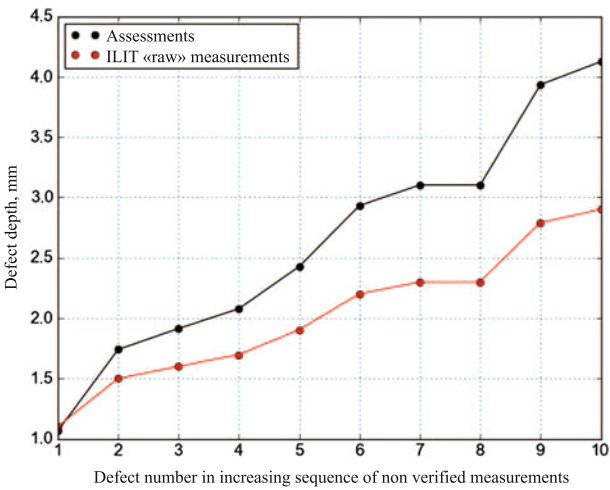


Fig. 4.34 Assessment of the true size of unverified defect depth, and the “raw” ILI tool measurements

The results of testing showed that the FSA method is accurate and robust, which allowed using it for analyzing real ILI data obtained during in-line inspection of multiple pipelines located in different parts of the world [5].

Example 4.5.6 ILI technology is not full without providing for the necessary verification of the ILI results. The main problem of this part of ILI technology, as perceived by pipeline operators, is the cost of verification and the actual underestimation of its value. A common consideration is to minimize the number of excavations, which is thought to lead to maximizing cost savings. Using risk analysis it is possible to show

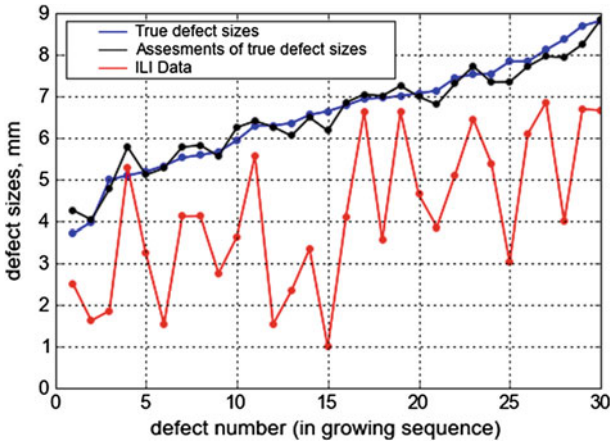


Fig. 4.35 True sizes of defects, their assessments, and the ILI readings (under reporting case)

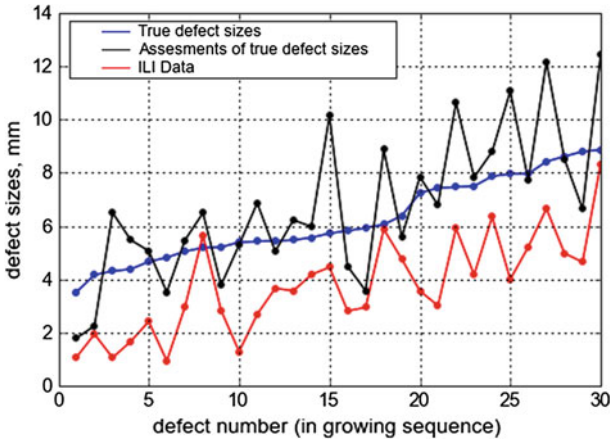


Fig. 4.36 True sizes of defects, their assessments, and the ILI readings for $SD_{el} = 1.5$, $SD_{eV} = 2.0$

that maximal savings can be achieved by conducting verification measurements after each ILI.

Without conducting verification, the ILI results are “tethered” to the verification of the ILI tool, conducted in-house by the vendor. Many operators believe that this kind of verifications, which find their way into the ILI tool specs, is enough. But the environment of the vendor’s warehouse/lab is dramatically different from the environment of the specific pipeline that is to be inspected by the specific ILI tool. The performance of the ILI tool (its sample variance) will be different from pipeline to pipeline, with the difference which could be of the order of tens of percents and

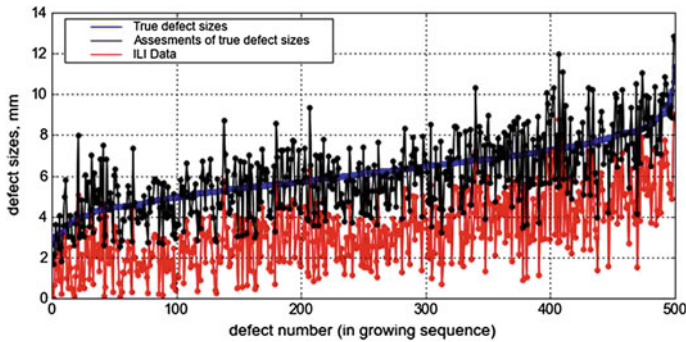


Fig. 4.37 True sizes of (500) defects, the ILI readings, and verification of 30 of them

more. *In order to account for this issue the verification is a must for the ILI technology. It should be pipeline—specific and ILI run-specific.*

Having said this, one would ask, how many verifications should be made? In order to answer this question, special computational experiments were conducted, the results given in Fig. 4.37.

It can be seen that just 30 verification points (which, in general, could be taken from a single dig) would be enough to dramatically enhance the ILI report, by providing, in this particular case, assessments of the true sizes of 470 unverified defect sizes.

The *iron rule of statistics* is to first prove (using some nonparametric methods) that it is applicable to use the selected for this purpose parametric method to analyze the raw data in consideration. If this rule is not followed, statistical methods used may produce results that are highly improbable.

According to Fig. 4.38, the absolute least number of verifications (needed to assess the variance of the ILI tool) is four. In order to be able to test the applicability of used methods to the analysis of raw ILI data the number of verification points should be not less than 20.

Example 4.5.7 Consider now the case when out of 500 measurements, obtained using the data from Table 4.10, only 30 are verified. Let the mathematical expectation of the ILI MEs be equal—3 mm, and leave other parameters in Table 4.10 without change. In this case the virtual ILI tool will underreport the true values of defect depths (Fig. 4.42). Define now the ILI tool accuracy. The RL is shown in Fig. 4.39.

The ILI tool calibration is performed using the parameters of the above RL and the assessments of the MEs of the measurement tools obtained using the Jaech method. The calibration line is given in Fig. 4.40.

Further, we obtained assessments of the true sizes of the defects for the 30 verified measurements, presented in Fig. 4.42, and assessments of all 500 measurements, 470 of which are obtained using the parameters of the calibration line, shown in Fig. 4.41.

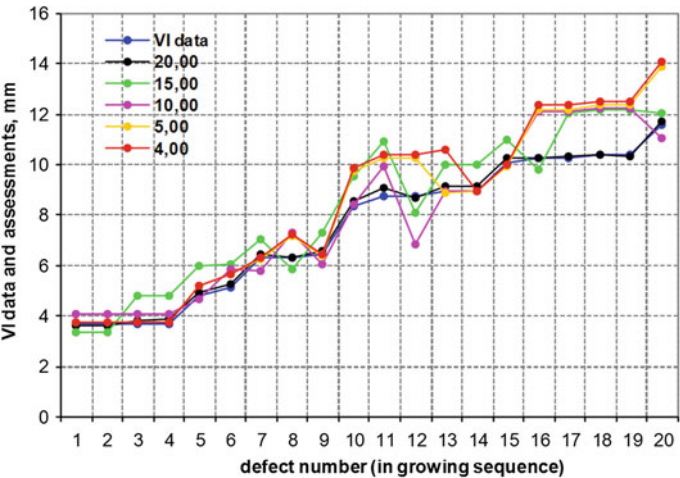


Fig. 4.38 VI measurements and assessments of the true sizes of defects as a function of the number of verified defects

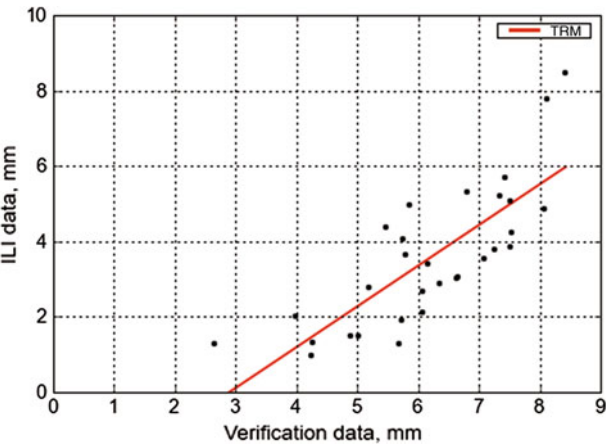


Fig. 4.39 The scatter diagram and the regression line

4.5.8 Some Results of Real Case Analysis

1. Application of the FSA method to API 1163 (Sects. 7, 9 and Annex E) [1]

First use this method to independently analyze the results of verification as given in API 1163 Standard [1]. Table 4.18 and Fig. 4.43 are excerpts from the Annex E of this Standard (in the Standard they are, respectively, Table 6 and Fig. 4). Numbers in bold in the third column from right and the word (“yes” in bold) in the right column are authors’ corrections of the actual mistakes in Table 4.18. The question mark at

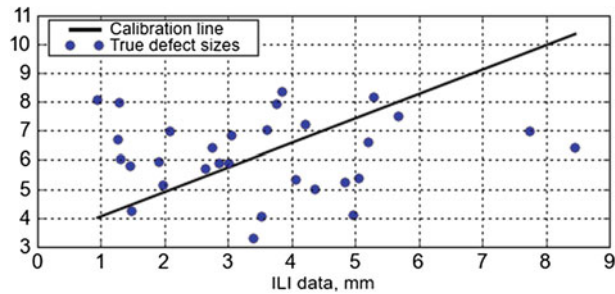


Fig. 4.40 The calibration line and the true sizes of the defects

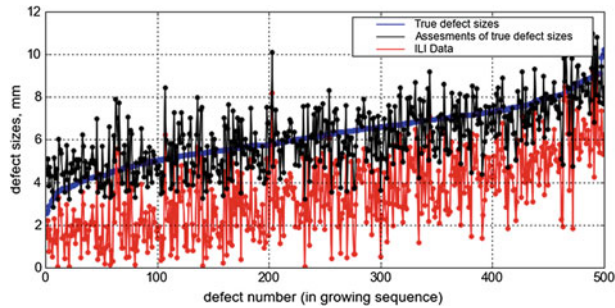


Fig. 4.41 True defect sizes, their assessments, and ILI measurements

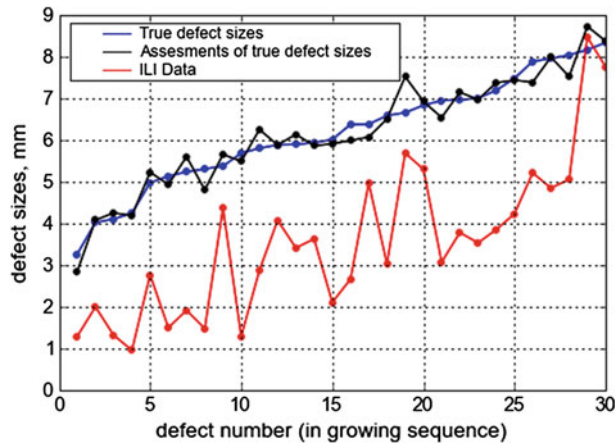


Fig. 4.42 The true sizes of 30 defects, their assessments, and the ILI readings

Table 4.18 Example: agreement test of two independent measurements

ILI report		Ultrasonic field investigation								$ D $, %	$\sqrt{S}$, %	Q
d/t (%) meas	$\Delta(d/t)$ (%) given (?)	t (mm) meas	t - d (mm) meas	d (mm) calc	d/t (%) calc	σ (mm) given (?)	$\sigma(t - d)$ (mm) given (?)	σ (mm) calc	$\Delta(d/t)$ (%) calc			
42	10	6.4	3	3.4	53	0.15	0.25	0.29	6.0	11.1 (11.0)	11.7	no
57	12	8.2	2.5	5.7	70	0.15	0.25	0.29	4.8	12.5 (13.0)	12.9	no (yes!)
21	5	4.9	4.3	0.6	12	0.15	0.25	0.29	7.6	8.8 (9.0)	9.1	no
33	10	6.3	4	2.3	37	0.15	0.25	0.29	6.0	3.5 (4.0)	11.7	no
33	10	6.3	5.8	0.5	8	0.15	0.25	0.29	5.9	25.1 (25.0)	11.6	yes

Note Q—Comparison: violates 80% criterion?

the top of a column indicates that the source of the numbers in this column is not specified by API 1163 [1].

In Table 4.18:

$$\begin{aligned}
 D &= (d/t)_{\text{ILI}} - (d/t)_{\text{Field}}; \\
 S &= \Delta(d/t)_{\text{ILI}}^2 + \Delta(d/t)_{\text{Field}}^2; \\
 \Delta(d/t) &= 1.28 \sqrt{(\sigma(d)/d)^2 + (\sigma(t)/t)^2} \cdot (d/t) \cdot 100, \%; \\
 \sigma(d) &= \sqrt{\sigma(t-d)^2 + \sigma(t)}, \text{ mm}; \\
 |D| &> \sqrt{S}.
 \end{aligned}$$

Using only the columns #1, #3, and #6 of Table 4.18 and applying straightforward the FSA algorithm, it is possible to construct the regression line as shown in Fig. 4.44. It can be seen that the ILI tool has a bias, which is not accounted for in Fig. 8 of the API 1163 RP (Fig. 4.43 in this book). According to Table 4.19 given below, the SDs of the measurement error of the ILI tool and the VI drastically differ, depending on what methodology of analysis is applied. According to API 1163, the ILI tool and the VI are more accurate than what the FSA method indicates. By all common sense standards the ILI run as given in Table 4.18 (when 2 out of 5 measurements are out of confidence interval bounds) should be declared a failure.

It is appropriate to point out here that the wording used in API 1163 when explaining the contents of Table 4.18 is rather ambiguous. When wanting to follow the logic of Annex E, API 1163, one would need to somehow interpret some of the most

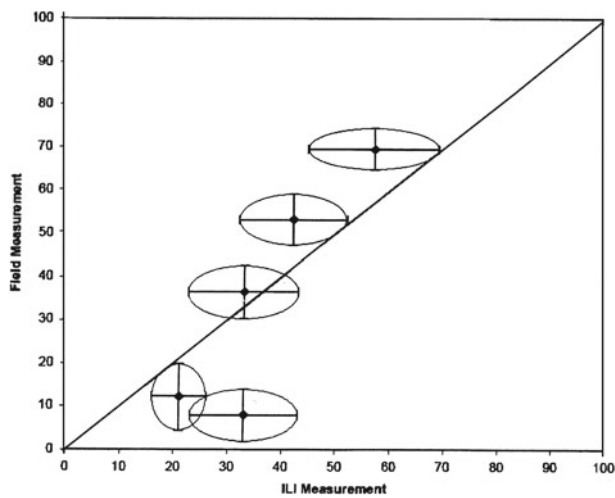


Fig. 4.43 Example: unity graph of two independent sets of measurements

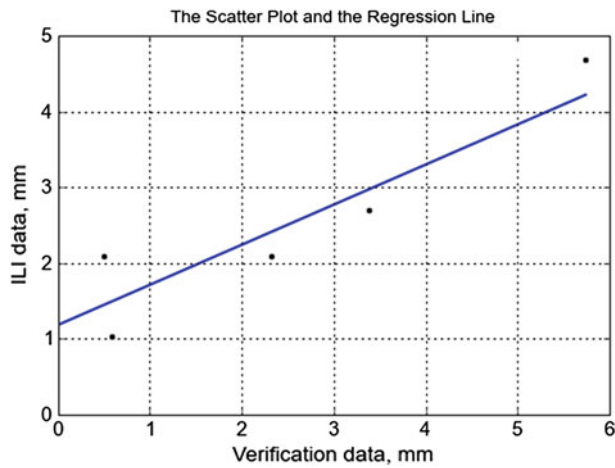


Fig. 4.44 The scatter plot and regression line

Table 4.19 Comparison of the assessments of SDs of the ILI tool and the VI measurement errors MEs

Measurement error ME SDs according to	ILI	VI
API 1163 algorithm, mm	0.49	0.29
FSA method, mm	0.81	0.47

crucial parts of the verbal algorithm. For instance, in the text on the Typical example (p. 33) the document states that “*The fact that the anomaly geometry was poorly defined gave cause to slightly increase the interval for the remaining wall measurement accuracy $\sigma(t - d)$* ”, and further, “*the fabrication tolerances of the nominal wall $\sigma(t)$ must be considered, as well as the possible misalignments of the apparatus $\sigma(t)$* .” The reader has to ponder what the words in italics actually quantitatively mean and whether it is possible, following this wording, to arrive at a *reproducible (by any other person) result*?

It should also be noted that according to Annex E the ILI tool’s ME variance contains the unknown variance of the diagnostician’s errors, which makes the above statements and decisions ambiguous (see italics). On the other side, the variance of VI ME also contains the unknown variance of the field technician’s errors, who conducts the field measurements.

Because of the nature of the MFL defect size assessment technology, it turns out that the confidence interval for the regression line is not symmetrical. This situation has to be explicitly accounted for when making decisions on whether the ILI results comply with the ILI tool specs.

Tables 4.20 and 4.21 give the numerical values of the relative bias, SDs of the prognosis for the true sizes of defects, and their assessments as compared to the ILI tool and the VI readings.

Figure 4.45 gives the results of the FSA in visualized form. One can see that in this particular case the assessment of the true sizes closely follows results of the verification measurements. Using Eq. (4.38) it is possible to produce a reliable and

Table 4.20 Assessment of the relative bias and the ME SDs for the assessments of the true sizes of defects

	API 1163	FSA method
Relative bias of VI measurements as compared to the ILI tool readings, mm	N/A	−0.001
SD of the assessment error of the true sizes of not verified defects, mm	N/A	0.450

Table 4.21 Comparison of the measurements and assessments of defect sizes

Defect #	Assessment of the true sizes of defects, mm	ILI tool measurements, mm	VI measurements, mm
1	3.35	2.69	3.39
2	5.81	4.67	5.74
3	0.51	1.03	0.59
4	2.28	2.08	2.33
5	0.60	2.08	0.50

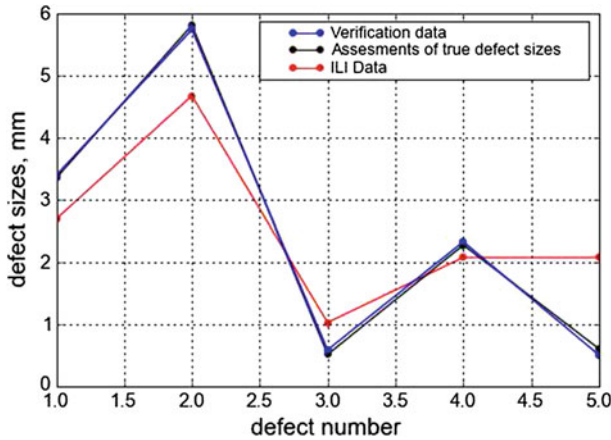


Fig. 4.45 Assessments of true sizes of defects, their assessments, and the ILI and VI readings

specific probability density function for every parameter of each and every discovered and measured defect.

Considering Sects. 7 and 9 of API 1163 [1] it should be noted that they, too, contain ambiguous wording and inconsistencies. For instance, Sect. 7 permits using the least squares method to draw the regression line, although it is well known [3, 26–28] that this method is not applicable when both measurements contain errors. Section 9, when describing process validation, recommends comparing reported inspection results to prior historical data on the pipeline inspected (if such data is available), with results from prior excavations and measurements of anomalies *similar* to those covered by the inspection, or with other data and analyses, *when supported by sound engineering practice*. The words in italics, again, have to be interpreted by the person who is conducting the analysis. Section 9 does not contain recommendations on how to quantify “*sound engineering practice*” in a way to deliver *repeatability* of results independent from the person who conducts the analysis. Section 9 also explicitly states that not all inspections require verification measurements. This is a nonconservative proposal. In [5, 29] life cases are given, which show what can be done using results of verification digs. The verbiage of recommendations should be more accurate and precise, aimed at delivering *repeatability* of results, independent from the person who conducts the analysis.

Case #1. Oil pipeline. Measurements of defect depths conducted by the ILI tool and the VI were used. Information about the accuracy of both the ILI tool and the VI are absent. This circumstance (here and everywhere below) is not an obstacle for assessing the accuracy of both instruments. In the calculations 86 pairs of independent measurements (ILI + VI) of 86 defects were used. Calculations were conducted for cases, when

- all measurements are verified (Fig. 4.46a); and
- only 30 measurements are verified (Fig. 4.46b).

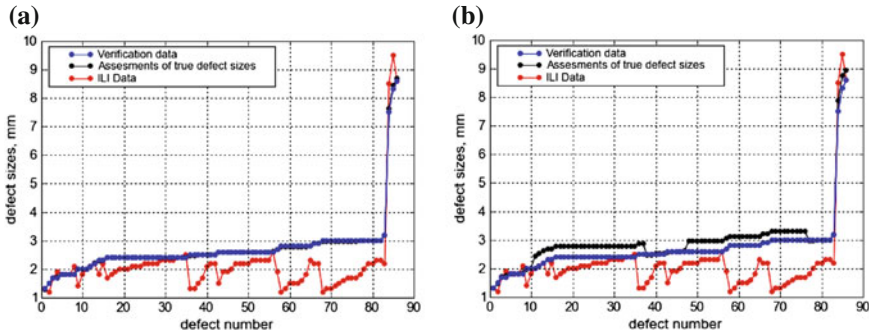


Fig. 4.46 **a** Verification data, assessments of true sizes of defects, and the ILI readings. **b** Verification data, assessments of true sizes of defects, and the ILI readings

Comparing these cases, it can be seen that just 30 verification measurements yield results which are very close to results obtained when total verification is performed.

Case #2. Oil pipeline. Measurements of defect depths conducted by the ILI tool and the verification instrument were used. Information about the accuracy of both the ILI tool and the Verification instrument are absent. This circumstance, as was said earlier, is not an obstacle to assess the accuracy of both instruments. In the calculations 1989 pairs of independent measurements (ILI + VI) of defects were used. All measurements are verified (see Fig. 4.47).

Case #3. Oil pipeline. Measurements of defect depths conducted by the ILI tool and the verification instrument were used. Information about the accuracy of both the ILI tool and the Verification instrument are absent. 20 measurements were used in the performed calculations. The confidence bands for the regression line built for ILI data and VI data versus assessments of true defect depths using sources [24, 26] are given correspondingly in Fig. 4.48a, b. According to these figure, the RV for the VI measurements is much narrower than the corresponding RV for the ILI measurements.

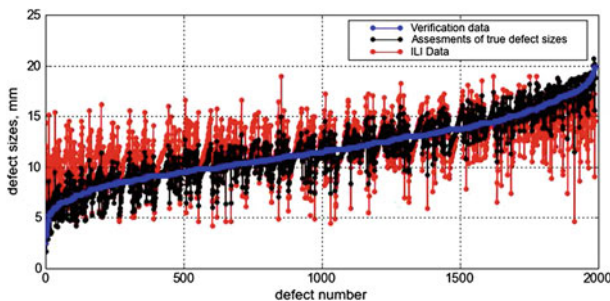


Fig. 4.47 True sizes of defects, their assessments, and the ILI readings

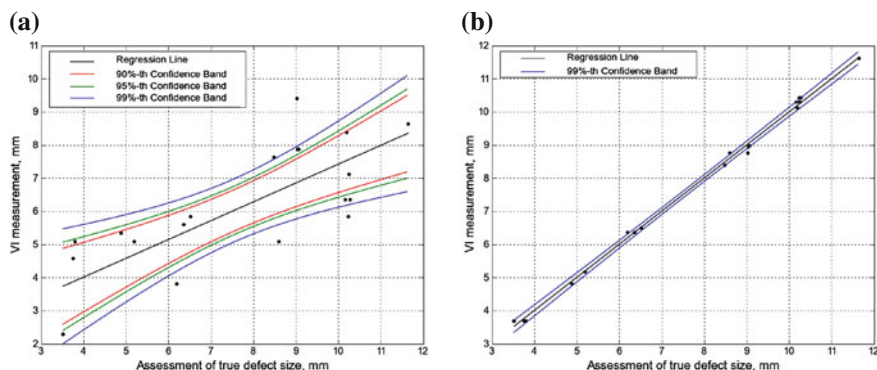


Fig. 4.48 a Confidence band for the ILI data. b Confidence band for the VI data

It can be seen (Fig. 4.49a) that the assessments of the true values of the defect sizes are closer to the verification results than to the ILI results. The ILI tool has a small bias. At the same time, according to Fig. 4.49b, c, this particular ILI vendor is remarkably accurate in assessing defect lengths and widths. After adjusting the ILI tool for the discovered bias in defect depth assessment, the Vendor would be able to produce a very high-quality ILI report.

Case #4. Gas pipeline. Analysis of the ILI results was performed as requested by the pipeline operator. It shows (see Fig. 4.50) that for some reason the ILI data is over reporting. It has a considerable (though conservative) bias and a large variance. This could be the result of a “safe” adjustment of the raw ILI data.

The difference between the variances of the ILI tool and the Verification instrument was larger than 10 %. According to the EPRI (USA) criteria, in such cases the ILI tool has to be recalibrated or rejected. Using the above algorithm allows the operator to independently assess the actual accuracy of the ILI tool as demonstrated on the specific inspected pipeline. The operator should take care that both measurements are conducted independently.

4.6 Criteria for Rejecting ILI Results

This paragraph contains a description of the method for assessing the allowed number of satisfactory (unsatisfactory) measurements when conducting ILI. The main goal of the method is to determine whether the results obtained using the ILI tool are adequate and acceptable. The case when too few defect parameter sizes (e.g., their depths) fall within the interval of values obtained as a result of verification is an evidence of poor assessment of the actual data by the ILI tool. Hence, it is necessary to assess the lower (upper) boundary for the number of successful (failed) ILI tool measurements.

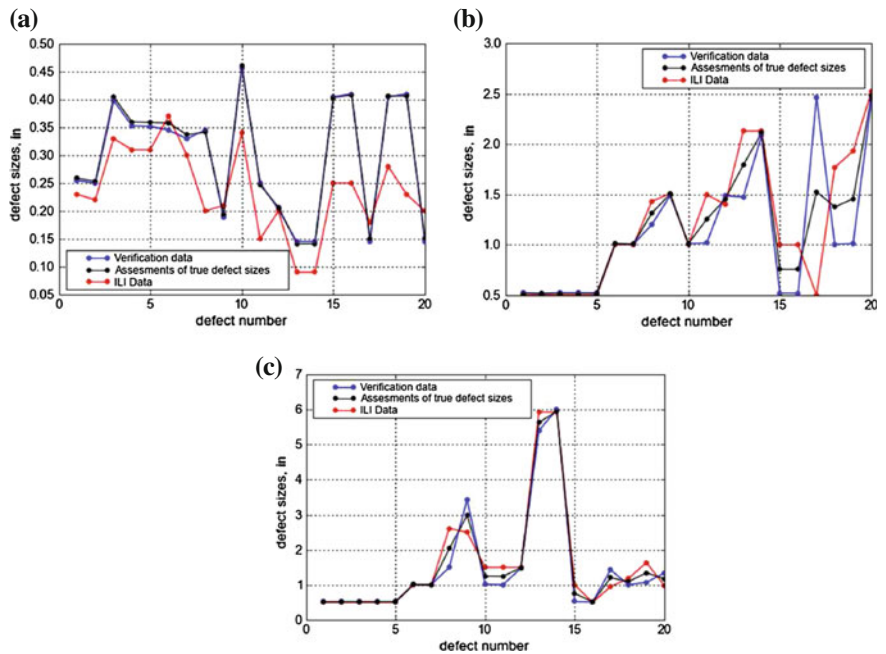


Fig. 4.49 **a** True sizes of defect depths, their assessments, and the ILI readings. **b** True sizes of defect lengths, their assessments, and the ILI readings. **c** True sizes of defect widths, their assessments, and the ILI readings

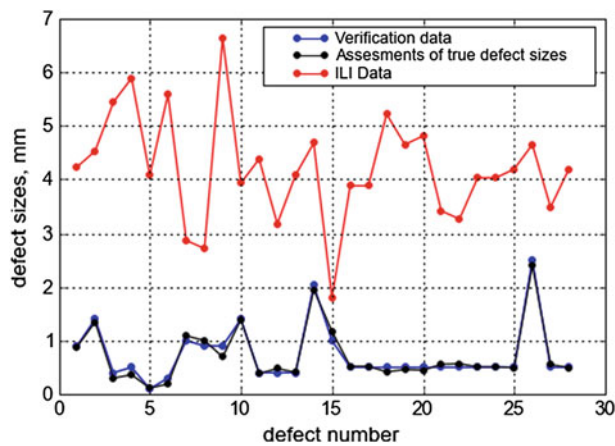


Fig. 4.50 True sizes of defects, their assessments, and the ILI readings

Since the measurement process, in fact, follows the scheme of independent Bernoulli trials (“success” or “failure” of a measurement), the distribution of the number of “successes” will follow the binomial distribution pattern. “Success” is the ILI tool measurement lying inside the ILI tool accuracy confidence interval. “Failure” is when the measurement lies outside the confidence interval of the ILI tool accuracy. If the number of the ILI tool measurements inside the confidence interval is too small, it means that this small number could not be accidental. Hence, the ILI tool produces unacceptable level of distortion of the true values of the measured parameters, which has to be rejected (put out of use).

Assessment of the minimum acceptable number of satisfactory and minimum acceptable number of unsatisfactory measurements, detected in the process of ILI and subsequently verified with the use of a more accurate MI, is performed in accordance with the API 1163 standard [1], which is based on the binomial distribution law.

Binomial probability distribution is the distribution of probabilities of the number of manifestations of a certain event in the course of a series of repeated independent tests (in our case, measurements). Let the number of “successes” M in the test sequence $X_1, X_2, \dots, X_n$ have binomial distribution with n degrees of freedom and “success” probability p , i.e., $M \in \text{Bin}(n, p)$. Then the PDF of random value M is determined by the formula

$$P(M = m) = f(m, n, p) = \frac{n!}{m!(n-m)!} p^m (1-p)^{n-m}. \quad (4.65)$$

With the help of this formula, the probability of occurrence of m successful results in a series of n tests with the “success” probability p is determined.

According to the definition of the binomial PDF the probability of the number of successful tests *not exceeding* k will be

$$P(M \leq N) = \sum_{m=0}^k P(M = m) = \sum_{m=0}^k f(m, n, p). \quad (4.66)$$

This formula is a CDF of the binomial law.

Let n defects be detected during an ILI and some parameter of these defects is measured (e.g., depth). Let p be measurement reliability (“success” probability). Then $q = 1 - p$ is the probability of occurrence of an unsatisfactory measurement (“failure” probability). Denote k as the number of satisfactory (successful) measurements. Then the probability of having at least k satisfactory measurements, when n defects are measured, equals

$$P_k = 1 - \sum_{m=0}^{k-1} f(m, n, p) = \sum_{m=k}^n f(m, n, p). \quad (4.67)$$

For existing high-resolution MFL tools the error of defect depth measurement is $\pm 10\%$ of the pipe wall thickness (*wt*) with 80% certainty, i.e., their ME will stay within the interval $[-10; +10\% \text{ wt}]$ with probability $p = 0.8$.

Thus in order to determine whether the ILI tool measurements lie within the acceptable accuracy range, it is necessary to calculate by formula (4.67) the probability of ILI results demonstrating at least k satisfactory measurements.

Overall tolerance for measurements taking into account the ME of both MI (ILI tool and the VI) is calculated by the formula

$$tol_t = \sqrt{tol_I^2 + tol_V^2},$$

where tol_I is the tolerance for ILI tool measurement (measurement error), % *wt*; and tol_V is the tolerance for the VI measurements, % *wt*.

For a given measurement reliability p the tolerance for the ILI tool measurement is calculated by assessing its ME variance:

$$tol_I = Q_{\frac{1+p}{2}} \sqrt{\hat{\sigma}_{\varepsilon I}^2},$$

where $Q_{\frac{1+p}{2}}$ is the quantile of level $\frac{1+p}{2}$ of standard normal distribution and $\hat{\sigma}_{\varepsilon I}^2$ is the assessment of ILI tool ME variance calculated by formula (4.48).

If the ILI tool ME variance cannot be assessed during the tool run, its value is taken from the technical specifications of the tool.

In order to determine whether the i th measurement lies within the overall tolerance range it is necessary to check whether it meets the condition

$$|V_i - I_i| \leq tol_t, \quad (4.68)$$

where I_i and V_i are the ILI tool and the VI measurements correspondingly, % *wt*.

If condition (4.68) is met, the measurement stays *within the tolerance range*, i.e., is considered satisfactory. Thus it is possible to determine the number k of *satisfactory* measurements.

Further, for the obtained value of k it is necessary to check the condition

$$P_k = \sum_{m=k}^n f(m, n, p) < P_c. \quad (4.69)$$

If it is met, the results of ILI are within the acceptable accuracy range. Otherwise, the ILI results do not meet the ILI tool specifications. In formula (4.69) P_c is the probability (confidence level), necessary for acceptance of the diagnostics results. This value may vary from vendor to vendor. Its determination is a separate problem.

It is assumed that the operating characteristics of the MI are manifested identically in all measurement points, and that the results of measurements are independent. It is recommended that the number of measurements meets the condition

$$n \cdot p > 5.$$

Table 4.22 was built on the basis of formula (4.66), giving the comparison of the total number of measurements n with the minimum number of measurements n_{in} , which should lie within the acceptable accuracy range for the ILI results to meet the technical specifications of the ILI tool. If the number of measurements lying within the overall tolerance range is less than n_{in} , the results of ILI must be rejected. This means that if the difference between the ILI tool measurements and the verification measurements does not exceed 10 % of the pipe wall thickness with probability $p = 80 \%$, the measurement is a “success,” otherwise the ILI tool measurement is considered unsatisfactory.

The maximum admissible number of unsatisfactory measurements of the defect parameters detected as a result of ILI is calculated by the formula

$$n_{ex} = n - n_{in}.$$

Example 4.6.1 Determine for the results of defect depth measurements set in Table 4.23 whether the ILI tool measurement results meet its rated accuracy range.

Number of measurements $n = 16$. ILI tool tolerance range (measurement error) $tol_I = \pm 10 \% wt$; tolerance range of the VI (measurement error) $tol_V = \pm 5 \% wt$; ILI tool measurement certainty $p = 80 \%$, confidence level $P_c = 95 \%$; and overall tolerance for measurements $tol_t = \sqrt{10^2 + 5^2} = 11.18 \% \approx 11 \% wt$.

According to the absolute values of the difference between the ILI tool and the VI measurements (see Table 4.23), $k = 12$ measurements lie within the overall tolerance range.

Using formula (4.65) calculate for each $m = 0, 1, \dots, k$ the value of binomial law PDF. The obtained results are shown in Table 4.24.

Using formula (4.67) calculate the probability of the case when the ILI results have *at least* $k = 12$ *satisfactory measurements*:

$$P_k = \sum_{m=12}^{16} f(m, n, p) \cdot 100 \% = 79.82 \% \approx 80 \%,$$

$P_k = 80 \% < P_c = 95 \%$, consequently the ILI results are within the acceptable accuracy range.

Apply data of Table 4.22 to the analyzed case. According to the table's data for $n = 16, p = 80 \%$ and $P_c = 95 \%$ the number of measurements within tolerance must be at least 10. By the ILI results 12 measurements stayed within the overall tolerance, and hence the ILI results need not be rejected.

Table 4.22 Minimum number of verified measurements which should be inside the tolerance range (for given level of confidence P_c and certainty p)

Number of verified measurements, n	Minimum number n_{in} of measurements inside the tolerance range								
	$p = 80\%$			$p = 85\%$			$p = 90\%$		
	P_c			P_c			P_c		
	85 %	90 %	95 %	85 %	90 %	95 %	85 %	90 %	95 %
5	3	3	2	3	3	3	4	4	3
6	4	4	3	4	4	4	5	4	4
7	5	4	4	5	5	4	6	5	5
8	5	5	4	6	5	5	6	6	6
9	6	6	5	7	6	6	7	7	7
10	7	6	6	7	7	7	8	8	7
11	7	7	7	8	8	7	9	9	8
12	8	8	7	9	9	8	10	9	9
13	9	9	8	10	9	9	11	10	10
14	10	9	9	11	10	10	11	11	11
15	10	10	9	11	11	10	12	12	11
16	11	11	10	12	12	11	13	13	12
17	12	11	11	13	13	12	14	14	13
18	13	12	12	14	13	13	15	15	14
19	13	13	12	15	14	14	16	15	15
20	14	14	13	15	15	14	17	16	16
21	15	14	14	16	16	15	18	17	17
22	16	15	14	17	17	16	18	18	17
23	16	16	15	18	17	17	19	19	18
24	17	17	16	19	18	17	20	20	19
25	18	17	17	19	19	18	21	21	20
26	19	18	17	20	20	19	22	21	21
27	19	19	18	21	21	20	23	22	22
28	20	20	19	22	21	21	24	23	22
29	21	20	20	23	22	21	24	24	23
30	22	21	20	24	23	22	25	25	24
31	23	22	21	24	24	23	26	26	25
32	23	23	22	25	25	24	27	27	26
33	24	23	23	26	25	25	28	27	27
34	25	24	23	27	26	25	29	28	28
35	26	25	24	28	27	26	30	29	28
36	26	26	25	28	28	27	31	30	29
37	27	27	26	29	29	28	31	31	30
38	28	27	26	30	29	29	32	32	31
39	29	28	27	31	30	29	33	33	32

(continued)

Table 4.22 (continued)

Number of verified measurements, n	Minimum number n_{in} of measurements inside the tolerance range								
	$p = 80\%$			$p = 85\%$			$p = 90\%$		
	P_c			P_c			P_c		
	85 %	90 %	95 %	85 %	90 %	95 %	85 %	90 %	95 %
40	29	29	28	32	31	30	34	34	33
41	30	30	29	33	32	31	35	34	34
42	31	30	29	33	33	32	36	35	35
43	32	31	30	34	34	33	37	36	35
44	33	32	31	35	34	33	38	37	36
45	33	33	32	36	35	34	38	38	37
46	34	33	32	37	36	35	39	39	38
47	35	34	33	37	37	36	40	40	39
48	36	35	34	38	38	37	41	41	40
49	36	36	35	39	38	38	42	41	41
50	37	36	35	40	39	38	43	42	41

Table 4.23 Measurements with the ILI tool and the VI and the difference between them, % *wt*

ILI tool measurements d_I	VI measurements d_V	$ d_V - d_I $
7	9	2
8	15	7
23	32	9
16	33	17
34	45	11
29	32	3
11	15	4
36	20	16
34	40	6
57	59	2
30	25	5
54	46	8
27	16	11
28	12	16
11	32	21
20	15	5

Table 4.24 Binomial PDF values

m	$f(m, n, p)$	$f(m, n, p)100\%$
0	0.000000	0.00
1	0.000000	0.00
2	0.000000	0.00
3	0.000000	0.00
4	0.000003	0.00
5	0.000029	0.00
6	0.000215	0.02
7	0.001228	0.12
8	0.005528	0.55
9	0.019654	1.97
10	0.055031	5.50
11	0.120067	12.01
12	0.200111	20.01
13	0.246291	24.63
14	0.211106	21.11
15	0.112590	11.26
16	0.028147	2.81

4.7 Analysis of Reproducibility and Repeatability of Measurements

The knowledge of uncertainties about the results of the defect depth measurements during the ILI of pipeline systems is important for their interpretation. Lack of this information may lead to the risk of wrong interpretation of the measurement results. In order to assess the uncertainty level of measurements, it is necessary to conduct repeatability and reproducibility (R&R) analysis of measurement system (MS). The MS is composed of the diagnostician who conducts the measurement and the measurement instrument. Analysis of R&R for MS is a method which is used to define which part of the general variability is due to the input by the MS (Operator and MI). The overall variability of the measurement process consists of the variability from one defect to another and of the MS per se. The R&R analysis brings clarity on how far the MS can go in producing consistent measurements, i.e., to understand, not only how accurate the MI is, but also to understand, how accurate and precise are the diagnosticians who perform the measurements, using the MI (are they performing with equal accuracy and precision). This permits revealing presence of inconsistencies in the measurements, independent from whether they appear due to instrument malfunctioning, or due to its incorrect usage. It also permits increasing of the level of confidence in obtained results and achieve substantial improvement of the measurement process.

The MS errors can be divided into categories of accuracy and precision.

Accuracy is characterized by the difference between the measurement value and the true value.

Precision is characterized by the variability which arises when a parameter (e.g., the depth) of one defect is measured several times by the same MI. Precision is closeness of independent measurements and depends on the distribution of random errors and is not connected with the true value of the parameter being measured. The measure of precision is usually expressed in terms of scatter and is calculated as the standard deviation of the results of measurements. Low precision has large standard deviation. The necessity for considering precision arises due to the fact that measurements performed on presumably, identical objects, and in presumably identical circumstances do not lead, as a rule, to identical results. This is due to unavoidable random errors, which are inherently present in every measurement process, and because factors which influence the measurements do not yield to full control.

In any MS both categories of measurement errors are present. For instance, MI can measure the defect parameters with small scatter (small variability in measurements), but not accurately. The MI could be accurate (the average value of the measurements is very close to the actual value), but allow large scatter (very large value of the variability of measurements). The MI could be not accurate and at the same time give large scatter. Precision is a measure of variability of the MS which consists of two components:

Repeatability is variability which appears when one and the same Operator (diagnostician) sequentially measures the depth of one and the same defect by one and the same measuring device. Repeatability actually shows capability of a MS to obtain similar results from repetitious measurements (see Fig. 4.51), and is also known as the inherent precision of the MI.

Reproducibility is variability which appears when different Operators measure the depth of one and the same defect by one and the same measuring device. Reproducibility shows the variability of the human factor (HF) in using one particular MI

Fig. 4.51 Probability density functions of the defect depths, which measured repeatedly by two MIs (A and B)

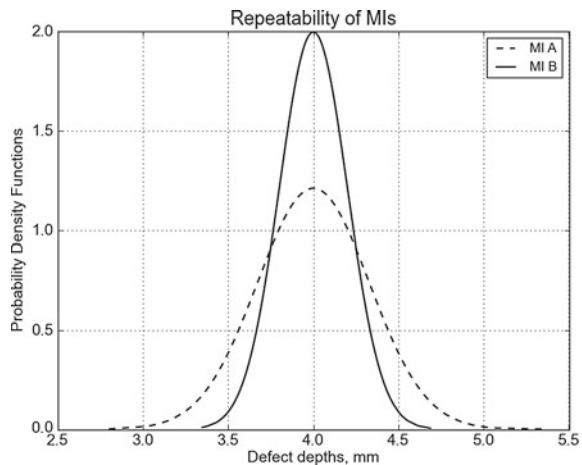
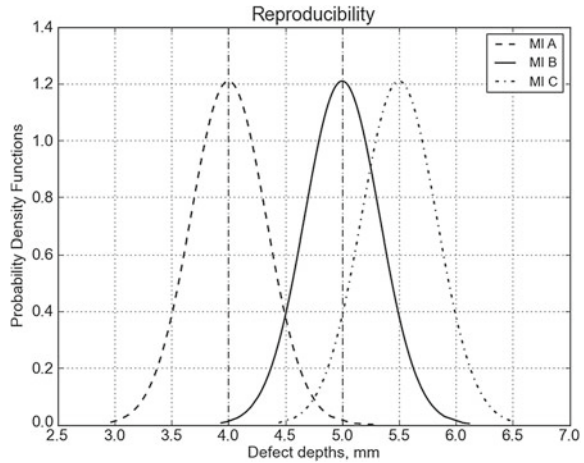


Fig. 4.52 Reproducibility demonstration



(see Fig. 4.52). Mathematically, it is the variability of the average values obtained by several Operators while measuring the same defect.

Consider the probability density functions (PDFs) shown in Fig. 4.51. These PDFs were constructed from measurements of the defect depth, which was measured repeatedly by the same Operator using MI A and MI B. The PDFs demonstrate that MI B is more repeatable than MI A.

Figure 4.52 displays the PDFs of the measurements made by three Operators, which used the same MI. The variability of the individual Operators is the same, but each Operator has a different bias, which means that each Operator inserts his own constant bias into the measurement.

The analysis of R&R for a MS can be performed using the range method, the method of average and range, and the variance analysis (VA) method.

The VA of R&R for a MS is based on the multifactor variance analysis and is the most accurate method. It permits assessing:

- the repeatability, reproducibility of a MS;
- the interaction between the Operator and the defect;
- the input of the MS into the observed measurement scatter; and
- variability of the MS.

4.7.1 Defect Parameters Measured by One Operator and Different Measurement Tools

Consider implementation of the VA in a case when defect depth is measured. Let each of n randomly selected defects be measured once by one Operator using each of m MIs. Consider the measurement model

$$d_{ij} = d_i^* + \alpha_j + e_{ij}, \quad (i = 1, \dots, n; j = 1, \dots, m; m \geq 3), \quad (4.70)$$

where d_{ij} is the measurement of the i th defect depth made by the j th MI; d_i^* is the true (but unknown) value of the i th defect; α_j is the fixed bias of the j th MI from the true value of the defect depth; and e_{ij} is the repeatability error component or random error of the j th MI, when measuring i th defect. The true values of defect depths d_i^* are distributed normally with mean μ and variance $\sigma_{d^*}^2$. The random components e_{ij} are assumed to be uncorrelated with the true values of defect depths, and distributed normally with zero mean and variance $\sigma_{e_j}^2$.

The variance $V(e_{ij}) = \sigma_{e_j}^2$ ($j = 1, \dots, m$) is called *repeatability variance* of the j th MI.

The given measurement model can be interpreted as the two-way ANOVA model with mixed factor. The fixed factor α_j is the effect of the used j -th MI, and the random factor d_i^* is the effect of true values of defect depths. The model of this two-factor ANOVA is presented in Table 4.25, in which SS_T is the total sum of squared deviations of measurements from the grand average $\bar{d} = \frac{1}{nm} \sum_{i=1}^n \sum_{j=1}^m d_{ij}$:

$$SS_T = \sum_{i=1}^n \sum_{j=1}^m (d_{ij} - \bar{d})^2 = \sum_{i=1}^n \sum_{j=1}^m d_{ij}^2 - \frac{1}{nm} \left(\sum_{i=1}^n \sum_{j=1}^m d_{ij} \right)^2;$$

SS_{d^*} is the sum of squared deviations of group averages $\bar{d}_i = \frac{1}{m} \sum_{j=1}^m d_{ij}$ over defects from the grand average $\bar{d}$, which characterizes variance between the groups of measurements over defects:

Table 4.25 ANOVA model with two mixed factors [15]

Source of variation	Model parameters			
	DF	SS	MS	EMS
True values of defect depths	$n - 1$	SS_{d^*}	$MS_{d^*} = \frac{SS_{d^*}}{n-1}$	$\sigma_e^2 + m\sigma_{d^*}^2$
MI's	$m - 1$	SS_{MI}	$MS_{MI} = \frac{SS_{MI}}{m-1}$	$\sigma_e^2 + \frac{n \sum_{j=1}^m \beta_j^2}{m-1}$
Error	$(n - 1)(m - 1)$	SS_e	$MS_e = \frac{SS_e}{(n-1)(m-1)}$	σ_e^2
Total sum	$nm - 1$	SS_T	—	—

Note DF is degrees of freedom; SS is sum of squared deviations; MS is mean of squared deviations; EMS is expected MS

$$SS_{d*} = m \sum_{i=1}^n (\bar{d}_i - \bar{d})^2 = \frac{1}{m} \sum_{i=1}^n \left(\sum_{j=1}^m d_{ij} \right)^2 - \frac{1}{nm} \left(\sum_{i=1}^n \sum_{j=1}^m d_{ij} \right)^2 ;$$

SS_{MI} is the sum of squared deviations of group averages $\bar{d}_j = \frac{1}{n} \sum_{i=1}^n d_{ij}$ over MIs from the grand average $\bar{d}$, which characterizes dispersion between the groups of measurements over MIs:

$$SS_{MI} = n \sum_{j=1}^m (\bar{d}_j - \bar{d})^2 = \frac{1}{n} \sum_{j=1}^m \left(\sum_{i=1}^n d_{ij} \right)^2 - \frac{1}{nm} \left(\sum_{i=1}^n \sum_{j=1}^m d_{ij} \right)^2 ;$$

SS_e is the residual sum of squared deviations of the observed values of group measurements from its group average, which characterizes the dispersion of measurements within the groups of MIs:

$$\begin{aligned} SS_e &= \sum_{i=1}^n (d_{i1} - \bar{d}_1)^2 + \sum_{i=1}^n (d_{i2} - \bar{d}_2)^2 + \cdots + \sum_{i=1}^n (d_{im} - \bar{d}_m)^2 \\ &= SS_T - SS_{d*} - SS_{MI}. \end{aligned}$$

The variation σ_e is the average repeatability variance of all used MIs. Hence, the variance of the measurement errors (MEs) of the j th MI is obtained by the expression [15]

$$\hat{\sigma}_{ej}^2 = \frac{mMS_{ej} - MS_e}{m-2}, \quad m \geq 3, \quad j = 1, \dots, m,$$

where MS_{ej} is the partial (i.e., related to a specific MI) average of the residual sum of squared deviations MS_e of the j th MI, defined in Table 4.26.

The partial sum of squared deviations SS_{ej} of j th MI from Table 4.26 is calculated by the formula

$$SS_{ej} = \sum_{i=1}^n \left(d_{ij} - \left[\frac{\sum_{j=1}^m d_{ij}}{m} + \frac{\sum_{i=1}^n d_{ij}}{n} - \frac{\sum_{i=1}^n \sum_{j=1}^m d_{ij}}{nm} \right] \right)^2 .$$

Table 4.26 ANOVA for calculating partial MS_e of the j th MI

Source of variation	DF	Partial SS_e	Partial MS_e
ME of the j th MI	$n-1$	SS_{ej}	$MS_{ej} = \frac{SS_{ej}}{n-1}$

Note DF is degrees of freedom; SS is squared deviations; MS is mean of squared deviations

The variances σ_{d*}^2 , σ_e^2 can be assessed using the equations of Table 4.25:

$$\begin{aligned}\hat{\sigma}_{d*}^2 &= \frac{MS_{d*} - MS_e}{m}, \\ \hat{\sigma}_e^2 &= MS_e.\end{aligned}$$

4.7.2 Defect Parameters Measured by Several Operators and One and the Same Measurement Tool

When more than one Operator uses a particular MI, the ME of that MS can include not only repeatability of the MI but also a variability component due to the Operator as well. In this case the measurement model has the form

$$d_{ijk} = d_i^* + \alpha + \gamma_j + (d^*\gamma)_{ij} + e_{ijk}, \quad (i = 1, \dots, n; j = 1, \dots, m; k = 1, \dots, r), \quad (4.71)$$

where d_{ijk} is the k th measurement of the i th defect depth made by the j th operator; α is the fixed deviation of MI; d_i^* is the true value of the i th defect (main effect of the defect); γ_j is the random deviation of the defect depth from true value due to the j th Operator, i.e., MEs, introduced by the Operator (main effect of the Operator); $(d^*\gamma)_{ij}$ is the random deviation of the defect depth from its true value due to the interaction of the i th defect and the j th operator (interaction effect of defect and Operator); and e_{ijk} is the repeatability error component (random MEs).

It is assumed that the true values of defect depths d_i^* are distributed normally with mean μ and variance σ_{d*}^2 . Further, the RVs γ_j , $(d^*\gamma)_{ij}$, e_{ijk} do not correlate with each other and with the true values of defect depth, and are distributed normally with zero mean and variances σ_γ^2 , $\sigma_{d*\gamma}^2$, σ_e^2 . Here σ_γ^2 is the variance of MEs due to the Operators; $\sigma_{d*\gamma}^2$ is the variance of MEs due to the interaction of true values of defect depths and Operators; and σ_e^2 is the repeatability variance of the MI (variance of MEs of MI).

According to measurement model (4.71), the mean and variance of the measurements d_{ijk} are

$$\begin{aligned}M[d_{ijk}] &= \mu_{d*} + \alpha, \\ D[d_{ijk}] &= \sigma_{d*}^2 + \sigma_\gamma^2 + \sigma_{d*\gamma}^2 + \sigma_e^2.\end{aligned}$$

The ANOVA random factors model for estimating these variances is presented in Table 4.27, where

$$SS_T = \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^r d_{ijk}^2 - \frac{1}{nmr} \left(\sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^r d_{ijk} \right)^2,$$

Table 4.27 ANOVA random effect model [15]

Source of variation	Model parameters			
	<i>DF</i>	<i>SS</i>	<i>MS</i>	<i>EMS</i>
True values of defect depths	$n - 1$	SS_{d*}	$MS_{d*} = \frac{SS_{d*}}{n-1}$	$\sigma_e^2 + r\sigma_{d*\gamma}^2 + mr\sigma_{d*}^2$
Operators	$m - 1$	SS_O	$MS_O = \frac{SS_O}{m-1}$	$\sigma_e^2 + r\sigma_{d*\gamma}^2 + nr\sigma_\gamma^2$
Interaction of defect depths and operators	$(n - 1)(m - 1)$	$SS_{d* \times O}$	$MS_{d* \times O} = \frac{SS_{d* \times O}}{(n-1)(m-1)}$	$\sigma_e^2 + r\sigma_{d*\gamma}^2$
MI	$nm(r - 1)$	SS_e	$MS_e = \frac{SS_e}{nm(r-1)}$	σ_e^2
Total sum	$nmr - 1$	SS_T	—	—

Note *DF* is degrees of freedom; *SS* is sum of squared deviations; *MS* is mean of squared deviations; *EMS* is expected *MS*

$$\begin{aligned}
 SS_{d*} &= \frac{1}{mr} \sum_{i=1}^n \left(\sum_{j=1}^m \sum_{k=1}^r d_{ijk} \right)^2 - \frac{1}{nmr} \left(\sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^r d_{ijk} \right)^2, \\
 SS_O &= \frac{1}{nr} \sum_{j=1}^m \left(\sum_{i=1}^n \sum_{k=1}^r d_{ijk} \right)^2 - \frac{1}{nmr} \left(\sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^r d_{ijk} \right)^2, \\
 SS_{d* \times O} &= \frac{1}{r} \sum_{i=1}^n \sum_{j=1}^m \left(\sum_{k=1}^r d_{ijk} \right)^2 - \frac{1}{nmr} \left(\sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^r d_{ijk} \right)^2 - SS_{d*} - SS_O, \\
 SS_e &= SS_T - SS_{d*} - SS_O - SS_{d* \times O}.
 \end{aligned}$$

The *reproducibility variance* of MS, which characterizes variability of MS resulting from the use of the MI by different Operators, can be calculated by the formula

$$\sigma_{reprod}^2 = \sigma_\gamma^2 + \sigma_{d*\gamma}^2.$$

The *repeatability and reproducibility variance* of the MS (precision of MS), also known as variance of MEs of MS, is calculated by the formula

$$\sigma_{R\&R}^2 = \sigma_{reprod}^2 + \sigma_e^2.$$

If repeatability is large as compared to reproducibility, the MI needs maintenance. If reproducibility is large compared to repeatability, the Operators need to be better trained.

Using the equations of Table 4.27, the variances σ_{d*}^2 , σ_γ^2 , $\sigma_{d*\gamma}^2$, σ_e^2 can be assessed by the formula

$$\begin{aligned}
\hat{\sigma}_{d*}^2 &= \frac{MS_{d*} - MS_{d* \times O}}{mr}, \\
\hat{\sigma}_{\gamma}^2 &= \frac{MS_O - MS_{d* \times O}}{nr}, \\
\hat{\sigma}_{d*\gamma}^2 &= \frac{MS_{d* \times O} - MS_e}{r}, \\
\hat{\sigma}_e^2 &= MS_e.
\end{aligned} \tag{4.72}$$

Then the variances σ_{reprod}^2 and $\sigma_{R\&R}^2$ are equal to

$$\begin{aligned}
\hat{\sigma}_{reprod}^2 &= \frac{n-1}{nr} MS_{d* \times O} + \frac{MS_O}{nr} - \frac{MS_e}{r}, \\
\hat{\sigma}_{R\&R}^2 &= \frac{n-1}{nr} MS_{d* \times O} + \frac{MS_O}{nr} + \frac{(r-1) MS_e}{r}.
\end{aligned} \tag{4.73}$$

The *total variance* of the measurements of defect depths, including the variability due to the different defect depths, variability due to the different Operators, and repeatability of MI, is expressed by the equation

$$\hat{\sigma}_d^2 = \hat{\sigma}_{d*}^2 + \hat{\sigma}_{R\&R}^2 = \hat{\sigma}_{d*}^2 + \sigma_{reprod}^2 + \sigma_e^2.$$

4.7.3 The Problem of Negative Values of Variances of Sources of Measurement Scatter and Its Possible Solution

The ANOVA estimates (4.72) and (4.73) are clearly unbiased, but they may take negative values. In this case the maximum-likelihood estimation (MLE) can be used. For model from Table 4.27, we define

$$\begin{aligned}
\theta_0 &= \sigma_e^2 + r\sigma_{d*\gamma}^2, \\
\theta_1 &= \sigma_e^2 + r\sigma_{d*\gamma}^2 + nr\sigma_{\gamma}^2, \\
\theta_2 &= \sigma_e^2 + r\sigma_{d*\gamma}^2 + mr\sigma_{d*}^2.
\end{aligned}$$

According to [30], the MLE equations for estimating parameters θ_i ($i = 1, 2, 3$) are

$$\begin{cases} \theta_0 = MS_{d* \times O} + \frac{\theta_0^2}{(n-1)(m-1)(\theta_1 + \theta_2 - \theta_0)}, \\ \theta_1 = MS_O - \frac{\theta_1^2}{(m-1)(\theta_1 + \theta_2 - \theta_0)}, \\ \theta_2 = MS_{d*} - \frac{\theta_2^2}{(n-1)(\theta_1 + \theta_2 - \theta_0)}. \end{cases}$$

This system of equations is nonlinear and can be solved numerically for the unknown parameters $\theta_0, \theta_1, \theta_2$. Then the MLE of the variances of measurement variability sources is defined by the formulas

$$\begin{aligned}\hat{\sigma}_{d*\gamma}^2 &= \frac{\theta_0 - MS_e}{r}, \\ \hat{\sigma}_\gamma^2 &= \frac{\theta_1 - \theta_0}{nr}, \\ \hat{\sigma}_{d*}^2 &= \frac{\theta_2 - \theta_0}{mr}.\end{aligned}\tag{4.74}$$

MLEs (4.74) are, by definition, nonnegative. However, the use of the ML approach requires the additional assumption of normality.

On the other hand, ANOVA-type estimators, based on expected values of MS (EMS), do not require any such assumption and are unbiased. Unfortunately, they can be negative. It has been shown [31] (see also [32]), that even under reasonably mild conditions, for variance component estimation, unbiasedness, and nonnegativity are incompatible and, hence, cannot be achieved simultaneously. A way to avoid this difficulty is given in [33, 34].

Another approach for obtaining nonnegative values of ANOVA variance estimates is to solve the matrix equation $m = A\sigma + \varepsilon$ of the model of the inequality restricted least square (or weighted least square), subject to the condition $\sigma \geq 0$ [35], where ε is the “random model error,” vector $m = (MS_{d*} \ MS_O \ MS_{d* \times O} \ MS_e)$; vector $\sigma = (\sigma_{d*}^2 \ \sigma_\gamma^2 \ \sigma_{d*\gamma}^2 \ \sigma_e^2)$ and matrix A for ANOVA model from Table 4.27 is

$$A = \begin{pmatrix} mr & 0 & r & 1 \\ 0 & nr & r & 1 \\ 0 & 0 & r & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

4.7.4 Cases of Practical Implementation of the Methodology

Consider the described above methodology for the case of Monte Carlo generated measurements of pipeline defect depths.

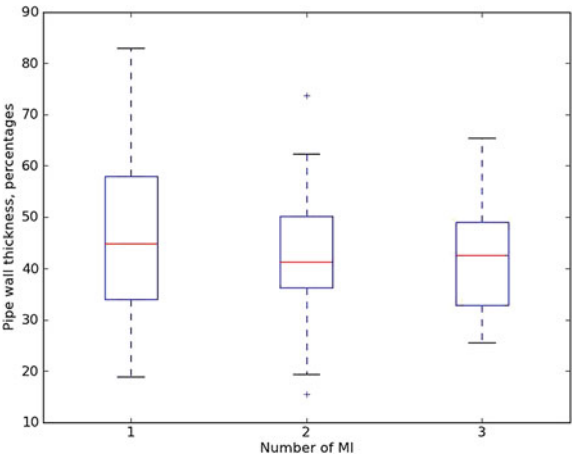
Case #1 (model (4.70) was used). Assume that the pipeline defect depth measurements during the verification of the ILI data are performed by one Operator using three MIs ($m = 3$). For this case 50 measurements ($n = 50$) of defect depth were generated using the model (4.70) with parameters as shown in Table 4.28. The fixed biases of the MIs from the true values of the defect depth are $\alpha_1 = 1.5$, $\alpha_2 = 1.0$, $\alpha_3 = 0.5$ (% wt), wt is the pipe wall thickness.

In Fig. 4.53 the simulated measurements made by the three MIs are given. Figure 4.53 is the box plot, also known as the box-and-whiskers diagram. The box plot is a convenient way of graphically depicting groups of numerical data through

Table 4.28 Initial data for modeling defect depths (normal distribution)

Source of variation		Mean, % wt	SD, % wt
True values of defect depths		40	10
MEs (repeatability component)	MI #1	0	10
	MI #2	0	8
	MI #3	0	5

Fig. 4.53 Box-and-whiskers diagram of generated measurements of three MIs



their five-number summaries: the smallest observation (sample minimum), lower quartile Q_1 , median Q_2 , upper quartile Q_3 , and largest observation (sample maximum). Box-and-whisker plots are uniform in their use of the box: the bottom and top of the box are always the 25-th (Q_1) and 75-th (Q_3) percentile (the lower and upper quartiles, respectively), the line inside the box is always the 50-th (Q_2) percentile (the median) and the ends of the whiskers are the sample minimum and maximum. By the symbol “+” in Fig. 4.53 outliers are indicated.

The ANOVA table for these measurements is given in Table 4.29, according to which the average repeatability SD of all used MIs is $\hat{\sigma}_e = \sqrt{66.46} = 8.15\%$ wt. As the true value of this SD is 7.66 % wt, magnitude of error is 0.49 % wt.

The assessments of partial MS_{e_j} and SD of the MEs of the j th MI $\hat{s}_{e_j}$ are presented in Table 4.30, according to which the assessments of SDs of MEs of MIs $\hat{s}_{e_j}$ almost coincide with their true value s_{e_j} . Assessment of the SD of true values of defect depths is 9.05 % wt, its true value is 10 % wt, hence the magnitude of error is 0.95 % wt.

Case #2 (model (4.71) was used). Assume that the defect depth measurements are performed by three Operators ($m = 3$) using one and the same MI. Each defect is measured by each Operator three times ($k = 3$). For the case in consideration 50 measurements ($n = 50$) of defect depth were generated according to the model (4.71), with parameters as shown in Table 4.31, and with the fixed bias of the MI equal to $\alpha = 0.5\%$ wt.

Table 4.29 Assessments of ANOVA parameters

Source of variation	DF	SS	MS
True values of defect depths	49	15286.80	311.98
MI	2	267.98	133.99
Errors (MEs of MI)	98	6512.96	66.46
Total sum	149	22067.73	–

Note DF is degrees of freedom; SS is sum of squared deviations; MS is mean of squared deviations

Table 4.30 Assessments of partial average of squared deviations, SD of MEs of MI, and their true values

Measurement errors	DF	SS_{ej}	MS_{ej}	$\hat{s}_{ej}, \% wt$	$s_{ej}, \% wt$	$\hat{s}_{ej} - s_{ej}, \% wt$
MEs of MI #1	49	2717.93	55.47	9.99	10.00	0.01
MEs of MI #2	49	2344.82	47.85	8.78	8.00	–0.78
MEs of MI #3	49	1450.20	29.59	4.73	5.00	0.27

Note DF is degrees of freedom; SS is sum of squared deviations; MS is mean of squared deviations

Table 4.31 Initial data for modeling defect depths (normal distribution)

Source of variation	Mean, % wt	SD, % wt
True values of defect depths	40.0	10.0
MEs of MI	0.0	5.0
MEs of Operator #1	0.0	0.3
MEs of Operator #2	0.0	0.2
MEs of Operator #3	0.0	0.1
MEs due to the interaction of defects and Operator #1	0.0	0.5
MEs due to the interaction of defects and Operator #2	0.0	0.3
MEs due to the interaction of defects and Operator #3	0.0	0.2

Table 4.32 Assessments of ANOVA parameters

Source of variation	<i>DF</i>	<i>SS</i>	<i>MS</i>
True values of defect depths	49	37014.25	755.39
Errors of Operators	2	52.24	26.12
Interaction of Operators and defects	98	2344.67	23.93
MEs of MI	300	7090.57	23.64
Total sum	449	46501.73	–

Note *DF* is degrees of freedom; *SS* is sum of squared deviations; *MS* is mean of squared deviations

Table 4.33 Assessments of SD of sources of variation and their true values

SD of source of variation	Assessments of SDs using			True value, % <i>wt</i>
	EMS of ANOVA	MLE	NNLS	
SD of true values of defect depths, % <i>wt</i>	9.02	8.92	9.02	10.00
Average SD of Operators errors, % <i>wt</i>	0.12	0.11	0.12	0.20
Average SD of interaction of Operators and defects, % <i>wt</i>	0.31	0.32	0.31	0.33
SD of MEs of MI (repeatability SD of MS), % <i>wt</i>	4.86	4.86	4.86	5.00
Reproducibility SD of MS, % <i>wt</i>	<i>N/A</i>	0.33	0.33	$0.20 + 0.33 = 0.53$
R&R SD of MS, % <i>wt</i>	4.42	4.87	4.87	$0.53 + 5.00 = 5.53$

Note *N/A*—in this case the variance of reproducibility is negative (-7.70)

The ANOVA table for these measurements is represented in Table 4.32, according to which the repeatability SD of used MI is $\hat{\sigma}_e = \sqrt{23.64} = 4.86$ % *wt*. As the true value of this SD is 5.00 % *wt*, magnitude of error is 0.14 % *wt*.

SD of RVs σ_{d*} , σ_γ , $\sigma_{d*\gamma}$, σ_{reprod} , $\sigma_{R\&R}$ are estimated on the basis of expected values of MS (EMS) of ANOVA and using the MLE and nonnegative least squares (NNLS) methods. The obtained results are presented in Table 4.33. The difference between the true values of SD of sources of variation and their estimates are presented in Table 4.34, according to which the best assessments were obtained using the NNLS method [35].

Table 4.34 Difference between the true values of SD of sources of variation and their estimates

SD of source of variation	Difference between the true values of SD of sources of variation and their estimates using		
	EMS of ANOVA	MLE	NNLS
SD of true values of defect depths, % <i>wt</i>	0.98	1.08	0.98
Average SD of Operators Errors, % <i>wt</i>	0.08	0.09	0.08
Average SD of interaction of Operators and defects, % <i>wt</i>	0.02	0.01	0.02
SD of MEs of MI (repeatability SD of MS), % <i>wt</i>	0.14	0.14	0.14
Reproducibility SD of MS, % <i>wt</i>	<i>N/A</i>	0.20	0.20
R&R SD of MS, % <i>wt</i>	1.11	0.66	0.66

4.8 Methods of Updating the True Number of Defects in a Pipeline Using ILI Results

From the point of view of ensuring the maximum certainty and consistency of the ILI quality assessment metrics, the most important is the metric characterizing the capability of the ILI technique to detect defects, since it affects, first of all, the completeness of the input events group (a *set of correctly detected defects*), on the basis of which all further metrics will be determined.

This section presents a description of the three practical methods for correcting the assessment of the true number of defects in a pipeline after conducting the ILI and the subsequent verification of measurement results with a second, independent verification tool:

1. direct statistical method;
2. a method based on Bayesian procedure taking into account the results of only one inspection (more accurate method); and
3. a generalized algorithm of Bayesian reassessment taking into account several independent inspections.

This section presents in an analytical form the prior and posterior distributions of the base parameter (random value and vector with coordinates) characterizing the ratio of the number of true defects to the number of defects detected in the process of ILI. The problem is solved of predicting the most probable number of true defects in each interval of the defect depth measurement by the inspection results. For the problem solution it is assumed that the defect depth is described in fractions

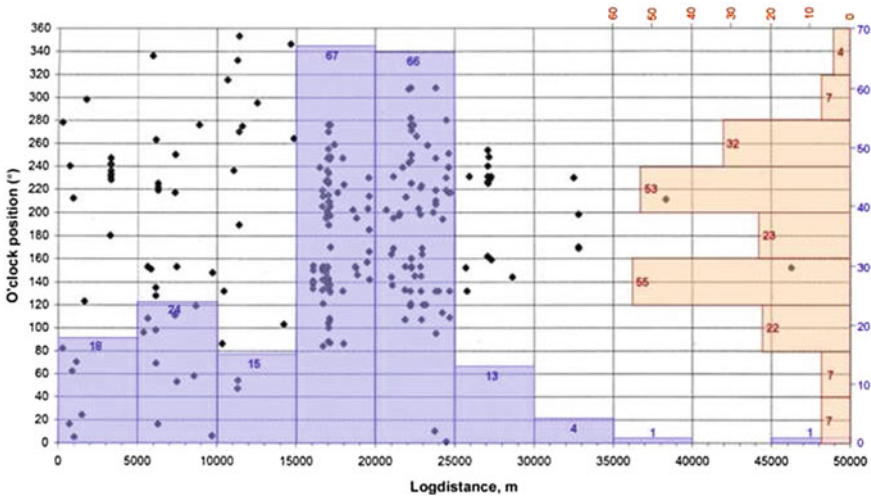


Fig. 4.55 O'clock position of metal loss defects

The preliminary nonparametric analysis permits further in-depth statistical analysis of the ILI data, in combination with prior information about the ILI tool, the pipeline being inspected, and the results of the latest ILI of the pipeline.

During the identification process each and every defect signature (no matter what size) is analyzed, and a decision is made on whether the signature belongs to a real or to a phantom defect.

As was noted in Sect. 4.3, the cornerstone of all probability calculations is the principle of the full group of events, which covers all possible outcomes of any ILI.

In Fig. 4.57, a geometrical interpretation of a typical result of any ILI is shown. The detection event is defined for arbitrary size discrete defects (depth d , length l , width w , area size s on the pipe wall surface, or volume size v in the overall pipe wall volume). The black spots are the discovered existing defects/anomalies (*true detection or true positive*), the light spots are the existing defects that were not discovered by the ILI tool (*false non-detection or false negative*), and the dashed-line spots are the nonexistent defects that were falsely diagnosed as existent (*false detection, or false positive*). The rest of the surface of the pipe comprised healthy pipe wall locations that were correctly diagnosed by the ILI tool as not having any defects (*true non-detection, or true negative*). The above four outcomes form a FGE. This means that in any ILI no other type of events is possible.

In Sect. 4.3 to define probabilities of the above four cases, the following symbols were introduced:

- P_{TD} —probability of true detection (detecting an existing feature by an ILI tool);
- P_{TND} —probability of true non-detection (non-detecting of a nonexistent feature by an ILI tool);

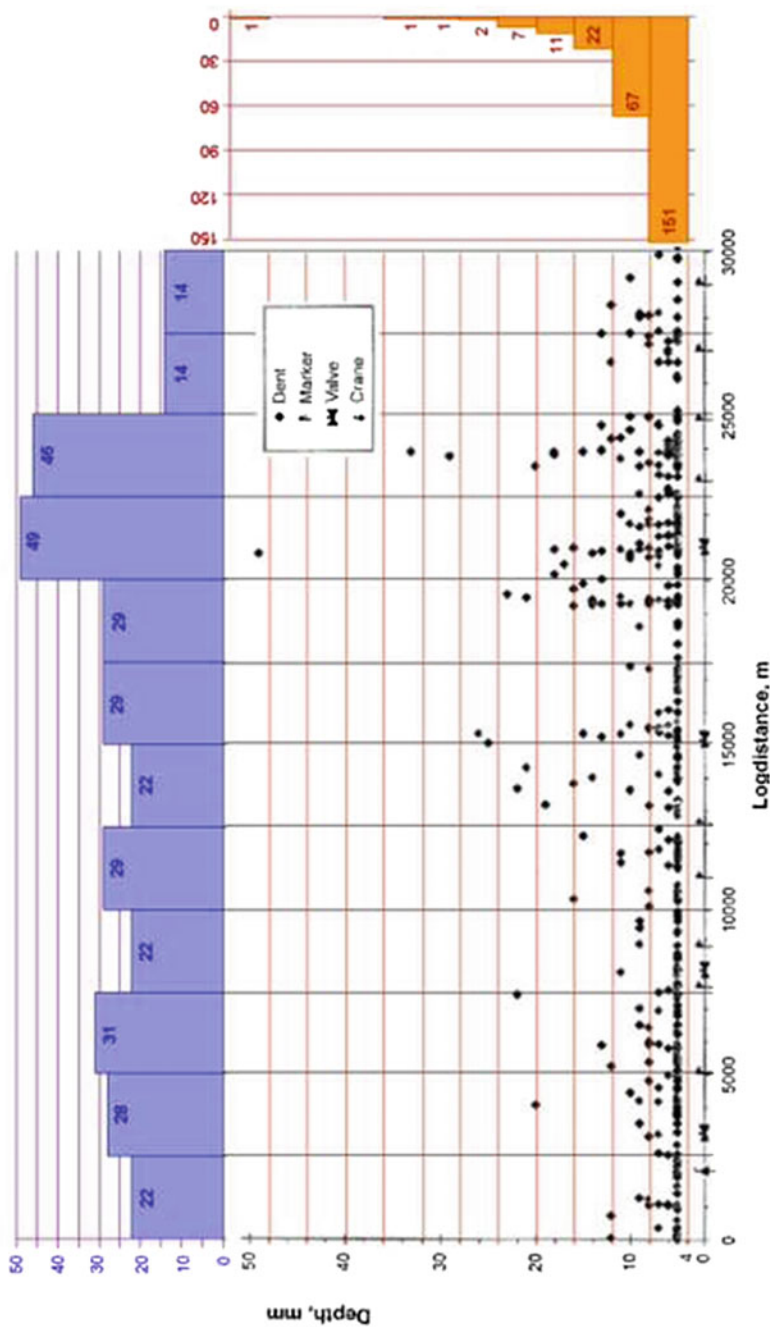


Fig. 4.56 Distribution of dents along the pipeline

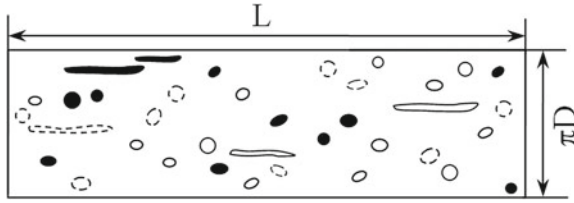


Fig. 4.57 Geometrical interpretation of an in-line inspection when detecting general types of defects (general corrosion, pitting, and longitudinal cracks)

- P_{FND} —probability of false non-detection (probability that an existing feature is not being detected by an ILI tool); and
- P_{FD} —probability of false detection (probability of a nonexisting feature being reported as a feature by an ILI tool).

The probability of each of the above events is a function of the defect size (Fig. 4.58) and they change with growth of the defect size x . As the probability of true detection (P_{TD} , Fig. 4.58a) grows with the defect size growth, the probability of false non-detection (P_{FND} , Fig. 4.58d) diminishes. In the same way, as the probability of false detection (P_{FD} , Fig. 4.58b) diminishes with defect size growth, the probability of true non-detection (P_{TND} , Fig. 4.58c) increases.

The sum of probabilities of a FGE, by definition, is always a unity. $P_{TND}(x)$ does not depend on defect size x . The argument x simply shows that P_{TND} associates with defect size x through Eq. (4.17). The fact that the sum of these four probabilities for every defect size x is unity is shown graphically in Fig. 4.58. The four bold ordinates

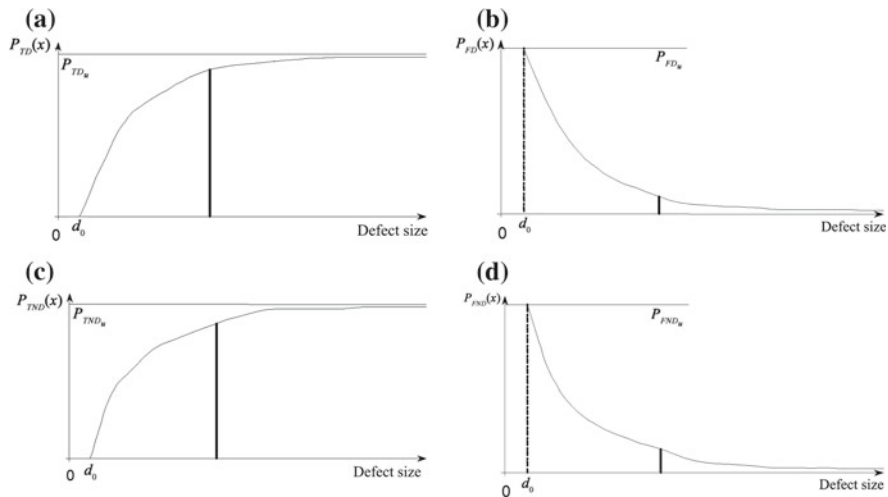


Fig. 4.58 Four possible (full group of) outcomes of an in-line inspection and their probabilities

(that represent the corresponding four probabilities) above the randomly selected defect size x (see Fig. 4.58a–d) comprise a unity.

Note that these four curves do not have the properties of a PDF, and their respective integrals do not amount to unity. They give the probability that the ILI tool is able to detect a defect larger than d_0 [36], for instance,

$$P_{TD}(d) = P(d > d_0),$$

where d is the defect depth and d_0 is the threshold defect size, below which the ILI tool is not capable of detecting defects. With defect size growing, the probability of its detection increases (see Fig. 4.58a).

The probability of true detection P_{TD} cannot exceed the value

$$P_{TD}(x) \leq \frac{S_d}{S_p} = P_{TD_u},$$

where S_d is the sum of areas of all existing defects and S_p is the full area of inspected surface of pipeline segment.

Conversely, the probability of true non-detection cannot exceed the value

$$P_{TND}(x) \leq \frac{S_{nd}}{S_p} = P_{TND_u},$$

where S_{nd} is the sum of areas of all healthy locations. In both cases, u stands for ultimate (see Fig. 4.58).

Using formula (4.17), the probability of false non-detection (missed calls) will be

$$P_{FND}(x) = 1 - P_{TND}(x) - P_{FD}(x) - P_{TD}(x),$$

and the probability of false indication (detection)

$$P_{FD}(x) = 1 - P_{TND}(x) - P_{FND}(x) - P_{TD}(x).$$

Currently, it could be observed that, in the ILI practice, mostly two components of the full group of events are utilized. It is assumed that the two pairs of events (true non-detection P_{TND} , false non-detection P_{FND}) and (true detection P_{TD} , false detection P_{FD}) are equivalent and therefore, only one of the pairs is necessary and sufficient to exhaustively assess the quality of ILI. Further, it is assumed that an inspection result can be entirely characterized by only the (P_{TD} and P_{FD}) set of events [37]. Within the ICON project [38] this approach is considered to be consistent with inspection calibration/inter-calibration aspects. But finding a nonexistent defect leads to a false scenario in the failure tree (changes the pipeline system reliability analysis), to useless repairs and, consequently, to substantial cost overruns. In harsh conditions false detections increase dramatically, and even large nonexistent cracks

can be detected [36]. A false non-detection is an even more dangerous event, because it may lead to pipeline leak or rupture.

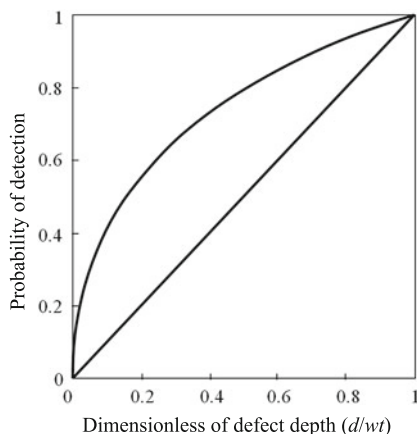
The main psychological cause of not reporting on missed defects is that if reported, the pipeline Operator may require a rerun. Some of the Providers are explaining/defending the current status quo by stating that (1) full-size verification digs are expense-wise prohibitive; (2) the final results will not influence the current common sense approach; and (3) the benefit would be negligible. These statements have yet to be proven experimentally. The ILI results could be allowed to be biased only to the safe side. It is necessary to improve the technology of verification digs. One possible way is to conduct automated total scanning of all the exposed pipeline in the verification digs in order to assess false negatives and false positives. This will reveal the actual input of false negatives/positives in the FGE. These efforts allow establishing a benchmark for assessing ILI quality.

In order to optimize inspection/maintenance/repair costs, inspection tools should be ranked in terms of cost and performance.

Currently, quantitative assessment of NDT tools is made by plotting the so-called Relative (or Receiver) Operating Characteristic curves (ROC) which plot probability of true detection P_{TD} and the probability of false detection P_{FD} and are used in analyzing diagnosticians' performance. This curve, basically the ratio of P_{TD}/P_{FD} , has the form of a convex function of defect size (Fig. 4.59).

The ROC quantifies the relationship between detection performance and decision criteria. ROC curves usually are used to examine a team's (or procedure's) inherent probability of detection (IPOD). IPOD is the performance that would be achieved if the optimum decision criteria were being employed. In actual field inspections a procedure with excellent IPOD may still yield poor results because a poor decision criterion is being employed or the decision criterion (DC) cannot be controlled. The DC may also vary from inspection to inspection and/or team (person) to team (person). Therefore, the actual laboratory DC that is used for extrapolation to field

Fig. 4.59 A typical ROC curve



experiments is very important. The problem of quantitative assessing and constructing the ROC is considered in detail in Sect. 4.9.

Missed defect location algorithm. The following initial data is needed to implement the defect location algorithm:

1. Histogram of the number of defects revealed by the latest ILI, constructed on each homogeneous (as related to the internal properties of the pipeline and its environment) pipeline segment;
2. Results of all dig verifications made by a second, more precise tool;
3. Prior ILI data (if available); and
4. P_{TD} , P_{FD} , P_{TND} , and P_{FND} curves for the ILI tool.

After the ILI of a pipeline of length L , it is divided into homogeneous segments, as related to the source of defect appearance and growth. Each of the segments is then assessed separately. The verification digs are performed in places where ILI indicated the presence of dangerous defects. The verification digs are performed in a manner that allows finding:

- the total number of defects present in the verification dig;
- the number of actual defects missed by the ILI tool; and
- the number of defects falsely detected by the ILI tool.

The verification dig also provides sizing of the defects by a tool, more precise than the ILI tool.

Further, a histogram is constructed for the discrepancies ξ_i , $i = 1, 2, \dots, n$ between the two sets of above measurements (ILI and VI), where n is the total number of discovered defects, and the hypothesis that the ξ_i have a Gaussian distribution is tested.

The actual number of defects and the PDF of their actual sizes on each of the segments that does not contain verification digs of the inspected pipeline is assessed using the above data. The PDF of the actual size of defects that remain after repair is assessed as a censored PDF.

Example application of algorithm. An oil pipeline 900 mm in diameter with a 9 mm wall thickness was inspected by an HR MFL tool. Consider the results of hybrid ILI (actual and computer simulated). ILI results of a one-kilometer segment are given in Table 4.35 (columns 1, 2).

Preliminary statistical analysis of ILI results shows that the segment contains 1001 flat-bottom corrosion (loss-of-metal type) defects, which are uniformly distributed along the length of the pipe segment. The defect depth is distributed according to lognormal distribution function with mathematical expectation m equal to 3.0 mm and variance $\sigma^2 = 0.25 \text{ mm}^2$. One mill pipe length (12 m) contained an above average number of defects, including dangerous ones. This segment was chosen for a verification dig. Results of this dig are presented in Table 4.36 (columns 1–6). The probabilities $P_{FD}(x)$ and $P_{FND}(x)$ of the tool based on previously obtained laboratory and field verification dig data are shown in columns 7 and 8 of Table 4.36.

Using the curves P_{FND} , P_{FD} of ILI tool performance metrics, the numbers of falsely detected defects and undetected defects in the whole inspected segment are

Table 4.35 Results of ILI of a pipeline segment

Defect depth interval, mm	Number of defects detected by ILI		Number of defects (assessments)			
			True	Correctly detected by ILI	Falsely non-detected by ILI	Falsely detected by ILI
1	2		3	4	5	6
1–2	564	500*	538	265	273	235
2–3	152	132*	113	73	40	59
3–4	81	70*	63	57	6	13
4–5	195	170*	170	163	7	7
5–6	8	7*	7	7	0	0
6–7	0	0	0	0	0	0
7–8	0	0	0	0	0	0
8–9	0	0	0	0	0	0
	$\Sigma = 1001$	879	891	565	326	314

*Without accounting for the length of the verification dig

Table 4.36 Verification dig results

Defect depth interval, mm	Number of defects detected by ILI	Number of defects in the verification dig					
		True	Correctly detected by ILI	Falsely undetected by ILI	Falsely detected by ILI	P_{FND}	P_{FD}
1	2	3	4	5	6	7	8
0–1	–	–	–	–	–	–	–
1–2	64	69	34	35	30	2×10^{-4}	2×10^{-4}
2–3	20	17	11	6	9	2×10^{-4}	2×10^{-4}
3–4	11	10	9	1	2	4×10^{-5}	9×10^{-5}
4–5	25	25	24	1	1	2×10^{-5}	2×10^{-5}
5–6	1	1	1	0	0	0	0
6–7	0	0	0	0	0	0	0
7–8	0	0	0	0	0	0	0
8–9	0	0	0	0	0	0	0
	$\Sigma = 122$	122	79	43	42	–	–

calculated (columns 5 and 6 of Table 4.35). Columns 3 and 4 of Table 4.35 give assessments of the updated true number of defects and defects correctly indicated by ILI.

According to Table 4.36, with defect depth growth both probability of false detection and of false non-detection decrease. In order to make a decision about further actions (leave as is/monitor/make another verification dig, etc.), some ultimate thresh-

old probability P_{FD}^l (P_{FND}^l) of false detection should be assigned. The deeper is the defect, the smaller should be this probability. The ultimate threshold probability for every defect size depth should reflect the current best practice and the currently reachable minimal (ultimate) probability of false non-detection and of false detection when using best ILI tools. These probabilities have to be adopted as threshold values by the pipeline transportation industry and by the regulation agencies on a consensus basis. For instance, $P_{FD,FND}^l$ for defect size (depth) of 80 % of pipe wall thickness (in our case, 7.2 mm) could be assigned as 10^{-6} , for defect size depth 5–6 mm as 10^{-5} . ILI tools that achieve these (and lower) probability values should be considered as “perfect” and tools with worse results should be considered additionally.

Pipeline companies/operators must carefully weigh the cost and value of additional verification digs (finding extra defects, missed out by the ILI) against the risk of leaving the pipeline “as is” with potential defect intact. By conducting systemic verification digs according to the above scheme it is possible to collect the necessary data for each ILI tool, and assess the ILI quality when using the tool. By conducting sequential verification digs it is possible to asymptotically update the number of false and undetected defects in a given pipeline segment. This research is in progress.

4.8.2 Bayesian Upgrade of the Number of Defects in a Pipeline Using Results of One Inspection

One of the most efficient methods of correction of probabilistic assessments of the physical parameters are the methods developed on the basis of a Bayesian approach. They are widely used in various spheres of science and technology [39–44]. In the following paragraphs the application of the general Bayesian procedure to the assessment of the true number of defects of a certain type on an operating pipeline is demonstrated. The Bayesian procedure may be briefly described as follows.

In order to obtain new information a decision maker considers a degree of confidence in the statistical results of the ILI—the competing PDF. In the process of obtaining of new data in the form of experimental or observed data the Bayes theorem allows correcting the existing probabilities and reviewing the confidence level of the employed model taking into account the received information. The method consists in summing up the already existing (prior to the experimental data analysis) knowledge about the unknown base parameter, which determines the selected statistical model with information obtained in the course of experiment. In this case the use of PDF is an evidence of uncertainty of the decision maker’s knowledge about the importance of the parameter, as well as about whether this uncertainty may be represented with the help of a suitable PDF.

On the basis of the Bayes theorem, an algorithm was developed for updating the number of true defects existing in the operating pipeline that allows:

- obtaining a prior distribution for parameter π_j (characterizing in the j th depth interval the ratio of the number of true defects to the number of the detected defects), which may be used for solving the problem of assessing pipeline reliability;
- assessing the most probable number of true defects in each depth interval for the expected sample of the defects detected during pipeline inspection; and
- building a 3D graph of the most probable distribution of the true defects by intervals.

On a broader scale the described approach permits assessing the actual mass of a discrete probability particle (see below), and ultimately, the probability of failure of each inspected pipeline as a system.

The described approach may be used for assessing ILI quality and/or the VI and/or the ILI tool, given the availability of only one set of measurements, as well as for the solution of the relevant problems of reliability of operating pipelines and the correction of reliability assessments in the course of their maintenance.

The granular nature of probability when assessing POF for a specific pipeline inspected by a specific ILI tool. When assessing the reliability of an operating pipeline with defects as a system the classical approach, imported from the structural reliability theory of sequentially connected elements—does not work (see Sect. 2.6). The correct solution to this problem is to describe the stochastic evolution of the whole set of defects, which are present in the pipeline, as a unity. This was achieved using Markov models of defect growth and Markov models of degradation of the remaining strength of the pipeline considered as a system (see Chap. 7). Rightfully considering these defects as a full group of events, it can be deduced that the probability has a granular nature as it can change only in non-dividable increments (granules), the increment being equal to $1/n$, where n is the total number of those defects present in the pipeline, which can in a given time frame actually contribute to pipeline failure. Hence, accounting for the phantom, nonexistent defects create a bias of the POF, as they dilute the probability mass of each probabilistic granule. Likewise, omitting from consideration some true defects may also give a large input into the bias of the assessed POF for a pipeline as a system.

Basics of Bayesian analysis of ILI data. In this section the Bayes' approach [39–45] is utilized when predicting the most probable values of a sample according to the previously obtained results. The following types of PDFs are utilized in this chapter: prior densities, likelihood functions (a.k.a. sampling densities), posterior densities, marginal densities, and predictive probabilities.

When updating prior information using the results of an additional experiment, it is assumed that the vector $\mathbf{y}$ is a component of a random vector which represents the experimental data, and the vector $\boldsymbol{\theta}$ is the basic parameter, which characterizes a family of PDFs $p(\boldsymbol{\theta})$ for the data obtained in the experiment. The value of the parameter is unknown, and only its prior PDF is assigned, which reflects our prior knowledge about the parameter.

The choice of the type of the prior PDF $p(\boldsymbol{\theta})$ is the first and *most important step* in constructing the probabilistic model. These densities should reflect the physical nature of conducted measurements. The other important step is assigning an

appropriate sample distribution $f(\mathbf{y}|\theta)$ for the sample of obtained data $\mathbf{y}$, with the parameter θ assigned. The term “sample” in the context of this chapter corresponds to the outcome of an experiment being accompanied by sampling of the objects from an aggregate of our interest. If the data $\mathbf{y}$ is known, the sample distribution can be viewed as function $f(\mathbf{y}|\theta)$ of the unknown model parameter θ . After obtaining an experimental realization of $\mathbf{y}$, the prior density $p(\theta)$ can be transformed/updated (using the new information) into the posterior density $p(\theta|\mathbf{y})$ by multiplying $p(\theta)$ by the likelihood function $f(\mathbf{y}|\theta)$ and then normalizing the obtained product. According to the Bayes formula the posterior distribution $p(\theta|\mathbf{y})$ of the parameter θ is defined from the relationship [43]:

$$p(\theta|\mathbf{y}) = \frac{f(\mathbf{y}|\theta)p(\theta)}{m(\mathbf{y})}, \quad (4.75)$$

where $m(\mathbf{y})$ is the normalizing coefficient, equal to

$$m(\mathbf{y}) = \int_{\theta} f(\mathbf{y}|\theta)p(\theta)d\theta. \quad (4.76)$$

Sometimes a quantitative assessment of the outcome of a future experiment for a planned sample $\mathbf{z}$ is needed. In this case the forecasted probability $p(\mathbf{z}|\mathbf{y})$ for this sample and the posterior distribution $p(\theta|\mathbf{y})$ derived using experimental data, and the sample distribution $f(\mathbf{z}|\theta)$ can be assessed as

$$p(\mathbf{z}|\mathbf{y}) = \int_{\theta} f(\mathbf{z}|\theta)p(\theta|\mathbf{y})d\theta. \quad (4.77)$$

Application of the Bayes approach to assessing the number of true defects in a pipeline. The above described approach is used for solving the practical problem of updating (predicting) the number of true defects in a pipeline segment, which contains a certain number of dangerous defects, according to ILI and verification measurements.

In [45] the methodology is described of revealing the missed out and false defects, using the histograms of the results of the ILI inspection and the subsequent verification digs, and constructing the full histogram of actual true defects in the full range $(0, t)$ of pipe wall thickness t . Each measurement, after its analysis, can yield either a true defect, a missed out defect, or a false (phantom) defect, and a true non-defect. Hence, for the algebraic sum of the missed out defects and the phantom defects the Bernoulli distribution can be adopted. The main assumption here is that the yield of a true or false defect (as the result of analysis of each defect's image and signature in the ILI and verification results) conditionally does not depend on the ratio (number of true defects/number of false defects) in other measurements, under the assumption that the probability of detection of true defects is known, at least for some of the measurements. After gathering new data about the detected and true defects in the inspected pipeline segment, a predictive assessment is given of the most probable

number of true defects in each of the intervals of defect sizes in consideration, for the assumed samples sizes of detected defects.

Assume that, as a result of ILI tool measurements and verification tool measurements conducted on a pipeline segment, followed by analysis of obtained results (as given in [45]), the following data is obtained:

- The general (total) number of detected defects in the pipe segment N_I ;
- The number of discovered defects in each j th interval, when the pipe web thickness (in general, any defect parameter size) is divided into intervals N_j intervals, ($j = 1, 2, \dots, k$) – N_j so that $\sum_j N_j = N_I$; and
- The number of true defects in the j th interval, $N_{t,j}$.

Denote the assumed sample of defects in the j th interval as $z_{1,j} = 0, 1, 2, \dots, m$. Assume the sample size to be $m = N_j^{(f)}$, where $N_j^{(f)}$ is the maximal number of the assumed defects. Introduce a generic parameter π_j of the j th defect size interval: π_j is the probability of establishing the number of true defects based on the number of detected defects. The value of π_j is unknown, and only its prior distribution $p(\pi_j)$ is assigned.

Now it is necessary for the prior distribution $p(\pi_j)$, assigned for the j th interval, to assess the most probable number of true defects $z_{1,j}^*$ in this interval, on the condition that $z_{1,j} = 0, 1, 2, \dots, m, m = N_j^{(f)}$.

Preliminarily, it is necessary to assess the being predicted (conditional) probabilities $p(z_{1,j}|N_{t,j})$ of finding in this interval $z_{1,j} = 0, 1, 2, \dots, m$ true defects on the condition, that during measurements $N_{t,j}$ true defects were detected. Now, from the assumed sample size $z_{1,j} = 0, 1, 2, \dots, m$ the most probable number of defects $z_{1,j}^* \leq m$ is selected, for which the corresponding value of the predicted probability $p(z_{1,j}^*|N_{t,j})$ will have maximal value:

$$p(z_{1,j}^*|N_{t,j}) = \max_z p(z_{1,j}|N_{t,j}).$$

Solution of the problem. Consider the case when the scalar parameters correspondingly are equal to

$$\begin{aligned} \theta &= \theta_1 = \pi_j (j = 1, 2, \dots, k); \quad 0 \leq \pi_j \leq 1; \\ \mathbf{y} &= y_{1,j} = 0, 1, 2, \dots, n, \quad n = N_{t,j}; \\ \mathbf{z} &= z_{1,j} = 0, 1, 2, \dots, m, \quad m = N_j^{(f)}. \end{aligned}$$

To represent the prior (informative) distribution of the parameter π_j Beta distribution is used:

$$\begin{aligned} p(\theta_1) &= p(\pi_j) = p(\pi_j|\alpha_j, \beta_j) = \text{Beta}(\alpha = \alpha_j, \beta = \beta_j) \\ &= \frac{\Gamma(\alpha_j + \beta_j)}{\Gamma(\alpha_j)\Gamma(\beta_j)} \pi_j^{\alpha_j-1} (1 - \pi_j)^{\beta_j-1}, \end{aligned} \quad (4.78)$$

where $\Gamma(\dots)$ is the Gamma function, $\alpha_j, \beta_j > 0$. This PDF of a continuous RV with values in the interval $(0, 1)$ meets the requirements to the PDF of a positive quantity π_j , that changes in the range of $(0, 1)$.

In the case of a nonsymmetrical Beta distribution, the parameters α_j, β_j are defined for each j th interval as the solution of a system of DEs (is cumbersome and not shown here), which describes the ratio of the values of the mathematical expectation to the mode at given parameters of the system $\pi_j^* = N_{i,j}/N_j$ and $\delta = (1, 05 - : -1, 1)$:

$$\alpha_j = \frac{1 - 2\delta\pi_j^*}{1 - \delta}, \quad \beta_j = \frac{(1 - \pi_j^*)(1 - 2\delta\pi_j^*)}{\pi_j^*(1 - \delta)}.$$

When choosing the value of δ recommendations [42] are followed.

The sample PDFs $f(y_1|\theta_1)$ and $f(z_1|\theta_1)$ for the obtained and the assumed data, which define the probability of the outcome of the inspection (the latter consisting of sampling of defects from the aggregate of defects of interest), are taken as binomial PDFs:

$$\begin{aligned} f(y_1|\theta_1) &= f(y_1|n, \pi_j) = f(y_1|\pi_j) = \binom{n}{y_1} \pi_j^{y_1} (1 - \pi_j)^{n-y_1}, \\ \binom{n}{y_1} &= \frac{n!}{(n - y_1)!(y_1)!}, \quad (y_1 = y_{1,j} = 0, 1, 2, \dots, n; \quad n = N_{i,j}; \quad 0 < \pi_j < 1). \\ f(z_1|\theta_1) &= f(z_1|\pi_j) = f(z_1|m, \pi_j) = \binom{m}{z_1} \pi_j^{z_1} (1 - \pi_j)^{m-z_1}, \\ \binom{m}{z_1} &= \frac{m!}{(m - z_1)!(z_1)!}, \quad (z_1 = z_{1,j} = 0, 1, 2, \dots, m; \quad m = N_j^{(f)}; \quad 0 < \pi_j < 1). \end{aligned} \quad (4.79)$$

The normalizing coefficient $m(y_1)$, given by formula (4.76), takes the following form:

$$\begin{aligned} m(y_1) &= \int_{\pi} f(y_1|\pi_j) p(\pi_j) d\pi_j \\ &= \frac{n!}{(n - y_1)!(y_1)!} \frac{\Gamma(\alpha_j + \beta_j)}{\Gamma(\alpha_j)\Gamma(\beta_j)} \frac{\Gamma(\alpha_j + y_1)\Gamma(\beta_j + n - 1)}{\Gamma(\alpha_j + \beta_j + y_1 + n - 1)}. \end{aligned}$$

In accordance with formula (4.75) for the posterior distribution of the parameter π_j the following expression holds:

$$p(\pi_j|y_1) = \frac{\pi_j^{\alpha_j-1+y_1} (1 - \pi_j)^{\beta_j-1+n-y_1}}{\int_0^1 \pi_j^{\alpha_j-1+y_1} (1 - \pi_j)^{\beta_j-1+n-y_1} d\pi_j}. \quad (4.80)$$

Then the predicted probability (4.77) for the assumed sample z_1 can be defined as

$$p(z_1|y_1) = \frac{m!}{(m-z_1)!(z_1)!} \frac{\int_0^1 \pi_j^{\alpha_j-1+y_1+z_1} (1-\pi_j)^{\beta_j-1+n-m-y_1-z_1} d\pi_j}{\int_0^1 \pi_j^{\alpha_j-1+y_1} (1-\pi_j)^{\beta_j-1+n-y_1} d\pi_j}. \quad (4.81)$$

Correctness of calculations using the proposed algorithm in its general form was verified by full coincidence of the results of calculation of a specific case [43] (not related to pipeline defect assessment in lieu of solved cases for pipelines; actually, for assessing the probability of safe launching of new meteorological sputniks), when $\theta_1 = \pi$; $y_1 = 3$; $n = 11$; $z_1 = 0, 1, 2, \dots, m$, $m = 5$; $\alpha = 2.4$; $\beta = 2$ by the proposed algorithm and by an independent algorithm used in [42]. The results coincide up to the first three digits of the assessments.

Analysis of real-life cases. The algorithm validated above can now be used when solving some real-life problems, particularly, when updating the number of true defects in an operating pipeline using the results of ILI and verification data, for assessing the quality of each pig run.

Case #1. Consider the data gathered by ILI from an oil pipeline, which diameter is 914 mm, and wall thickness wt is 9 mm [45]. In one of its 12-m-long segments, which contained, according to ILI readings, the maximal numbers of defects, including dangerous ones, verification measurements were made. The results of measuring the defect depth are shown in Table 4.37 (option A). The pipe wall thickness is divided into nine intervals.

Table 4.37 Initial data and results of analysis

Interval number, $j = 1, 2, \dots, 9$ for defect depth		1	2	3	4	5	6	7	8	9
Defect depth interval, mm		0–1	1–2	2–3	3–4	4–5	5–6	6–7	7–8	8–9
N_j	A	0	64	20	11	25	1	0	0	0
	B	0	64	20	19	25	1	0	0	0
$N_{t,j}$	A	0	42	17	10	25	1	0	0	0
	B	0	52	18	18	25	1	0	0	0
$N_j^{(f)}$	A	–	90	27	18	–	–	–	–	–
	B	–	90	28	27	–	–	–	–	–
$z_{1,j}^* = N_{t,j}^{(p)}$	A	60	24	17	–	–	–	–	–	–
	B	74	26	27	–	–	–	–	–	–

Note N_j is number of detected defects; $N_{t,j}$ is number of true defects; $N_j^{(f)}$ is assumed sample size of detected defects; $z_{1,j}^* = N_{t,j}^{(p)}$ is most probable number of actual defects

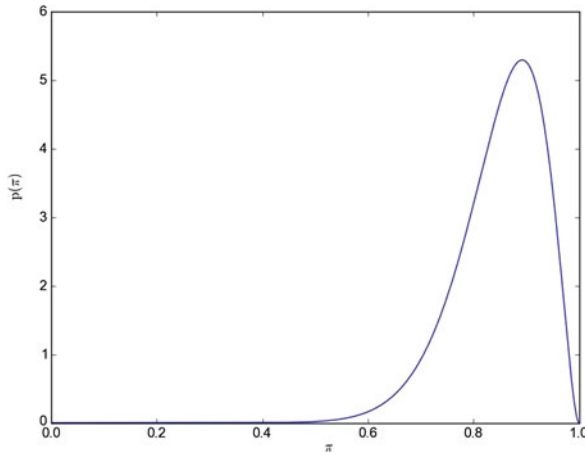


Fig. 4.60 Prior distribution of parameter π_j in interval #3

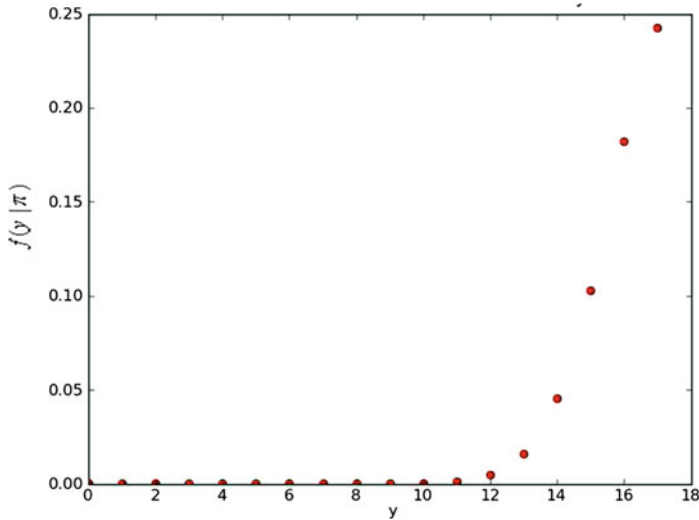


Fig. 4.61 The likelihood function $f(y|\pi_3) = f(y|n, \pi_3)$ for the sample of true defects of size $y = 0, 1, 2, \dots, N_{t,3}$ on the condition that $n = N_3$, $\pi = \pi_{3*} = N_{t,3}/N_3$

The details of the results of the analysis are shown in Figs. 4.60, 4.61, 4.62, 4.63, 4.64 and 4.65 for one interval (#3) where the number of detected defects is $N_3 = 20$, and the number of true defects is $N_{t,3} = 17$ (see Table 4.37). The predicted probabilities $p(z_{1,3}|N_{t,3})$, calculated by formula (4.81) for the assumed sample of discovered defects (for the interval #3) $z_{1,3} = 0, 1, 2, \dots, m$, $m = N_3^{(f)} = 27$, where the number of true (real) defects in this interval $N_{t,3} = 17$, are given in Table 4.38. The value $p(z_{1,3}|N_{t,3})$ is the probability that in the assumed sample size of detected

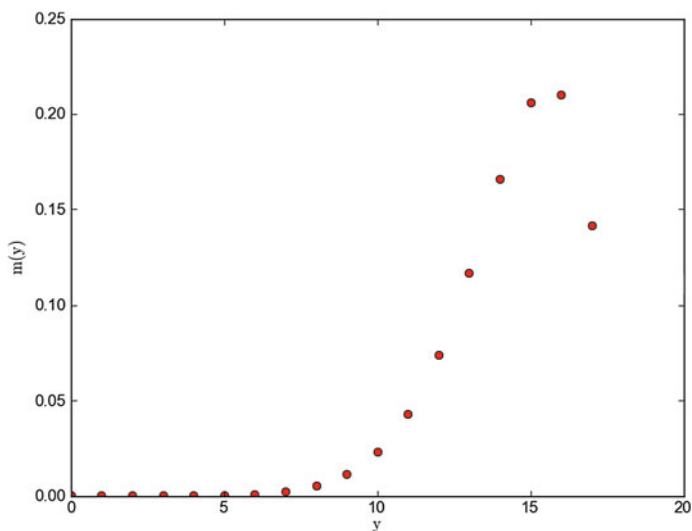


Fig. 4.62 The marginal distribution of true defects in interval #3

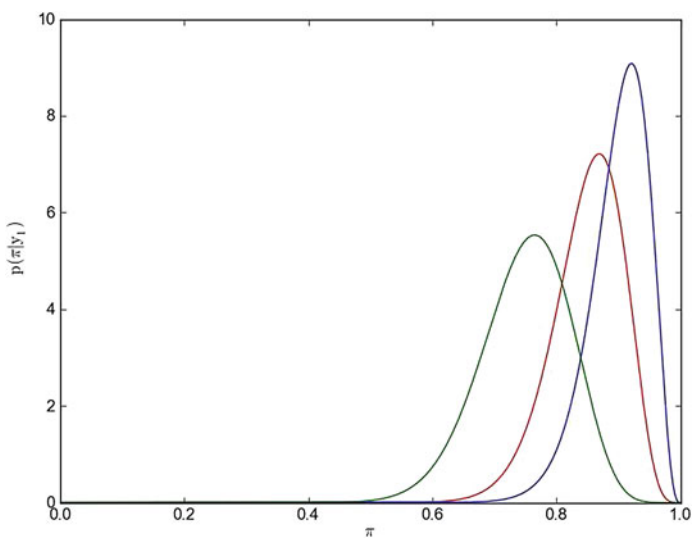


Fig. 4.63 The posterior PDF $p(\pi_3|N_{l,3})$ of parameter $\pi = \pi_3$, for interval #3, on the condition that the size of the sample of true defects in this interval is $y_1 = N_{l,3}$

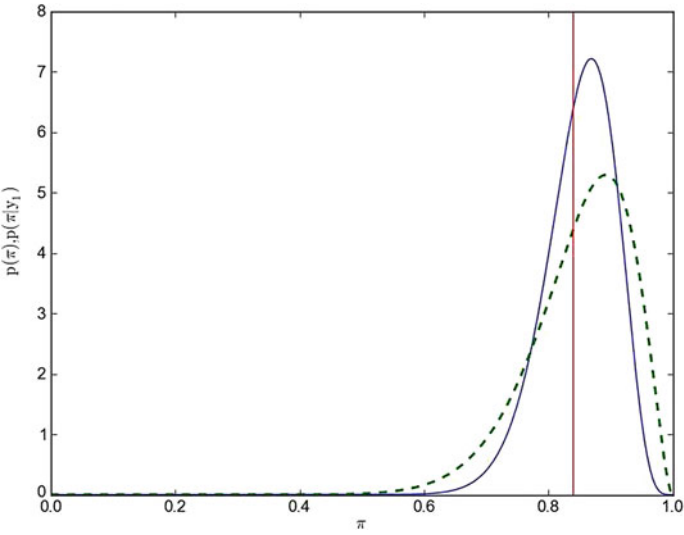


Fig. 4.64 The prior (dashed line) and posterior (solid line) PDF of the parameter π_j for interval #3. The vertical line shows the value of $\pi_3 = \pi_3^*$

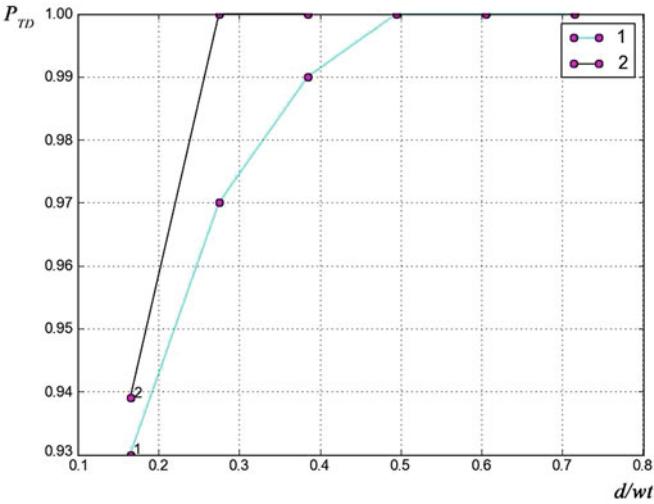


Fig. 4.65 Experimental curve P_{TD} , based on data $N_{t,j}/N_j$ —line 1; result of Bayesian update P_{TD} —line 2

Table 4.38 The predicted probabilities for the expected number of defects in interval #3

Parameter	Value							
$z_{1,3}$	17	20	22	23	24	25	26	27
$p(z_{1,3} N_{t,3})$	0.01	0.07	0.12	0.16	0.17	0.15	0.10	0.04

defects the number of true defects is $z_{1,3}$ on the condition that the experimental data gives the number of true defects as $N_{t,3}$.

According to Table 4.38, the maximal value of probability $p(z_{1,3}|N_{t,3}) = 0$, 17 is related to $z_{1,3} = 24$. Hence, for an assumed for the interval #3 sample of discovered defects, with size $N_3^{(f)} = 27$, the most probable number of true defects will be $z_{1,3}^* = N_{t,3}^{(p)} = 24$.

The PDF graphs of Figs. 4.60, 4.61, 4.62, 4.63 and 4.64, which visualize the developed algorithm, are related to the interval #3 ($N_3 = 20$; $N_{t,3} = 17$; $N_3^{(f)} = 27$; $\pi_3^* = N_{t,3}/N_3 = 0.85$; $\alpha_3 = 15.70$; $\beta_3 = 2.77$; $\delta = 1.05$).

The graph of the prior PDF $p(\pi_j)$ for the generic parameter π_j , assumed to be a Beta function (4.78), is given in Fig. 4.60.

Sample distributions (the likelihood function) $f(y|\pi_3) = f(y|n, \pi_3)$ for the sample $y = 0, 1, 2, \dots, N_{t,3}$ of true defects in the interval on the condition that the number of anomalies discovered in it is equal to $n = N_3$, and the corresponding value of the parameter $\pi_3 = \pi_3^* = N_{t,3}/N_3$ is considered as having a Binomial distribution (4.79) are shown in Fig. 4.61.

Marginal distribution $m(y)$ for the data $y = 0, 1, 2, \dots, y_1$, $y_1 = N_{t,3}$ for the third interval is shown in Fig. 4.62. Marginal distribution is a specific distribution of an RV or a set of RVs (multidimensional distribution), considered as a component or a set of components of a certain random vector with a given distribution.

Posterior distribution $p(\pi_3|N_{t,3})$ of the generic parameter $\pi = \pi_3$ in the third interval on the condition that, based on experimental data of size n in the interval in consideration, the sample of size $y_1 = N_{t,3}$ is defined according to formula (4.80) and shown in Fig. 4.63. Calculations were performed for different numbers of true defects: the middle line on Fig. 4.63 corresponds to $N_{t,3} = 17$ true defects, the right line corresponds to $N_{t,3} = 18$, left line— $N_{t,3} = 15$. When the number $N_{t,3}$ of true defects is growing, the maximal value of the posterior density is also growing. A shift of the values of π_3 to unity is also observed. In this case the share of the true defects in the number of overall detected defects is also growing.

Comparison of the prior and posterior densities for the parameter π is done by plotting them together (see Fig. 4.64). It can be seen that, for all posterior densities, the compression effect holds true, manifesting itself by concentrating the prior probability around its center, proportionate to the experimentally observed ratio y/n to the prior mean value $\alpha_j/(\alpha_j + \beta_j) = \pi_3^*$ (this phenomenon is also mentioned in [40, 42, 44]).

Next, the probability of detection POD curve is constructed. In the API 1163 Standard [1] the POD is defined as the probability of establishing the existence of an

anomaly using non-destructive testing techniques. In this book POD is the probability of discovering a true defect (P_{TD} is probability of true detection). The curve P_{TD} can be constructed only by simultaneously accounting for the three probabilities of true detection, false non-detection, and false detection, which, in their entirety, characterize the specifics of the measurement instrument (here we deliberately do not consider the probability of correct defect identification, which also gives its input to the final assessment of P_{TD}). For the data presented in Table 4.37 (variant B) the P_{TD} curve is shown in Fig. 4.65.

It can be also seen that the Bayesian machinery permits upgrading the experimental results.

Case #2. This case represents the same pipeline as in Case #1, but describes results of ILI and verification of another of its segments (see Table 4.39). Analysis of the Bayesian assessments for data according to case A shows that the most probable number of true defects $z_{1,j}^* = N_{1,j}^{(p)}$ in intervals ##2–5 depend linearly on the size of the expected sample of detected defects, but the proportionality coefficients in the intervals differ.

For intervals #6 and #7 which comprised large depth defects some nonlinearity was discovered (in the limit of 9%).

Most probable distribution of true defects $z_{1,j}^*$ depending on the changes (in broad band) of size $N_j^{(f)}$ of the expected sample of detected defects is given in a 3D graph, shown in Fig. 4.66. Any specific measurement tool (technology) has “intrinsic” detection errors, which lead to increase/decrease of the number of detected true defects.

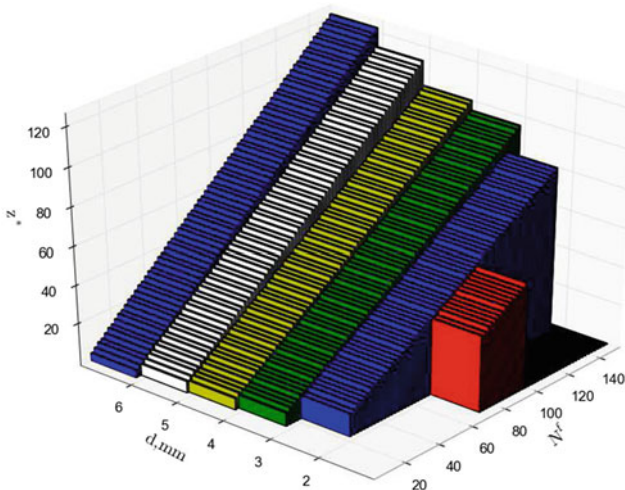


Fig. 4.66 Most probable distribution of the number of true defects $z_{1,j}^*$ across intervals ##2-7 for the expected sample of the detected defects of size $N^{(f)}$ (maximum $N^{(f)}$ is the same for all intervals, except interval #2)

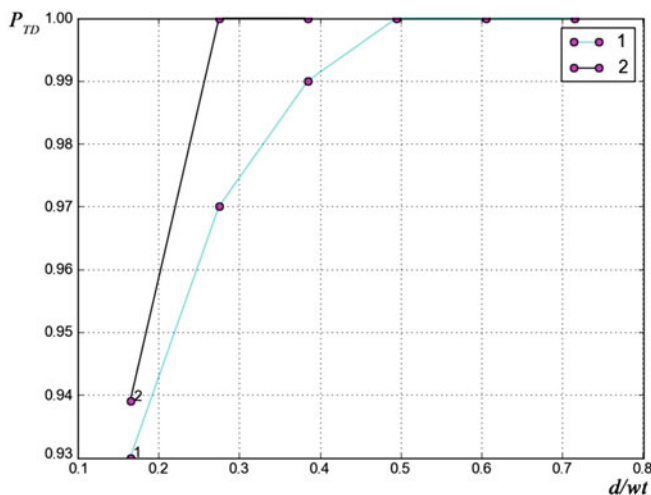


Fig. 4.67 Curves P_{TD} (according to case B of Table 4.39): 1 experimental; 2 Bayesian update

Table 4.39 Results of defect depth measurement

Depth interval number, $j = 2, \dots, 7$		2	3	4	5	6	7
The defect depth interval d , 1 mm		1–2	2–3	3–4	4–5	5–6	6–7
N_j	A	68	20	11	9	8	5
	B	68	33	100	3	1	1
$N_{t,j}$	A	40	12	7	6	6	4
	B	63	32	99	3	1	1
$N_j^{(f)}$	A	75	27	15	12	11	8
	B	82	43	130	4	1	1
$z_{1,j}^* = N_{t,j}^{(p)}$	A	44	17	10	8	9	7
	B	77	43	–	–	–	–
$N_j^{(f)}/N_j$	A	1.1	1.3	1.4	1.3	1.4	1.6
	B	1.2	1.3	1.3	1.3	1	1
$N_{t,j}/N_j$	A	0.59	0.60	0.64	0.67	0.75	0.80
	B	0.93	0.97	0.99	1	1	1
$N_{t,j}^{(p)}/N_j^{(f)}$	A	0.59	0.63	0.67	0.69	0.82	0.88
	B	0.94	1	–	–	–	–

Note N_j is number of detected defects; $N_{t,j}$ is number of true defects; $N_j^{(f)}$ is expected sample size of detected defects; $z_{1,j}^* = N_{t,j}^{(p)}$ is most probable number of true defects

Using the results of the calculations performed above, it would be possible to account for these errors and consistently assess the number of true defects present in a pipeline.

In Fig. 4.67 the ratio $N_{t,j}/N_j$ (curve 1) was obtained using the observed numbers of detected and true defects in intervals ##2-7 (see Table 4.39) as given by the ILI and verification procedures. The Bayesian updating of curve #1 taking into account new data (ratio $N_{t,j}^{(p)}/N_j^{(f)}$) is shown as curve #2. It can be seen from Figs. 4.65, 4.66 and 4.67, that the Bayesian machinery gives different results in each of the intervals, depending on the specific numbers of detected and true defects.

This flexibility of the proposed method permits assessing the quality of the pig run with respect to different sizes of defects.

4.8.3 Bayesian Update of the Number of Defects in a Pipeline Using Results of Several Inspections

Assume that for a pipeline segment, results of several experiments (inspections using ILI and verification procedures) are known. Consider generalization of the above algorithm using the Bayes formula and the data gathered during one experiment, given in Sect. 4.8.2, for the case when results of n_e experiments are known. Assume also that the defect depth is described in parts of pipe wall thickness, which is divided into k equal size intervals. Assume that the data of the i th ($i = 1, 2, \dots, n_e$) experiment are represented in the ($j = 1, 2, \dots, k$) by the number of true $N_{t,j}^{(i)}$ and detected $N_j^{(i)}$ defects, as defined by the ILI and subsequent verification [45]. In order to generalize the algorithm for the case when n_e experimental results are known, introduce, instead of the basic scalar parameter (random value) π_j ($j = 1, 2, \dots, k$), $0 \leq \pi_j \leq 1$ a random vector $\theta = \pi_j(\pi_{1j}, \pi_{2j}, \dots, \pi_{n_e,j})$, and substitute $\pi_j^* = N_{t,j}/N_j$ by parameters $\pi_{ij}^* = N_{t,j}^{(i)}/N_j^{(i)}$, $i = 1, 2, 3, \dots, n_e$. Take into account that the prior PDF $p(\theta_1) = p(\pi_j)$ of the scalar parameter π_j is a continuous RV in the interval $(0, 1)$, and was earlier presented by a Beta distribution. Assuming independence of the RVs $\pi_{1j}, \pi_{2j}, \dots, \pi_{n_e,j}$ and generalizing the PDF $p(\pi_j)$, present the prior distribution of the basic vector π_j in the following form:

$$\begin{aligned} p(\theta_1) &= p(\pi_j) = p(\pi_{1j}, \pi_{2j}, \dots, \pi_{n_e,j}) = \text{Beta}(\alpha = \alpha_{ij}, \beta = \beta_{ij}) \\ &= \prod_{i=1}^{n_e} \frac{\Gamma(\alpha_{ij} + \beta_{ij})}{\Gamma(\alpha_{ij})\Gamma(\beta_{ij})} \pi_{ij}^{\alpha_{ij}-1} (1 - \pi_{ij})^{\beta_{ij}-1}. \end{aligned} \quad (4.82)$$

Here parameters $\alpha_{ij}, \beta_{ij} > 0$ are defined by the formulas which are generalizations of corresponding formulas from [46] for α_j, β_j :

$$\alpha_{ij} = \frac{1 - 2\delta\pi_{ij}^*}{1 - \delta}, \quad \beta_{ij} = \frac{(1 - \pi_{ij}^*)(1 - 2\delta\pi_{ij}^*)}{\pi_{ij}^*(1 - \delta)}, \quad (4.83)$$

and the parameter δ value is chosen from the interval $(1.05 - 1.1)$, according to recommendations of [42] for such types of problems.

We introduce the further following notations: y_i , $i = 1, 2$ for the coordinates of vector $\mathbf{y}$ in the j th interval, and $y_{1,i} = 0, 1, 2, \dots, n_i$ is the data sample of size n_i . In our case $y_i = n_i = N_{t,j}^{(i)}$ is the number of true defects for the j th interval, found during the i th inspection. Assume $z_1 = 0, 1, 2, \dots, m$ is the sample of the expected data about the defects which would be detected in the j th interval, where $m = N_j^{(f)}$ is its size. The sample PDFs $f(y_{1,i}|\pi_j)$ and $f(z_1|\pi_j)$ in the form of binomial distributions will be

$$f(y_{1,i}|\pi_j) = f(y_{1,i}|n, \pi_{ij}) = \binom{n}{y_{1,i}} \prod_{i=1}^{n_e} \pi_{ij}^{y_{1,i}} (1 - \pi_{ij})^{n-y_{1,i}}, \quad (4.84)$$

$$\binom{n}{y_{1,i}} = \frac{n!}{(n - y_{1,i})!(y_{1,i})!}, \quad 0 < \pi_{ij} < 1, \quad n = N_{t,j}^{(i)},$$

$$f(z_1|\pi_j) = f(z_1|m, \pi_{ij}) = \binom{m}{z_1} \prod_{i=1}^{n_e} \pi_{ij}^{z_1} (1 - \pi_{ij})^{m-z_1}, \quad (4.85)$$

$$\binom{m}{z_1} = \frac{m!}{(m - z_1)!(z_1)!}, \quad 0 < \pi_{ij} < 1.$$

Taking into account Eqs. (4.82) and (4.84) the normalizing coefficient can be written as

$$\begin{aligned} m(y_{1,i}) &= \int_{\pi_{1j}} \dots \int_{\pi_{2j}} f(y_{1,i}|\pi_j) p(\pi_j) d\pi_j \\ &= \frac{n!}{(n - y_{1,i})!(y_{1,i})!} \prod_{i=1}^{n_e} \frac{\Gamma(\alpha_{ij} + \beta_{ij})}{\Gamma(\alpha_{ij})\Gamma(\beta_{ij})} \cdot \frac{\Gamma(\alpha_{ij} + y_{1,i})\Gamma(\beta_{ij} + n - 1)}{\Gamma(\alpha_{ij} + \beta_{ij} + y_{1,i} + n - 1)}. \end{aligned}$$

Then the posterior distribution of the vector π_j , which accounts, in accordance with formula (4.75), for the new experimental data about the true defects $y_{1,i}$, can be obtained from the equation

$$p(\pi_j|y_{1,i}) = \frac{f(y_{1,i}|\pi_j)p(\pi_j)}{m(y_{1,i})}. \quad (4.86)$$

In this case, according to formula (4.77), the forecasted probability $p(z_1|y_{1,i})$ for the expected sample z_1 using the posterior distribution $p(\pi_j|y_{1,i})$ of the parameter π_j is found as follows:

$$p(z_1|y_{1,i}) = \left[\frac{m!}{(m - z_1)!(z_1)!} \right]$$

$$\times \frac{\int_0^1 \dots \int_0^1 \prod_{i=1}^{n_e} \pi_{ij}^{\alpha_{ij}-1+y_{1,i}+z_1} (1-\pi_{ij})^{\beta_{ij}-1+n+m-y_{1,i}-z_1} d\pi_{1j} d\pi_{2j} \dots d\pi_{n_e,j}}{\int_0^1 \dots \int_0^1 \prod_{i=1}^{n_e} \pi_{ij}^{\alpha_{ij}-1+y_{1,i}} (1-\pi_{ij})^{\beta_{ij}-1+n-y_{1,i}} d\pi_{1j} d\pi_{2j} \dots d\pi_{n_e,j}}. \quad (4.87)$$

Application of the Bayes approach to assessing the number of true defects in a pipeline using results of two subsequent IIL. If results of two experiments are known, $n_e = 2$, then the basic parameter for the j th interval ($j = 1, 2, \dots, k$) takes the form $\theta = \pi_j(\pi_{1j}, \pi_{2j})$, and $\pi_{ij}^* = N_{t,j}^{(i)}/N_j^{(i)}$, $i = 1, 2$. Parameters α_{ij} , β_{ij} are defined by formula (4.83).

In accordance with formula (4.82) the prior distribution of the parameter $\pi_j(\pi_{1j}, \pi_{2j})$ has the form

$$p(\pi_j) = p(\pi_{1j}, \pi_{2j}) = \prod_{i=1}^2 \frac{\Gamma(\alpha_{ij} + \beta_{ij})}{\Gamma(\alpha_{ij})\Gamma(\beta_{ij})} \pi_{ij}^{\alpha_{ij}-1} (1-\pi_{ij})^{\beta_{ij}-1},$$

and the sample distributions $f(y_{1,i}|\pi_j)$ and $f(z_1|\pi_j)$, according to formulas (4.84) and (4.85), are presented as functions

$$f(y_{1,i}|\pi_j) = f(y_{1,i}|n, \pi_{ij}) = \binom{n}{y_{1,i}} \prod_{i=1}^2 \pi_{ij}^{y_{1,i}} (1-\pi_{ij})^{n-y_{1,i}},$$

$$\binom{n}{y_{1,i}} = \frac{n!}{(n-y_{1,i})!(y_{1,i})!}, \quad (y_{1,i} = 0, 1, 2, \dots, n; n = N_{t,j}^{(i)}; 0 < \pi_{ij} < 1),$$

$$f(z_1|\pi_j) = f(z_1|m, \pi_{ij}) = \binom{m}{z_1} \prod_{i=1}^2 \pi_{ij}^{z_1} (1-\pi_{ij})^{m-z_1},$$

$$\binom{m}{z_1} = \frac{m!}{(m-z_1)!(z_1)!}, \quad (z_1 = 0, 1, 2, \dots, m; m = N_j^{(f)}, 0 < \pi_{ij} < 1).$$

The normalizing coefficient in this case can be written as

$$m(y_{1,i}) = \int_{\pi_{1j}} \int_{\pi_{2j}} f(y_{1,i}|\pi_{ij}) p(\pi_{1j}, \pi_{2j}) d\pi_{1j} d\pi_{2j}$$

$$= \frac{n!}{(n-y_{1,i})!(y_{1,i})!} \prod_{i=1}^2 \frac{\Gamma(\alpha_{ij} + \beta_{ij})}{\Gamma(\alpha_{ij})\Gamma(\beta_{ij})} \cdot \frac{\Gamma(\alpha_{ij} + y_{1,i})\Gamma(\beta_{ij} + n - 1)}{\Gamma(\alpha_{ij} + \beta_{ij} + y_{1,i} + n - 1)}.$$

The posterior distribution of vector $\pi_j(\pi_{1j}, \pi_{2j})$ can be obtained using Eq. (4.86) when $n_e = 2$. The predicting probability $p(z_1|y_{1,i})$ for the expected sample z_1 of

detected defects can be found from the relation (4.87), with $n_e = 2$, using the posterior distribution of the parameter $p(\pi_j|y_{1,i})$, constructed with accounting for the experimental data about the true defects $y_{1,i}$.

Example 4.8.1 Consider results of two inspections of an oil pipeline with diameter of 918 mm and pipe wall thickness of 9 mm [45]. On one of its segments 12 m long which contains the largest number of defects (according to the ILI data) verification measures were conducted. The results of measurements of defect depth as well as the number of detected and true defects are presented in Table 4.40 (lines 7 and 8), as the results of the second experiment. Results of the first (modeled) experiment are shown in lines 4 and 5 of Table 4.40. The pipe wall thickness t is divided into 9 one mm intervals.

In this case the vector $\mathbf{y}$, which represents the experimental data, is defined by two coordinates— $N_{t,j}^{(1)}$ and $N_{t,j}^{(2)}$, which correspondingly give the number of true defects in the first and second experiment. All computations were conducted according to the described above algorithm for the interval #3 ($j = 3$). For this interval described above, the two coordinates basic vector $\boldsymbol{\theta} = \pi_j(\pi_{1j}, \pi_{2j})$ will take the form $\pi_3(\pi_{13}, \pi_{23})$. Coordinates π_{13} and π_{23} of the vector are RVs, and characterize, correspondingly, the ratio of the number of true defects to the number of detected defects in interval #3 in the first and second experiments.

In Fig. 4.68 graphs are shown of the prior $p(\pi_3)$ and posterior $p(\pi_3|N_{t,3})$ distributions of the basic vector parameter $\pi_3(\pi_{13}, \pi_{23})$ for different versions of initial data. According to the obtained results, the forms of the surfaces which represent the prior distribution $p(\pi_3)$ differ for the two considered versions of data about the detected and true defects. As could be expected, the larger value of the maximum of the function $p(\pi_3) = p(\pi_{13}, \pi_{23})$ relates to the larger number $N_{t,3}^{(2)}$ of true defects of the second experiment. The graphs in Fig. 4.68 are constructed for $N_{t,3}^{(1)} = 6$; $N_3^{(1)} = 12$; $N_{t,3}^{(1)}/N_3^{(1)} = 0.5$; $N_3^{(2)} = 20$; $\delta = 1.01$.

Table 4.40 Initial data

Defect depth interval number, $j = 1, 2, \dots, 9$	1	2	3	4	5	6	7
Defect depth interval d , mm	0–1	1–2	2–3	3–4	4–5	5–6	6–7
Experiment #1							
$N_j^{(1)}$	0	50	12 (11)	7	5	3	1
$N_{t,j}^{(1)}$	0	22	6	4	3	2	1
Experiment #2							
$N_j^{(2)}$	0	64	20	19	25	1	0
$N_{t,j}^{(2)}$	0	52	18 (12)	18	25	1	0

Note $N_j^{(i)}$ is number of detected defects, $N_{t,j}^{(i)}$ is number of true defects

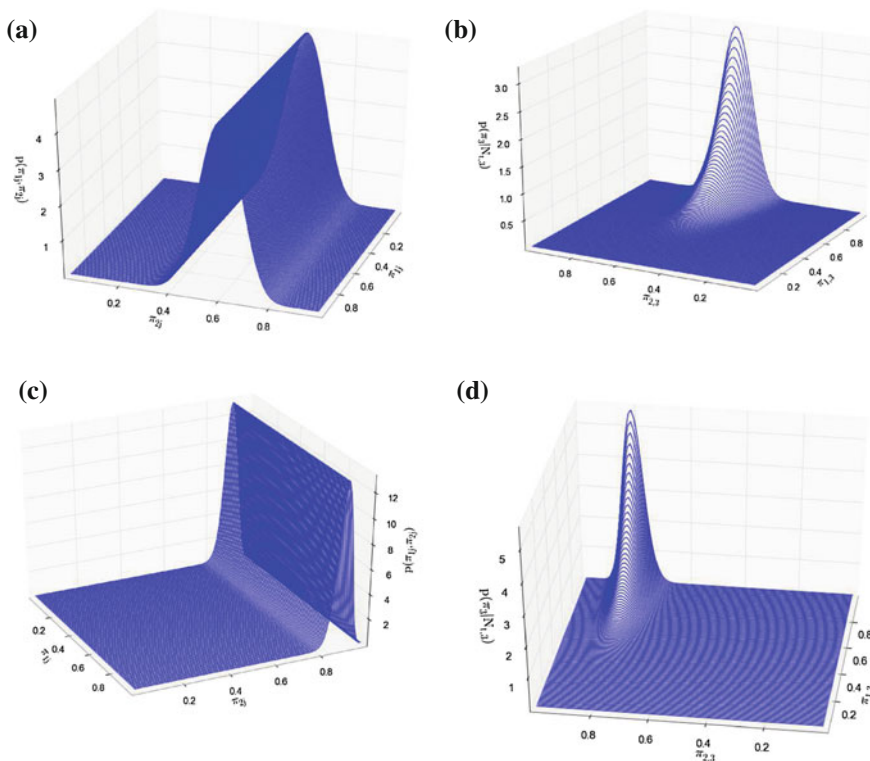


Fig. 4.68 Comparison of the parameter $\pi_3(\pi_{13}, \pi_{23})$ PDF in interval #3: prior $p(\pi_3)$ and posterior $p(\pi_3|N_{t,3})$, obtained with accounting for two inspections. **a** $p(\pi_3)$ at $N_{t,3}^{(2)} = 12$, **b** $p(\pi_3|N_{t,3})$ at $N_{t,3}^{(2)} = 12$, **c** $p(\pi_3)$ at $N_{t,3}^{(2)} = 18$, **d** $p(\pi_3|N_{t,3})$ at $N_{t,3}^{(2)} = 18$

When $N_{t,3}^{(1)}/N_3^{(1)} = 0, 5$ the prior PDF $p(\pi_3) = p(\pi_{13}, \pi_{23})$ does not depend on the parameter π_{13} ; hence, the cross sections which are parallel to the π_{23} axis are all similar to each other (see Fig. 4.68). Indeed, whereas $\alpha_{13} = 1$ and $\beta_{13} = 1$, then for $i = 1$ in the product $\prod_{i=1}^2 \frac{\Gamma(\alpha_{i3} + \beta_{i3})}{\Gamma(\alpha_{i3})\Gamma(\beta_{i3})} \pi_{i3}^{\alpha_{i3}-1} (1 - \pi_{i3})^{\beta_{i3}-1}$ for any value of π_{13} the equality $\pi_{13}^{\alpha_{13}-1} (1 - \pi_{13})^{\beta_{13}-1} = 1$ will hold true, so that the product will depend only on the parameter π_{23} . Changing π_{23} in the range of 0–1 will result in different values of function $p(\pi_{13}, \pi_{23})$, depending on the value of this parameter.

The graphs in Figs. 4.68, 4.69 and 4.70 of the posterior PDFs vividly show how dramatically the uncertainty is diminished when using the Bayes procedure, as the probability mass is concentrated under one peak.

For both versions shown in Fig. 4.68, the forms of the surfaces of the prior $p(\pi_3)$ and posterior $p(\pi_3|N_{t,3})$ distributions differ substantially—the maximal values of the

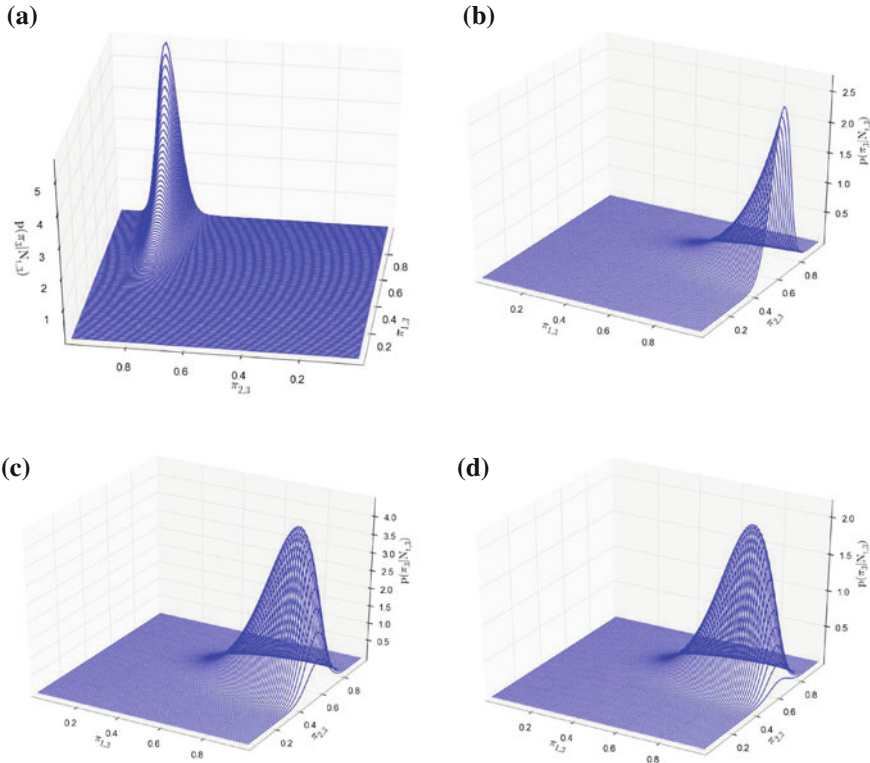


Fig. 4.69 Posterior PDFs $p(\pi_3|N_{t,3})$ of the parameter π_3 for interval #3 and different values of parameter δ on the condition that data of two experiments is known. **a** $\delta = 1.07$; $N_3^{(1)} = 12$; $N_{t,3}^{(1)}/N_3^{(1)} = 0.5$, **b** $\delta = 1.05$; $N_3^{(1)} = 12$; $N_{t,3}^{(1)}/N_3^{(1)} = 0.5$, **c** $\delta = 1.07$; $N_3^{(1)} = 11$; $N_{t,3}^{(1)}/N_3^{(1)} = 0.54$, **d** $\delta = 1.05$; $N_3^{(1)} = 11$; $N_{t,3}^{(1)}/N_3^{(1)} = 0.54$

posterior functions are significantly smaller (1.5–2 times less) than the maximums of corresponding prior functions.

The influence of the parameter δ on the form of the surfaces, which represent the posterior PDFs is, according to Fig. 4.69, insignificant. At the same time the maximums of obtained functions $p(\pi_3|N_{t,3})$ for the considered values of δ differ significantly. From analysis of graphs in Fig. 4.69b, c, related to inspection results with smaller share of true defects in both experiments, it follows that the maximum of the posterior distribution $p(\pi_3|N_{t,3})$ is 1.9 times smaller than the maximum of $p(\pi_3|N_{t,3})$, although the discrepancy between the two values of π_{23} and π_3 in this case is insignificant. Graphics in Fig. 4.69 are constructed for $N_{t,3}^{(1)} = 6$; $N_3^{(2)} = 20$; $N_{t,3}^{(2)} = 18$.

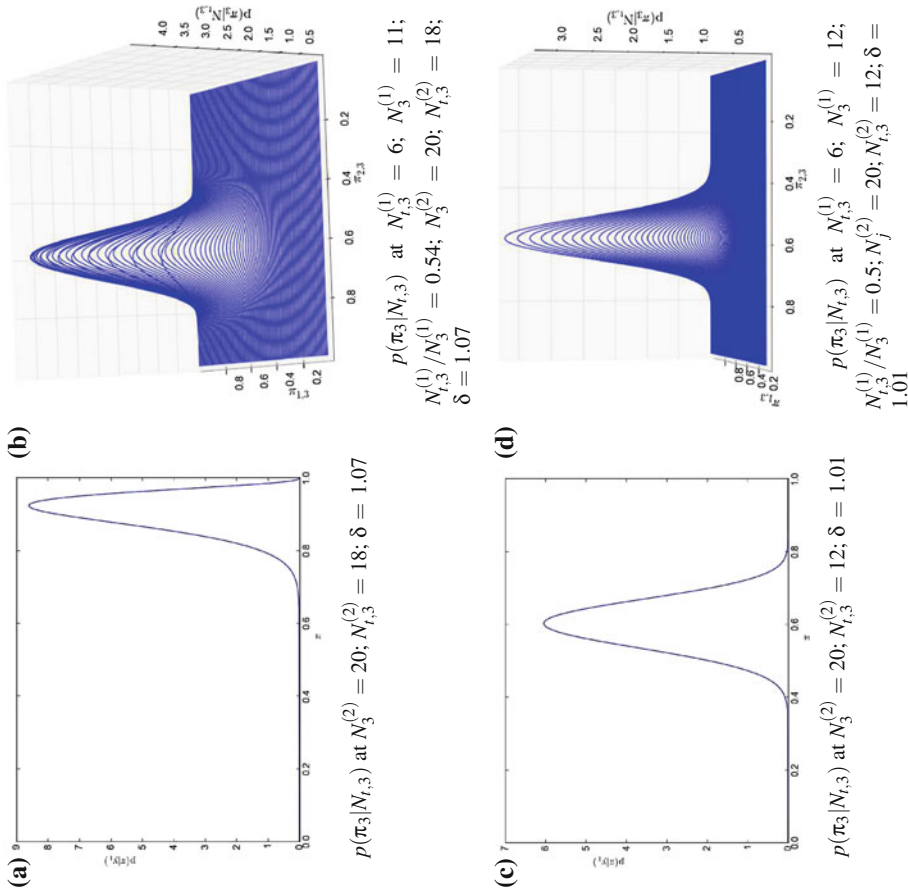


Fig. 4.70 Posterior PDFs of $p(\pi_3|N_{t,3})$ and $p(\pi_3|N_{t,3})$ for the scalar π_3 and the vector π_3 parameters for interval #3, taking into account results of (a), (b) one inspection; (c), (d) two inspections

In Fig. 4.70 the posterior distributions $p(\pi_3|N_{t,3})$ and $p(\pi_3|N_{t,3})$ are shown for the scalar parameter π_3 (when results of only one inspection/experiment are available, as in [45, 46]) and for the vector $\pi_3(\pi_{13}, \pi_{23})$ (when accounting for data from two inspections). Comparison of graphs (a) and (b) shows that for the same value of $\delta = 1.07$ the maximum of function $p(\pi_3|N_{t,3})$, for the case of two inspections is significantly (2.15 times) smaller than the maximum of function $p(\pi_3|N_{t,3})$ obtained using results of only one inspection. Moreover, it is reached at a lesser value of the basic parameter, which characterizes the ratio (number of true defects/ number of detected defects detected in interval #3), than in the case when results of only one inspection are accounted for ($\pi_{23} = 0.6 < \pi_3 = 0.9$), i.e., it corresponds to significantly smaller share of true defects.

The obtained results can be utilized when solving reliability problems for a pipeline segment; for instance, when finding the value of the quantile $\hat{\pi}_j(\pi_{1j}, \hat{\pi}_{2j})$ of the posterior distribution $p(\pi_j|N_{t,j})$, to which, with a given probability λ_j (which reflects the level of qualitative reliability of the results), corresponds to the number $N_{t,j}$ of true defects in the j th ($j = 1, 2, \dots, k$) interval. In this case it is necessary to find the value of $\hat{\pi}_{2j}$, at which the following equations hold true:

$$F(\hat{\pi}_j) = \lambda_j = \int_0^{\hat{\pi}_j} p(\pi_j|N_{t,j})d\pi_j = \int_0^1 \int_0^{\hat{\pi}_{2j}} p(\pi_j|y_{1,i})d\pi_{1j}d\pi_{2j},$$

$$y_{1,i} = 0, 1, 2, \dots, N_{t,j}^{(i)}; i = 2.$$

The number of true defects $N_{t,j}^{(2)}(\lambda_j)$ (if larger than the actual number of true defects detected in the pipeline segment during the inspection) is a clear indicator of the level of risk involved in not discovering the other defects, especially when they are in a range of 50–80 % of pipe wall thickness.

4.9 Construction of the ROC Curve Using ILI Results and Approximation of the Standard POD Curve

In this section:

- Numerical examples are presented of constructing the curves using the ILI and consequent verification results of a pipeline segment; and
- A consistent approximation is offered of the curve P_{TD} (see Sects. 4.3.1 and 4.3.2) by two analytical functions, which pass through points, where coordinates are the essential variables of the ILI technology.

The ROC curves are used for assessing the quality of performance of different types of diagnostic tools in non-destructive testing technology [47, 48]. The decision on whether to inspect, maintain, and/or repair equipment of different kinds of structures in operation largely depends on the form of these curves. A detailed analysis of the

influence of the ROC curve on the process of decision making can be found in [47]. The ROC curve reflects the dependence of the number of correctly classified (true positive) test results on the number of wrongly classified (false negatives) test results. The division of the test results into positive results and negative results depends every time on the specifics of the problem in consideration. It is assumed that there exists some parameter, namely, the cut-off threshold, by varying which from 0 to 1, using the inspection data, a corresponding division of the data into two classes can be achieved. Depending on the outcome, different values of the I order and the II order errors are obtained.

In the API 1163 Standard [1], *POD* is defined as the probability of detecting an indication, sign, or symptom of an anomaly or defect discovered by NDT means and technology. In [1] the *POD* curve is tethered to the deepest defect and is approximated by an exponent.

In this book the *POD* is defined as the probability of detection of a true defect and is defined as P_{TD} . The proposed P_{TD} curve is, according to physical laws, a convex monotonically increasing function of the defect size, with two asymptotes. One of them stems from the fact that when the defect size x is smaller than some threshold value x_0 , which is called *resolution* of the measurement instrument (technology), and is invisible, and $P_{TD} = 0$. When the defect parameter size is x_u (detectable by the ILI technology practically with a 100% probability), the value of P_{TD} is approximately unity.

4.9.1 Construction of the ROC Curve Using ILI Results

Consider a set of inspection data X_l with l different test (inspection) outcomes. Further down the following notations will be used, as proposed in [49, 50]:

- *TP (True Positives)*—correctly classified positive test results (true positive cases);
- *TN (True Negatives)*—correctly classified negative test results (true negative cases);
- *FN (False Negatives)*—positive test results classified as negative test results (falsely negative test results—type I error). The existing event is falsely not detected; and
- *FP (False Positives)*—negative test results classified as positive test results (falsely positive test results—type II error). In other words, a false judgment is made about the presence of the event.

Assume that N_p is the number of positive test outcomes, equal to the number of tests with outcomes *TP* and *FN*; N_n is the number of negative test outcomes, equal to the number of tests with outcomes *TN* and *FP* (so that $l = N_p + N_n$); and l_1 is the total number of tests with outcomes *TP* and *FP*. When constructing the ROC curve consider two versions, which correspond to different methods of defining the abscissa and the ordinate of points of this curve [48, 49].

Version 1. Ordinate is the *TPR* (*True Positive Rate*) = $S_e = TP/N_p$, abscissa is the *FPR* (*False Positive Rate*) = $(1 - S_p) = FP/N_n$, where S_e is the sensitivity parameter which is defined as the percentage share of the correctly identified positive cases, and S_p is the specificity parameter, which is defined as the percentage share of correctly identified negative cases.

Version 2. Ordinate is the *CRR* (*Correct Rejection Rate*) = $TP/(N_p + N_n)$, abscissa is the *FCRR* (*False Call Rate to Rejection*) = $FP/(N_p + N_n)$.

Main steps of the proposed algorithm, constructed using recommendations [45], are as follows:

1. Introduce a new numeration (from 1 to l_1) but only for those l_1 test results in the sample set X_l , where outcome is *TP* and *FP*. This numeration is conducted from the bottom of the table up (as shown in Table 4.41, column 3).
2. For each of the i test results, starting from number 1 (according to the new numeration) and up to number l_1 , it is assumed that *TP* is equal to the number of the test results with outcome *TP*, taken from those results from the sample set X_l , which have numbers from 1 to i inclusive; and *FP* is equal to the number of the test results with outcome *FP*, taken from those results from the sample set X_l , which have numbers from 1 to i inclusive;
 - (a) For these data pairs of parameters are calculated:
 - *Version 1:* $TPR = S_e = TP/N_p$ and $FPR = (1 - S_p) = FP/N_n$.
 - *Version 2:* $CRR = TP/(N_p + N_n)$ and $FCRR = FP/(N_p + N_n)$.

Table 4.41 Calculation of the ROC curve coordinates using test outcomes as per sample set #1

Number of the test result in the sample	Inspection out come	The threshold cut-off number (from 0 to l_1)	ROC curve coordinates			
			Version 1		Version 2	
			FPR	TPR	FCRR	CRR
1	<i>TP</i>	12	0.75	0.9	0.21	0.64
2	<i>TN</i>	–	–	–	–	–
3	<i>FP</i>	11	0.75	0.8	0.21	0.57
4	<i>TP</i>	10	0.50	0.8	0.14	0.57
5	<i>FP</i>	9	0.50	0.69	0.14	0.50
6	<i>TP</i>	8	0.25	0.69	0.07	0.50
7	<i>TP</i>	7	0.25	0.59	0.07	0.42
8	<i>FN</i>	–	–	–	–	–
9	<i>TP</i>	6	0.25	0.50	0.07	0.35
10	<i>TP</i>	5	0.25	0.40	0.07	0.28
11	<i>FP</i>	4	0.25	0.29	0.07	0.21
12	<i>TP</i>	3	0.00	0.29	0.00	0.21
13	<i>TP</i>	2	0.00	0.20	0.00	0.14
14	<i>TP</i>	1	0.00	0.10	0.00	0.07

(b) The points obtained using different values of i (i.e., for different values of the cut-off thresholds, which correspond to each subsequent value of the test results in the sample set) with coordinates:

- for Version 1: horizontally (abscissa) FPR and vertically (ordinate) TPR ; and
- for Version 2: horizontally (abscissa) $FCRR$ and vertically (ordinate) CRR .

The adjacent points are then interconnected by straight lines, forming the corresponding ROC curves. It should be noted that all variables FPR , TPR , $FCRR$, and CRR change from 0 to 1. Then in the quadrant 1×1 the diagonal is drawn from point (0; 0) to point (1; 1).

Table 4.42 Calculation of the ROC curve coordinates using test outcomes as per sample set #2

Number of the test result in the sample	Inspection out come	The threshold cut-off number (from 0 to I_1)	ROC curve coordinates			
			Version 1		Version 2	
			FPR	TPR	FCRR	CRR
1	TP	24	0.66	1.00	0.15	0.76
2	TN	–	–	–	–	
3	TP	23	0.66	0.94	0.15	0.73
4	FP	22	0.66	0.90	0.15	0.69
5	FP	21	0.50	0.90	0.11	0.69
6	TP	20	0.33	0.90	0.07	0.69
7	TP	19	0.33	0.80	0.07	0.65
8	TP	18	0.33	0.80	0.07	0.61
9	TP	17	0.33	0.75	0.07	0.57
10	TP	16	0.33	0.69	0.07	0.53
11	TP	15	0.33	0.65	0.07	0.50
12	FP	14	0.33	0.59	0.07	0.46
13	TP	13	0.16	0.59	0.03	0.46
14	TP	12	0.16	0.55	0.03	0.42
15	TP	11	0.16	0.50	0.03	0.38
16	TP	10	0.16	0.45	0.03	0.34
17	TP	9	0.16	0.40	0.03	0.30
18	FP	8	0.16	0.34	0.03	0.26
19	TP	7	0.00	0.34	0.00	0.26
20	TP	6	0.00	0.29	0.00	0.23
21	TP	5	0.00	0.25	0.00	0.19
22	TP	4	0.00	0.20	0.00	0.15
23	TP	3	0.00	0.14	0.00	0.11
24	TN	–	–	–	–	
25	TP	2	0.00	0.10	0.00	0.07
26	TP	1	0.00	0.05	0.00	0.03

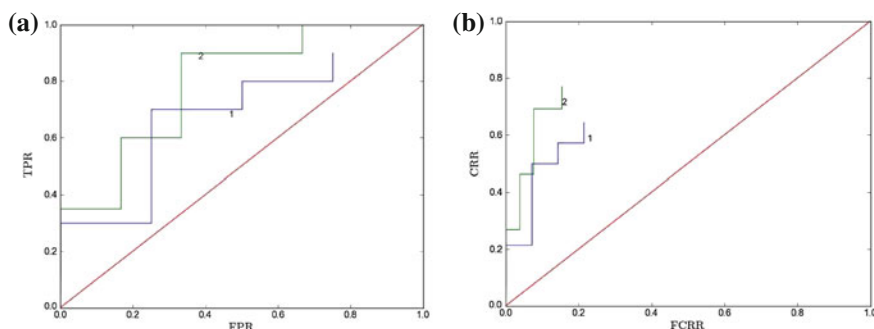


Fig. 4.71 ROC curves 1 and 2 for corresponding samples of inspection results for two versions of defining the ROC point coordinates. **a** Version 1, **b** Version 2

For illustrating this methodology consider two sample sets of virtual ILI results for a pipeline segment, shown in Tables 4.41 and 4.42. Using this data and the described above algorithm, ROC curves are constructed, using the two versions for computing the coordinates of the curve (Fig. 4.71).

The visual assessment of the mutual disposition of the ROC curves in the 1×1 quadrant permits judgment on the level of effectiveness of the instruments used during an inspection. The curve which is higher and more to the left manifests a higher level of effectiveness of the inspection process. The curve which is closer to the benchmark diagonal [which connects points (0; 0) and (1; 1) of the quadrant 1×1], and is flatter, testifies that the two classes of test results considered above are close to being fully indistinguishable and point to a lesser efficacy of the inspection process. For the considered case all the constructed ROC curves are above the benchmark diagonal. According to the experimental graphs, the effectiveness of the measurement instruments used during inspection which yielded the second sample set was higher.

The most accurate method of comparing ROC curves is by assessing the areas under the curves: the larger area under the curve relates to higher efficacy of the measurement technology used. In the case being considered the assessment of areas under the curves is not a problem. For instance, for version 1 the areas under the curves 1 and 2 are equal correspondingly to 0.445 and 0.465, which concurs with the conclusion made earlier, where the second inspection is more successful (has higher utility) than the first one.

4.9.2 A Consistent Approximation of the POD Curve

The POD curve for the probability of detection which is used in the API 1163 Standard [1] is based on the deepest defect and shown in Fig. 4.72. On the assumption that d is the defect depth, and $d_{\max}$ is its maximal value, the API 1163 Standard approximates this curve as a simple exponential function

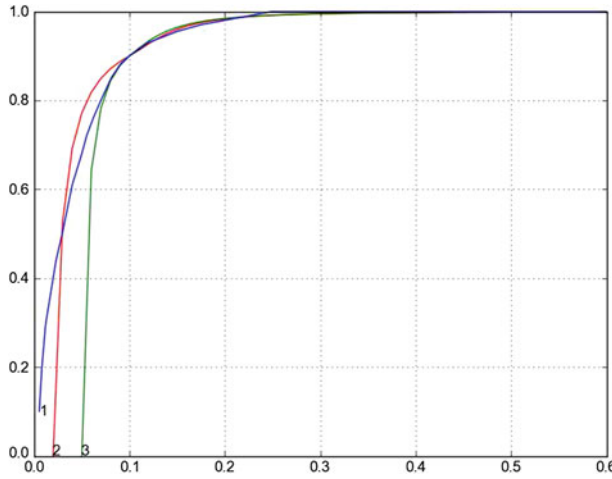


Fig. 4.72 The POD curve (line 1) from the API 1163 Standard, and the approximations of the P_{TD} curve for $d_0^* = 0, 02$ (line 2) and $d_0^* = 0, 05$ (line 3) and $P_{TD}(d^*) = 0.999$

$$\text{POD}(d_{\max}) = 1 - \exp(-qd_{\max}), \quad (4.88)$$

where $q = -[\ln(1 - \text{POD}_0)]/d_{\max 0}$, POD_0 is the value of POD for the *threshold depth of the defect*, and $d_{\max 0}$ is the *defect depth detection threshold*.

A consistent approximation of the P_{TD} curve (probability of true detection) has to have two asymptotes: a horizontal, at $P_{TD} = 1$ and a vertical, at $d = d_0 - \varepsilon$ (ε is a small value). One such curve was proposed as a *composition* of two hyperbolic-type functions (4.89) [46], which pass, correspondingly, through points $(d_0^*; 0)$, $(0.1; 0.9)$ and $(0.1; 0.9)$, (d_u^*, y_u) , and their coordinates, namely d_0^* , d_u^* , 0.1 and 0.9 are the so-called [1] essential variables of the ILI technology:

$$P_{TD}(d^*) = \begin{cases} 1 - \frac{a_0}{d^* - (d_0^* - a_0)} & \text{at } d_0^* \leq d^* \leq 0.1, \\ 1 - \frac{b_0}{d^* + b_1(d^*)^2 - b_2} & \text{at } 0, 1 \leq d^* \leq 1, \end{cases} \quad (4.89)$$

where $d^* = d/wt$; $d_0^* = d_0/wt$; $d_u^* = d_u/wt$; w is the pipe wall thickness; y_u is the close to unity value of the P_{TD} curve ($y_u = P_{TD_u} = 0.9999 - 0.999999$).

In formula (4.89) the first function is a hyperbole with parameter $a_0 = (0.01 - 0.1d_0^*)/0.9$. The second curve is given as an inverse quadratic function. It passes through points $(0.1; 0.9)$ and (d_u^*, y_u) , and in point $(0.1; 0.9)$ has a first-order derivative with respect to defect size equal to the same first derivative of the first function. Moreover, this curve has a horizontal asymptote $P_{TD} = 1$. Taking into consideration

the above conditions, the parameters of the second curve will be

$$\begin{aligned} b_0 &= 0.1(0.1 + 0.01b_1 - b_2); \\ b_1 &= C/B; \\ b_2 &= [0.1(A - 1) + 0.01b_1(A - 2)]/A. \end{aligned}$$

Here the following notations are used:

$$\begin{aligned} A &= a_0[0, 1 - (d_0^* - a_0)]^{-2}; \\ B &= -A[(y_u - 1)(d_u^*)^2 + 0.001] + 0.01(A - 2)(y_u - 0.9); \\ C &= A[(y_u - 1)d_u^* + 0.01] - 0.1(A - 1)(y_u - 0.9). \end{aligned}$$

The POD curves from the API 1163 Standard and the proposed approximation of the P_{TD} function in the form of a compound function (4.89), for $y_u = 0.9999$, $d_u^* = 0, 6$, $wt = 9$ mm, and different values of the parameter $d_0^* = d_0/wt$, which characterize the resolution d_0 of the instrument (measurement technology), are shown in Fig. 4.72.

4.10 Statistical Clusterization of the “Loss-of-Metal” Type Defects

Currently, when assessing the residual strength of pipelines with multiple geometrical pipe wall defects of the loss-of-metal type, some methods of their clusterization are used, by merging groups of closely located defects into one large defect.

The rules of clustering defects into one may differ from method to method. But the principle is one: if the distance between the edges of two adjacent defects is equal or less than a predetermined value, then such defects are combined into one. This rule is applied to both distances between defects—in the longitudinal and transverse (circumferential) directions as related to the pipeline.

Currently, all existing clusterization methods are *deterministic*. This means that all the sizes of defects and the distances between them are considered to be deterministic values (DVs). In reality, all these parameters are *random values*, because they are results of specific measurements, conducted by some ILI or DA tool (technology).

When schematizing, surface corrosion defects use designations as shown in Fig. 4.73.

The corrosion defects are subject to clusterization (are recognized as being interactive) if *simultaneously* following conditions hold true [51]:

$$\begin{aligned} l_{12} &\leq 2\sqrt{D \cdot wt}, \\ w_{12} &\leq \pi\sqrt{D \cdot wt}, \end{aligned} \tag{4.90}$$

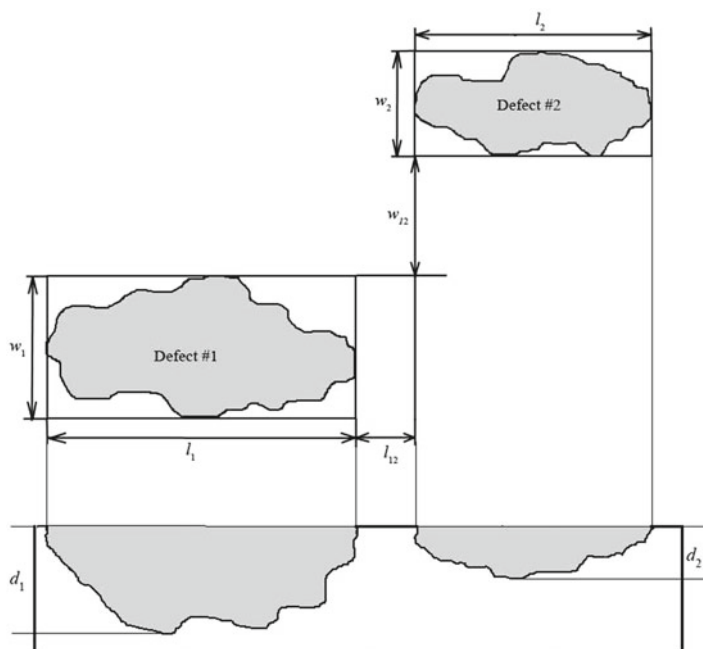


Fig. 4.73 Parameters of surface corrosion defects

where D is the outer diameter of the pipeline; and wt is the pipe web thickness.

In this case it is necessary to account for the interaction of adjacent defects on the inspected segment of the pipeline, and combine such defects into a group. Schematization of group defects with accounting for their interaction is conducted using the following rules [51].

A pipeline segment containing an extended zone with multiple corrosion defects is (virtually) divided into pieces, which extend in the longitudinal direction for not less than $5.0\sqrt{D \cdot wt}$, with an overlap of size $2.5\sqrt{D \cdot wt}$, as shown in Fig. 4.74. For each piece of the pipe a set of projection lines parallel to the pipe axis is arranged (see Fig. 4.74). These lines are spread in the circumferential direction of the pipe at a distance of $\pi\sqrt{D \cdot wt}$.

Now all the defects located in the considered piece of the pipe, which are at a distance less or equal to $\pi\sqrt{D \cdot wt}$, from both sides of each projection line (called current projection line), are projected on it (see Fig. 4.75).

The “thunderbolt type” arrows in Fig. 4.75 indicate that corresponding to them defects should be also projected on other (in the direction of the “thunderbolt type” arrow) projection lines.

If the projections of two or more defects on the current projection line overlap, they are merged into one defect, in which the length is equal to the length of the

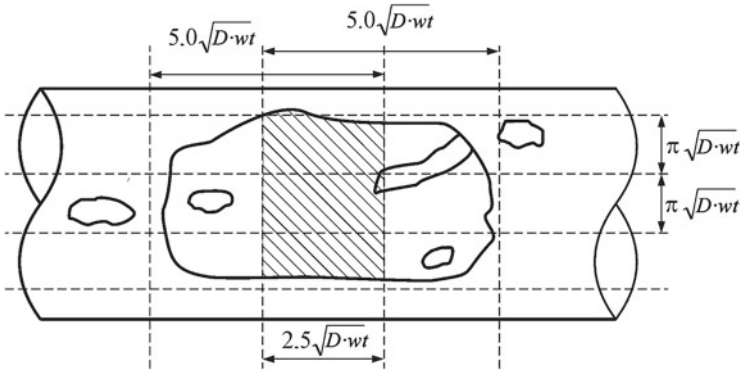


Fig. 4.74 Division of pipeline segment for accounting of the interaction of group defects [51]

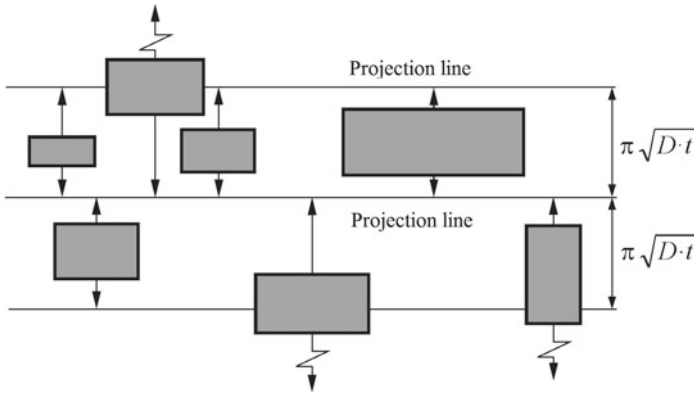


Fig. 4.75 Schematization of accounting for the interaction of the defects in the circumferential direction of the pipe [51]

total projection, and its depth is equal to the maximal depth among the defects being clustered (see Fig. 4.76).

The total depth, length, and width D , L , and W of the amalgamated defect, which consists of defects from number n to number m of the combined defect, are calculated using the following expressions [51]:

$$L = l_m + \sum_{i=n}^{m-1} (l_i + l_{i+1}), \quad n, m = 1, \dots, N,$$

$$W = w_m + \sum_{i=n}^{m-1} (w_i + w_{i+1}), \quad n, m = 1, \dots, N,$$

$$D = \max (d_m, d_{m+1}, \dots, d_n).$$

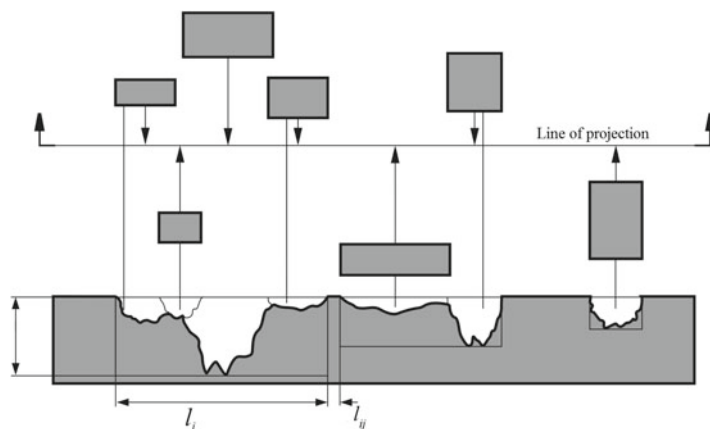


Fig. 4.76 Overlapping of the projections of single defects on the projection line which produce combined defects [51]

When conducting interim merger of an internal and an external defect of the pipe wall, the depth of the combined defect is taken as the sum of the depths of the clusterized defects (see Fig. 4.77). After this the obtained defect is considered to be external when conducting its subsequent unification with another defect.

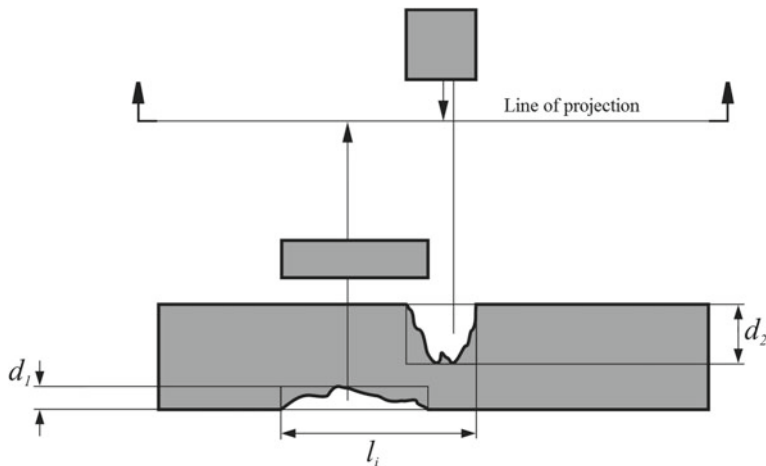


Fig. 4.77 Unification of an external and an internal defect [51]

4.10.1 Probabilistic Approach to Defect Clustering

In the general case, MEs could be comprised of *systematic* error (constant bias of the measurement instrument) as well as of random MEs, which change their value and sign from one measurement to another. In this case the mathematical model of the i th measurements takes the form

$$m = m^* + \varepsilon_m,$$

where m is the reading of the ILI tool; m^* is the true (immeasurable) value of the measured parameter (depth, length, width) of the defect; and ε_m is the random ME.

It is assumed that the random measurement errors ε_m are normally distributed with a mean of μ_ε (instrument bias) and variance σ_ε^2 .

The distances between the defects also contain MEs

$$\begin{aligned} d_{12} &= d_{12}^* + \varepsilon_d, \\ l_{12} &= l_{12}^* + \varepsilon_l, \\ w_{12} &= w_{12}^* + \varepsilon_w, \end{aligned} \tag{4.91}$$

where d_{12}^* (l_{12}^* , w_{12}^*) are the true values of the distances between the parameters of the two defects and ε_d (ε_l , ε_w) is the random MEs for the distance between the defects.

It is assumed that the random MEs ε_d , ε_l , ε_w are distributed with corresponding values of its means $\mu_{\varepsilon d}$, $\mu_{\varepsilon l}$, $\mu_{\varepsilon w}$ (constant bias or systematic ME) and variances $\sigma_{\varepsilon d}^2$, $\sigma_{\varepsilon l}^2$, $\sigma_{\varepsilon w}^2$.

As was shown above, in order to merge two defects, the following principle is used: if the distance between the edges of two adjacent defects is equal to or less than some predefined number R_c , such two defects are merged into one. The critical threshold R_c is found from conditions (4.90).

Hence, in order to make a decision in the stochastic format on whether to cluster or not to cluster two adjacent defects, all the defect parameters and the distances between them are considered to be RVs with known PDFs and corresponding cumulative distribution functions. These probabilistic characteristics are obtained via statistical analysis of the accumulated data when conducting ILI measurements, verification measurements, and/or DA measurements.

The proposed methodology of stochastic clusterization of corrosion defects permits conducting more accurate clusterization of defects, taking into account the random nature of their measurements. This permits avoiding cases of unnecessary clusterization, as well as preventing missing out on needed cases of clusterization, which, in the deterministic format, are considered safe and avoid clusterization. This permits obtaining more accurate assessments of the residual strength, reliability, and remaining life of pipelines with such defects.

Consider the proposed method in the case of the distance l_{12} between defects, measured along the pipeline axis. For other types of distances between the defects similar considerations apply.

Denote the CDF of l_{12} as $F_{l_{12}}(x)$. According to the properties of CDF

$$F_{l_{12}}(R_c) = P\{l_{12} \leq R_c\} = p_l. \quad (4.92)$$

Therefore, in order to check the conditions (4.90) for merging effects it is necessary to construct the CDF for the corresponding distances between the defects. By definition, from Eq. (4.92) it follows that R_c is a quantile of order p_l .

In the stochastic problem of clustering it is additionally necessary to know the ultimate permissible probability R_c that the indicated above conditions of merger of the defects are fulfilled. For instance, it is possible to assume that $P_c = 0.997$.

Then, in the stochastic setting, in order to make a decision on clustering two adjacent defects into one, the following condition should hold true:

$$p_l \geq P_c.$$

Now consider methods of defining the CDF for the distances between the defects, depending on the method of their measurement.

4.10.2 Probabilistic Clustering of Defects Based on Measurements by a Single Instrument

As the base in this model, distances between two arbitrary adjacent defects are taken, produced by an arbitrary measurement instrument. As was shown above, these distances d_{12} , l_{12} , w_{12} are RVs, which contain MEs.

The specifics of this problem consists in that here averaging over a set of measurements d_{12} , l_{12} , w_{12} is forbidden, because the decision on clusterization is done for each pair of adjacents separately, independent of the results of measuring other pairs of defects.

Rewrite Eq. (4.91) in the form

$$l_{12}^* = l_{12} - \varepsilon_l.$$

Because a separately taken distance between two arbitrary defects is considered, it is possible to maintain that the statistical assessment of the true value of the parameter (in our case, of the distance between defects) will have a PDF, which is analogous to the PDF of MEs. In other words, the true value of l_{12}^* will have the same PDF as the ME, with the same variance $\sigma_{\varepsilon_l}^2$, but with the mean equal to $l_{12} - \mu_{\varepsilon_l}$.

If the MEs for the distance l_{12} are normally distributed, then the decision on merging two defects for the distance l_{12} will be taken, depending on the outcome of fulfillment of the inequality

Table 4.43 Gas pipeline parameters

Parameter	Value
Outside diameter, mm	1420.0
Pipe wall thickness, mm	18.7

Table 4.44 Defect parameters

Defect #	Length l , mm	Width w , mm	Depth d , mm
1	50	30	2
2	100	50	6
3	100	120	3
4	200	150	4

Table 4.45 Distances between the defects

Pair of defects (ij)	Distance along the pipeline l_{ij} , mm	Circumference distance w_{ij} , mm
1–2	100	100
2–3	230	200
3–4	310	150

$$F_{l_{12}}(R_c) = \frac{1}{2} \left[1 + \operatorname{erf} \left(\frac{R_c - (l_{12} - \mu_{\varepsilon l})}{\sigma_{\varepsilon l} \sqrt{2}} \right) \right] = p_l \geq P_c. \quad (4.93)$$

In this formula CDF of the normal distribution is expressed through the error function $\operatorname{erf}(x)$, a.k.a. the Gauss error function, or the probability integral. It should be noted that preliminary analysis of the statistical data on the lengths and widths of corrosion defects shows that they depend on their depths. Some researchers/authors split the defects, depending on their depth, into three separate groups: shallow, medium, and deep. Each group has its own MEs for the length and width of the defects. Hence, when clusterizing defects from different groups it is necessary to account for the different values of their ME PDF parameters.

Example 4.10.1 Consider a pipeline segment with four surface corrosion defects. Parameters of the gas pipeline, the defects, and the distances between them are given in Tables 4.43, 4.44 and 4.45.

Check the necessity for accounting for the interaction of defects using conditions (4.90):

$$\begin{aligned} 2.0\sqrt{D \cdot wt} &= 2.0\sqrt{1420 \cdot 18.7} = 326 \text{ mm}, \\ \pi\sqrt{D \cdot wt} &= \pi\sqrt{1420 \cdot 18.7} = 512 \text{ mm}. \end{aligned}$$

The conditions being checked show that the distances between the considered defects in the longitudinal and circumferential directions are smaller than the above

values. Hence, in the deterministic case, it is necessary to account for their interaction and combine them into one group defect.

According to the specification of the used measurement tool, the tolerances when measuring the length and the width of the defect are correspondingly ± 10 and ± 12 mm with an 80 % certainty. Assume that the MEs are normally distributed, and then the SD of the ILI tool ME when measuring the lengths and the widths of the defects are equal, correspondingly, to $10/1.28 = 7.81$ mm, $12/1.28 = 9.38$ mm, where 1.28 is the quantile of order $(1 + 0.8)/2$ of the normal PDF of the ME. Assume that the mean values of the MEs for the defect lengths and widths are correspondingly -3.00 and -5.00 mm.

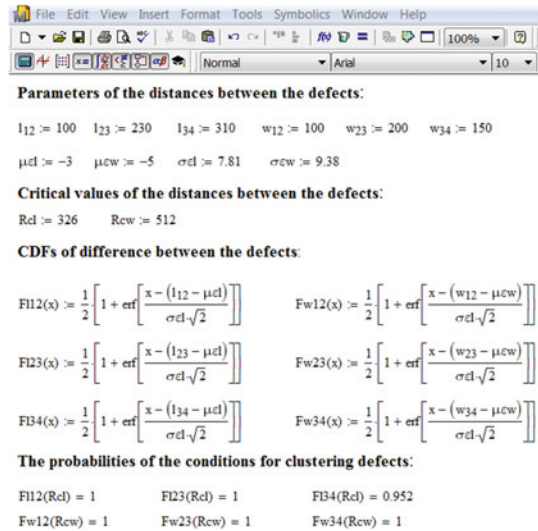
According to Sect. 4.10.2, the distances between the defects will have a normal distribution with the following parameters:

$$\begin{aligned} l_{12}^* &\in N(100 + 3, 4.69), & w_{12}^* &\in N(100 + 5, 6.25), \\ l_{23}^* &\in N(230 + 3, 4.69), & w_{23}^* &\in N(200 + 5, 6.25), \\ l_{34}^* &\in N(310 + 3, 4.69), & w_{34}^* &\in N(150 + 5, 6.25). \end{aligned}$$

Conduct probabilistic clusterization of defects using the MathCAD system. The calculation of the values of the CDF for the distances between defects for critical values $R_{cl} = 326$, $R_{cw} = 512$ is shown in Fig. 4.78.

Take the ultimate permissible probability $P_c = 0.997$. Then, according to Fig. 4.78, it is necessary to combine the first defect with the second, and then cluster the resulting group defect with the third defect, because for each of these defects simultaneously hold true for the following conditions:

Fig. 4.78 Probabilistic clusterization of defects based on measurements of one tool, conducted in MathCAD



$$\begin{cases} F_{l12}(R_{cl}) = 1 > 0.997, \\ F_{w12}(R_{cw}) = 1 > 0.997, \end{cases} \quad \begin{cases} F_{l23}(R_{cl}) = 1 > 0.997, \\ F_{w23}(R_{cw}) = 1 > 0.997. \end{cases}$$

At the same time these conditions are not fulfilled simultaneously for the distance between the third and the fourth defect $F_{l34}(R_{cl}) = 0.952 < 0.997$.

The parameters of the combined defect will be

$$L = l_1 + l_{12} + l_2 + l_{23} + l_3 = 50 + 100 + 100 + 230 + 100 = 580 \text{ mm},$$

$$W = w_1 + w_{12} + w_2 + w_{23} + w_3 = 30 + 100 + 50 + 200 + 120 = 500 \text{ mm},$$

$$D = \max \{2, 6, 3\} = 6 \text{ mm}.$$

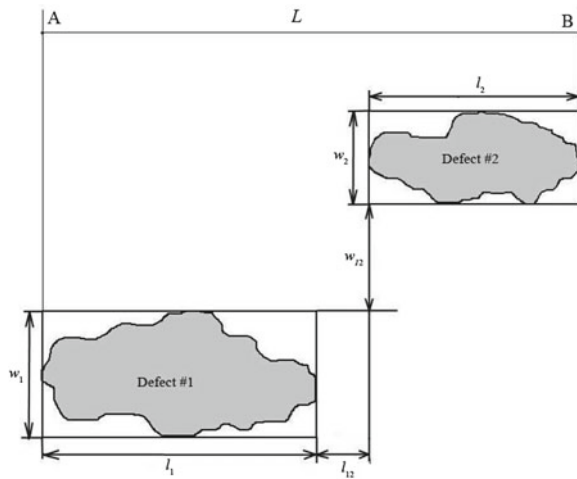
4.10.3 Probabilistic Clustering of Defects Using Results of Measurements of Screen Images of Defects as Provided by the ILI Tool

It is not always possible to directly measure the distance between the edges of two adjacent defects. This is due to the fact that during the computer analysis of defect images, obtained during ILI, these distances are not measured, but are calculated. The ILI data provides a possibility to define coordinates of points A and B (Fig. 4.79) and, hence, the distance L between them.

Then it is possible to write

$$L = l_1 + l_{12} + l_2 \Rightarrow l_{12} = L - (l_1 + l_2).$$

Fig. 4.79 Defining the distance between defects using their images



Due to the facts that l_1, l_2, l_{12} are RVs, it is necessary first to find the probabilistic characteristics of the sum of RVs $l_s = l_1 + l_2$, using the convolution formula for the sum of two independent RVs:

$$f_{l_s}(x) = \int_{-\infty}^{\infty} f_{l_1}(x-y)f_{l_2}(y)dy,$$

where $f_{l_1}(x)$ is the PDF of RV l_1 , $f_{l_2}(x)$ is the PDF of RV l_2 .

Then the CDF for l_s is equal to

$$F_{l_s}(x) = \int_{-\infty}^x dz \int_{-\infty}^{\infty} f_{l_1}(z-y)f_{l_2}(y)dy.$$

According to [52] CDF of l_s can be rewritten in the form

$$F_{l_s}(x) = \int_{-\infty}^{\infty} F_{l_1}(x-y) dF_{l_2}(y) = \int_{-\infty}^{\infty} F_{l_1}(x-y)f_{l_2}(y)dy,$$

where $F_{l_1}(x)$ is the CDF of RV l_1 .

As L also is a RV, the CPF l_{12} is found using the convolution integral for the difference of two RVs L and l_s :

$$F_{l_{12}}(x) = \int_{-\infty}^{\infty} F_L(x+y)f_{l_s}(y)dy,$$

where $F_L(x)$ is the CDF of RV L , and $f_{l_s}(x)$ is the PDF of RV l_s .

If the lengths of the two considered defects are distributed normally, the RV l_{12} will also have a normal distribution with parameters $\mu_{l_{12}} = \mu_L - \mu_{l_1} - \mu_{l_2}$; $\sigma_{l_{12}}^2 = \sigma_L^2 + \sigma_{l_1}^2 + \sigma_{l_2}^2$, where $\mu_L, \mu_{l_1}, \mu_{l_2}$ are the means of RVs L, l_1, l_2 accordingly, and $\sigma_L^2, \sigma_{l_1}^2, \sigma_{l_2}^2$ are their variations.

Consider some cases when RVs l_1, l_2, L are distributed not normally.

Case 1. RVs l_1, l_2, L are distributed lognormally. In this case the distribution of the RV $l_s = l_1 + l_2$ is approximated by another lognormal distribution, i.e., $l_s \in \text{LogN}(m, \sigma^2)$, where

$$\mu = \ln \left(\exp \left[\mu_1 + \frac{\sigma_1^2}{2} \right] + \exp \left[\mu_2 + \frac{\sigma_2^2}{2} \right] \right) - \frac{\sigma^2}{2},$$

$$\sigma^2 = \ln \left(\frac{\exp(2\mu_1 + \sigma_1^2) (\exp(\sigma_1^2) - 1) + \exp(2\mu_2 + \sigma_2^2) (\exp(\sigma_2^2) - 1)}{\left(\exp \left[\mu_1 + \frac{\sigma_1^2}{2} \right] + \exp \left[\mu_2 + \frac{\sigma_2^2}{2} \right] \right)^2} + 1 \right).$$

In this formula μ_1, σ_1 are the parameters of the PDF of the RV and l_1, μ_2, σ_2 are the parameters of the PDF of the RV l_2 :

$$\begin{aligned}\mu_1 &= \ln m_1 - \frac{\sigma_1^2}{2}, \quad \sigma_1^2 = \ln \left(1 + \frac{s_1^2}{m_1^2} \right), \\ \mu_2 &= \ln m_2 - \frac{\sigma_2^2}{2}, \quad \sigma_2^2 = \ln \left(1 + \frac{s_2^2}{m_2^2} \right),\end{aligned}$$

where m_1, s_1^2 (m_2, s_2^2) are the mean and variation of RV l_1 (l_2).

Then the CDF of RV l_{12} has the form

$$F_{l_{12}}(x) = \frac{1}{2\sigma\sqrt{2\pi}} \int_0^\infty \left(1 + \operatorname{erf} \left(\frac{\ln(x+y) - \mu_L}{\sigma_L\sqrt{2}} \right) \right) \frac{1}{y} \exp \left(-\frac{(\ln y - \mu)^2}{2\sigma^2} \right) dy.$$

Case 2. RVs l_1, l_2, L are distributed according to exponential law. In this case the PDF of RV l_s has the form

$$f_{l_s}(x) = \lambda_1 \lambda_2 \int_0^\infty \exp(-\lambda_1(x-y)) \exp(-\lambda_2 y) dy = \frac{\lambda_1 \lambda_2 \exp(-\lambda_1 x)}{\lambda_1 - \lambda_2}, \quad \lambda_1 < \lambda_2,$$

where λ_1 is the distribution parameter of RV l_1 , and λ_2 is the distribution parameter of RV l_2 .

Then the CDF of RV l_{12} has the form

$$\begin{aligned}F_{l_{12}}^*(x) &= \frac{\lambda_1 \lambda_2}{\lambda_1 - \lambda_2} \int_0^\infty [1 - \exp(-\lambda_L(x+y))] \exp(-\lambda_1 y) dy \\ &= -\frac{\lambda_2}{\lambda_1 - \lambda_2} \left(1 + \frac{\lambda_L \lambda_2^2 \exp(-\lambda_L x)}{\lambda_L - \lambda_2} \right), \quad \lambda_1, \lambda_L < \lambda_2.\end{aligned}$$

Case 3. RVs l_1, l_2, L are distributed according to the Weibull law. In this case the PDF of RV l_s has the form

$$f_{l_s}(x) = \frac{k_1}{\lambda_2} \frac{k_2}{\lambda_2} \int_0^\infty \left(\frac{x-y}{\lambda_1} \right)^{k_1-1} \left(\frac{y}{\lambda_2} \right)^{k_2-1} \exp \left(-\left(\frac{x-y}{\lambda_1} \right)^{k_1} \right) \exp \left(-\left(\frac{y}{\lambda_2} \right)^{k_2} \right) dy, \quad (4.94)$$

where λ_1, k_1 are the distribution parameters of RV l_1 , and λ_2, k_2 are the distribution parameters of RV l_2 , which can be evaluated via mathematical expectation and variance of these RV.

The integral from formula (4.94) could not be expressed analytically; however, the Weibull distribution can be well approximated by a lognormal distribution, i.e.,

if the $X \in W(\lambda, k)$, then [25]: $X \approx LN(m, \sigma)$, where parameters of the distribution are connected with each other by the following relations: $m = \mu_x / (1 + v_x^2)$, $\sigma = \ln(1 + v_x^2)$, μ_x is the mathematical expectation of RV X , and v_x is the variation coefficient of the RV X . Hence, this case can be boiled down to Case #1.

The defined above integrals can be calculated numerically for each specific value of x using, for instance, the MathCAD programming system.

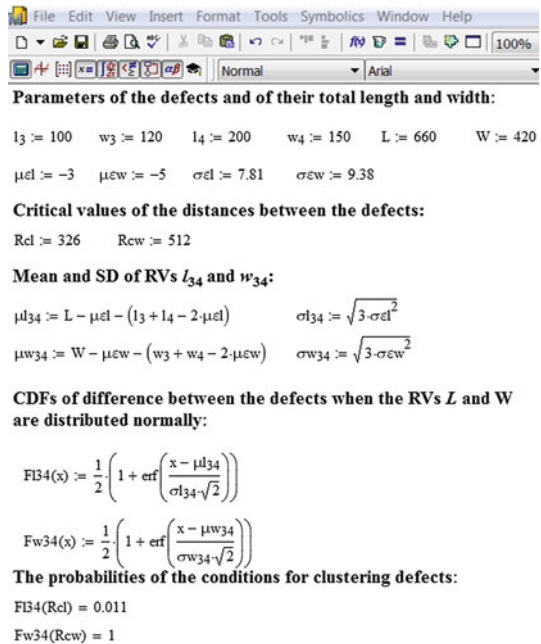
Example 4.10.2 Consider probabilistic clusterization of defects #3 and #4 from the previous Example 4.10.1. According to case #1, the lengths and widths of the defects are distributed normally with parameters:

- for defect #3: length with mean $\mu_{l_3} = l_3 - \mu_{\varepsilon l} = 100 + 3$ mm and SD $\sigma_{\varepsilon l} = 7.81$ mm; width with mean $\mu_{w_3} = w_3 + \mu_{\varepsilon w} = 120 + 5$ mm and SD $\sigma_{\varepsilon w} = 9.38$ mm;
- for defect #4: length with mean $\mu_{l_4} = l_4 - \mu_{\varepsilon l} = 200 + 3$ mm and SD $\sigma_{\varepsilon l} = 7.81$ mm; width with mean $\mu_{w_4} = w_4 + \mu_{\varepsilon w} = 150 + 5$ mm and SD $\sigma_{\varepsilon w} = 9.38$ mm.

Then RVs $l_s = (l_3 + l_4) \in N(\mu_{l_3} + \mu_{l_4}; \sqrt{2 \cdot \sigma_{\varepsilon l}^2})$ and $w_s = (w_3 + w_4) \in N(\mu_{w_3} + \mu_{w_4}; \sqrt{2 \cdot \sigma_{\varepsilon w}^2})$.

Let RV $L = l_3 + l_{34} + l_4$ is distributed normally with mean $\mu_L = L - \mu_{\varepsilon l} = 610 + 3$ mm and SD $\sigma_{\varepsilon l} = 7.81$. RV $W = w_3 + w_{34} + w_4$ is distributed normally with mean $\mu_w = W - \mu_{\varepsilon w} = 420 + 5$ mm and SD $\sigma_{\varepsilon w} = 9.38$. Then CDFs of RVs l_{34} , w_{34} for critical values $R_{cl} = 326$; $R_{cw} = 512$ are calculated by formula (4.93).

Fig. 4.80 Probabilistic clusterization of defects using measurements of defect images, and MathCAD



Calculations for this case, conducted in the MathCAD system, are given in Fig. 4.80, according to which the clusterization of defects #3 and #4 is not necessary, as the conditions (4.90) are not being fulfilled (not occur) simultaneously.

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Chapter 5

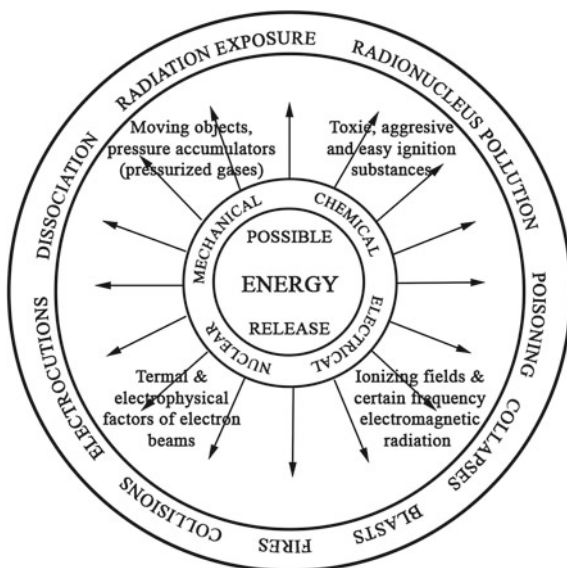
The Human Dimension of Pipeline Integrity and Safety

This chapter describes a new method of quantitative assessment of the influence of the human factor (HF) reliability on safety and risk analysis of pipelines throughout their life cycle, based on applied theory of orgraphs (oriented graphs). The chapter describes the main components, means and methods of a holistic and quantitative human reliability analysis (QHRA) using quantitative values of human error. A generalized model of the decision-maker is used. Three types of DMs are considered: members of maintenance/repair crews, ILI diagnosticians, and different rank DMs who operate or own the pipeline.

The scenario of developing a pipeline catastrophe with possible casualties, environmental pollution, and large economic losses is presented as a chain of losses of pipeline performance homeostasis by the DM (or a group of DMs) who makes a mistake each time there is some unexpected input during the pipeline operation, when trying to bring back the existed homeostasis. The scenario incorporates some quantitative description of human behavior based on the results of laboratory, shop and field experiments and statistical observations, conducted and accumulated over the years in the pipeline and adjacent industries. It also accounts for individual human errors, which arise during ILI; for quality and time of performing different types of pipeline maintenance and repair, and for probabilities of making wrong decisions by a high-rank DM.

The applied orgraph theory is used to choose, out of a set of possible measures (the effect and cost of implementation of each of them is a known value), a subset of measures that: (1) delivers maximal decrease of the probability of pipeline disaster-type failure or (2) for a given amount of total available financial means, selects a subset of measures that maximizes the decrease of the disaster-type failure. Two real life cases are described.

Fig. 5.1 The nature of technological hazards



5.1 Intrinsic Energy–Entropy Source of Risk in Pipelines

According to the second principle of thermodynamics, creation of synthetic substances, chemically clean elements, production and accumulation of energy, processing, refining and transportation of natural materials and the like, are all “illegal,” because they lower (not raise) the level of entropy. Moreover, they are dangerous, because they overcome natural energy barriers and by this virtue, bring the systems, which perform the above processes, into an unstable and, therefore, dangerous state. Being unstable, these systems tend to stability with a corresponding release of energy and growth of its entropy. The possible sources of danger that arise here are illustrated by Fig. 5.1.

5.2 Holistic Approach to Assessing the Role of Human Factor

Industrial activity is a process where specifics of a human organism and environmental factors tightly intermingle. Technical systems become interdependent exactly because of the human connections between them. According to statistics, around 70–80% of all dangerous situations and failures directly or indirectly are due to human mistakes. Therefore, in order to correctly assess the role of human factor a holistic approach should be used. In the case under consideration this means that the system should be a generalized man–machine–structures–environment system

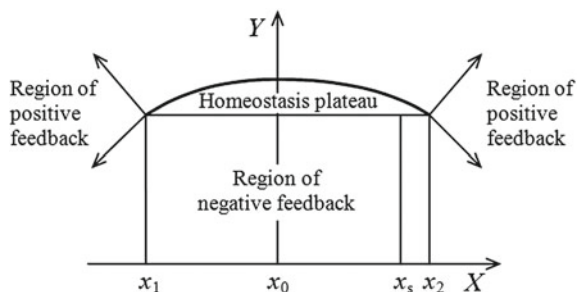
(MMSES). Its model includes HF, machines, structures, facilities, industrial environment, operational technology, and modes of their interaction.

Modern pipeline systems are critical infrastructures in the form of complex automated systems with control contours that are being locked (closed) by human beings. Pipeline systems during their life cycle are undergoing stages of design, manufacture, construction, commissioning, diagnostics and control, maintenance, repair, rehabilitation and upgrade, decommissioning and disposal. A correct and justified account of the human factor on each of the above stages is needed to achieve maximal efficacy and safety.

5.3 The Homeostasis Concept

Homeostasis is the relative stationarity of content and properties of the body's internal environment and stability of the main psychological functions of the organism; e.g., the ability of the organism to autoregulate itself with the change of the external environment [1]. Homeostasis can be violated by chemical substances, extreme psychological stress, caused by different types of external nonchemical causes—loss of self-control, fear, panic, anger, death threat, etc. Autoregulation of a biological system (in our case human being) should be considered as a regulation of the dynamic state of an open system, influenced by a biological rhythm. At this, homeostasis includes not only the dynamic stationarity, but also the stability of its main biological functions. Influence of a detrimental substance may cause not only changes of certain parameters of a biological object, but also damage of the homeostasis regulating systems, e.g., violation of the latter. Relatively small amounts of detrimental substance or reasonable stress levels do not violate the homeostasis (Fig. 5.2) [1]. In this figure x_1, x_2 is the homeostasis region. Usually, it is convex, with somewhat fuzzy boundaries, because the optimal parameters Y of the biological object themselves change in time. Outside the x_1, x_2 region the homeostasis is violated, which means abrupt change of the Y values. The x_1 and x_2 are called the threshold values of X . The region of homeostasis is the region of the negative feedback, because here the organism works to bring itself back into the initial, stationary condition/state. When

Fig. 5.2 The homeostasis scheme: Y is some property of a biological object; X is the concentration/dose of a harmful detrimental substance or stress intensity level; x_s is the ultimate safe level of influence by this substance stress; x_1 and x_2 are the threshold values of x



homeostasis is severely violated, the biological object enters the region of positive feedback. In this case the changes caused by detrimental substances/stresses become irreversible and the object more and more deviates from the stationary state, and, correspondingly, makes increasing number of dangerous mistakes.

The outlined above permits addressing the psychological problems of homeostasis in general, and human behavior and mistakes, specifically.

5.4 Workability (Capacity for Work)

Human capacity for work is a function of time of the day, shift, and type of work being executed (Fig. 5.3). It depends on external (information signal structure, workplace, environment, relations in the team), and internal (level of training, emotional stability) factors. During the 24-hour day human capacity for work cyclically changes (Fig. 5.4). Between 6:00–15:00 the capacity is growing, being maximal in the time interval of 10:00–12:00. In the second interval (15:00–22:00) capacity grows again, being maximal at 18:00. In the third interval (22:00–6:00) capacity is well below average. Historically, the worst mistakes with grave consequences (e.g., Bhopal catastrophe) were made in the interval between 2:00 and 4:00, when human physiological activity and alertness are at their lowest.

The capacity for work also changes during the week. The work-in acclimatization falls on Monday, high capacity—on Tuesday—Thursday. On Friday and, especially, on Saturday one sees signs of developing fatigue. The intensity of human mistakes/errors is directly correlated with work capacity.

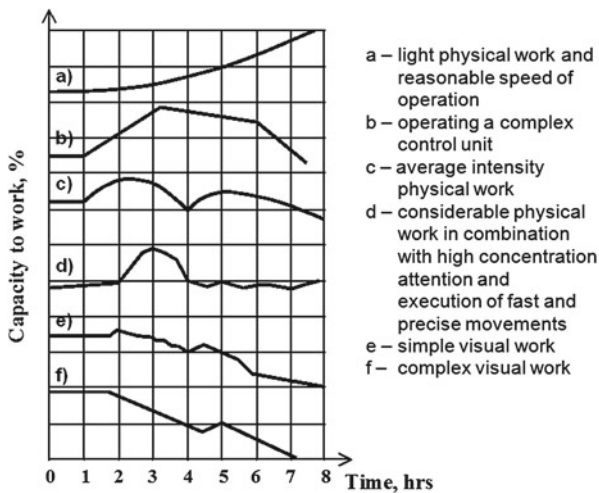


Fig. 5.3 The change of human workability during one shift depending on the type of executed work

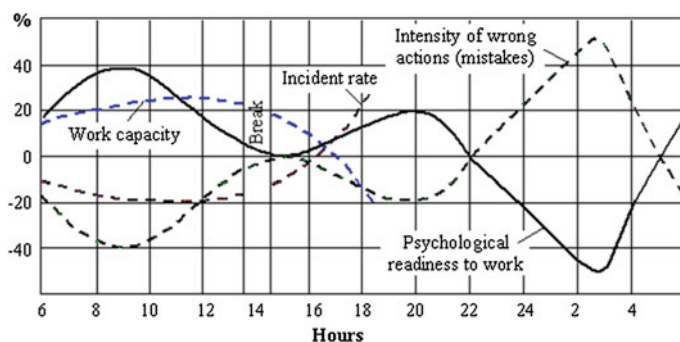


Fig. 5.4 24-hour change of human properties and actions

5.5 Three Types of Human Factor

When analyzing reliability and safety of pipeline systems, three categories of HF should be accounted for: HF1, HF2, and HF3:

1. HF1 describes repair/maintenance/ILI crew members behavior;
2. HF2 describes monitoring, NDT specialists, and diagnosticians/data analysts performance;
3. HF3 describes reliability of DMs of different levels—from plant line operators and up to DMs who own or run the pipelines (influence the total plant modus operandi).

These three groups of human factors are discussed below.

5.6 Psychological Causes of Mistakes

In any MMSE system (including a pipeline) the human being is the most variable component. In any given problem his/her behavior is influenced by some million individual factors.

Performance of an operator (HF1–HF3) in general consists of the following stages: perception of information, its assessment, analysis, and generalization on the basis of criteria formulated and given beforehand; decision-making on actions; execution of the decision. In all these stages a human being can make mistakes.

By erroneous action one understands an action that deviates from normal; e.g., anticipated, expected and, by virtue of this, leads to grave consequences: casualties,

fatalities, loss of property. Generally speaking, mistakes are unconscious dangerous actions. In some cases such dangerous or inadequate actions are committed consciously, deliberate, and are classified as violations; in other cases when the operator does not realize he is executing a dangerous action, it is classified as a mistake. Going one step further, one can say that a malicious, conscious act aimed at putting in danger innocent human beings can be classified as a terrorist act.

The causes of mistakes can be divided into direct, main, and contributing.

Direct causes depend on their placing in the psychological structure of operators action (perception; decision-making, return action, etc.) and the type of this action; e.g., on psychological pattern that defines optimal action: disparity of psychological ability of data processing (volume or speed, relation to the distinction threshold, insufficient duration of the signal, etc.); insufficient skills (standard actions in a nonstandard situation, etc.) and attention structure. *Main* causes are connected with the workplace, work organization, operator preparedness, state of mind and health. *Contributing* causes depend on particular failures of the personality, state of her/his health, external environment, selection, and training.

The causes of mistakes can be also classified as orientation mistakes (insufficient information); decision mistakes (wrong decision); action mistakes (wrong action).

Using other principles mistakes can be classified as irreversible and reversible, systematic, and random. In most cases mistakes are the result of change in operators physical and mental state.

5.7 General Classification of Human Errors

In general, error is a departure from the accepted practice. If it is unintentional, and due to insufficient knowledge, it is dubbed as *conceptual error*. If it is done during execution of a right decision, it is an *error of execution*. *Error of intention*, by definition, is an intentional departure from the accepted practice. The logical paths that lead to the above types of errors are shown in Fig. 5.5.

The personnel (HF1–HF3) may commit conceptual errors by:

- Not being aware of the appropriate method, model, technology, tool, information;
- Not knowing how to use the method, model, technology, tool, or information;
- Failing to do something because she/he did not know it should be done;
- Not knowing the acceptable level of effort or care;
- Not knowing the possible consequences;
- Failing to understand assumptions or limitations;
- Using simplifying assumptions which were incorrect.

Errors of execution occur when a person:

- Misread, miswrote, misdrew;
- Misheard, misspoke;
- Misoperated;

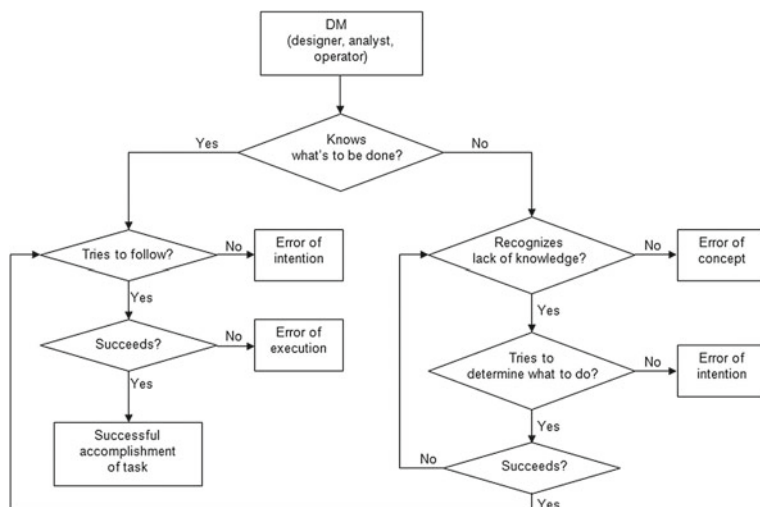


Fig. 5.5 Logical paths to different types of errors (of concept, of execution, of intention)

- Forgot, lost, misplaced, left out;
- Did not think of, did not hear, did not see;
- Heard, saw but did not recognize.

A person may commit an intentional error for any number of reasons, including, but not restricted to:

- Expedience;
- To save time, money, energy, or bother;
- To avoid responsibility or liability;
- To avoid embarrassing someone else;
- Because she/he was requested or required by a higher rank DM, contract, or regulations to complete current work/obtain future work;
- Because he/she did not have the capability to do the work according to accepted practice;
- Because it is impossible for anyone to do the work under accepted practice;
- Because the DM accepted risk which was recognized as unacceptable;
- Because the DM chose to depart from common practice within acceptable reason.

The professional reader can add to the above three lists of causes of errors by drawing from his own experience.

The role of human error in structural failures is being extensively studied [2–4].

A considerable discrepancy is being observed between the theoretical and actual failure rates. This discrepancy is due to incompleteness of existing theoretical models. Most of the failures occur as a result of human errors which were not included in the analysis.

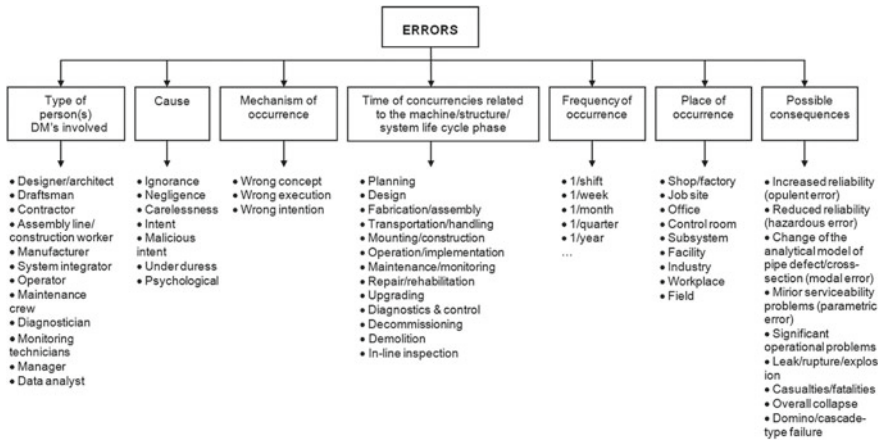


Fig. 5.6 General classification of human error

Classification of human errors made at different stages of their interaction in the MMSE system is important in identification of the error occurrence mechanisms and selection of efficient control measures.

Errors can be classified by who made the error, at what phase of the system life (time), where the error was made, root cause (why was it made), frequency of occurrence, mechanism of occurrence, consequences (see Fig. 5.6). Additional types of classification with respect to pipelines are given below.

Surveys of structural failures indicate that human error is the major cause [4]. Moreover, error in design or construction often greatly exacerbates the damaging effect of other hazards and may lead to cascade failures and domino effects. Even more so this is true for pipeline systems.

5.8 Possible Causes of Errors in the Life Cycle of Pipeline Systems

The probability of pipeline structural failure due to a human factor depends mostly on the quality of the control of human errors—their causes and consequences.

Causes of error during design and defect assessment may be specified as follows:

- Incomplete understanding of pipeline structural behavior;
- Insufficient analysis of loads during construction and operation stages;
- Time pressure;
- Specification ambiguity;
- Discontinuity in design process;

- Lack of experience;
- Communication problems.

Errors in defect assessment depend on the method of assessment, experience of the person who does the assessment and the checker. There are three ways to perform defect assessment: by hand, by computer, and by using standardized tables and charts.

Typical **errors in by hand calculations** include:

- Calculation errors;
- Omissions of critical loading conditions;
- Use of wrong units;
- Incorrect interpretation of codes.

Errors in computer calculations are hard to detect. Moreover:

- It is easy to add errors when updating a program;
- The user often does not know the assumptions of the program;
- Programs may not be suited for some defects;
- Complicated programs increase the probability of errors.

Error when assessing defects using standardized tables and charts may result from misuse of tables or charts.

Results of surveys indicate that errors result from wide variety of causes and can affect any part of the pipeline or pipeline system component.

5.9 Classification of Human Errors Associated with In-Line Inspections (Analysis of API 1163)

In this section our main efforts are to assess the influence of the HF on ILI. Main sources and possible root causes of ILI are given in Table 5.1. Human involvement in the process of in-line inspection is given in Fig. 5.7. The human part of the process of anomaly detection and evaluation (API 1163 Standard) is given in Fig. 5.8. The human involvement in the ILI verification process is shown in Fig. 5.9. A typical chain of errors, causes, and consequences is given in Fig. 5.10.

A human mistake/error can enter at any place in the chain of events that characterize the ILI process. Some of these errors do not influence the quality/precision of the ILI inspection, others do.

Sources of errors in ILI can be classified as those due to the ILI system itself and those due to hands-on measurements made of a given parameter (i.e., evaluating/sizing characteristic). Errors due to the ILI system proper can be further classified as:

Table 5.1 Main sources and possible root causes of ILI mistakes/errors/limitations (API-1163)

PL intrinsic properties	ILI tool			ILI technology	Human factor
	Basic performance metrics	Hardware	Software		
Metallurgy anomaly orientation; Max/Min pipe thickness	Detection identification location: log distance; o'clock position. Sizing/Measuring: depth; length; width	Magnet strength; Magnetization system; Components dimension; Amplitude and angle	Analysis algorithms: preprocessing; identification; characterization of signals; measurement; interaction rules	Energy characteristics; Poor cleaning; ILI tool speed out of range; Sensor lift-off	Before ILI; During ILI; After ILI

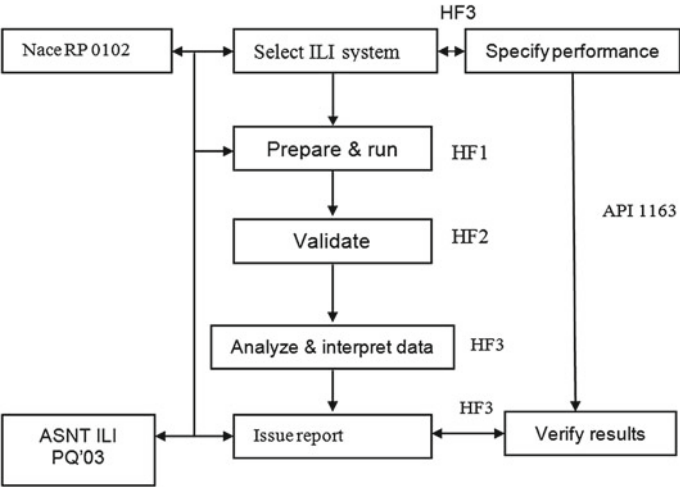


Fig. 5.7 Human involvement in the process of in-line inspection (API-1163 Standard)

- **Systematic** (result from known but unaccounted for causes, such as sensor lift-off);
- **Random** (non repeatable, and other errors without repeatability, due to a plethora of man-related sources from physical condition to interpretation of the obtained data);
- **Anomaly specific** (when sizing the geometry of an anomaly or assembly of anomalies).

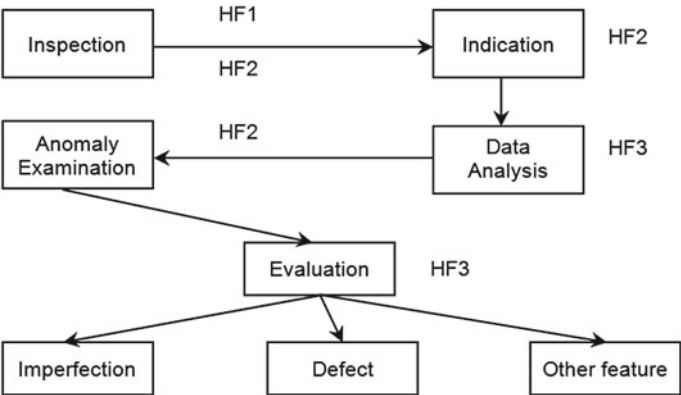


Fig. 5.8 Human involvement in the process of anomaly indication and evaluation (API-1163 Standard)

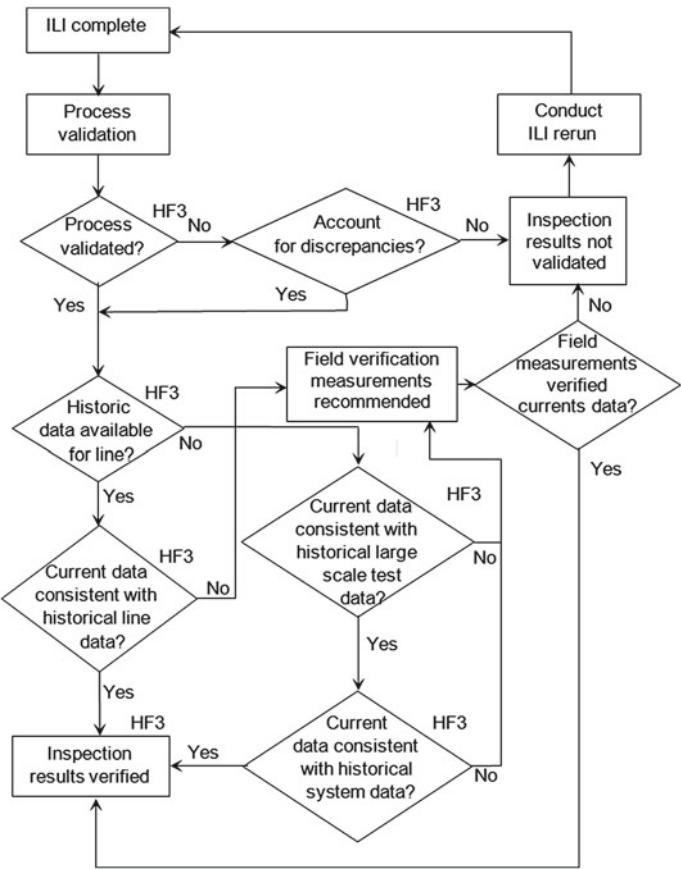


Fig. 5.9 Human involvement in the process of in-line inspection verification (API-1163 Standard)

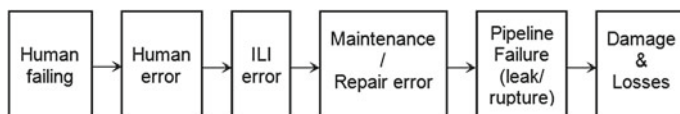


Fig. 5.10 Typical chain of errors, causes, and its consequences

The errors due to hands-on measurements made of a given parameter can be classified as:

- Systematic, for instance, due to using a measurement with an intrinsic systematic error;
- Random (due to a plethora of man-related sources from physical condition to interpretation of the obtained data).

Significant sources of errors in aboveground measures can result from:

- Topography effects;
- Discrepancy between the actual and the aboveground pipeline route;
- Erroneous placement/interpretation of AGMs.

Errors in distances measured by ILI tools usually result from odometer wheels slippage, sticking, or traveling over debris. In order to minimize these errors ILI distances are recalibrated using as-built pipeline data.

Errors during defect identification/sizing can be related (but not restricted) to:

- Poor data base of images of different types of defects;
- Distortion of image of defects;
- Overlapping of images of adjacent anomalies;
- Low resolution of defect images;
- Insufficient diagnostician qualification;
- Poor defects sizing algorithms;
- New type of uncovered defect(s), etc.

According to ASNT—ILI PQ 2003 and API 1163 Standard human factor permeates all operations of data handling:

- Taking (HF1);
- Reducing (HF2);
- Analyzing (HF2, HF3);
- Reporting the resultant data (HF3).

In the ILI process validation the HF manifests itself when following operations are conducted:

- Review of the pipeline route, geometry and ILI operation conditions (HF2):
 - Review of the setup and operation of the ILI tool (HF2);
 - Automated analyses (HF2);
 - Manual or other adjustments of data or grading (HF2, HF3);
 - Identification, evaluation, and integration of supplemental data (HF2, HF3);
- Review of reported anomaly types and characteristics relative to performance specifications (HF1);
- Comparison of reported and actual locations of components and appurtenances (HF1);
- Evaluation and resolution of revealed inconsistencies (HF2, HF3).

In the verification measurements process the HF is present when:

- Cleaning pipe thoroughly (HF1);
- Inspecting for cracking (HF2);
- Providing a rubbing of the anomaly geometry, take a photo (HF1);
- Measuring actual wall thickness, mark on sketch/ photo feature type, log distance, o' clock position;
- Marking on feature location sheet the distance to gird weld, and mark feature dimensions;
- Measuring and documenting exposed anomalies (HF1).

In the ILI data analysis HF3 is present when:

- Creating corresponding software;
- Preprocessing of ILI raw data;
- Characterizing/identifying signals;
- Applying interaction rules;
- Pressure-based assessment of different types of defects.

In an **ILI quality management** system, HF is present in the stages of:

- ILI tool design (HF3);
- Testing (HF2, HF3);
- Field operations (HF1, HF3);
- Data analysis (HF2, HF3);
- Support services (HF1, HF2);
- Communications and interfaces (HF2, HF3);
- Procedures and work instructions (HF1, HF2);
- Record keeping (HF2);
- Design change control (HF2);
- Quality control (HF3).

5.10 ILI Error Frequency Reduction

Frequency of errors during ILI can be reduced by:

- Online monitoring of the ILI process;
- Double-checking the process of data analysis and interpretation;
- Using foolproof ILI tool design and technology;
- Using most sophisticated defect sizing algorithms;
- Motivating, increasing experience, improving physiological conditions of the ILI team members and data analysts;
- Eliminating/reducing opportunities to make a mistake when following the ILI procedure;
- Verifying each ILI step and its quantifiable results;
- Implementing high quality data analysis software;
- Employing specially trained data analysts and ILI DM.

5.11 Efficient Human Error Control Strategy

An efficient error control strategy must concentrate on the most consequential errors. Identification of the latter usually is accomplished by sensitivity analysis (SA). The objective of SA is to relate type and magnitude of error to pipeline integrity/ILI quality. For each considered random parameter (i.e., defect size), a reliability analysis is performed to determine the reliability corresponding to various possible values of errors (to develop a sensitivity function). Only error consequences are considered.

The sensitivity analysis is performed to identify the most important ILI parameters that affect integrity of a pipeline. The basic steps of a SA procedure can be defined as follows:

- Develop (adapt) structural model for defect/anomaly; identify parameters and limit state functions;
- Generate possible scenarios of concept errors, execution errors, intention errors;
- Calculate the risk for each scenario;
- Calculate the average risk (over a representative set of scenarios);
- Identify the most sensitive parameters;
- Examples of possible sensitivity functions are shown in Fig. 5.11.

The technology of error finding includes systemic checking and inspections of workplaces to assess the quantity of errors. Then the severity of their consequences is estimated through sensitivity analyses. The sensitivity functions are often used as a key element in error control technique.

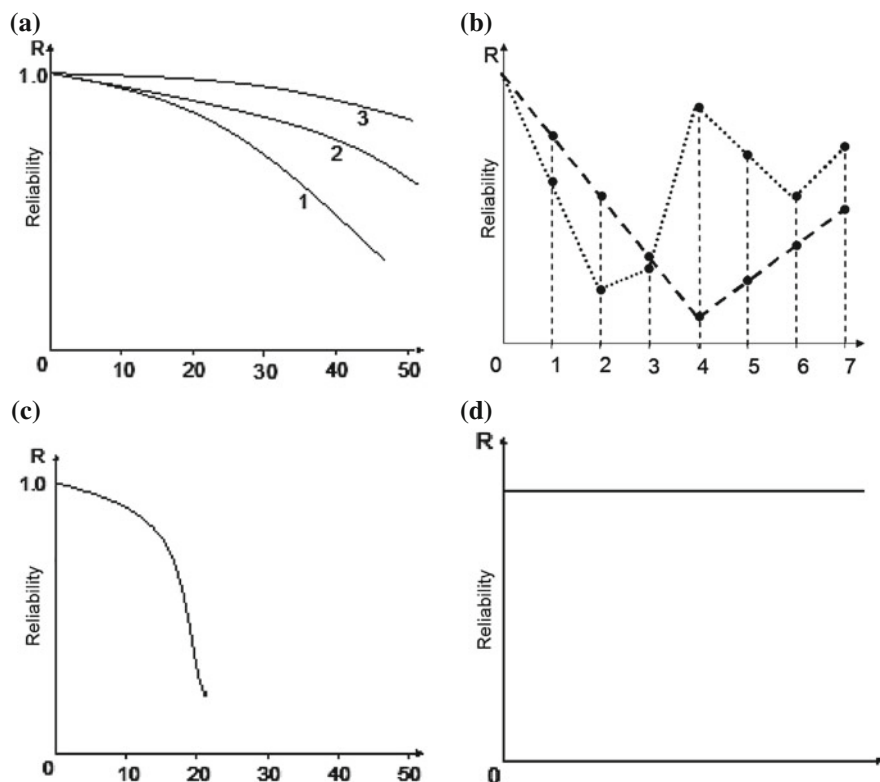


Fig. 5.11 Sensitivity functions for the performance metrics parameters. **a** Hazardous error in defect parameter, %: 1—*d*; 2—*l*; 3—*w*. **b** Hazardous detection or identification error: 1–7—types of defects. **c** Hazardous log distance, % error. **d** O'clock position, % error

5.12 Most Often Used Human Error Quantification Methods (1989, CPQRA)

All the HRA basically come down to:

- identification of relevant tasks performed by operators;
- decomposition of the task to identify opportunities for error and points of interaction with the plant;
- use of actuarial data;
- identification of performance—shaping factors (stress, training, quality of operator's displays and controls).

Results of an HRA are usually expressed in the form of HE probabilities/rates:

$$HEP = \text{Number of errors} / \text{Number of opportunities for error} \quad (5.1)$$

$$HER = \text{Number of errors} / \text{Total task duration} \quad (5.2)$$

Technique for Human Error Rate Prediction (THERP). This method requires breaking down a task into unit tasks and creating an event tree (ET) using this information. The ET calculations are performed by estimating conditional probabilities of success/failure (S/F) for each branch of the tree. The important errors affecting ILI quality and reliability can be identified and their inference assessed, using event/failure tree analysis and fault tree analysis. A failure/event tree is a schematic diagram showing the possible consequences of a particular event, called initiating event. Probability of this event can be assessed using structural mechanics and reliability theory. Usually any consequence occurs only after one or more intermediate events occur between the initiating event and the consequence being considered. Because of this, each path (sequence of events) of the tree diagram can be viewed as a possible scenario of events, leading to a specific consequence. A fault tree diagram (FTD) is a schematic diagram that shows how an event of particular interest (a failure), usually referred to as the top event, can occur, given different scenarios of faults (errors) that may happen. By virtue of this, the FTD shows possible scenarios that can lead to an undesirable event, whereas an event/failure tree diagram shows the possible consequences due to the occurrence of the undesirable event. Fault tree focuses on the potential causes of the undesirable event; the event/failure tree focuses on the potential consequences of an event.

The Accident Sequence Evaluation Program (ASEP) is used mainly for initial screening of the importance of human error. This short and conservative method estimates the HEP for two sequential stages: pre-accident and post-accident. The pre-accident screening analysis is performed to identify those components of a pipeline system that are vulnerable to human errors. If the probability of system failure is acceptable, human error is not important.

The post-accident HRA is performed to evaluate the probability of the operators to have detected and corrected their error. Once the accident sequence started, the most important variable is time the operators/DMs have to detect and correct their errors before the accident turns into a catastrophe. Before corrective action can be taken, the operators/diagnosticians/DMs must diagnose that there is a problem.

The time available for diagnosis can be computed as

$$T_d = T_m - T_a, \quad (5.3)$$

where T_d is the time available for the pipeline system/ILI tool operator to diagnose that an abnormal event has occurred; T_m is the maximal time available to correctly diagnose that the abnormal event happened and to have completed all corrective actions necessary to prevent the resulting accident; T_a is the time required to complete all post-diagnosis required actions to bring the system under control.

The maximum time T_m to diagnose and correct a problem is determined by a detailed analysis of each accident sequence, including possible time delays (due to different technological reasons).

Next determined is the time T_a needed to correct the problem. This time is estimated using a list of the operator tasks that must be completed to correct the problem created in each accident sequence.

Once the times T_m and T_a have been estimated, the time available for the operators to correctly diagnose an abnormal event is determined using Eq. (5.3). The probability that operators will fail to diagnose the problem can be assessed using different charts and figures [1].

5.13 Human Factor #1 Analysis

Out of the three categories of human factor, the HF1 is the easiest factor to account for. The main parameters that are needed in this case are [5]:

- The quality of maintenance/repair, which either brings the system to the “as new” state or to a point somewhere in the safe space, depending on the number and character of made mistakes (sensitivity analysis).
- Time needed to perform the prescribed quality maintenance/repair. This time is random and is characterized by its mean m and variance (Fig. 5.12). The actual times of performance of a maintenance team/repair crew of a given size and skill to do a specific maintenance/repair job create a statistical database. The probability density function PDF of the maintenance/repair time depends on the time of the day, health and stress level the maintenance/repair crew is exposed to during the operation (Fig. 5.13).

Therefore, in general

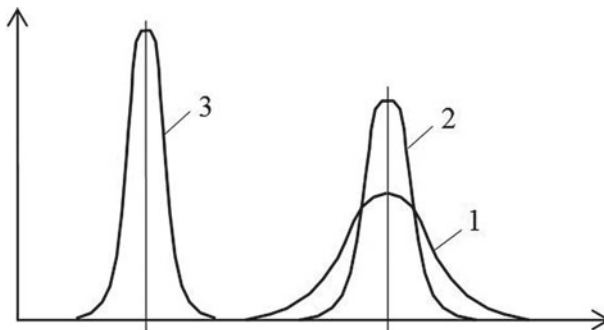


Fig. 5.12 Change of m as a random variable (1, 2, 3—PDFs describing quality and speed of repair/maintenance by different crews)

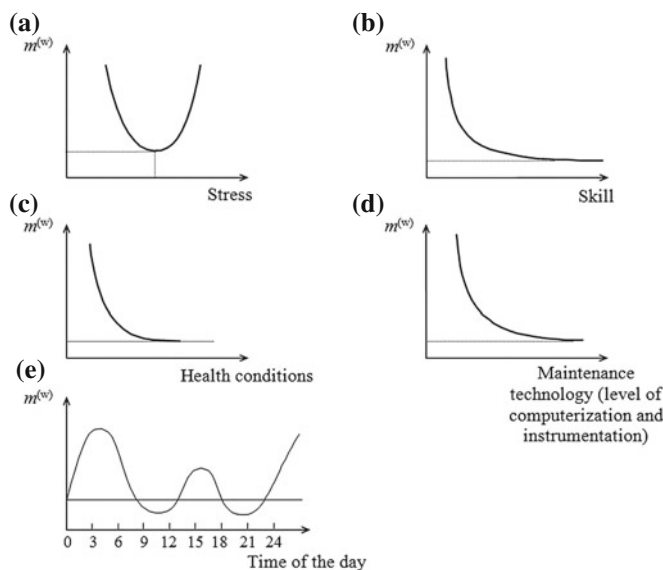


Fig. 5.13 Dependencies of m on levels of team stress (a), skill (b), health (c), maintenance technology (d), and the time of the day (e)

RV (maintenance/repair time) = function of (maintenance/repair budget, team/crew size, maintenance technology, stress level, skill level, health conditions, time of day, types, number of made mistakes, etc.)

Knowledge of concrete values of the mean time and quality of performance and their variances as functions of different consequential mistakes allows assessing the quality of maintenance/repair as a human factor.

5.14 Quantitative Assessment of Diagnosticians Errors (Human Factor #2)

The quantitative assessment errors of a NDE technician/diagnostician are rather complicated because it depends on many interrelated factors which are not easily quantified. Usually the following are important characteristics for “good” NDT diagnosticians/technicians [6]:

- ability to concentrate;
- understanding of NDT theory;
- personal patience;
- tolerance of environment conditions;
- manual dexterity;
- mathematical ability.

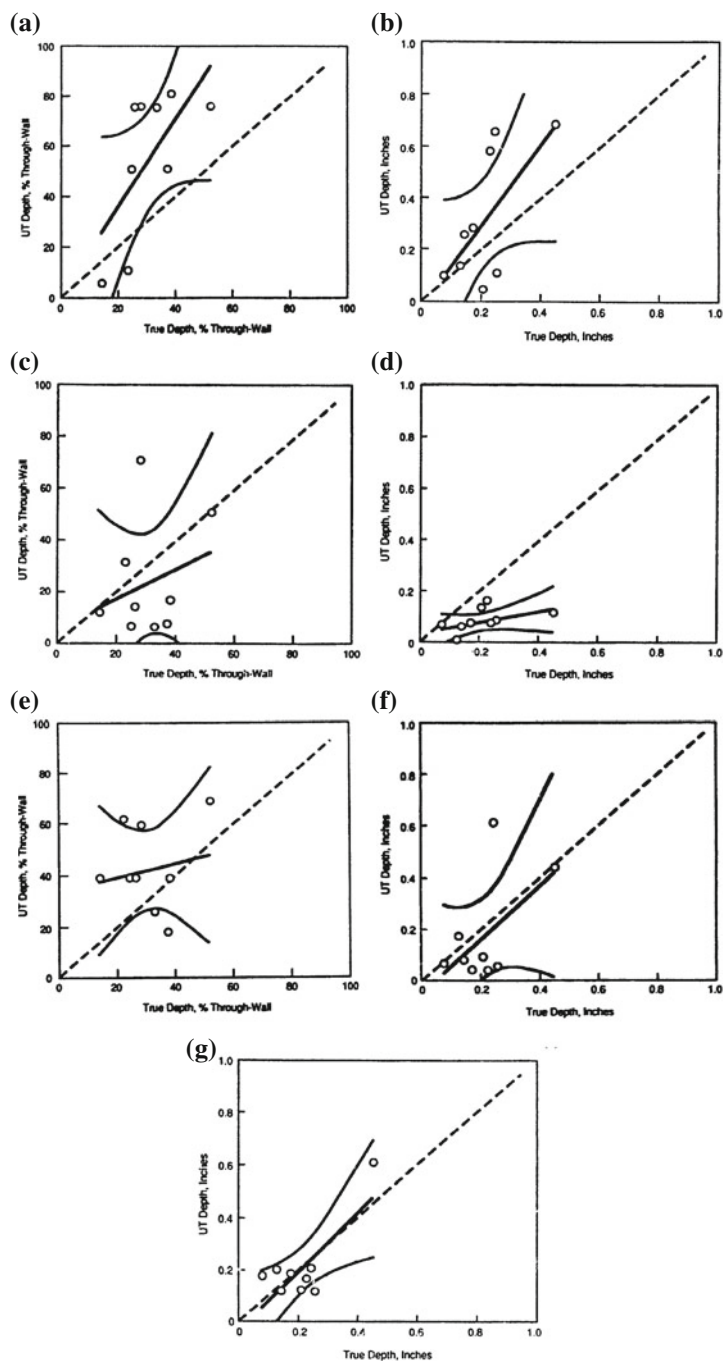


Fig. 5.14 Absolute sizing results for teams with 90% confidence bounds: **a, b** team #1; **c, d** team #4; **e, f** team #6; **g** team #8

The qualitative assessments of the above human characteristics are obtained through direct observations and critical incident interviews. Some results of measurements conducted in the nuclear energy industry by NDT diagnosticians are shown in Fig. 5.14. It can be seen that individual diagnosticians and teams vary substantially in precision.

Quantitative assessment often is made by plotting the so called ROC curves which plot Probability of Detection and the False Call Probability and are used in analyzing diagnosticians performance. The ROC quantifies the relationship between detection performance and decision criteria (see Sec. 4.9) ROC curves usually are used to examine a team's (or procedure's) inherent detection probability (IDP). IDP is the performance that would be achieved if the optimum decision criteria were being employed. In actual field inspections a procedure with excellent IDP may still yield poor results because a poor decision criterion is being employed, or the decision criterion cannot be controlled. The DC may also vary from inspection to inspection and/or team (person) to team (person). Therefore, the actual laboratory DC that is used for extrapolation to field experiments is very important. ROC curves are not exhaustive and give only partial understanding of the quality of the in-line inspections. ROC does not incorporate the seven basic metrics of ILI (see Chap. 4).

5.15 Human Factor #3 Reliability as a Pipeline or ILI System Component

According to ASNT ILI-PQ [7] and the API 1163 Standard [8], the ILI personnel have to demonstrate they have the ability (qualification) to do the following:

- interrupt the ILI process when a quality control nonconformance is discovered;
- initiate immediate corrective action procedures to prevent further nonconformance.

This ability can be tested using following approach.

Quality of ILI tool operator activity is characterized by his/her operation speed and reliability. The operation speed criteria are the time needed to solve a problem; e.g., the time from the moment of operator initial reaction to the moment of the end of control action. Usually, this time is directly proportional to the volume of processed data by the operator.

Reliability of a human operator as a component of the pipeline system is characterized by her/his infallibility, readiness, renewability, timeliness and precision. When assessing reliability of pipeline systems, the following assumption are usually made: hardware failures and human mistakes are rare, random and independent events; appearance of more than one event during time t_0 , $0 + \Delta t$ is impossible; operator capabilities of compensating mistakes and infallible work are independent.

Infallibility is defined as the probability of infallible operation (single or in whole). The probability P_j of infallible execution by the operator of a j -th type operation, and the intensity of mistakes λ_j during this operation is assessed through relevant statistics

$$P_j = (N_j - S_{mj})/N_j\lambda_j = S_{mj}/N_jT_j, \quad (5.4)$$

where N_j, S_{mj} are the total numbers of executed j -th type operations and made mistakes at this; T_j is the average time of executing a j -th type operation.

The **probability of infallible execution** by the operator of the whole operation, when T_j is a random, exponentially distributed variable

$$P_0 = \exp \left(- \sum_{j=1}^r \lambda_j T_j K_j \right) = \exp \left(- \sum_{j=1}^r (1 - P_j) K_j \right), \quad (5.5)$$

where K_j is the number of executed j -th type operations; r is the number of different types of operations ($j = 1, \dots, r$).

The **coefficient of operator's readiness** will be

$$K_r = 1 - (T_b/T),$$

where T_b is the operators blackout time; T is the total time of operator performance.

Operator's renewability is assessed by the probability P_r that she/he can carry out a correction of the mistake she/he made

$$P_r = P_c \cdot P_d \cdot P_{cor},$$

where P_c is the probability the control system will signal the operator's *mistake*; P_d is the probability that the operator will detect the signal; P_{cor} is the probability that the operator corrects the erroneous actions when repeating the whole operation.

The **operator's timeliness** is assessed by the probability of fulfillment the task in a given time

$$P_t = P(t \leq t_m) = \int_0^{t_m} f(t) dt, \quad (5.6)$$

where $f(t)$ is the probability density function of the operator execution time; t_m is the time limit, beyond which execution is considered a *mistake*.

The same probability P_t can be calculated by use of statistics as

$$P_t = (N - N_{nt})/N,$$

where N and N_{nt} are, correspondingly, the total and non-timely executed number of tasks.

Precision is the degree of deviation of **operator's measurement** of a system parameter from the true, given or nominal value. Quantitatively this parameter is assessed by the operator's discrepancy in measuring, adjusting, or regulating a parameter A :

$$\Delta A = A_t - A_m,$$

where A_t is the true value of parameter A ; A_m is the measured value of the same parameter.

If the discrepancy ΔA exceeds some allowable value, it should be considered as a mistake and accounted for when assessing system reliability.

The above formulas are a tool to assess the degree of compliance of HF1–HF3 with different requirements of various standards related to ILI.

5.16 Human Factor Risk Minimization in Pipeline Operation

It is well established that risk is the product of probability of an accident and the consequences of the same accident. Currently, the main approach is to assess the consequence of a disaster and define (minimize) the relevant mitigation procedures. Mostly overlooked is the second way of minimizing risk by lowering the frequency of pipeline system incidents which is an economically effective method. In the case of human factor the risk minimization boils down to error control, which can be achieved by reducing error frequency (and minimizing its consequences). This situation can be partially explained by objective difficulties of the a priori assessment of the probability of incidents in the pipeline. In Table 5.2 main danger components and the industry average numbers (specific for Russian industry) are given. Analysis of this table reveals that main causes of incidents in the industry in general is human factor.

This method permits solving two reciprocal types of problems. Their general mathematical description is given below.

Problem #1

With *given means* for improving pipeline's safety S_{giv} choose such a set of measures, that *maximizes reduction* of incident probability $Q_i = P(A)$.

$$\left\{ \begin{array}{l} \sum_i \Delta Q_i \rightarrow \max; \\ \sum_i S_i \leq S_{giv}, \end{array} \right.$$

where $\Delta Q_i = (Q - Q_i)$ is the reduction of incident probability due to implementation in the pipeline of the i -th set of safety measure; S_i is the i -th set of safety measures implementation expenditures; Q_i is the incident probability after implementation of

Table 5.2 Probability of incidents caused by human factor

Component	Code	Danger factor	Partial share of overall causes (incidents and injuries)	
Work environment	WE01	Level of work environment comfort regarding its physical and chemical parameters	0.028	
	WE02	Quality of information model of environment state	0.048	
	WE03	Possibility of dangerous external influences	0.045	
	WE04	Possibility of external unfavorable effects	0.025	
			$\Sigma = 0.146$	
Human factor	HF01	Physiological fitness	0.02	
	HF02	Technological discipline	0.04	
	HF03	Quality of receiving and decoding of information	0.062	max
	HF04	Ability to perform	0.04	
	HF05	Quality of motivation to work	0.04	
	HF06	Knowledge of operation technology	0.033	

(continued)

Table 5.2 (continued)

Component	Code	Danger factor	Partial share of overall causes (incidents and injuries)	
	HF07	Knowledge of physical essence of processes that take place in the system	0.04	
	HF08	Ability to correctly assess information	0.043	
	HF09	Quality of decision making	0.06	
	HF12	Self-control and composure in critical situations	0.056	
	HF13	Level of training on how to act in critical situations	0.047	
	HF14	Precision of corrective actions	0.06	
			$\Sigma = 0.541$	
Equipment	E01	Quality of operator work place	0.045	
	E02	Level of accounting for specifics of human workability	0.015	
	E03	Presence of sources of dangerous and damaging factors	0.02	
	E04	Reliability of auxiliary units and elements	0.03	
	E05	Serviceability of main units and elements	0.055	
	E06	Duration of dangerous and detrimental factors	0.007	min

(continued)

Table 5.2 (continued)

Component	Code	Danger factor	Partial share of overall causes (incidents and injuries)	
	E07	Potential level of dangerous and damaging factors	0.007	min
	E08	Serviceability of safety instruments and devices	0.026	
			$\Sigma = 0.205$	
Technology	T01	Comfort level of preparing for and executing jobs	0.02	
	T02	Comfort level of maintenance and repair	0.038	
	T03	Operator's algorithms complexity	0.012	
	T04	Possibility of appearance of people in the dangerous zone	0.008	
	T05	Possibility of appearance of other unprotected elements in the dangerous zone	0.01	
	T06	Reliability of technological means that ensure safety	0.02	
			$\Sigma = 0.108$	
			$\Sigma = 1.000$	

the j -th danger factor assessment when implementing the i -th set of measures. At this:

$$Q_i = P_i(A) = f(V_{H_1} + \Delta V_{H_{1i}}, V_{H_2} + \Delta V_{H_{2i}}, \dots, V_{H_j} + \Delta V_{H_{ji}}, \dots),$$

where $\Delta V_{H_{ji}}$ is the improvement of the j -th danger factor after implementing the i -th set of measures; V_{H_j} is the assessment of the j -th danger factor before implementing the safety measures.

Problem #2

With *minimal expenditures* $\sum_i S_i$ choose such a set of measures, implementation of which lowers the incident probability $Q_i = P(A)$ down to an *acceptable* (assigned) level $P_{acc}(A)$:

$$\begin{cases} \sum_i S_i \rightarrow \min; \\ Q - \sum_i \Delta Q_i \leq P_{acc}(A), \end{cases}$$

where $\Delta Q_i = (Q - Q_i)$ is the decrease of the incident probability when implementing the i -th set of safety improvement measures in the pipeline; S_i are the expenditures on implementation of the i -th set of measures; Q_i is the incident probability after implementing the i -th set of safety measures. With this:

$$Q_i = P_i(A) = f(V_{H_1} + \Delta V_{H_{1i}}, V_{H_2} + \Delta V_{H_{2i}}, \dots, V_{H_j} + \Delta V_{H_{ji}}, \dots),$$

where $\Delta V_{H_{ji}}$ is improvement in the j -th danger factor after implementation of the i -th set of measures; V_{H_j} is the assessment of the j -th danger factor before implementing the safety measures.

5.17 Illustrative Cases

In this section three cases of human factor risk minimization using the above approach are described. They reflect real-life situations.

Case #1. Consider the problem of minimization of the probability of third-party incidents by choosing from a set of measures. Third-party damage (TPD) incidents historically have produced the most serious consequences for oil and gas pipelines. A third-party is a person not involved in operating or maintaining the pipeline (e.g., excavator, construction cranes, farmers, homeowners, etc.). In the course of their normal activities they may come in contact with and damage a pipeline, causing a spill. According to [9] in the U.S. onshore pipeline within a right-of-way, third-party incidents dominated, involving damage at the time, with 97 % of the volume released. The same source found that, between 1999 and 2001, TPD incidents accounted for only 7 % of the 1,882 spills reported to the Pipeline Performance Tracking System (PPTS). But it accounted for

1. 100 % of incidents involving a death;
2. 52 % of incidents involving an injury;
3. 8 % of incidents involving fire or explosion;
4. 56 % of all volumes released from onshore pipe;
5. 54 % of the largest 2 % of all spills (more than 5.575 bbl).

Table 5.3 Sets of possible measures, their ICs and APRs

#	Possible measure	IC, \$10 ³ or CU							APR			ARP/CU		
		5	4	3	2	1			0.072	0.048	0.04	6/1	7/1	8/1
1	Teach excavator correct action	5	4	3	2	1			0.072	0.048	0.04	0.0144	0.0096	0.008
2	Install warning signs	5	4	3	2	1			0.36	0.24	0.12	0.072	0.048	0.024
3	Install a warning mesh	7	6	5	2	1			0.084	0.06	0.036	0.012	0.008571	0.00514
4	Bury pipe deeper	25	20	15	10	5			0.0072	0.0048	0.0024	0.000288	0.000192	0.000096
5	Cover pipe with concrete slabs	50	40	30	20	15			0.012	0.0012	0.00012	0.000024	0.000024	2.4×10^6
6	Install warning security alarm system	55	50	45	40	30			0.006	0.006	0.0006	0.000109	0.000109	1.09×10^5
		1	2	3	4	5			6	7	8	9	10	11

IC is implementation cost; CU is conditional cost unit; APR is accident probability reduction; $P_a = 0.4$; $P_u = 0.20$; $P_u = 0.10$; $P_u = 0.05$; $P_u = 0.01$

Table 5.4 Results of safety means optimization

P_u	Initial data, columns	Optimal means	IC	ΔQ
0.2	1 + 7	2 or 1&2 or 1&2&3	5 or 10 or 17	0.24 or 0.288 or 0.348
0.1	1 + 7	1&2&3 or 2&3&4 or 1&2&3&4	17 or 37 or 42	0.348 or 0.3048 or 0.3528
0.05	1 + 7	1&2&3&4 or 1&2&3&4&5 or 1&2&3&4&6	42 or 92 or 97	0.3528 or 0.354 or 0.3588
0.01	1 + 7	Unreachable with available means	–	–
0.2	1 + 8	Unreachable with available means	–	–
0.1	1 + 8	Unreachable with available means	–	–
0.05	1 + 8	Unreachable with available means	–	–
0.01	1 + 8	Unreachable with available means	–	–

It is, therefore, of great interest and practical value to analyze the role of human factor in TPD incidents and consider the means that would minimize the probability of TPD incident as related to human factor at the time of failure.

These means widely used in the industry are shown in Table 5.2, along with their implementation costs and accident probability reduction. The implementation costs (IC) of different means and measures vary from country to country and company to company. They also vary in time due to market variations.

The accident probability reduction (APR) due to implementation of a measure is one of the parameters that is most hard to assess. Actually, it is by itself a separate problem that has to be solved before attempting to solve the overall minimization problem. There are two ways in general to assess these parameters:

1. Analysis of actual statistics on monies and time spent on implementation of a means and APR achieved due to this measure;
2. Computer simulation of pipeline operation incidents and their consequences, using different preventive means and measures and event/fault tree analysis (E/FTA).

The first approach is simpler, but needs extensive statistics, which are not always available. The second approach is based on multiple Monte Carlo type computer simulations of accidents. Before starting to solve the problem one has to establish the current accident probability (CAP) P_a and the ultimate permissible (desirable) accident probability (UPAP) P_u . The CAP is assessed using available industry statistics in each country or region. The UPAP for a given type of accident can be assigned

Table 5.5 Sets of possible measures, their ICs and APRs

		IC (CU)				APR DQ 10^{-7}					ARP/CU			
		200	100	80		0.79	0.869	8.91	8.58	4/1	5/1	6/1	7/1	
1	Clean the pipe more thoroughly before inspection (a prerequisite for any ILI)	200	100	80		0.79	0.869	8.91	8.58	0.00395	0.00434	0.04455	0.0429	
2	Choose a more precise and appropriate tool for the jobs (EMAT, HRUT, HRMFL, etc)	300	200	150		2	2.255	22.66	21.89	0.00666	0.00751	0.07553	0.07296	
3	Use more comprehensive ILI technology (e.g., combination of calipers, AGM, GPS, geometry tools, etc.)	50	25	20		0.9	0.935	9.57	10.45	0.018	0.0187	0.1914	0.209	
4	Implement more precise algorithms/sophisticated analysis software for processing ILI data, pattern recognition/sizing (basic set of performance metrics, advanced ANN, Kohonen networks, etc.)	40	20	15		2	2.145	21.78	22.33	0.05	0.05362	0.5445	0.55825	
5	Upgrade qualification of ILI crew members (HF1), providing extra training	15	10	5		0.9	1.045	10.56	9.79	0.06	0.06966	0.704	0.65266	
6	Upgrade qualification of computer data analysts diagnosticians (HF2)	50	30	20		1.7	1.925	19.25	18.7	0.034	0.0385	0.385	0.374	
7	Upgrade qualification of high-rank top level expert diagnostician – final decision maker	75	50	25		1.7	1.815	17.16	18.15	0.02266	0.0242	0.2288	0.242	
		1	2	3		4	5	6	7	8	9	10	11	

 $P_a = 10^{-6}, 10^{-5}; \text{Desirable risk level} - 10^{-7}$

Table 5.6 Results of safety means optimization

P_a	Initial data, columns	Optimal means	IC	$\Delta Q \cdot 10^{-6}$
10^{-6}	2 + 4	1&2&3&4&6&7 or 1&2&3&4&5&6&7	425 or 435	909 or 999
10^{-6}	2 + 5	1&2&3&4&5&6&7	425	9944
10^{-5}	2 + 6	1&2&3&4&5&6&7	425	9933
10^{-5}	2 + 7	Unreachable with available means	–	–
10^{-6}	3 + 4	1&2&3&4&6&7 or 1&2&3&4&5&6&7	310 or 315	909 or 999
10^{-6}	3 + 5	1&2&3&4&5&6&7	310	9944
10^{-5}	3 + 6	1&2&3&4&5&6&7	310	9933
10^{-5}	3 + 7	Unreachable with available means	–	–

as the current lowest rate of accident achieved throughout the industry (or as a fraction of that rate). The approach described above permits establishing UPAP as the solution of the conditional optimization problem.

Due to fluctuations in time of IC and APR for different regions, countries, pipeline, Table 5.3 contains several sets of possible measures, their ICs and APRs, that cover the possible scatter of their values and reflect different possible functional relations between APR and IC. These relations allow calculating sensitivities for each measure and means. The sensitivity is the differential $dAPR/dIC$ and shows the size of APR for a unit of IC. The larger the sensitivity, the more effective is the measure or means.

The results are given in Table 5.4.

The initial data shown in Table 5.3 was used to solve the risk minimization. It can be seen that the smaller the desirable incident probability, the more means should be used. It is notable that the HF1 is present in all optimal solutions and that for some combinations of IC and APR it is impossible to reach the goal. This means that special care should be taken to meet the requirements of the problem: to create more effective means or/and spend more money to provide the necessary result.

Case #2. Consider a pipeline that has to be inspected by an ILI tool. Poor inspection may lead to pipe leak/burst with a probability called *accident probability*. Reduce the accident probability down to requested probability (with minimal expenditures) using the measures described in Table 5.5. Assessment of alternatives is performed using the discrete optimization method.

The initial data shown in Table 5.5 was used to solve the risk minimization problem for $P_a = 10^{-6}$, $P_a = 10^{-5}$ and $P_u = 10^{-7}$. The results of minimization are given in Table 5.6, and can be summed up as follows.

Under certain circumstances (combinations of IC and APR's and P_a and P_u) several optimal solutions are available, which decrease the current risk to desirable risk and even lower, but at different costs. Some combinations of means listed in

Table 5.6 are not capable of satisfying the condition of bringing the current risk (10^{-5}) to $P_u = 10^{-7}$.

In the setting of the Table 5.5 the most effective means are: comprehensive ILI technology; sophisticated software and upgrading the data analyst's and the final DMP's qualification. For the extreme cases, however, when the precision of the inspection has to be very high, it can be achieved only including the ILI team member qualification. Unfortunately, there are very few data on ILI team member qualification.

Results shown in Cases #1 and #2 are rough estimates because they do not take into account the two following facts: (1) the safety/reliability is constrained by unity, and (2) when a new safety measure is introduced into the implemented set, all partial safety increments change, to comply with the above restriction.

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Chapter 6

Probability of Failure (Reliability) of Pipelines

Consistent estimate of the probability of failure of pipeline systems plays a critical role in optimizing their operation. To prevent pipeline failures due to actively growing defects it is necessary to be able to assess the pipeline system failure-free operation probability (reliability) during a certain period, taking into account its actual level of defectiveness. This problem can be reduced to a typical prognosis problem when, using a restricted volume of data, gathered during a specific period of pipeline operation, it is required to predict the future behavior of the system in time to reach the ultimate state and, on this basis, to assess the pipeline or pipeline element reliability. The pipeline limit state comes when the burst pressure, considered as a random variable, reaches an unacceptable level, or when the defect depth, also a random variable, exceeds the predetermined limit value.

Currently, all existing reliability methods could be classified based on RVs and RFs. In the literature devoted to pipeline reliability the RVs methodology is overwhelmingly used as being algorithmically more simple and easier to be equipped with needed statistical data for practical use.

Among the latter, the most popular reliability methods are of the first-order/second-order FORM/SORM type, and the universal computer simulation Monte Carlo method, which, up to now, was the *only method* which could be used to produce benchmark reliability numbers needed for comparison with results produced by other reliability methods. The classical MC method is the most versatile, and has no limitations related to possible nonlinearity of the limit state function, but has a serious drawback when assessing very small values of POF. The number of simulations has to be in the order of tens and hundreds of millions to tens of billions and more.

It should also be noted that up to now no methods existed which would give absolutely correct POF assessments.

This chapter presents a revision of a well-known method of assessing reliability of the pipeline cross section containing a surface longitudinally oriented “metal loss” type defect of arbitrary size. This method is based on the expansion

of the unknown probability density function of the limit state function into the Gram–Charlier–Edgeworth’s series. When assessing reliability the following two main criteria of pipeline integrity loss (leak and rupture) are used:

- reaching or exceeding by the corrosion defect depth of the specified maximum allowable fraction of the pipe wall thickness;
- decrease of the value of pipeline cross-section failure pressure to the operating pressure level.

The pipeline strength is estimated using internationally recognized pipeline design codes (B31G [1], B31Gmod [2], Shell92 [3], DNV [4], PCORRC (Battelle) [5]), described in Sect. 1.5. According to these codes the burst (failure) pressure is a function of the operating pressure and parameters of the pipeline and the defect, which weakens the pipeline section at its location. The developed method allows taking into account the random nature of these parameters, which is important for correctly assessing the safety of pipeline operation.

Also in this chapter the problem assessing of POF (see [6, 7]), empirically embedded in international codes for pipeline design, was solved, presumably for the first time, analytically and in closed form, using the probability density function (PDF) of the limit state function of an ideal pipeline (without defects), constructed in this chapter.

6.1 Formal Description of the Pipeline Reliability Assessment Method

We introduce the LSF for a single pipeline cross section with a surface and longitudinally oriented defect of the “metal loss” type, which describes its two possible conditional limit states, as follows:

$$Y(t) = \begin{cases} P_f(t) - P_{op}, \\ k \cdot wt - d(t), \end{cases} \quad (6.1)$$

where $P_f(t)$ is the defect failure pressure, as defined by any of the considered in Sect. 1.5 design codes for calculating the PS strength; P_{op} is the pipeline operating pressure; wt is the pipeline wall thickness; k is the parameter representing the pipeline warning (alarm) failure (usually equal to 0.6, 0.7, or 0.8); $d(t)$ is the defect depth at moment of time t .

LSF (6.1) takes into account two types of conditional failures (leak and rupture): (1) decrease of the value of failure pressure down to the operating pressure (rupture) and (2) increase of the corrosion depth (defect) up to the specified ultimate permissible fraction of pipe wall thickness (leak).

If the change in depth and length of corrosion defects in time is close to linear, the defect parameters’ dimensions at time t are given by

$$\begin{aligned} d(t) &= d_0 + a_d \cdot t, \\ l(t) &= l_0 + a_l \cdot t, \end{aligned} \quad (6.2)$$

where d_0 , l_0 are the defect depth and length at the time of ILI; a_d , a_l are the corrosion rates in the radial and longitudinal axis, respectively.

POF of the “leak” type can be written as

$$P_f^l = \int_{k \cdot wt}^{\infty} f(x) dx = 1 - \int_0^{k \cdot wt} f(x) dx,$$

where $f(x)$ is the PDF of defect depth. PDF of $d(t)$ is found using the functions of random variables in the expressions (6.2) at fixed time t .

POF of the “rupture” type is defined as

$$P_f^b = \int_{\Omega} f(P_{op}, P_f^d) dP_{op} dP_f^d.$$

where $f(P_{op}, P_f^d)$ is the joint density function of two RVs: P_{op} and P_f^d are, respectively, operating and failure pressures of pipeline cross section with a random size defect; Ω is the region of integration according to the first equation in (6.1).

The cumulative probability of failure associated with each defect is formally defined by the formula

$$P_f^d = P_f^b \cup P_f^l - P_f^b \cap P_f^l.$$

Reliability of a defective pipeline segment when accounting for both types of failure according to criteria “leak” and “rupture” is determined from the expression

$$R^d = 1 - P_f^d = 1 - (P_f^b + P_f^l - P_f^b \cap P_f^l).$$

If the operating pressure P_{op} and the bearing capacity of a defective pipeline segment are normally distributed with mean equal, respectively, $\mu_{P_{op}}$ and μ_S and variances $\sigma_{P_{op}}^2$ and σ_S^2 , then the safety factor (reliability) of the element (defective section of the pipeline) is defined [8, 9] as:

$$R^{t*} = \beta = \mu_{(R-S)} / \sigma_{(R-S)}^2 = (\mu_S - \mu_{P_{op}}) / (\sigma_{P_{op}}^2 + \sigma_S^2).$$

In practice, some RVs of the limit states equations may be correlated. Most commonly observed correlations are between the depth, length, and width of defect and are given in Chap. 4. In these cases it is necessary to use known decomposition algorithms for decoupling joint PDFs into independent functions for each of the joint density parameters [8].

6.2 Reliability Assessment of a Defective Pipeline Segment Using Monte–Carlo Simulation Method

The method of statistical experiments (Monte–Carlo simulation method) is often applied for assessing reliability of a defective pipeline cross section. The estimate of the POF of the i th defect is calculated by formula

$$Q^{di} = \frac{n(LSF \leq 0)}{N}, \quad (6.3)$$

where N is the total number of experiments; $n(LSF \leq 0)$ is the number of experiments that led to failure of the defect.

For the estimate of the total number N of necessary tests following ratio is used [10]

$$P \left\{ |\bar{m}_Y - m_Y(t)| < \varepsilon = \frac{3\sqrt{\mu_{2Y}(t)}}{\sqrt{N}} \right\} \approx 0.997, \quad (6.4)$$

where $\mu_{2Y}(t)$ is the second central moment of RV $Y(t)$ (given in the next section).

This expression allows finding N for a given accuracy ε :

$$N = \frac{9\mu_{2Y}(t)}{\varepsilon^2}. \quad (6.5)$$

The MC method is the most versatile, but has a serious drawback when assessing very small values of POF (10^{-6} – 10^{-9}). In these cases to get results with high confidence level ($\geq 90\%$) the number of simulations has to be in the order of tens and hundreds of millions to tens of billions and more, which demands large amounts of usually unavailable and /or expensive computer time. This drawback is minimized using the updated version of the method, namely, the importance of sampling MC method (see Chap. 8).

From formula (6.5) it comes out that

$$\varepsilon = 3\sqrt{\frac{\sigma^2}{N}}.$$

Hence, one order reduction of ε increases 100 times the number of needed MC realizations.

For instance, in order to get an accuracy of 10^{-2} for a defect with 55 % wt depth, using the B31Gmod code, more than 200 thousands realizations are needed; for accuracy 10^{-3} —more than 20 million and for accuracy 10^{-4} —more than 20 billion.

6.3 Reliability Assessment of a Defective Pipeline Segment Using the Gram–Charlier–Edgeworth Series Method

Consider the problem of evaluating reliability of a pipeline cross section with a surface longitudinally oriented defect of the “loss of metal” type.

The POF/reliability of pipeline defective cross section is estimated, using the probabilistic approach based on the Gram–Charlier’s series (G-C) [11, 12]. This method allows assessing the POF/reliability of a defective cross section of a pipeline, while taking into account the probabilistic nature of the pipeline and defects geometry parameters, material properties, and operating pressure. In this method both “leak” and “rupture” criteria of the pipeline integrity can be used.

The following main uncertainties of a specific cross section of a pipeline are considered: defect depth $d(t)$ and length $l(t)$; pipe wall thickness wt and diameter D ; specified minimum yield strength $SMYS$ and ultimate tensile strength UTS of the pipe material, and the design operating pressure P_{op} .

The G-C method is an assessment of the probability that the LSF (6.1) of a defective pipeline cross section has a positive value at an arbitrary moment of time t (i.e., assessment of defect reliability).

We denote the above parameters, considered as RVs, as x_i , $i = 1, \dots, 6$, where $x_1 = wt$, $x_2 = D$, $x_3 = l_0$, $x_4 = d_0$, $x_5 = SMYS$ or $x_5 = UTS$, $x_6 = P_{op}$.

The essence of this method is the approximation of the unknown PDF $f(y)$ of the random variable $Y(t)$ by an orthogonal polynomial, which is a partial sum of the Gram–Charlier series

$$f(y) = \left[\varphi(y) - \frac{S}{3!} \varphi^{(3)}(y) + \frac{E}{4!} \varphi^{(4)}(y) \right] / \sigma_Y, \quad (6.6)$$

where $\varphi(y) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{y^2}{2}\right]$ is PDF of the standard normal distribution, exponents n of this function indicate its n -th derivative; y is the normalized value of $y = \frac{Y - \mu_Y}{\sigma_Y}$; $\mu_Y(t)$ is the mean of the RV $Y(t)$, which represents the value of the LSF $Y(t)$, obtained by substituting into function $Y(t)$ the values of the mathematical expectations of RVs x_i at considered moment of time t :

$$\mu_Y(t) = Y(t, m_{x_1}, \dots, m_{x_n}), \quad i = 1, 2, \dots, 6.$$

Here m_{x_i} is the mean of i -th RV, included in LSF (D , wt , d_0 , l_0 , $SMYS$ or UTS , P_{op}); $\sigma_Y(t)$ is the standard deviation of $Y(t)$:

$$\sigma_Y(t) = \sqrt{\mu_{2Y}(t)}, \quad (6.7)$$

$S(t)$ is the skewness of $Y(t)$:

$$S(t) = \frac{\mu_{3Y}(t)}{\sigma_Y^3(t)}, \quad (6.8)$$

$E(t)$ is the kurtosis of $Y(t)$:

$$E(t) = \left(\frac{\mu_{4Y}(t)}{\sigma_Y^4(t)} - 3 \right). \quad (6.9)$$

In formulas (6.7)–(6.9) $\mu_{2Y}(t)$, $\mu_{3Y}(t)$, $\mu_{4Y}(t)$ are the second, third, and fourth central moments of $Y(t)$, respectively, obtained by the linearization method [13]:

$$\mu_{2Y}(t) = \sum_{i=1}^6 \left[\left(\frac{\partial Y(t)}{\partial x_i} \right)^2 \bigg|_{m_{x_1}, \dots, m_{x_7}} \mu_{2x_i}(t) \right], \quad (6.10)$$

$$\mu_{3Y}(t) = \sum_{i=1}^6 \left[\left(\frac{\partial Y(t)}{\partial x_i} \right)^3 \bigg|_{m_{x_1}, \dots, m_{x_7}} \mu_{3x_i}(t) \right], \quad (6.11)$$

$$\begin{aligned} \mu_{4Y}(t) = & \sum_{i=1}^6 \left[\left(\frac{\partial Y(t)}{\partial x_i} \right)^4 \bigg|_{m_{x_1}, \dots, m_{x_7}} \mu_{4x_i}(t) \right] \\ & + 6 \sum_{\substack{i, k=1 \\ i < k}}^6 \left[\left(\frac{\partial Y(t)}{\partial x_i} \right)^2 \bigg|_{m_{x_1}, \dots, m_{x_6}} \left(\frac{\partial Y(t)}{\partial x_k} \right)^2 \bigg|_{m_{x_1}, \dots, m_{x_6}} \mu_{2x_i}(t) \mu_{2x_k}(t) \right]. \end{aligned} \quad (6.12)$$

From the formula (6.6) the CDF of RV $Y(t)$ is obtained by integration:

$$F(y) = \left[\Phi(y) - \frac{S}{3!} \varphi^{(2)}(y) + \frac{E}{4!} \varphi^{(3)}(y) \right] / \sigma_Y.$$

Taking into account properties of the CDF, reliability of defective pipeline cross section (the probability that LSF $Y(t) > 0$) can be assessed as

$$P(Y > 0) = 1 - F(0) = 1 - \left[\Phi(z) - \frac{S}{3!} \varphi^{(2)}(z) + \frac{E}{4!} \varphi^{(3)}(z) \right] / \sigma_Y, \quad (6.13)$$

where the normalized quantity $z = \frac{0 - \mu_Y}{\sigma_Y}$.

Then the POF of the defective pipeline cross section is calculated by formula

$$F(0) = \left[\Phi(z) - \frac{S}{3!} \varphi^{(2)}(z) + \frac{E}{4!} \varphi^{(3)}(z) \right] / \sigma_Y. \quad (6.14)$$

Expression (6.14) may not always be positive, hence, it is not a true probability distribution. In some cases the G-C series deviate from $F(0)$ and converge only if

$F(0)$ decreases more rapidly than $\exp[-x^2/4]$ tends to infinity [14]. If the series does not converge, it is not a true asymptotic expansion, since the error of the expansion remains unknown. Because of this the G-C-E series is more preferable than the G-C series [14]. When using the G-C-E series the additional (underlined) term is introduced in formulas (6.13) and (6.14):

$$F(0) = \left[\Phi(z) - \frac{S}{3!} \varphi^{(2)}(z) + \frac{E}{4!} \varphi^{(3)}(z) + \frac{10S^2}{6!} \varphi^{(5)}(z) \right] / \sigma_Y, \quad (6.15)$$

$$P(Y(t) > 0) = 1 - F(0). \quad (6.16)$$

Formulas (6.15) and (6.16) allow to determine an arbitrary time t of pipeline operation for the numerical value of the reliability index (POF) for the pipeline cross section with a defect of arbitrary size, for a given LSF (6.1).

It should be noted that calculation by formulas (6.15) and (6.16) is always made for one value—zero. In different calculations only the statistical characteristics (mean, variance, and moments) of LSF will vary. Thus, the LSF mean for a less dangerous defect will be farther away from zero, hence, POF will decrease. For a more dangerous defect, the burst pressure will decrease, hence, the difference between the burst and operating pressure will decrease, and the POF will increase.

We introduce some modifications to the method. Since LSF is nonlinear, the linearization method is applied to the LSF when determining statistical characteristics (expectation, variance, third and fourth moments) of the RV $Y(t)$. Any continuous and differentiable function in a rather narrow range of variation of its arguments can be substituted by a linear approximation. The narrower are the boundary changes of its arguments the smaller is its error [13].

To account for the nonlinearity of LSF expand it in a Taylor series in the vicinity of the point $m_{x_1}, m_{x_2}, \dots, m_{x_6}$ [13]:

$$Y(y) = Y(t, m_{x_1}, m_{x_2}, \dots, m_{x_6}) + \sum_{i=1}^6 \frac{\partial Y}{\partial x_i} (x_i - m_{x_i}) + \frac{1}{2} \sum_{i=1}^6 \frac{\partial^2 Y}{\partial x_i^2} (x_i - m_{x_i})^2 + \dots \quad (6.17)$$

To simplify calculations keep in the decomposition (6.17) only components of no more than second order and find more accurate expressions for the expectation and variance of RVs $Y(t)$. Using their properties and taking into account that the expectation value of a centered, quantity $x_i - m_{x_i}$ is equal to zero, and the RVs, included in LSF, are independent and uncorrelated, define improved expectation and variance of RV $Y(t)$ [13]:

$$\mu_Y = Y(m_{x_1}, m_{x_2}, \dots, m_{x_6}) + \frac{1}{2} \sum_{i=1}^6 \left[\left(\frac{\partial^2 Y}{\partial x_i^2} \right)_{m_{x_1}, \dots, m_{x_6}} D_{x_i} \right], \quad (6.18)$$

$$D_Y = \sum_{i=1}^6 \left[\left(\frac{\partial Y}{\partial x_i} \right)_{m_{x_1}, \dots, m_{x_6}}^2 D_{x_i} \right] + \frac{1}{4} \sum_{i=1}^6 \left[\left(\frac{\partial^2 Y}{\partial x_i^2} \right)_{m_{x_1}, \dots, m_{x_6}}^2 (\mu_4[x_i] - D_{x_i}^2) \right], \quad (6.19)$$

where M_Y , D_Y are correspondingly, mathematical expectation and variance of $Y(t)$; D_{x_i} is variance of the i th RV, present in the LSF; $\mu_4[x_i]$ is the fourth central moment of RV x_i .

The second component in the expression (6.18) and (6.19) is the correction which accounts for the nonlinearity of LSF.

In practice, the LSF $Y(t)$ is normalized to make it a real PDF, at the same time taking into account the intervals, where it may be negative.

After normalizing and calibrating the G-C-E method it is possible to use it for comparative study of various pipeline designs and to assess their sensitivity to different load and environment parameters.

6.4 Recommendations for Choosing Probabilistic Characteristics of Pipeline Parameters

For practical use of the G-C-E method probabilistic characteristics have to be known of the initial data: geometric parameters of pipeline and defects, load parameters and mechanical properties of pipe steel. The probabilistic characteristics of these parameters are recommended in [15] by the Canadian company “C-FER” which conducts complex testing and provides engineering consultations to oil and gas pipeline companies.

Probabilistic characteristics of the geometric parameters of the pipelines.

Table 6.1 presents the probabilistic characteristics of the relationship between the actual and nominal values of the pipeline geometric parameters.

Table 6.1 Probabilistic characteristics of the relationship between the actual and the nominal values of the pipeline geometric parameters

Parameter	Distribution law	Mean	Coefficient of variation	Source
Outside diameter	Deterministic	1.00	0.00	[16]
	Normal	1.00	0.06 %	[17]
Pipe wall thickness	Normal	1.00	0.25/wt	[18]
	Normal	1.10	3.30 %	[18]
	Normal	1.01	1.00 %	[17]

Probabilistic characteristics of the pipe diameter (second row of Table 6.1) were obtained from pipes 16 to 56 in. (40–1400 mm) in diameter. In this case the coefficient of variance COV was lower than 0.1 %. Hence, without increasing calculation error, the pipeline diameter can be regarded as a deterministic quantity. The data from the third row of Table 6.1 is obtained from welded pipes with wall thickness from 15 to 37 mm. In terms of COV wt is the nominal pipe wall thickness, i.e., standard deviation = 0.25 mm. The data from fourth row of Table 6.1 is based on tolerance for wall thickness of seamless pipes.

The SD of pipeline geometrical parameters can be also calculated on the assumption that these parameters are normally distributed (i.e., that the width of the deviation from the nominal value on both sides is three sigma) [19].

It should be noted that the use of a normal distribution for pipeline geometry parameters is not in contradiction with their physical properties (strictly positive values), as the scatter of a RV around the mean value is so small, that the occurrence of negative values is practically impossible. For example, according to Table 6.1, the mean of pipe wall thickness (wt) is equal to 110 % of its nominal value and the COV is equal to 3.3 % (the largest value in Table 6.1). Hence, the SD is 3.63 % of wt . With this value of SD, the negative values of wt are outside the 30.3SD range. Using properties of the normal distribution, the probability of hitting a RV outside six SD is equal to 1.97×10^{-9} (0.002 cases per million), for seven SD such probability is equal to 2.56×10^{-12} (see next section), and for 30.3SD this probability is infinitesimal.

Probabilistic characteristics of the operating pressure. The relationship between operating pressure (OP) and the design pressure (DP) at an arbitrary time can be described by a beta distribution with a mean of 0.865 and coefficient of variation (COV) 0.084. In this case, the operating pressure is varying in the interval of 60–110 % of the design pressure. This distribution is based on the assumption that the maximum operating pressure in the pipeline is equal to the design pressure. In the pipeline section located immediately after the pumping or compressor stations, the ratio between the maximum annual operation and design pressure has a Gumbel distribution with mean between 1.03 and 1.07 and COV of 1–2 %. This distribution provides a conservative estimate of the annual maximum operating pressure for those pipeline sections, which are farther downstream from the pumping/compressor stations.

Probabilistic characteristics of the pipe material mechanical properties. Probabilistic characteristics of the relationship between the actual yield strength and ultimate strength and SMYS and UTS of the pipe material are presented in Table 6.2. These characteristics are based on extensive data collected from plant tests. In general, the PDF for pipe material strength does not depend on the steel grade [15]. It is shown [18] that the COV may vary depending on the quality of the pipe steel from different plants. Hence, results of plant tests should be used as much as possible. Using the normal distribution for the properties of pipe material with parameters from Table 6.2 also totally excludes negative values of RVs.

Probability characteristics of the defect depth growth rate. Growth rate of the surface corrosion defects in many respects depends on the type of anticorrosion coating, operational conditions, cathodic protection level of a particular pipeline, and corrosivity of soil in which it is laid [15].

Table 6.2 Probabilistic characteristics of pipe material properties

Parameter	Distribution law	Mean	Coefficient of variation	Source
SMYS	Normal	1.11	3.40	[18]
	Normal	1.08	3.30	[18]
	Normal or lognormal	1.10	3.50	[15]
	Lognormal	1.08	4.00	[17]
UTS	Normal	1.12	3.00	[19]
	Normal	1.12	3.50	[19]

Significant amount of data on the defects sizes are collected during the ILI. Most of these data are properties of pipeline operators and/or inspection companies. The [15] sums up the probability characteristics of the growth rate of the average surface corrosion defects depth with Weibull law distribution and an average value of 0.01–0.2 mm/year and variation factor (VF) of (30–70) %. The data was collected from nine pipelines which total length is 700 km. Most of these pipes had tape anticorrosion coating. The growth rates of the defects depth during the period of the pipelines operation were assessed assuming their linear growth from zero. These data were later confirmed in [20] by the results of field testing of pipes. The growth rate variation factor was also confirmed in [16], where Weibull law distribution with VF = 60 % for corrosion growth rate in water injection lines was proposed.

6.4.1 Adequacy Test of the G-C-E Method

Consider the real life PL segment with parameters set in Table 6.3.

Table 6.3 Nominal values of the pipeline parameters

Parameter	Symbol	Value
External pipeline diameter, mm	D	325.00
Pipe wall thickness, mm	wt	9.00
Pipe material specified minimum yield strength of the, MPa	$SMYS$	245.00
Pipe material ultimate tensile strength of the, MPa	UTS	410.00
Design operating pressure, MPa	P_{op}	6.40

Calculate probability characteristics of the geometric parameters of the pipeline assuming [18], that they are normally distributed. According to standards, for steel grade of the given PL the ultimate deviation of the external diameter is ± 2 mm, of the pipe wall thickness $+0.6$ and -0.8 mm. Assuming that the geometric parameters of the pipeline are distributed normally, using the three-sigma rule and the stated ultimate deviation, it is possible to determine their mathematical expectation and standard deviation. For the diameter the mathematical expectation equals 325 mm, standard deviation— $2/3$ mm, for pipe wall thickness the average value equals $(9.6 + 8.2)/2 = 8.9$ mm, standard deviation— $(9.6 - 8.2)/2/3 = 0.23$ mm.

For the yield strength and pipe material strength the PDF and its parameters were chosen in accordance with Table 6.2. Input data for further analysis are shown in Tables 6.3 and 6.4.

It is not difficult to demonstrate that given the distribution parameters as per Table 6.4, the probability of occurrence of negative values of pipeline parameters is practically zero. It is true that for the pipe wall thickness the negative values are outside the range of 38.7 standard deviation ($8.90/0.23 \approx 38.69$), for the pipeline diameter—outside of 485.1 standard deviation ($325.00/0.67 \approx 485.07$), for operating pressure—outside of 9.1 standard deviation ($6.40/0.70 \approx 9.14$). In all these cases the probability of negative values occurrence is infinitely small. For the mechanical properties of the pipe material the impossibility of negative values occurrence is proven in a similar way.

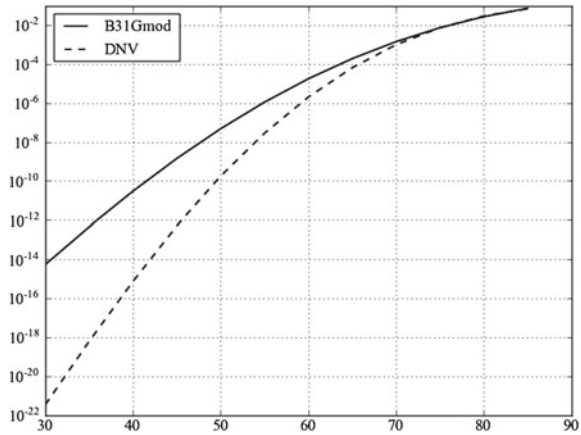
In the process of pipeline system PS deterministic design, or when considering any of the pipeline parameters as a deterministic value, using the G-C-E method, it is necessary to use the nominal parameter values as given in Table 6.3.

Consider a single defective section of a pipeline with the defect depth 30 % of the pipe wall thickness wt and length 100 mm. Give the defect depth a 5 % wt increment and perform calculations with the G-C-E method to the depth of 85 % wt . The results of calculations for two methodologies of strength assessment (B31Gmod [2] and DNV [4]) are presented in Fig. 6.1. It is seen that for shallow defects the B31Gmod

Table 6.4 Pipeline parameters assumed to be random, normally distributed values

Parameter	Symbol	Mathematical expectation, mm	SD
External pipeline diameter, mm	D	325.00	0.67
Pipe wall thickness, mm	wt	8.90	0.23
Pipe material specified minimum yield strength, MPa	$SMYS$	269.50	9.43
Pipe material ultimate tensile strength, MPa	UTS	459.00	16.07
Design operating pressure, MPa	P_{op}	6.40	0.07

Fig. 6.1 Pipeline POF as a function of the defect depth



is more conservative, but at the depth of defect over 60 % *wt* the pipeline POF of both methodologies yield practically the same results.

The adequacy of the unknown LSF probability density expansion in G-S-E series was checked by comparing calculation results with the data obtained by the MC method, which is described in Sect. 6.2. Since POF for shallow defects is practically zero and the POF of the potentially dangerous defects is of a significant interest, the calculation was performed for a defect depth ranging from 55 to 85 % *wt*. Statistical error ε was assumed equal to 0.005. The results of calculation are shown in Tables 6.5, 6.6 and in Figs. 6.2, 6.3.

From Tables 6.2 and 6.3 it is clear that the G-C-E method produces systemically lower assessments than the MC method. However with the increase of the defect depth this difference is rapidly shrinking. It should be noted that it is important that the POF assessments must be sufficiently accurate in the area of their practical application (10^{-4} – 10^{-6}). At a distance from this zone (less than 10^{-5} – 10^{-6})

Table 6.5 Comparative table of calculation results for the pipeline POF using the MC and the G-C-E methods (code B31Gmod)

Defect depth, % wt	MC method		G-C-E method
	POF	Number of realizations	POF
55	1.1×10^{-4}	803,055	1.1×10^{-6}
60	7.8×10^{-4}	872,244	1.8×10^{-5}
65	4.0×10^{-3}	951,593	1.9×10^{-4}
70	1.7×10^{-2}	1,042,800	1.4×10^{-3}
75	5.8×10^{-2}	1,148,109	7.3×10^{-3}
80	1.5×10^{-1}	1,270,566	2.7×10^{-2}
85	3.1×10^{-1}	1,414,426	7.3×10^{-2}

Table 6.6 Comparative table of calculation results for the pipeline POF using the MC and the G-C-E methods (code DNV)

Defect depth, % wt	MC method		G-C-E method
	POF	Number of realizations	POF
55	2.1×10^{-4}	1,932,966	2.8×10^{-8}
60	1.7×10^{-3}	2,272,955	2.0×10^{-6}
65	9.5×10^{-3}	2,714,097	6.5×10^{-5}
70	3.9×10^{-2}	3,297,508	9.7×10^{-4}
75	1.2×10^{-1}	4,089,145	7.3×10^{-3}
80	2.8×10^{-1}	5,200,135	2.9×10^{-2}
85	5.0×10^{-1}	6,828,199	6.9×10^{-2}

Fig. 6.2 Pipeline probability of failure as function of the defect depth (code B31Gmod)

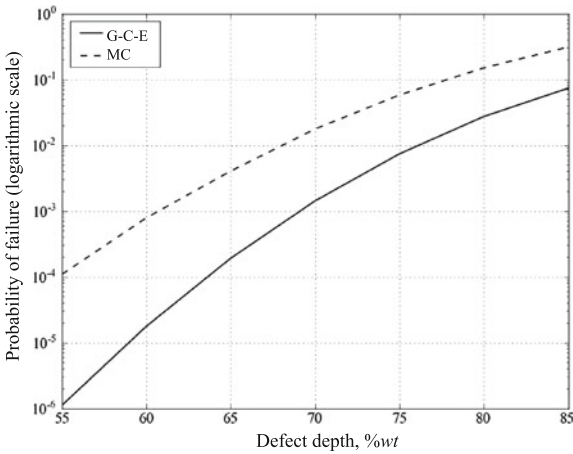
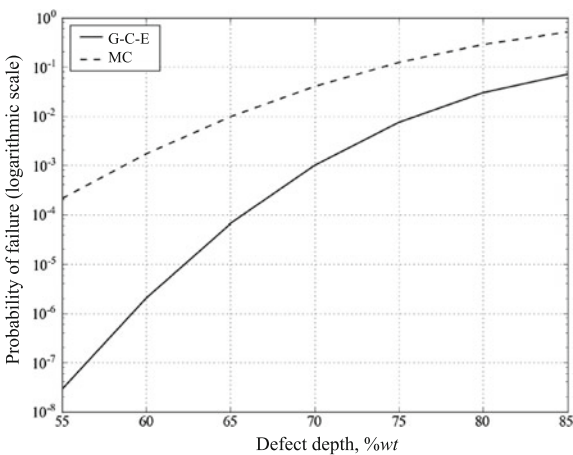


Fig. 6.3 Pipeline probability of failure as function of the defect depth (code DNV)



the accuracy of assessments is not that important, but they still may be used for comparative assessments.

Full assessment of the G-C-E method accuracy on the basis of the MC method is difficult to accomplish, since it would require a significant number of computer simulations (about 10^{-9}), since the MC method accuracy depends on the used statistical accuracy (error) ε . For instance, to achieve the accuracy 10^{-2} the defect depth 55 % *wt* using code B31Gmod, over 200,000 simulations is needed; for 10^{-3} —over 20 mln, and for 10^{-4} —already over 20 bln. According to formula (6.5), a decrease of ε by one order of magnitude increases the required number of simulations by 100 times.

6.4.2 Computer Time Needed for Using the MC and the G-C-E Methods

It is interesting to compare efficiency of various methods for assessing pipeline reliability by calculating costs required for obtaining similar results.

Consider a “standard” problem for assessing reliability of a pipe cross section with one defect when all RVs are normally distributed. Calculate the reliability function for a defect 75 % *wt* deep.

Assessment of the calculation time is performed when using a computer with following specifications: processor Intel Celeron SPU 2.60 GHz; RAM 768 MB. The time spent for generating tables, figures, and other supplementary calculations was not taken into account. Calculation time for code B31Gmod using the MC method was about 20 s of computing time, when using the G-C-E method—about 0.05 s. This means that the G-C-E calculations are approximately 400 times quicker.

The longest computing time was required for solving problems of reliability assessment as a function of the coefficient of variation (COV) of some random pipe parameters.

6.5 Assessment of the Reliability Level Embedded in Pipeline Design Codes

Recently, a long time discussion among specialists about the meaning of the probabilities of failure (POF) produced by different reliability analysis methods surfaced in pipeline journals [6, 7]. This section analyses the actual reliability level which was empirically embedded in codes for pipeline design [B31G, B31Gmod, Shell92, and Battelle (PCORRC)] and Building Regulations (BR) using a real pipeline as an example.

Assessment of the actual reliability level empirically embedded in BS is based on assessing the order of the quintiles of strength parameters (design values of tensile

strength and yield strength of the pipe material) and load (internal pressure) on the pipeline. This approach allows direct connection of the deterministic safety coefficients used in the BR with the level of reliability of the pipelines associated with these coefficients.

The actual reliability level, empirically embedded in international codes, is calculated as the probability that the limit state function (LSF) of ideal pipeline (without defects) is positive: $LSF = P_f - P_{op}$, where P_f is the failure pressure of an ideal pipe, which is estimated by any design code; P_{op} is the operating pressure. The failure and operating pressure are considered random variables. The expression for this probability is obtained analytically and in closed form.

Extensive calculations permitted revealing the reliability levels which are actually present in the analyzed international pipeline design codes. In a nutshell, the international codes under consideration are very reliable, as they produce very safe designs of pipelines with very low POF, and, hence, provide large safety coefficients. The algorithm developed in this section permits connecting the current level of pipeline degradation (in terms of POF), with its current safety coefficient, which, in this case, is a function of time.

The conducted analysis of international pipeline design codes explains and validates the origin and values of small, yet real and trustable probabilities of pipeline failure.

All calculations in the section were performed using MathCAD. Illustrations of these calculations are also presented.

6.5.1 Reliability Level Empirically Embedded in International Codes

All existing international pipeline design codes are based on the allowable stress principle, except for code [21], which utilizes the limit states concept and the method of partial reliability coefficients. All codes are based on the solution of deterministic problems of mechanics and results of numerous full size experiments. It was only recently that some elements of probabilistic assessment of strength capacity of pipelines were introduced in the Building Codes and Regulations [21] and the DNV methodology. However, the achieved in this case reliability level remains unknown.

In this connection, we evaluate the “hidden” reliability of BR for the design of main pipelines [21]. First of all, it is necessary to note that these codes do not account for the existence of various types of defects in the operating pipeline. All calculations are performed for ideal pipes, without defects. Consideration of the effect of defects on the reduced pipeline reliability requires a separate study. Also note that the main pipelines, even despite their uniqueness, due to their length and invariability (as a rule) of its main geometric parameters and material properties, have a rather significant and continuously growing statistical database of their parameters, which, in principle, makes the solution of this problem much easier.

BR [21] are based on the limit states concept. The first limit state of a pipeline is its destruction under internal pressure. Therefore, the design pipeline bearing capacity is described by the temporary fracture resistance of pipe metal (tensile strength).

When determining the design resistance a number of separate safety coefficients are introduced, which reflect the probabilistic nature of the various factors affecting the carrying capacity of the pipeline [21, 22]:

- *safety coefficient m for pipe operation conditions* reflects and takes into account the possible inconsistency of the adopted calculation scheme of the actual pipeline structure, including specifics of pipeline interaction with environment;
- *deterministic safety coefficients for pipe material*, which are applied to the normative (minimum) values of the pipe material strength. These coefficients were assigned by authors of the BR [21] through engineering judgments and reflect possible decrease of tensile strength of pipe metal as compared to its normative value, possible reduction of pipe wall thickness compared to its nominal value, and the desired reliability of the pipeline structure;
- *safety coefficient which takes into account the pipeline purpose*, and is applied to the stresses in the structure due to design loads, with pipe material having the design strength. This coefficient takes into account following factors affecting the pipeline system reliability:
 - with pipe diameter increase its contact surface with the ground increases, hence, in the case of ground deformation/movement the large-diameter pipelines are in more severe conditions than the small-diameter pipelines;
 - with pipeline diameter increase its flexural rigidity sharply increases, therefore, when laying the pipeline its contact with the bottom of the trench along the entire pipe length may have some loose seats, whereby creating in it some additional bending stresses;
 - with pipeline diameter increase it needs more pipe steel and weld metal, as the total length of welded joints also increases. Hence, the probability of flaw in the pipeline construction process also increases;
 - with increasing operating pressure and pipeline diameter the pipeline system capacity increases, so PS failure may lead to greater environmental and economic losses.

When designing pipelines it is necessary to take into account the stress loads and impacts originating during their construction, testing, and operation. The main load is the operating pressure for transporting the product, set by design. In pipeline design possibility of this pressure growth is taken into account, by applying a safety factor for the load.

The pipeline geometry parameters, material properties, and the load acting on the pipeline are *independent random variables (or even functions of time)*. Therefore, the adopted in BR [21] method of splitting the overall safety factor for partial coefficients and giving them a probabilistic meaning leads to the probability of *simultaneous* fulfillment of the failure conditions of the pipeline (the load is more than the design value, the material properties and structure dimensions are less than the

design values) being calculated as the *product of the probabilities for the corresponding design values*. This product, actually, is the (conditional) POF of a pipeline designed according to the BR [21] rules.

Consider now the statistical content which is carried by the parameters of pipe material and geometry, and loads acting on the pipeline, when used in formulas of BR [21] as RVs.

According to BR [21], to obtain the design strength parameters (tensile strength R_1 and yield strength R_2), the SMYS R_1^* and UTS R_2^* are multiplied by a safety factor m which accounts for operating pipeline conditions, when calculating its strength, stability, and deformability, and are divided by the product of the safety coefficients for pipe material, k_1 or k_2 (depending on the pipeline structure and kind of pipe steel used), and the safety coefficient which accounts for the purpose of the pipeline k^* . In this case, the formulas for the design tensile strength (TS) R_1 and yield strength (YS) R_2 have the form:

$$R_1 = \frac{R_1^* m}{k_1 k^*}; \quad R = \frac{R_2^* m}{k_2 k^*}. \quad (6.20)$$

According to the *tabulated in [21] values* of safety factors and when considering the algebraic product of the above coefficients in the form of a generalized coefficient k_{eff} at the corresponding value R_1^* or R_2^* , we find that

$$\begin{aligned} R_1 &= \frac{m}{k_1 k^*} R_1^* = k_1^{eff} R_1^* = (\text{from } 0, 34 \text{ to } 0, 67) R_1^*, \\ R_2 &= \frac{m}{k_2 k^*} R_2^* = k_2^{eff} R_2^* = (\text{from } 0, 44 \text{ to } 0, 82) R_2^*. \end{aligned} \quad (6.21)$$

Thus, depending on the technology of pipe manufacture, its diameter, steel grade, and the design operating pressure, BR [21] reduce the values of strength parameters (tensile strength R_1^* and yield strength R_2^*) of the pipe material by an amount varying from 34 to 67 % for R_1^* and from 44 to 82 % for R_2^* . In the statistical sense thus determined reduced values R_1^* and R_2^* correspond to quintiles [i.e., the probabilities that the actual strength of the pipe material is less than R_1 (R_2)] of infinitesimal order.

Using the distribution parameters of the actual properties of the pipe material, recommended in [15] and presented in Table 6.7, the quintile orders of the reduced tensile and yield strength have values presented in Table 6.8 and Figs. 6.4, 6.5.

When calculating the quintiles from Table 6.8 the property of the normal distribution was used, according to which the probability that a normally distributed RV X will deviate from its mean m more than by $k \cdot \sigma$ (σ is the standard deviation) is equal to

$$P(k) = P(|X - m| \geq k\sigma) = 1 - P\left(\left|\frac{X - m}{\sigma}\right| < k\right) = 2\Phi(-k),$$

where $\Phi(x)$ is the CDF of the standard normal distribution.

Table 6.7 Probabilistic characteristics of relationship between the actual and nominal values of the properties of pipe material

Parameter	Distribution law	Mean	COV, %
YS/SMYS	Normal	1.11	3.4
	Normal	1.08	3.3
	Normal or Lognormal	1.10	3.5
	Lognormal	1.08	4.0
TS/UTS	Normal	1.12	3.0
	Normal	1.12	3.5

Table 6.8 Probabilistic characteristics of the actual properties of pipe material and the corresponding quintile order of the design strength parameters, according to BR [21]

Distribution law	Mean μ	COV ($\%\mu$)	Quantile order
<i>Tensile strength</i>			Value $0.67 \cdot R_1^*$
Normal	1.12	3.0	1.48×10^{-40}
Normal	1.12	3.5	3.01×10^{-30}
<i>Yield strength</i>			Value $0.82 \cdot R_2^*$
Normal	1.11	3.4	1.02×10^{-14}
Normal	1.08	3.3	1.96×10^{-13}
Normal	1.10	3.5	2.39×10^{-13}

The probability $P(k)$ for different values of k is shown in Fig. 6.6, according to which the probability of hitting a RV outside six SD is equal to 1.97×10^{-9} (0.002 cases per million), for seven SD the probability is equal to 2.56×10^{-12} .

The value of $k_1^{eff} \cdot R_1^*$ is less than $r \cdot SD$, where coefficient r is calculated by the formula $r = (\mu - k_1^{eff}) / SD$. At SD equal to 3.0 and 3.5 % of the mean [15] the value $0.67 \cdot R_1^*$ is less than 13.33SD and 11.43SD accordingly. Consequently, its quintile order is practically equal to zero (see Fig. 6.4).

Graphical interpretation of this fact is shown in Fig. 6.7. It explains the origin of very small, yet real and trustable probabilities of failure of pipelines designed using the code in consideration.

A safety factor n for the load, applied to the internal operating pressure in the pipeline, according to BR [21] is characterized by low variability (from 1.10 to 1.15), which is due to several reasons. Primarily, the compressors in gas compressor stations (GCS) and pumps in oil pumping stations (OPS) when in normal stationary mode of operation are not able, in principle, to produce significant exceedance of nominal operating pressure. Mathematically, this is expressed by the fact that the operating pressure can be correctly represented by a stationary Gaussian random function with a small correlation scale and variance, which is overlapped by the value of the coefficient n . Furthermore, the operating pressure is realized only at the outlet of a pump or compressor. From there downstream this pressure only decreases

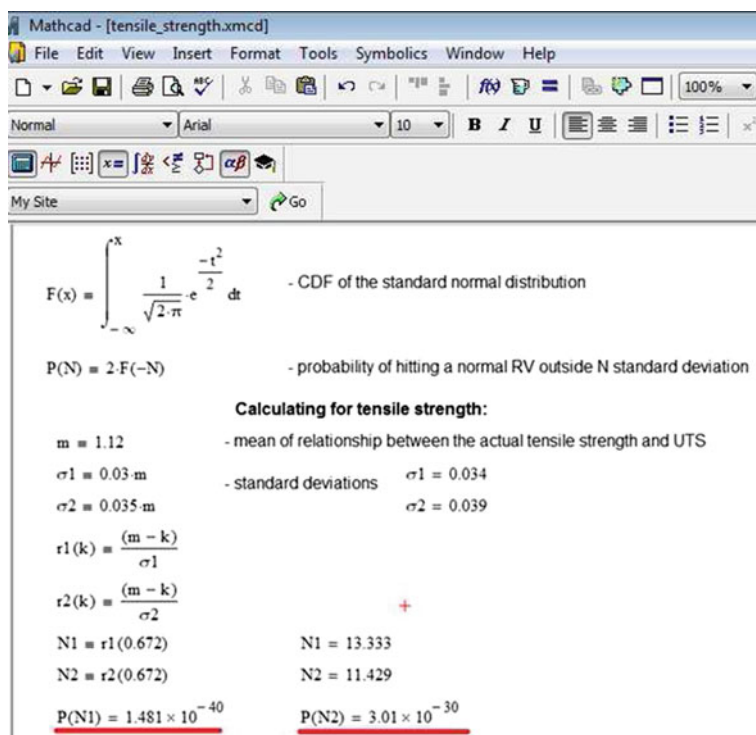


Fig. 6.4 Calculating the quintile order of the design tensile strength, according to BR [21]

monotonically (due to the roughness of internal pipe wall, internal resistance of the pumped fluid/gas, and the changes of the vertical pipeline profile), until it reaches its minimum on the suction side of the compressor/pump of the next GCS/OPS, where the pressure is raised to pump the product further downstream.

Thus, if the load quintile has the order α , then the probability of exceeding this load is equal to $1 - \alpha$.

Consider structure of the formula for calculating the needed pipe wall thickness wt . For the case when the longitudinal axial compressive stresses in the pipe are absent, the formula has the form

$$wt = \frac{nP_{op}D}{2(R_1 + nP_{op})}$$

where P_{op} is the internal (operating) pressure; D is the external pipeline diameter.

This formula shows that when defining the design pipe wall thickness all the safety factors present in BR [21] are involved. Given the load and the strength of pipe material are independent RVs, the probability of the “design failure event”, i.e., the event, against which the pipeline is actually designed/protected, is equal to

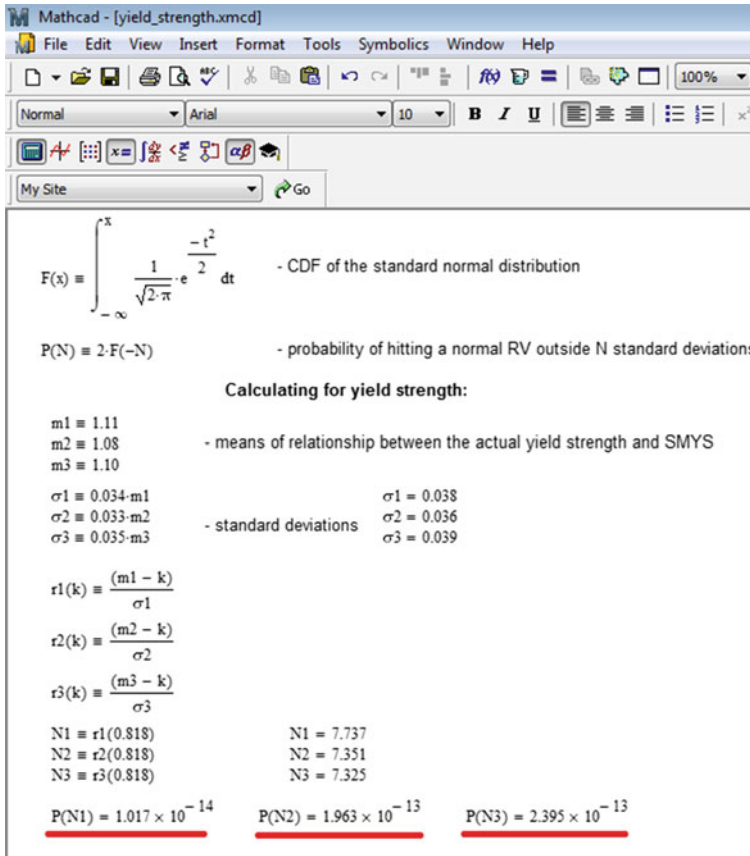


Fig. 6.5 Calculating the quintile order of the design yield strength, according to BR [21]

$$P = P(R_1) [1 - P(nP_{op})] \quad (6.22)$$

where $P(R_1)$ is the probability that the actual strength of the pipe material is *less than* R_1 ; $P[1 - P(nP_{op})]$ is the probability that the load on the pipeline will be *more than* nP_{op} .

Having in mind that the probabilities $P(R_1)$ and $P(nP_{op})$ from Table 6.8 in the above equation are very small, the probability of failure of the pipeline, calculated using [21] becomes vanishingly small.

Hence, BR [21] permits designing practically “absolutely reliable” pipelines at the *stage of their design* (more on this below). The main problem then shifts to correctly assessing the changes in pipeline reliability at the stages of its construction, operation, maintenance, and repair.

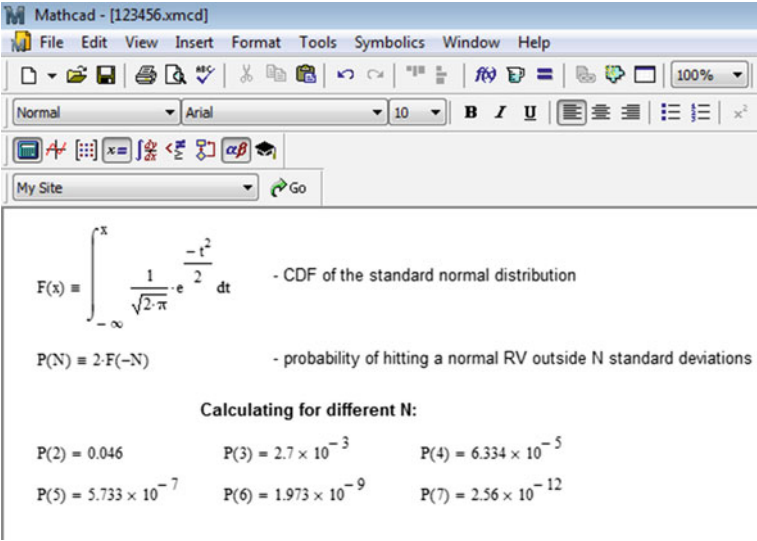


Fig. 6.6 Calculation procedure for assessing the probability of hitting a normal RV outside k SDs ($k = 2 - 7$)

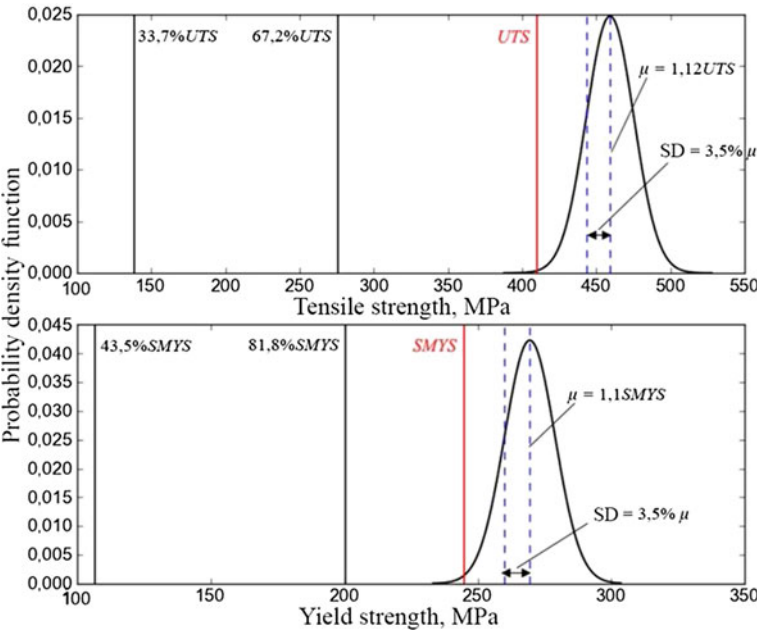


Fig. 6.7 The PDF of the actual properties of pipe material and the values of reduced design strength parameters according to BR [21]

6.5.2 Method of Assessing the Reliability Level Embedded in Pipeline Design Codes Based on a Single Safety Coefficient

To assess the actual level of reliability, empirically embedded in the codes: B31G [1], B31Gmod [2], Shell92 [3], and PCORRC (Battelle) [5] the problem of evaluating POF of an ideal pipeline (without defects) is considered.

Assess the reliability level embedded in the method of evaluating the pipe burst pressure, which is the base for all the above codes. According to Sect. 1.5, the failure pressure for the ideal pipe is given by formula:

$$P_f = \frac{2wt \cdot \sigma_f}{D}, \quad (6.23)$$

where wt is the pipe wall thickness; D is the pipeline diameter; σ_f is the flow stress.

The basic Eq. (6.23) of each code varies depending on which expression for the flow stress is utilized. Since all the above codes are either SMYS based or UTS based, in Eq. (6.23) the UTS or SMYS is used, instead of the flow stress:

$$P_f = \frac{2wt \cdot SMYS}{D} \quad \text{or} \quad P = \frac{2wt \cdot UTS}{D}. \quad (6.24)$$

Assume according to recommendations [15] that the pipe diameter is a deterministic value and the pipe wall thickness and material strength are normal RVs.

Now, in order to assess the POF of an ideal (virgin) pipe (without any defects) it is necessary to find the burst pressure PDF. According to Eq. (6.23) this PDF is the product of two normally distributed RVs: pipe wall thickness and the SMYS/UTS of pipe material. We introduce the RV U :

$$U = wt \cdot SMYS \quad \text{or} \quad U = wt \cdot UTS \quad (6.25)$$

Denote $wt = X$, $SMYS(UTS) = Y$. Then formulas (6.25) can be rewritten as

$$U = XY. \quad (6.26)$$

According to [23, 24], the PDF of two normal-centered RVs is expressed by the modified Bessel function of the second kind and zero order (a.k.a. the Macdonald function):

$$f_U(u) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{e^{-\frac{x^2}{2\sigma_X^2}}}{\sqrt{2\pi}\sigma_X} \frac{e^{-\frac{y^2}{2\sigma_Y^2}}}{\sqrt{2\pi}\sigma_Y} \delta(xy - u) dx dy = \frac{1}{\pi\sigma_X\sigma_Y} K_0\left(\frac{|u|}{\sigma_X\sigma_Y}\right) \quad (6.27)$$

where σ_X^2, σ_Y^2 are accordingly the variance of RVs X and Y , $K_0(z)$ is the modified Bessel function of the second kind and zero order.

Because formula (6.27) is applicable only to centered normal RVs, it is necessary to generalize this specific case for the case of noncentered RVs, X and Y .

According to properties of PDF, the connection between the PDF $f_{Z^*}(z)$ of centered RV Z^* and PDF $f_Z(z)$ of noncentered RV Z is defined by expression

$$f_{Z^*}(z) = f_Z(z + m), \quad (6.28)$$

where m is the mathematical expectation of the RV Z .

In other words, the transition from PDF of a centered RV is performed by shifting this PDF along the abscissa axis to the right by the mathematical expectation (provided its value is positive). In our case, the variable is under the module sign, hence the PDF (6.27) takes the form:

$$f_U(u) = \frac{1}{\pi \sigma_X \sigma_Y} K_0 \left(\frac{|u - m_U|}{\sigma_X \sigma_Y} \right), \quad (6.29)$$

where m_U is the mathematical expectation of RV U , which, according to the property of the mathematical expectation of the product of two independent RVs is

$$m_U = m_X m_Y, \quad (6.30)$$

where m_X, m_Y are accordingly the mathematical expectation of RVs, X and Y .

According to the property of the product of two independent RVs, the variance of RV U is equal to

$$\sigma_U^2 = \sigma_X^2 \sigma_Y^2 + m_X^2 \sigma_Y^2 + m_Y^2 \sigma_X^2. \quad (6.31)$$

For centered RVs X and Y this formula takes the form $\sigma_U^2 = \sigma_X^2 \sigma_Y^2$. Hence, it is easy to prove that *the PDF of the product of two noncentered normally distributed RVs will take the form*

$$f_U(u) = \frac{1}{\pi \sigma_U} K_0 \left(\frac{|u - m_U|}{\sigma_U} \right). \quad (6.32)$$

where SD σ_U of RV U is calculated from formula (6.31).

Then the CDF of the RV U is defined by formula

$$F_U(u) = \int_{-\infty}^u f_U(t) dt = \int_{-\infty}^u \frac{1}{\pi \sigma_U} K_0 \left(\frac{|t - m_U|}{\sigma_U} \right) dt. \quad (6.33)$$

The burst pressure is connected with the RV U by relation $P_f = 2U/D$, hence the statistical parameters, PDF and CDF of burst pressure will take the following forms:

$$\begin{aligned}
m_{P_f} &= \frac{2}{D} m_X m_Y, \\
\sigma_{P_f} &= \frac{2}{D} \sqrt{\sigma_X^2 \sigma_Y^2 + m_X^2 \sigma_Y^2 + m_Y^2 \sigma_X^2}, \\
f_{P_f}(t) &= \frac{1}{\pi \sigma_{P_f}} K_0 \left(\frac{|t - m_{P_f}|}{\sigma_{P_f}} \right) \\
F_{P_f}(z) &= \int_{-\infty}^z f_{P_f}(t) dt = \int_{-\infty}^z \frac{1}{\pi \sigma_{P_f}} K_0 \left(\frac{|t - m_{P_f}|}{\sigma_{P_f}} \right) dt.
\end{aligned} \tag{6.34}$$

From the above it follows that knowing the burst pressure PDF for an ideal pipe, it is possible to assess its POF, i.e., the probability that the burst pressure will be less than the design operating pressure P_d :

$$F_{P_f}(P_d) = P(P_f < P_d) = \int_{-\infty}^{P_d} \frac{1}{\pi \sigma_{P_f}} K_0 \left(\frac{|t - m_{P_f}|}{\sigma_{P_f}} \right) dt. \tag{6.35}$$

This solution of the posed problem is found on the assumption that the operating pressure P_{op} is a deterministic quantity. But, in practice, the operating pressure (OP) is also a RV.

In order to assess the POF of an ideal pipe taking into account randomness of the OP, consider the LSF:

$$LSF = P_f - P_{op}. \tag{6.36}$$

Find PDF of the LSF as a RV. As LSF is the difference of two RVs, its PDF is defined (according to [13]) by the convolution formula:

$$f_{LSF}(z) = \int_{-\infty}^{\infty} f_{P_f}(z + y) f_{P_{op}}(y) dy, \tag{6.37}$$

where $f_{P_f}(z)$, $f_{P_{op}}(z)$ are the PDFs of failure and operating pressures, respectively.

Then the CDF of the LSF as RV is defined by formula

$$F_{LSF}(z) = \int_{-\infty}^z f_{LSF}(t) dt = \int_{-\infty}^z \int_{-\infty}^{\infty} f_{P_f}(t + y) f_{P_{op}}(y) dy dt. \tag{6.38}$$

According to recommendations [15], the relationship between the operating pressure P_{op} and the design pressure P_d can be described by a beta distribution (for which the RV takes values from 0 to 1). As the design pressure is a deterministic quantity, it is necessary to determine the PDF of OP. To achieve this use the generalized beta distribution [25], which describes the following RV:

$$Y = P_d X, \quad (6.39)$$

where RV X is the ratio of the operating pressure P_{op} to the design pressure P_d , which is distributed according to the classic beta distribution. Hence, the RV Y is the OP P_{op} in the pipeline.

According to [25], parameters of the classical beta distribution of the RV X can be calculated using formulas:

$$\begin{aligned} a &= m_X \left(\frac{m_X(1-m_X)}{\sigma_X^2} - 1 \right), \\ b &= (1 - m_X) \frac{a}{m_X}, \end{aligned} \quad (6.40)$$

where m_X , σ_X^2 are accordingly the mathematical expectation and variance of RV X .

PDF of RV Y has the form [25]:

$$f(y) = \frac{y^{a-1} (P_d - y)^{b-1}}{B(a, b) P_d^{a+b-1}}, \quad (6.41)$$

where $B(a, b)$ is the beta function. In the case of generalized beta distribution the quantity P_d is the upper boundary for the RV $Y(OP)$, i.e., RV Y changes from 0 to P_d .

The mathematical expectation and variance of RV Y are defined using formulas [25]:

$$\begin{aligned} m_Y &= \frac{aP_d}{a+b}, \\ \sigma_Y^2 &= \frac{abP_d^2}{(a+b)^2(a+b+1)}. \end{aligned} \quad (6.42)$$

Hence, formulas (6.37) and (6.38) will take following form:

$$\begin{aligned} f_{LSF}(z) &= \int_0^{P_d} \frac{1}{\pi \sigma_{P_f}} K_0 \left(\frac{|z+y-m_{P_f}|}{\sigma_{P_f}} \right) \frac{y^{a-1} (P_d - y)^{b-1}}{B(a, b) P_d^{a+b-1}} dy, \\ F_{LSF}(z) &= \int_{-\infty}^z \int_0^{P_d} \frac{1}{\pi \sigma_{P_f}} K_0 \left(\frac{|t+y-m_{P_f}|}{\sigma_{P_f}} \right) \frac{y^{a-1} (P_d - y)^{b-1}}{B(a, b) P_d^{a+b-1}} dy dt. \end{aligned} \quad (6.43)$$

Then, knowing the PDF of the LSF as a RV, it is possible to calculate in closed form the exact POF of an ideal pipe, i.e., the probability that the $LSF \leq 0$:

$$F_{LSF}(0) = \int_{-\infty}^0 \int_0^{P_d} \frac{1}{\pi \sigma_{P_f}} K_0 \left(\frac{|t+y-m_{P_f}|}{\sigma_{P_f}} \right) \frac{y^{a-1} (P_d - y)^{b-1}}{B(a, b) P_d^{a+b-1}} dy dt, \quad (6.44)$$

where parameters a, b are calculated using formulas (6.40), parameters, and m_{P_f}, σ_{P_f} are calculated using formulas (6.34).

6.5.3 Numerical Analysis of the Reliability Level Actually Embedded in Pipeline Design Codes

Real case study #6.5.1. Apply the described in Sect. 6.5.1 approach to a real III category land pipeline made out of 17GS steel, strength class 52, 720 mm in diameter, and 8 mm pipe wall thickness, designed according to BR [21], with design operating pressure $P_d = 6.2$ MPa and allowable operating pressure $P_{op} = 5.5$ MPa.

The minimum yield strength for this pipeline steel is equal to 353 MPa and minimum tensile strength is 510 MPa. According to BR [21] for this pipeline, the partial safety coefficients take the following values: safety coefficient for pipe operation conditions $m = 0.90$; safety coefficients for pipe material $k_1 = 1.47$ and $k_2 = 1.15$; safety coefficient which accounts for the pipeline purpose $k^* = 1.0$; and safety load factor $n = 1.1$.

Following [15] assume that pipe material strength values are normally distributed, with parameters:

- tensile strength with mean $m_1 = 1.12 \cdot 510.00 = 571.20$ MPa and SD $\sigma_1 = 0.035m_1 = 19.99$ MPa;
- yield strength with mean $m_2 = 1.10 \cdot 353.00 = 388.30$ MPa and SD $\sigma_2 = 0.035m_2 = 13.59$ MPa.

Assess now the order of the quintile of pipe material strength parameters R_1 , R_2 and the probability $P(R_1)$ that the actual strength of the pipe material is less than R_1 . The obtained results are shown in Fig. 6.8, according to which the estimates of the strength parameters of the pipe material are

$$\begin{aligned} R_1 &= 312.25 \text{ MPa;} \\ R_2 &= 276.26 \text{ MPa.} \end{aligned}$$

The generalized safety coefficients for this case are $k_1^{eff} = 0.61$, $k_2^{eff} = 0.78$.

According to Fig. 6.8, the calculated values of strength parameters R_1 and R_2 have the quintile order of 11.31×10^{-39} and 83.32×10^{-18} , respectively. Hence, the probability $P(R_1)$ that the actual strength of the pipe material is less than R_1 , practically is equal to zero (11.31×10^{-39}).

Now assume, according to recommendations [15], that the ratio between the operating pressure and the design pressure P_{op}/P_d is described by a *Beta distribution* with mean value $m = 0.865$ and SD $\sigma = 0.084$ m. Then the quantity $nP_{op} = 1.1 \cdot 5.5 = 6.05$ has the quintile order of 0.984. Consequently, the probability $P(1 - P(nP_{op}))$ that the load on the pipeline will be greater than nP_{op} , is equal to 0.016.

Thus, the probability $P = P(R_1) \cdot P(1 - P(nP_{op}))$ is infinitesimal ($11.31 \times 10^{-39} \cdot 0.016$).

Real case study #6.5.2. Apply the described in Sect. 6.5.2 approach to a real pipeline, which parameters are shown in Table 6.9.

Probabilistic characteristics of the pipeline wall thickness were calculated on the assumption [19] that it is normally distributed.

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$$\begin{aligned}
 &UTS \equiv 510 & SMYS \equiv 353 \\
 &m1 \equiv 1.12 \cdot UTS & m2 \equiv 1.1 \cdot SMYS \\
 &\sigma1 \equiv 0.035 \cdot m1 & \sigma2 \equiv 0.035 \cdot m2 \\
 &F1(x) \equiv \int_{-\infty}^x \frac{e^{\frac{-(t-m1)^2}{2 \cdot \sigma1^2}}}{\sigma1 \cdot \sqrt{2\pi}} dt & F2(x) \equiv \int_{-\infty}^x \frac{e^{\frac{-(t-m2)^2}{2 \cdot \sigma2^2}}}{\sigma2 \cdot \sqrt{2\pi}} dt \\
 &R1 \equiv \frac{UTS \cdot 0.9}{1.47 - 1} & R2 \equiv \frac{SMYS \cdot 0.9}{1.15 - 1} \\
 &R1 = 312.245 & R2 = 276.261 \\
 &\underline{F1(R1) = 11.307 \times 10^{-39}} & \underline{F2(R2) = 83.322 \times 10^{-18}}
 \end{aligned}$$

Fig. 6.8 Calculation of the probability that the actual strength of pipe material is less than R_1

Table 6.9 Nominal values of pipeline parameters

Parameter	Symbol	Value
External pipeline diameter, mm	D	325.00
Pipe wall thickness, mm	wt	9.00
Specified minimum yield strength, MPa	$SMYS$	245.00
Ultimate tensile strength, MPa	UTS	410.00
Design operating pressure, MPa	P_d	6.40

Table 6.10 Pipeline parameters

Parameter	Symbol	Distribution law	Mean, mm	SD, mm
External pipeline diameter, mm	D	Deterministic	325.00	0
Pipe wall thickness, mm	wt	Normal	8.90	0.23
Specified minimum yield strength, MPa	$SMYS$	Normal	269.50	9.43
Ultimate tensile strength, MPa	UTS	Normal	459.00	16.07
Relationship between operating pressure and the design pressure	P_{op}/P_d	Beta	0.865	0.084-mean

The maximum deviations for the pipe wall thickness are $+0.6$ and -0.8 mm. Using the three-sigma rule and the parameter values, as specified by Table 6.7, it is possible to calculate its mean and standard deviation, which are, respectively, equal to $(9.6 + 8.2)/2 = 8.9$ mm (wt) and $(9.6 - 8.2)/6 = 0.23$ mm (SD). The PDFs for $SMYS$ and UTS and their parameters were chosen according to Table 6.8.

Following [15], assume that the relationship between the OP and the DP is described by a beta distribution with mean 0.865 and coefficient COV 0.084. The initial data needed for further analysis are presented in Table 6.10.

Start with checking that the obtained PDF (6.34) of the burst pressure RV in our case is the true PDF, i.e., the integral of the PDF over the whole region of its existence is strictly equal to unity. Also check that the mathematical expectation and standard deviation, calculated using the obtained PDFs, coincide with their initial (empirical) values. Then calculate the POF of an ideal pipe for the case when the operating pressure is considered as a deterministic value.

The results of calculation using formulas (6.34) are shown in Figs. 6.9 and 6.10, according to which the POF of an ideal pipe, for the case when the operating pressure is deterministic, is equal to 2.349×10^{-7} and 3.4×10^{-9} , when using as flow stress the $SMYS$ and the UTS , respectively. These numbers, calculated analytically and in closed form do not contain any calculation errors and, therefore, can be used as *benchmarks*, and show the origin and validity of small values POF for pipeline without defects.

Now solve the posed problem for the case when operating pressure is a RV. First, check that the obtained PDF (6.41) of the operating pressure RV in our case is the true PDF, i.e., the integral of the PDF over the whole region of its existence is strictly equal to unity. Also check that the mathematical expectation and standard deviation, calculated using the obtained PDFs, coincide with their initial (empirical) values. The results of these tests and the OP PDF graph are shown in Figs. 6.11 and 6.12.

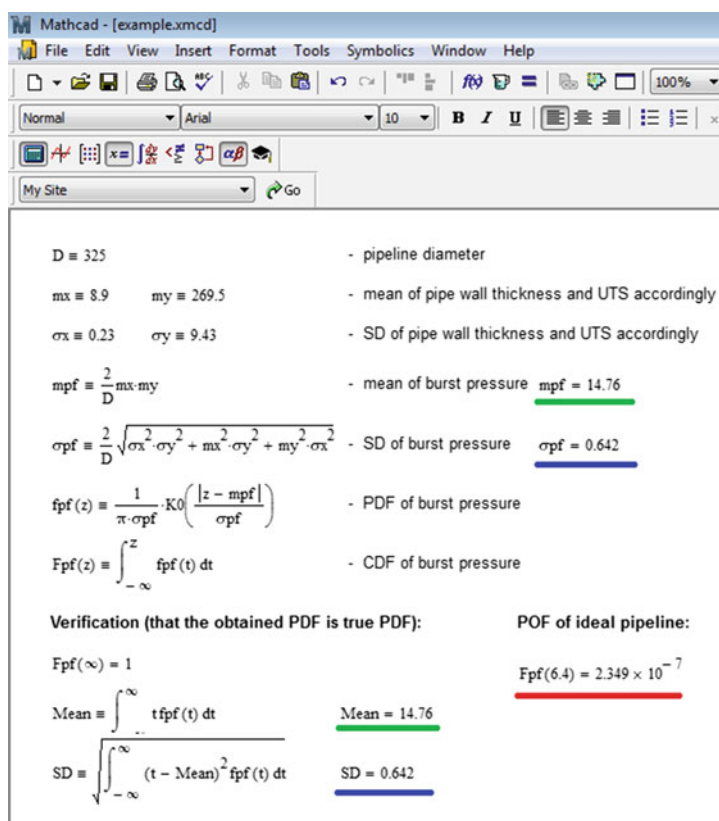


Fig. 6.9 Calculation of the POF for an ideal pipe (OP deterministic; SMYS is used as flow stress)

Further calculate the POF of an ideal pipe for the case when the OP is a RV. Results of calculus are shown in Figs. 6.13 and 6.14, according to which the POF of an ideal pipe is equal to 7.351×10^{-8} and 1.644×10^{-9} , respectively, when using the SMYS and the UTS as flow stress.

Assess now the POF of an ideal pipe according to the procedures of the B31G, B31Gmod, Battelle, and Shell92 design codes. Burst pressure of an ideal pipe in this case is calculated using one of the following formulas:

$$B31G : P_f(t) = \frac{2wt \cdot 1.1SMYS}{D};$$

$$B31Gmod : P_f(t) = \frac{2wt \cdot (SMYS + 68.95MPa)}{D};$$

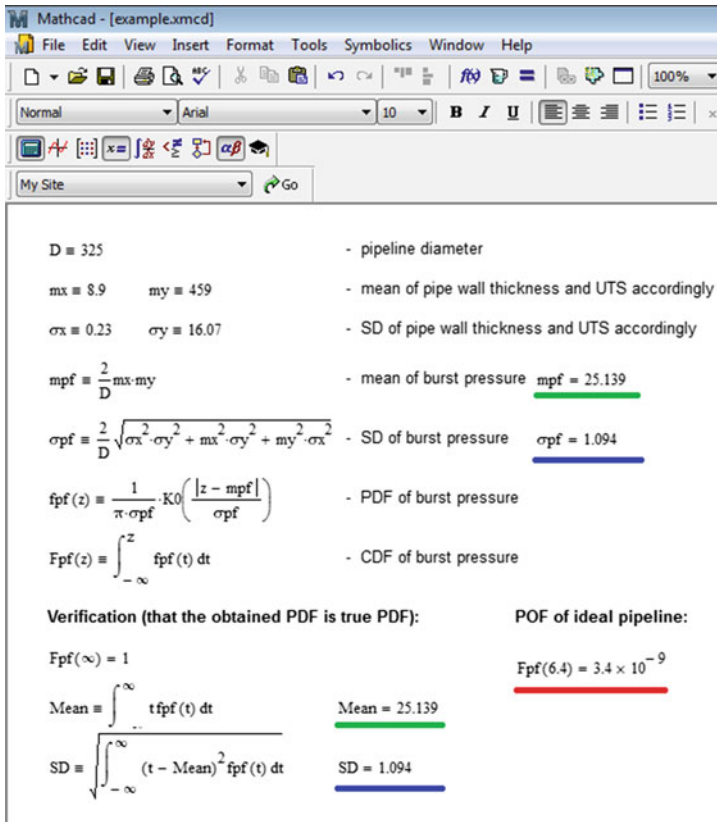


Fig. 6.10 Calculation of the POF for an ideal pipe (OP is deterministic; UTS is used as flow stress)

$$Battelle : P_f(t) = \frac{2wt \cdot UTS}{D};$$

$$Shell92 : P_f(t) = \frac{2wt \cdot 0.9UTS}{D}.$$

The POF of an ideal pipe using Battelle code coincides with the already considered case (#2), when the UTS was used as the flow stress. Calculate the POF according to the three remaining codes. The obtained results are given in Table 6.11.

It should be noted that when assessing POF of other pipelines, only the value of the POF mean may change, but not its order of magnitude.

The results obtained above need a comprehensive interpretation. First of all, it should be noted that all POF values obtained in this study are exact to the point of used pipeline codes and, hence, expressions for the limit state functions.

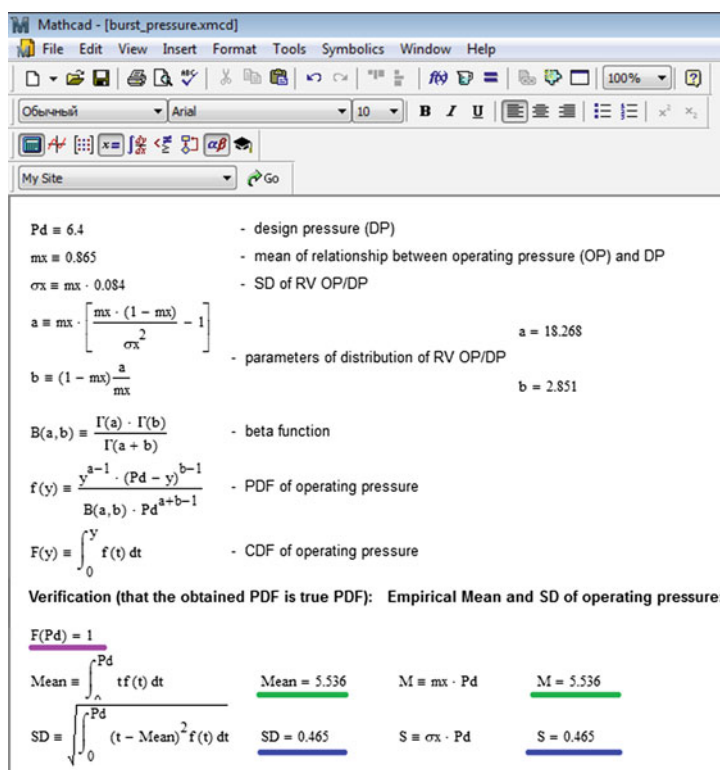


Fig. 6.11 Calculation of PDF and CDF of operating pressure

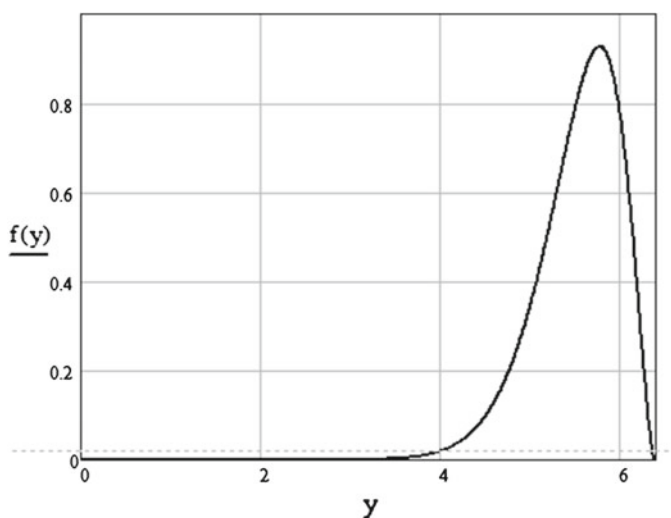


Fig. 6.12 PDF of operating pressure

These results are also absolutely dependent on the PDFs of pipe geometry, pipe material strength, and load parameters used, and the values of the deterministic safety factors used in some of the considered codes.

The values of POF reflect each change in the initial data used in the design codes and pipeline practice. The small values of POFs for pipe designs revealed in this study are a direct consequence of the used design assumptions and statistics about the pipeline parameters.

The main problem now is in establishing a connection of the design reliability of pipelines with the reliability of the same pipelines during their construction, commissioning, operation, diagnostics, maintenance, and repair/rehabilitation. Research along this avenue is under way.

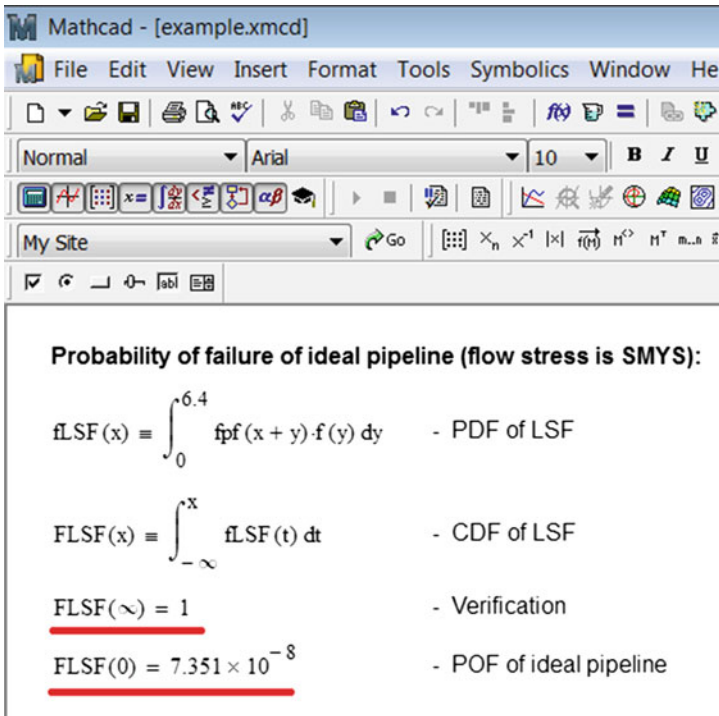


Fig. 6.13 Calculating the POF for an ideal pipe (SMYS used as flow stress)

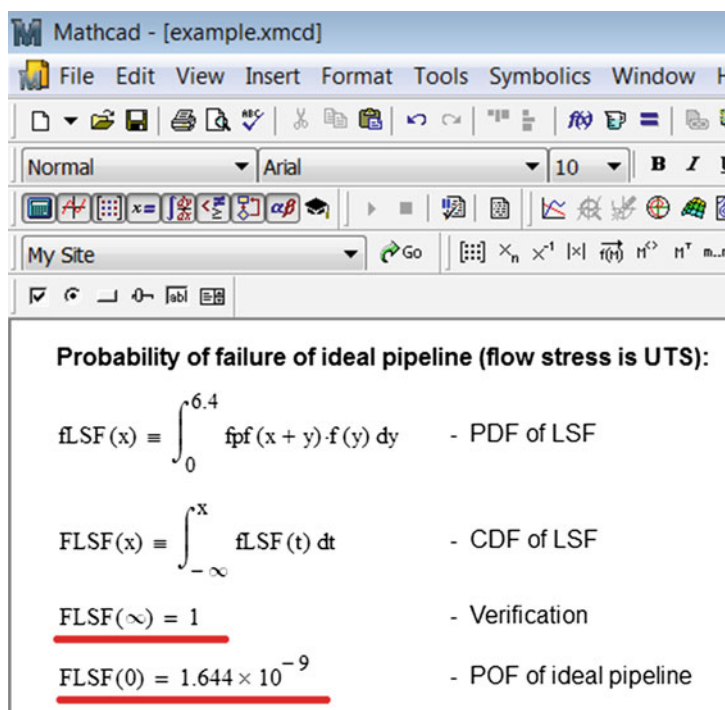


Fig. 6.14 Calculating the POF for an ideal pipe (UTS used as flow stress)

Table 6.11 POF of a geometrically ideal pipeline, using different pipeline design codes

Code	POF
B31G (SMYS)	3.16×10^{-8}
B31Gmod (SMYS)	1.06×10^{-9}
Battelle (UTS)	1.64×10^{-9}
Shell92 (UTS)	2.98×10^{-9}

6.6 Classical Approach to Reliability Assessment of the Whole Pipeline as a System

For a whole pipeline as a system of individual defective segments the two-sided probability of failure assessment is determined as follows [26]:

$$\max_{i=1, \dots, n} P^{d_i}(t) \leq P^{PL}(t) \leq 1 - \prod_{i=1}^n (1 - P^{d_i}(t)), \quad (6.45)$$

where $P^{d_i}(t)$ is the probability of failure of the i th dangerous defect ($i = 1, 2, \dots, n$) at a given point in time t ; P^{PL} is the probability of failure of the whole pipeline.

The left side of Eq. (6.45) for the most dangerous defect corresponds to the lower valuation of $P^{PL}(t)$ for probability of failure of the pipeline (or the upper valuation of reliability $R^{PL}(t)$):

$$P^{PL}(t) = \max_{i=1, \dots, n} P^{d_i}(t), \quad (6.46)$$

$$R^{PL}(t) = \max_{i=1, \dots, n} R^{d_i}(t), \quad (6.47)$$

where $R^{d_i}(T)$ is the assessment of reliability of the i th defect.

The upper assessment of $P^{PL}(t)$ probability of failure of a pipeline (or the lower reliability assessment $R^{PL}(t)$) is determined correspondingly by formulas:

$$P^{PL}(t) = 1 - \prod_{i=1}^n (1 - P^{d_i}(t)), \quad (6.48)$$

$$R^{PL}(t) = \prod_{i=1}^n R^{d_i}(t). \quad (6.49)$$

In this case the two-sided assessment of reliability of the whole pipeline is determined as follows:

$$\prod_{i=1}^n R^{d_i}(T) \leq R^{PL}(T) \leq \max_{i=1, \dots, n} R^{d_i}(T).$$

For a pipe with n mutually independent corrosion defects failure probability equals

$$P^{PL} = 1 - (1 - P^{d_1})(1 - P^{d_2}) \dots (1 - P^{d_n}).$$

The reliability function of the whole pipeline as a system with n mutually independent corrosion defects has the form

$$R^{PL} = \prod_{i=1}^n (R^{d_i}(T)), \quad i = 1, \dots, n,$$

To implement the described approach it is necessary to perform a preliminary virtual segmentation of a pipeline by means of dividing it into statistically uniform segments with respect to corrosion, which would allow avoiding mistakes in assessment of its reliability.

Given a relatively large prognosis depth, when the corrosion processes have sufficient time to stabilize, linear approximation of corrosion growth becomes possible (see [27–29]).

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Chapter 7

Markov Models of Pipeline Degradation Process

Presentation of a pipeline system in the form of series-connected defective cross sections (see Sect. 6.6) is not always applicable in practice. When using this scheme, the probability of failure of the whole system is equal to unity minus the product of the probability of failure-free operation of all its elements. The reliability index of such a system is low compared to the reliability of its elements and, given an increase in the number of elements (defects), the system is drastically reduced, even when the reliability of each element is high (see Sect. 2.6). If the number of elements in the system is large, it is practically impossible to create a high reliability system, as required, without providing it with a highly effective pipeline inspection, maintenance, and renewal subsystem. The main cause is that all defects are involved in the POF calculation and essentially influence its value. In distributed systems not all the defects present in the pipeline are capable of creating an input into the POF of the pipeline as a system. To account for this circumstance it was suggested to take into consideration in the calculations only those “significant” defects which can actually affect the system’s reliability. At the same time there are no recommendations on how to select the “significant” defects. Practically, to select from the entire set of defects, those which possess this quality, it is necessary to perform fairly complex calculations.

In this chapter the pipeline degradation—growth of many corrosion defects and reduction of residual strength (burst pressure) are described by Markov processes of pure birth and pure death type, respectively. *This allows considering collective (joint) behavior of the set of actively growing defects in the pipeline as a distributed system, and to eliminate the restrictions of the classical approach.*

On the basis of constructed (see below) Markov models the following methods are proposed:

- a method for assessing the POF (reliability) of a single defective pipeline cross section and of a pipeline as a distributed system;
- practical assessment of the gamma-percent residual life of PS;

- an adequate economic model for assessing the optimum time for performing the next ILI or PS maintenance/repair, which minimizes maintenance expenditures;
- a method of estimating the information entropy generated by degradation of the defective pipeline cross section. This permits establishing relations between different physical and probabilistic states of the PS and opens new possibilities for its early diagnostics and optimizing its maintenance.

The main cause of pipeline systems degradation is destruction of pipe walls due to corrosion, fatigue damage accumulation, effects of shock loads, etc. The distinctive feature of degradation of such systems is, as a rule, the presence of multiple actively growing defects, each of which is a potential threat to its integrity. Violation of pipeline integrity usually leads to enormous losses, which can reach several million dollars per accident. There are two types of pipeline integrity loss: leak and rupture. In general, the distributed system is a system for which the location of its elements (or groups of its elements) plays an important role from the standpoint of its functioning and, therefore, of its analysis. In classical structural reliability theory the pipeline system models as a chain of series-connected elements (defects). In this case the POF of a PS is equal to the product of the POFs of all the elements in the structure. The reliability of such a system is lower than the reliability of its elements, and with increase of the number of elements (defects) the system reliability rapidly decreases. If the number of elements in the system is large, it is practically impossible to create a system with required (high) reliability. The developed Markov models are capable of describing the joint behavior of the set of growing defects in the pipeline as a distributed system, eliminates the drawback of the classical approach of the structural reliability theory when applied to a pipeline system.

A methodology has been developed for estimating the information entropy generated by the Markov process of degradation of corrosion-type defects and establishing relationships between physical and probabilistic conditions of structural systems as shown on the examples of pipelines. According to the results of conducted analysis, the value of the defect entropy maximum is invariant with respect to the used design codes, defect depth and its corrosion rate, all of which confirms its fundamental nature. This entropy measure could be useful for early diagnostics of pipeline systems condition.

In general, the described methodology provides consistent and transparent mathematical logistics for solving main problems associated with reliability and risk-based pipeline design, operation and predictive maintenance. The specifics of this approach is in the form of a string of interconnected problems when the output of the first problem serves as the input to the second problem, and so on, until the solution of the last problem does not yield the needed result.

7.1 Formal Description of the Pure Birth (Death) Markov Process

In reliability analysis of technical systems, their operation is generally regarded as a random process of transition from one state to another, caused by the degradation and failure of its components (elements). This process under certain conditions can be quite strictly described by a Markov process.

It should be noted that the assessment of the technical systems reliability usually is based on an exponential distribution of pipeline uptime and does not depend on the previous time of safe operation. The only condition needed for applicability of the pure birth (death) Markov process is that the transition probabilities must not depend on the past, and the sojourn time for a process to be in any particular state should be exponentially distributed. Since the uptime of each element of the technical system (in our case, the pipeline defective cross sections) is exponentially distributed, the moment of element failure in the future does not depend on how much time it operated before a failure. Therefore, the probability that in future the system will stay in a state or leave it does not depend on the process “prehistory.”

Consider a system S , which can be in one of the following states $S_0, S_1, S_2, \dots$, which form a set that is finite or countable and the time t is continuous, i.e., the transition of the system from one state to another is occurring at random unknown beforehand moments of time t .

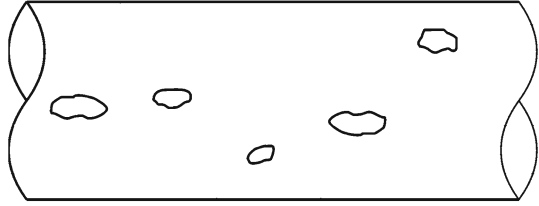
Denote as $S(t)$ the state of system S at the moment of time t . The probability $P_i(t)$ of the system being in the i -th state at time t is called “probability of an event,” which means that at the moment of time t the system S is in the S_i state:

$$P_i(t) = P[S(t) = S_i].$$

A random process that evolves in the system S with discrete states $S_0, S_1, S_2, \dots$, is called a Markov process, if for any arbitrary moment of time t_1 the probability of each of the system states in the future (at $t > t_1$) depends only on the current state the system is in (at $t = t_1$), and does not depend on when and how system entered this state, i.e., does not depend on the system’s behavior in the past (at $t < t_1$).

The system S is changing only by transition from one state to the closest, adjacent state (from S_n to S_{n+1} or to S_{n-1}). If at some moment of time t the system S is in the state S_n , then the probability that during an incremental time Δt , which immediately follows t , a transition $E_n \rightarrow E_{n+1} (E_{n-1})$ will take place, is approximately equal to $\lambda_n(\mu_n)\Delta t$, where the quantity $\lambda_n(\mu_n) \geq 0 [1/time]$ and does not depend on how the system S arrived at the current state. This means that the process in consideration is a Markov process [11]. The probability that during the small time span of Δt more than one transition will occur is of higher order of magnitude smaller than Δt . The quantity $\lambda_n(\mu_n)$ for the pure birth (death) Markov process is called “transition intensity” of system S from one state to another.

Fig. 7.1 Pipeline segment with multiple corrosion type defects



7.2 Pure Birth Markov Model of Corrosion Defects Growth

This section presents a new effective model which describes simultaneous growth of a set of independent corrosion defects (see Fig. 7.1).

Divide the pipe wall thickness into M nonoverlapping intervals with numbers $i = 1, \dots, M$. The defect depth at moment of time t is the random value $d(t)$, which takes values from the interval $(0; wt]$, where wt is the pipe wall thickness.

The process of the depth growth of a set of defects is considered as a pure birth Markov process. The defect depth with time can only monotonically grow, i.e., at random moments of time can transit from the i th state only to the $(i + 1)$ -th state.

The system of differential equations (SDE) describing this process, which is characterized by a discrete number of states and continuous time, has the form

$$\begin{cases} \frac{dP_1(t)}{dt} = -\lambda_1 P_1(t); \\ \frac{dP_i(t)}{dt} = \lambda_{i-1} P_{i-1}(t) - \lambda_i P_i(t), i = 2, \dots, M, \end{cases} \quad (7.1)$$

where $P_i(t)$ is the probability that the defect depth is in the i th state at time t , λ_i is the intensity of transition of the defect depth from the i th state to the $(i + 1)$ -th state.

We carry out a consistent solution of the system of differential equations (7.1) with initial conditions corresponding to the distribution of states (intervals) of defects depths at the initial moment of time $t = 0$:

$$\begin{aligned} P_i(T_0) &= p_i^*, i = 1, 2, \dots, k, \\ P_i(T_0) &= 0, i > k. \end{aligned}$$

Here

$$p_i^* = \frac{n_i^*(0)}{N^*(0)}, i = 1, 2, \dots, k, \quad (7.2)$$

p_i^* is the frequency of occurrence of defect depth in the i -th interval at the initial time $t = 0$; $n_i^*(0)$ and $N^*(0)$ is the number of defects, whose depth is in the i -th interval and the total number of defects detected in the pipeline at the initial time $t = 0$ respectively.

The first equation of system (7.1) has the solution

$$P_1(t) = c \exp \{-\lambda_1 t\}.$$

The constant c is calculated from the initial condition. Then the general solution of this equation is

$$P_1(t) = p_1^* \exp \{-\lambda_1 t\}.$$

We solve the second equation of (7.1) by the variation of the constant method:

$$\frac{dP_2(t)}{dt} + \lambda_2 P_2(t) = \lambda_1 p_1^* \exp \{-\lambda_1 t\}. \quad (7.3)$$

The solution of the homogeneous equation $\frac{dP_2(t)}{dt} + \lambda_2 P_2(t) = 0$ has the form

$$P_2(t) = C \exp \{-\lambda_2 t\}.$$

Then the general solution is found as

$$P_2(t) = C(t) \exp \{-\lambda_2 t\}.$$

Insert this solution into equation (7.3):

$$\begin{aligned} C'(t) \exp \{-\lambda_2 t\} - \lambda_2 C(t) \exp \{-\lambda_2 t\} + \lambda_2 C(t) \exp \{-\lambda_2 t\} &= \lambda_1 p_1^* \exp \{-\lambda_1 t\} \\ \Rightarrow C'(t) &= \lambda_1 p_1^* \exp \{(\lambda_2 - \lambda_1) t\}. \end{aligned}$$

Integrating the last equation

$$C(t) = \frac{\lambda_1 p_1^*}{(\lambda_2 - \lambda_1)} \exp \{(\lambda_2 - \lambda_1) t\} + c_1$$

we obtain the general solution:

$$P_2(t) = C(t) \exp \{-\lambda_2 t\} = \frac{\lambda_1 p_1^*}{(\lambda_2 - \lambda_1)} \exp \{-\lambda_1 t\} + c_1 \exp \{-\lambda_2 t\}.$$

The constant c_1 is calculated from the initial condition:

$$P_2(0) = \frac{\lambda_1 p_1^*}{(\lambda_2 - \lambda_1)} + c_1 = p_2^* \Rightarrow c = p_2^* - \frac{\lambda_1 p_1^*}{(\lambda_2 - \lambda_1)}.$$

Then the general solution of the second equation of (7.1) has the form

$$P_2(t) = \frac{\lambda_1 p_1^*}{(\lambda_2 - \lambda_1)} \exp \{-\lambda_1 t\} + \left(p_2^* - \frac{\lambda_1 p_1^*}{(\lambda_2 - \lambda_1)} \right) \exp \{-\lambda_2 t\}.$$

Applying the same method to solve the third equation, we obtain

$$P_3(t) = \frac{\lambda_1 \lambda_2 p_1^*}{(\lambda_2 - \lambda_1)(\lambda_3 - \lambda_1)} \exp\{-\lambda_1 t\} + \frac{\lambda_2}{\lambda_3 - \lambda_2} \left(p_2^* - \frac{\lambda_1 p_1^*}{(\lambda_2 - \lambda_1)} \right) \exp\{-\lambda_2 t\} \\ - \left\{ p_3^* - \left[\frac{\lambda_1 \lambda_2 p_1^*}{(\lambda_2 - \lambda_1)(\lambda_3 - \lambda_1)} + \frac{\lambda_2}{\lambda_3 - \lambda_2} \left(p_2^* - \frac{\lambda_1 p_1^*}{(\lambda_2 - \lambda_1)} \right) \right] \right\} \exp\{-\lambda_3 t\}.$$

Thus, the general solution of system (7.1) with the initial conditions (7.2) can be written as:

$$P_i(t) = \sum_{j=1}^i \mu_{ij} \exp\{-\lambda_j t\} \quad (i = 1, \dots, M), \quad (7.4)$$

where

$$\left\{ \begin{array}{l} \mu_{11} = p_1^*, \\ \mu_{i-1,j} = \frac{\lambda_{i-1}}{\lambda_i - \lambda_j}, i \neq j, \\ \mu_{ij} = \left\{ \begin{array}{l} p_i^* - \sum_{q=1}^{i-1} \mu_{iq}, i = j, i \leq k, \\ - \sum_{q=1}^{i-1} \mu_{iq}, i = j, i > k. \end{array} \right. \end{array} \right. \quad (7.5)$$

The unknown intensities λ_i ($i = 2, 3, \dots, M$) are calculated numerically by sequentially solving equations

$$P_i(t_1) = p_i = \sum_{j=1}^i \mu_{i,j} \exp[-\lambda_j(t_1)],$$

where $p_i = \frac{n_i(t_1)}{N(t_1)}$, $i = 2, \dots, M$; $n_i(t_1)$ is the number of defects, whose depths are in the i -th interval; $N(t_1)$ is the total number of defects detected in the pipe segment at the initial time $t = t_1$.

7.3 Algorithm for Assessing the Predicting Probabilities of the Defect Depths Being in Given States

Typically, the first maintenance or risk based inspection of the pipeline in operation occurs after many years of its operation, when the defects of different depths caused by corrosion, are already present.

Denote the beginning of the pipeline operation as $t_0 = 0$. Assume that at moment $t = t_1 > t_0$ $N(t_1)$ defects in the pipeline were detected, which depth is in the first intervals, with numbers from 1 to k . Assume that (according to the last conducted ILI), the distribution of initial defects over the states (intervals) at time t_0 (i.e., frequencies

$P_i(0) = p_i^*$ is known. Without loss of generality, it can be assumed that at time $t_0 = 0$ all the defects depths are inside the first interval, which can be selected as being from 0 to 10 % wt , so that the intervals width $h = 0.1wt$. In this case, the initial conditions (7.2) take the form

$$P_1(0) = p_1^* = 1; P(0) = 0, i > 1.$$

On the basis of these initial data it is necessary to determine:

- the transition intensity λ_i of defects depths from the i -th state to the $(i + 1)$ -th state;
- the values of predicting probabilities that the defects depths will be in the i -th state ($i = 1, 2, \dots, M$) at $t > t_1$.

The algorithm for calculating the transition intensities and predicting probabilities that the defects depths are in a given state consists of the following *successive* stages.

Step 1. Formation of intervals for initial defects depths. The range $0 - k \cdot wt$ is partitioned into $M - 1$ equal nonoverlapping intervals, where wt is the pipe wall thickness, k is the warning coefficient, which may be equal to 0.6; 0.7 or 0.8. The last interval, which is the conditional failure state, should be taken as $[k \cdot wt; wt]$.

Step 2. Plotting histograms of depths of detected defects. For each of the $i = 1, 2, \dots, M$ intervals, the number $n_i(t_1)$ of defects is defined, using results of the ILI measurements of the defects $x_i(t_1)$ depths at time t_1 and the ratio $p_i = \frac{n_i(t_1)}{N(t_1)}$ is calculated. Based on the frequencies p_i the histograms for the defects depths are plotted for time t_1 .

It should be noted that at time t_1 the defects depth is already distributed over all intervals, i.e., throughout the pipe wall thickness. Otherwise, this step is necessary to determine the number of first M_1 intervals, in which defects are actually found, and further calculations are performed on M_1 number of intervals. This prevents making predictions for other $M - M_1$ states, which include the last, most dangerous failure state.

Step 3. Calculation of unknown intensities of transition from state to state. Based on the frequencies $P_i(t_1) = p_i$, calculated in the previous step, intensities $\lambda_i(t_1) = \lambda_i$, $i = 1, 2, \dots, M$ of transition from the i -th to the $(i + 1)$ -th state are found as follows:

$$\lambda_1 = -\frac{\ln [P_1(t_1) / p_1^*]}{t_1}, \quad (7.6)$$

while other intensities λ_i , $i = 2, \dots, M$ are determined sequentially by solving the equation

$$P_i(t_1) = p_i = \sum_{j=1}^i \mu_{ij} \exp [-\lambda_j t_1], \quad (7.7)$$

where parameters μ_{ij} are determined by formula (7.5).

Step 4. *Evaluation of the predicting probabilities of finding defects in each state.* Forecasting calculation consists in that, based on the transition intensities found in the previous step, the predicting probabilities $P_i(t)$, $i = 1, 2, \dots, M$ of finding of defects in each of the intervals are calculated for any time $t > t_1$:

$$P_i(t) = \sum_{j=1}^i \mu_{ij} \exp[-\lambda_j t]. \quad (7.8)$$

7.4 Validation of the Markov Model for Corrosion Defect Growth

A model of defects parameters (length, depth, and width) growth can be constructed not only on the basis of using ILI and verification results, but also by using a combination of the Monte Carlo simulation method and the differential equations method (DEM), which adequately describes the defect parameter growth and has the form [8]:

$$\frac{dx(t)}{dt} = kx^n(t), \quad (7.9)$$

where t is time, $x(t)$ is the defect parameter at time t ; k is the proportionality coefficient; $n > 0$ is the defect parameter growth rate.

Differential equation (7.9) is solved for the initial condition

$$x(0) = x_0. \quad (7.10)$$

For $n = 1$ the solution of differential equation (7.9) with the initial condition (7.10) has the form

$$x(t) = x_0 \exp[kt]. \quad (7.11)$$

For $n \neq 1$

$$x(t) = \left[k(1-n)t + x_0^{1-n} \right]^{\frac{1}{1-n}}. \quad (7.12)$$

To verify the adequacy of PBMP compare the results of two independent methods—PBMP and DE with Monte Carlo (DEMC). This comparison for moments of time $t = 18, 19, 20$ years is given in Table 7.1, according to which both methods give probability values $P_i(t)$, which are in very good agreement. The observed discrepancy for the 9th failure state is in the range of 2–4.6%; hence, the PBMP method provides for a more conservative estimate. This comparison shows that the DEMC method is an effective tool for verifying adequacy of the PBMP method.

Table 7.1 Probabilities of finding defects depths (at intervals 1–9 at $t = 18, 19, 20$ years) using PBMP and DEMC methods

Interval #	PBMP			DEMC		
	$P_i(18)$	$P_i(19)$	$P_i(20)$	$P_i(18)$	$P_i(19)$	$P_i(20)$
1	0.1369	0.1226	0.1098	0.1445	0.1365	0.1290
2	0.0552	0.0495	0.0444	0.0565	0.0555	0.0560
3	0.0346	0.0311	0.0279	0.0395	0.0355	0.0285
4	0.0176	0.0158	0.0142	0.0230	0.0225	0.0250
5	0.0189	0.0170	0.0153	0.0145	0.0160	0.0175
6	0.0162	0.0146	0.0132	0.0135	0.0115	0.0095
7	0.0136	0.0122	0.0110	0.0155	0.0115	0.0110
8	0.0208	0.0188	0.0169	0.0245	0.0215	0.0165
9	0.6860	0.7182	0.7472	0.6685	0.6895	0.7070

Example 7.4.1 Apply the empirical Markov model to the growth of defects depths found in a pipeline with following parameters: length $L = 10$ km, pipe wall thickness $wt = 11.2$ mm, diameter $D = 1200$ mm, design life $t_p = 20$ years.

Consider the PBMP method applied to simulated defects depths from the start of pipeline operation. The defects depths $x_i(t_0)$, $i = 1, 2, \dots, N$, at the time $t = 0$ (start of pipeline operation) are simulated as realizations of a random variable with a lognormal distribution by adjusting its parameters m and σ so that all $N = 2000$ realizations are placed in the range $(0; 0.1wt]$: $X = \exp(\sigma \cdot \eta + m)$, where $\eta \in N(0, 1)$. Thus, it is assumed that at initial time $t = 0$ all existing defects depths are less than 10% of the pipe wall thickness, which is quite plausible.

Divide the interval $[0; 0.8wt]$ into eight equal intervals (states), with width $h = 1.1$ (interval size; for example, can be equal to the ILI tool sensitivity threshold—the smallest size of defect which still can be detected by the tool). In our case the last, ninth interval is $[0.8wt; wt]$.

Find the initial distribution of defects depths over constructed states. Since the initial time $t_0 = 0$ the defects depths are less than 10% wt , the initial conditions (7.2) take the form

$$P_1(t_0) = p_1^* = 1; P(t_0) = 0, i > 1.$$

To determine the size of defects depths at time $t = t_1$ use the DEMC combination of methods as described by formulas (7.9)–(7.12). MPPB is applicable when the defects depths are spread among all the states, without exclusion.

To describe the defect depth growth use the solution (7.11) of differential equation (7.9) for $n = 1$. From a certain moment of time the defects depths will be distributed over all intervals. The growth rate of each defect is given through the coefficient k from equation (7.11). Modeling of coefficients k is conducted for a uniform distribution with parameters $a = 0$ and $b = k_{\max}$. The maximum value of coefficient $k_{\max}$ is chosen such that for $t_1 = 5$ years (after the start of pipeline operation) at least one

Fig. 7.2 The initial distribution of defects depths over the pipe wall thickness at $t_0 = 0$ (initial state)

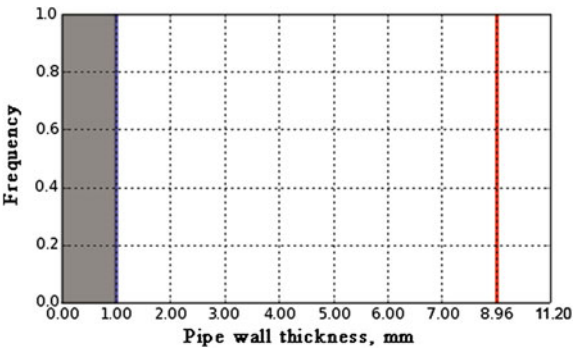


Fig. 7.3 The distribution of defects depths over the pipe wall thickness at $t = 5$ years (DEMC method)

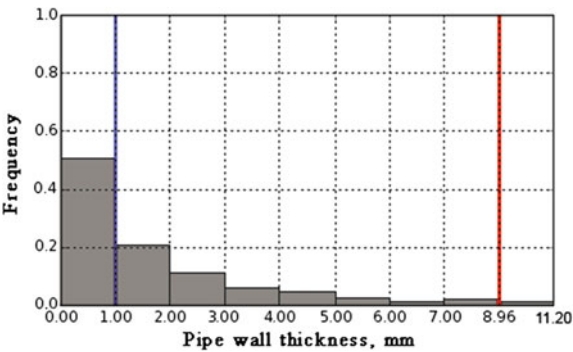
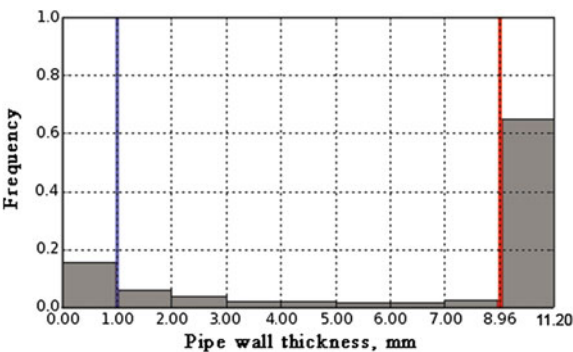


Fig. 7.4 The distribution of defects depths over the pipe wall thickness at $t = 17$ years (DEMC method)



defect passes into the last interval (at least one maintenance/repair has occurred), i.e., the set of defects is distributed over all states. In this example, $k_{\max}$ was found to be 0.68 (1/year). Now, for any time $t > t_1$, using formula (7.11), for each of the defects its new depth can be assessed and the new PDF, spread over the pipe wall thickness, can be obtained.

Figures 7.2, 7.3 and 7.4 show the distributions of the obtained defects depth values over the pipe wall thickness at the initial time $t_0 = 0$, as well as at $t = 5$ and 17 years.

The intensities $\lambda_i(t_1) = \lambda_i, i = 1, 2, \dots, M$ of transition from the i th to the $(i + 1)$ th state were obtained using formulas

$$\lambda_1 = -\frac{\ln [P_1(t_1) / p_1^*]}{t_1}, \quad (7.13)$$

while other intensities $\lambda_i, i = 2, \dots, M$ were determined sequentially by solving the equation

$$P_i(t_1) = p_i = \sum_{j=1}^i \mu_{ij} \exp [-\lambda_j t_1], \quad (7.14)$$

where parameters μ_{ij} were determined by formula (7.5).

The transition intensities for $t = 5, 17$ years are shown in Figs. 7.5 and 7.6.

The predictive probabilities of finding defects depths in the i th state for times $t > 5$ years were calculated by formula

$$P_i(t) = \sum_{j=1}^i \mu_{ij} \exp [-\lambda_j t] \quad (7.15)$$

by substituting in them the found values of μ_{ij}, λ_i for the time $t = 5$ years (Fig. 7.7).

Fig. 7.5 Transition intensities λ_i of defects depths over pipe wall thickness at $t = 5$ years

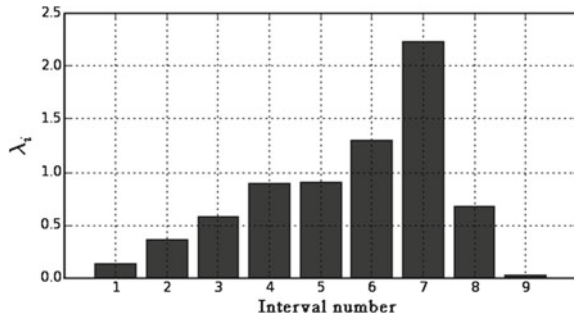
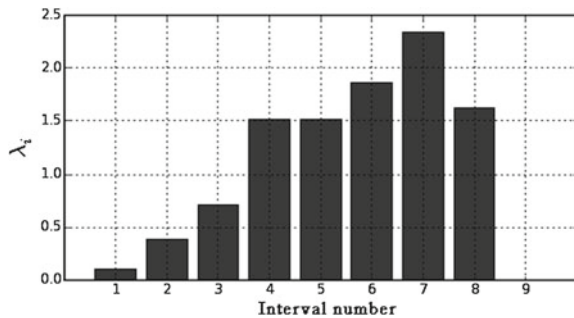


Fig. 7.6 Transition intensities λ_i of defects depths over pipe wall thickness at $t = 17$ years



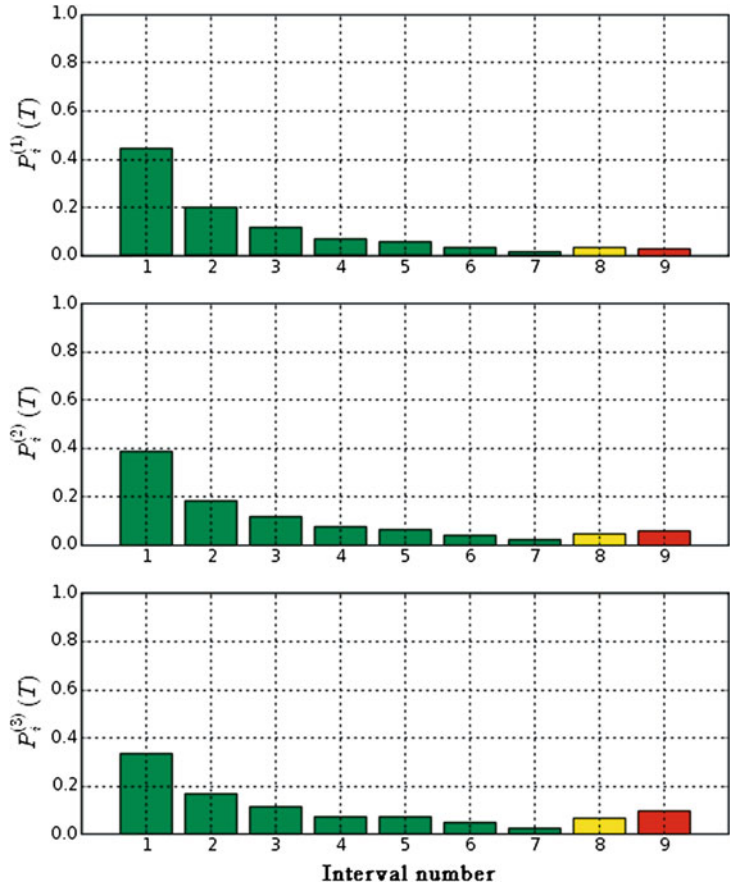


Fig. 7.7 Predictive probabilities of finding defects depths in the i th state (MPPB method) for the moments of time $t = 6, 7$ and 8 years

7.5 Markov Model for the Pipeline Residual Strength Degradation Process

Apply the empirical Markov model to describe the degradation (reduction of the residual strength) of the pipeline, which is assessed by the international codes described in Sect. 2.5.

7.5.1 Residual Strength Degradation Model for a Pipeline Cross Section with a Growing Defect

Consider a pipeline cross section with a defect. The burst (failure) pressure (BP) of a performing pipeline defective cross section at some fixed time t is a random variable $P_f(t) \geq P_{op}$, where P_{op} is the pipeline operating pressure. The defect failure pressure is assessed using one of the five internationally recognized pipeline design codes, which are described in Sect. 2.5.

Divide the possible range of change of the burst pressure of a pipeline defective cross section ($P_{op}; P_f(0)$] into $M - 1$ nonoverlapping equal intervals I_i ($i = M - 1, \dots, 1$). Here $P_f(0)$ is the defect failure pressure at initial time $t = 0$. The last interval (conditional failure state) I_M , which includes the lowest values of failure pressure, is taken as $(0; P_{op}]$.

The failure pressure of the defective cross section can only monotonically decrease over time, i.e., transit at random moments of time from the i -th state only to the $(i + 1)$ -th state, where state is one of the intervals I_i ($i = 1, \dots, M$). The SDE that describes this process has the form

$$\begin{cases} \frac{dP_1(t)}{dt} = -\mu_1(t)P_1(t), \\ \frac{dP_i(t)}{dt} = \mu_{i-1}(t)P_{i-1}(t) - \mu_i(t)P_i(t), \quad (i = 2, \dots, M - 1), \\ \frac{dP_M(t)}{dt} = \mu_{M-1}(t)P_{M-1}(t), \end{cases} \quad (7.16)$$

where $P_i(t)$ is the probability that the BP of defective cross section is in the i -th state at time t ; $\mu_i(t)$ is the intensity of transition from the i -th state to the $(i + 1)$ -th state.

System (7.16) describes the nonhomogeneous pure death Markov process (NPDMP) which is characterized by a discrete number of states and continuous time.

For the pure birth/pure death Markov processes the flow of events, which transit the system from one state to another, is a nonstationary Poisson process (it is the only flow of events without aftereffects, which provides the Markov property) [11]. Hence, according to the definition of a nonstationary Poisson flow of events, the expected number of events, which change the value of burst pressure within a time interval $(0, t]$, is calculated by formula:

$$\rho(t) = \int_0^t \mu(\tau) d\tau. \quad (7.17)$$

The physical meaning of the intensity (density) $\mu(t)$ of the nonstationary Poisson flow of events (transitions from one state to another) is the average number of events per unit time for an elementary (infinitesimal) time interval $[0; t]$. The quantity $\rho(t)$ is the average number of states through which the random variable $P_f(t)$ passes within

a small time interval $[0; t]$. The intensity $\mu(t)$ can be expressed by any nonnegative function and has the dimension $[1/\text{time}]$ [11].

Consequently, the quantity $\mu(t)$ may be associated with the rate of change of RV $P_f(t)$ as follows:

$$\mu(t) = -\frac{P'_f(t)}{\Delta I},$$

where ΔI is the interval length, $P'_f(t)$ is the derivative of the function $P_f(t)$ with respect to time at time t . The minus sign in this formula is due to the fact that the derivative of monotonously decreasing function has negative values in the whole domain of its definition.

Now the system (7.16) can be rewritten as

$$\begin{cases} \frac{dP_1(t)}{dt} = -\mu(t)P_1(t); \\ \frac{dP_i(t)}{dt} = \mu(t)P_{i-1}(t) - \mu(t)P_i(t), \quad (i = 2, \dots, M-1); \\ \frac{dP_M(t)}{dt} = \mu(t)P_{M-1}(t). \end{cases} \quad (7.18)$$

It is obvious that at the initial moment of time $t = 0$ the RV $P_f(0) \in I_1$. Hence, the initial conditions for the SDE (7.18) will be:

$$P_1(0) = 1, P_i(0) = 0, (i = 2, \dots, M). \quad (7.19)$$

Solve the SDE (7.18) for initial conditions (7.19). The first equation of the system (7.18) is

$$\frac{dP_1(t)}{dt} = -\mu(t)P_1(t).$$

The solution of this homogeneous differential equation is

$$P_1(t) = c \exp \{-\rho(t)\}.$$

The constant c is calculated from the initial condition: $c = 1$, then

$$P_1(t) = \exp \{-\rho(t)\},$$

where $\rho(t)$ is calculated by formula

$$\rho(t) = \int_0^t \mu(\tau) d\tau = -\int_0^t \frac{P'_f(\tau)}{\Delta I} d\tau = \frac{P_f(t) - P_f(0)}{\Delta I}. \quad (7.20)$$

Solve the second equation from (7.18) by the variation of the constant method:

$$\frac{dP_2(t)}{dt} + \mu(t)P_2(t) = \mu(t) \exp \{-\rho(t)\}. \quad (7.21)$$

The solution of this homogeneous differential equation (7.21) has the form

$$P_2(t) = c \exp \{-\rho(t)\}.$$

Then the general solution (7.21) is found as

$$P_2(t) = C(t) \exp \{-\rho(t)\}.$$

Then the general solution (7.21) will be:

$$\begin{aligned} C'(t) \exp \{-\rho(t)\} - C(t) \mu(t) \exp \{-\rho(t)\} + \mu(t) C(t) \exp \{-\rho(t)\} \\ = \mu(t) \exp \{-\rho(t)\}, \\ C'(t) \exp \{-\rho(t)\} = \mu(t) \exp \{-\rho(t)\}, \\ C'(t) = \mu(t), \\ C(t) = \int_0^t \mu(\tau) d\tau + c_1 = \rho(t) + c_1. \end{aligned}$$

The constant c_1 is found from the initial conditions (7.19):

$$P_2(0) = (\rho(0) + c_1) \exp \{-\rho(0)\} = 0 \Rightarrow c = 0.$$

Finally, the general solution of the differential equation (7.21) has the form

$$P_2(t) = \rho(t) \exp \{-\rho(t)\}.$$

Apply the same method to solve the third equation of (7.18). Then the general solution of this equation is:

$$P_3(t) = C(t) \exp \{-\rho(t)\}, \quad (7.22)$$

where

$$C(t) = \int_0^t \rho(\tau) \mu(\tau) d\tau + c_1.$$

Represent the integral $\int_0^t \rho(\tau) \mu(\tau) d\tau$ in the form $\int_0^t \rho(\tau) d\rho(\tau)$, and solve it by the method of integration by parts:

$$\int_0^t \rho(\tau) d\rho(\tau) = \rho^2(\tau) - \int_0^t \rho(\tau) d\rho(\tau) \Rightarrow 2 \int_0^t \rho(\tau) d\rho(\tau) = \rho^2(\tau) \Rightarrow$$

$$\int_0^t \rho(\tau) \mu(\tau) d\tau = \frac{\rho^2(t)}{2}.$$

Then

$$C(t) = \frac{\rho^2(t)}{2} + c_1.$$

The constant c_1 is found from the initial conditions (7.19):

$$P_3(0) = \left(\frac{\rho^2(0)}{2} + c_1 \right) \exp\{-\rho(0)\} = 0 \Rightarrow c_1 = 0.$$

Finally, the general solution of (7.22) takes the form

$$P_3(t) = \frac{\rho^2(t)}{2} \cdot \exp\{-\rho(t)\}.$$

Solving the remaining equations of the system (7.18), except the last, by the variation of the constant method, obtain

$$P_k(t) = \frac{\rho^{k-1}(t)}{(k-1)!} \cdot \exp\{-\rho(t)\}, k = 2, \dots, M-1. \quad (7.23)$$

Solve the last equation of SDE (7.18). Accounting for (7.23), it has the form

$$P_M(t) = \mu(t) \frac{\rho^{M-2}(t)}{(M-2)!} \cdot \exp\{-\rho(t)\}.$$

Then

$$P_M(t) = \frac{1}{(M-2)!} \int_0^t \rho^{M-2}(\tau) \mu(\tau) \exp\{-\rho(\tau)\} d\tau + c_1. \quad (7.24)$$

Solving the integral from (7.24) by the method of partial integration $(M-2)$ times, or taking into account that $\sum_{i=1}^M P_i(t) = 1$, the solution of the last equation from (7.18) takes the form

$$P_M(t) = 1 - \sum_{i=1}^{M-1} P_i(t) = 1 - \left[P_1(t) + \sum_{i=2}^{M-1} \frac{\rho^{i-1}(t)}{(i-1)!} \exp\{-\rho(t)\} \right].$$

Thus, the general solution of SDE (7.18) will be as follows:

$$\begin{cases} P_i(t) = \frac{\rho^{i-1}(t)}{(i-1)!} \cdot \exp\{-\rho(t)\}, i = 1, \dots, M-1, \\ P_M(t) = 1 - \left[\exp\{-\rho(t)\} + \sum_{i=2}^{M-1} \frac{\rho^{i-1}(t)}{(i-1)!} \cdot \exp\{-\rho(t)\} \right], \end{cases} \quad (7.25)$$

where $P_i(t)$ is the probability that the BP of defective cross section is in the i -th state at the moment of time t , and $\rho(t)$ is calculated using formula (7.20).

7.5.2 Model of Residual Strength Degradation of a Pipeline with Multiple Defects as a Distributed System

The Markov model for a PS with a set of defects regarded as a distributed system is constructed using the same reasoning as for a single defective cross section of a pipeline.

Assume that at the initial moment of time $t = 0$, using some inspection tools, N defects were found, their geometric parameters sized, and for each defect an estimate of burst pressure was obtained. Now calculate the frequency of occurrence of the failure pressure in each of the $i = 1, \dots, M$ intervals (states) at time $t = 0$:

$$P_i(0) = p_i^* = \frac{n_i}{N} \quad (i = 1, 2, \dots, M) \quad (7.26)$$

where n_i is the number of defects, whose burst pressure at the moment of time $t = 0$ is in the i -th interval, N is the overall number of defects. Expressions (7.26) are the initial conditions for the SDE (7.18).

Solving consistently the SDE (7.18) with initial conditions (7.26) by the variation of the constant method, the general solution (7.18) for a *distributed PS* with a set of defects takes the form (compare with Eq. (7.25))

$$\begin{cases} P_k(t) = \sum_{i=1}^k \left[p_i^* \frac{\rho^{k-i}(t)}{(k-i)!} \right] \exp\{-\rho(t)\}, k = 1, \dots, M-1; \\ P_M(t) = 1 - \left[p_1^* + \sum_{k=2}^{M-1} \left(\sum_{i=1}^k \left[p_i^* \frac{\rho^{k-i}(t)}{(k-i)!} \right] \right) \right] \exp\{-\rho(t)\}, \end{cases}$$

where $P_i(t)$ is the probability that the value of burst pressure $P_f(t)$ of the PS with a set of defects is in the i th state at time t .

For a PS with a set of defects, the value of its $\rho(t)$ at a given moment of time t is a problem which has to be solved. In this section the generalized value of $\rho(t)$ which characterizes the PS as a whole is defined as the sample quantile of order α of the set of values $\rho_i(t)$ ($i = 1, \dots, N$), where N is the number of defects discovered in the PS. Here $\rho_i(t)$ is the value of $\rho(t)$ of the i -th defect, which is calculated by

formula (7.20). In other words, $\rho(t) = \rho^{(k)}(t)$, where $\rho^{(k)}(t)$ is the k th order statistic of the ordered series $\rho^{(1)}(t) \leq \rho^{(2)}(t) \leq \dots \leq \rho^{(N)}(t)$ of the sample values of $\rho_1(t), \rho_2(t), \dots, \rho_N(t)$ at time t and $k = [\alpha N + 1]$, where $[\dots]$ is the integer part of the value in brackets. The order α is chosen for safety reasons. It should be noted that the quantile approach has an important place in the arsenal of probabilistic tools for analysis of statistical data. By controlling (assigning) the quantile it is possible to assess POF of the whole PS with needed reliability (confidence level).

7.5.3 Assessment of the Gamma-Percentile Pipeline Residual Strength

Assessment of the gamma-percentile of a pipeline's residual strength is based on the Markov pure death process, constructed in Sects. 7.5.1 and 7.5.2.

Assume that the Markov process of residual strength degradation of a pipeline system or its defective cross section is successfully constructed.

Denote as T_i the time the burst pressure $P_f(t)$ is in the subset of states $S_i = [I_1, \dots, I_i]$, $1 \leq i < M$. According to [11], the cumulative distribution function of RV T_i is equal to

$$F_{T_i}(t) = P(T_i < t) = \tilde{P}_i(t),$$

The $\tilde{P}_i(t)$ is the probability that at time t the burst pressure (BP) will transit from subset S_i to the subset of states $S_{i+1} = \{I_{i+1}, \dots, I_M\}$, where M is the number of the subset states. In other words, $\tilde{P}_i(t)$ is the probability that BP is found in the subset S_{i+1} . The subset S_{i+1} is considered to be absorbing, i.e., that burst pressure, once entering this subset, cannot leave it. By this a Markov process is constructed, which has only two states, represented by subsets S_i and S_{i+1} .

Now find, sequentially, the cumulative distribution function of time the burst pressure is in each of the subsets of states.

Let time T_1 be the time when the BP is in the first state I_1 . Then the second state of this process is the subset $S_2 = \{I_2, \dots, I_M\}$. Since the subset S_2 is absorbing, from formula (7.25) it follows that the probability of finding the BP in the first state I_1 is equal to $\exp\{-\rho(t)\}$. Then the cumulative distribution function of time T_1 takes the form

$$F_{T_1} = \tilde{P}_1(t) = 1 - \exp\{-\rho(t)\},$$

In this case, for a distributed PS with defects it is necessary that, at the initial time, the failure pressure of all defects is in the first state, as only the time of being in this state is considered.

Now find the cumulative distribution function of time T_2 of the BP being in the first and second states, that is, the time after which the BP will transit to the third state. In this case we have the following two subsets of states: $S_2 = \{I_1, I_2\}$ and $S_3 = \{I_3, \dots, I_M\}$. Since in this format subset S_3 is absorbing, from formula (7.25)

it follows that the probability of finding the BP in the first and second states is equal to $\exp\{-\rho(t)\} + \rho(t) \exp\{-\rho(t)\}$. Then the cumulative distribution function of time T_2 takes the form

$$F_{T_2} = \tilde{P}_2(t) = 1 - [1 + \rho(t)] \exp\{-\rho(t)\}.$$

For a distributed PS with a set of defects

$$F_{T_2} = \tilde{P}_2(t) = 1 - [p_1^* + p_1^* \rho(t) + p_2^*] \exp\{-\rho(t)\},$$

on the condition that the failure pressure for all defects at the initial time $t = 0$ is found only in the first and second states.

Reasoning similarly, the distribution function of time T_i the BP being in subset $S_i = [I_1, \dots, I_i]$, $2 \leq i \leq M - 2$, that is, of the time after which the BP will transit to the $(i + 1)$ -th state, has the form

$$F_{T_i} = \tilde{P}_i(t) = 1 - \left[\exp\{-\rho(t)\} + \sum_{j=2}^i \frac{\rho^{j-1}(t)}{(j-1)!} \cdot \exp\{-\rho(t)\} \right].$$

For a distributed PS with a set of defects

$$F_{T_i} = \tilde{P}_i(t) = 1 - \left[p_1^* + \sum_{k=2}^i \left(\sum_{j=1}^k \left[p_j^* \frac{\rho^{k-j}(t)}{(k-j)!} \right] \right) \right] \exp\{-\rho(t)\},$$

provided the failure pressure of all defects at initial time $t = 0$ is found only in the first i -th states.

Then the distribution function of time T_{M-1} the burst pressure is in the first $(M - 1)$ -th states or, in other words, the time after which the burst pressure will transit to the last (conditional failure, or limit) state, is given by formulas: for a single defect (cross section)

$$F_{T_{M-1}} = \tilde{P}_{M-1}(t) = 1 - \left[\exp\{-\rho(t)\} + \sum_{j=2}^{M-1} \frac{\rho^{j-1}(t)}{(j-1)!} \cdot \exp\{-\rho(t)\} \right]. \quad (7.27)$$

for a distributed PS with a set of defects

$$F_{T_{M-1}} = \tilde{P}_{M-1}(t) = 1 - \left[p_1^* + \sum_{k=2}^{M-1} \left(\sum_{i=1}^k \left[p_i^* \frac{\rho^{k-i}(t)}{(k-i)!} \right] \right) \right] \exp\{-\rho(t)\}, \quad (7.28)$$

provided the failure pressure of all defects at initial time $t = 0$ is located only in the first $(M - 1)$ -th states.

Knowing the cumulative distribution function of time T_i of failure pressure being in the first i -th states, the time $t_{i\gamma}$ can be estimated, at which the failure pressure transits into the $(i + 1)$ -th state with probability γ . This is achieved by numerically solving the following equation relative to time $t_{i\gamma}$:

$$t_{i\gamma} : F_{T_i}(t_{i\gamma}) - \gamma = 0. \quad (7.29)$$

For time T_{M-1} function (7.29) takes the form

$$t_\gamma : F_{T_{M-1}}(t_\gamma) - \gamma = 0. \quad (7.30)$$

Thus, formula (7.30) gives an estimate of the gamma-percent residual life (GPRL) from time of pipeline diagnostics ($t = 0$) to time of failure—the moment of time t_γ , at which the burst pressure $P_f(t_\gamma) \leq P_{op}$ with probability γ , where P_{op} is the pipeline operating pressure.

The formulas (7.27), (7.28), (7.30) allows evaluating the GPRL of a single defective cross section as well as a distributed PS with a set of defects, that is, the time during which the defect (PS with defects) does not reach the “rupture,” type of failure (limit) state with probability γ , given as a percentage:

$$t_\gamma : F_{T_{M-1}}(t_\gamma) = 1 - \frac{\gamma}{100}. \quad (7.31)$$

It should be noted that in formulas (7.29)–(7.31) gamma is a value prescribed by codes [1, 3]. Hence, the corresponding quantile will be $(1 - \frac{\gamma}{100})$.

7.5.4 Adequacy Test of Markov Model for the Residual Strength Degradation

Check adequacy of the Markov model of residual strength degradation by comparing safety factors (SF) of defects, which correspond to the GPRL calculated by the Markov model, with SF prescribed by the Pipeline Design Code [2].

Estimate the GPRL of a real pipeline, 325 mm in diameter, with a 9 mm thick wall, made out of pipe steel with specified minimum yield strength 245 MPa, ultimate tensile strength 410 MPa and operating under a 6.4 MPa pressure.

The last ILI revealed 3372 defects of the “metal loss” type in the pipeline and assessed their true depths. Using the method of conditional maximum rate of defects growth [4, 5] it was found that the growth rate of the defects depth and length is 0.20 mm/year and 2.34 mm/year, respectively. Predicted future defects depths and lengths were calculated. Comparative analysis was performed using all the five pipeline design codes: B31G, B31Gmod, DNV, Battelle, and Shell92.

According to Guidance documents [1, 3], assessment of GPRL for potentially dangerous objects, supervised by the Federal Environmental, Industrial and Nuclear Supervision Service, should be performed with $\gamma \geq 90\%$. Consequently, a minimum value of 90% is used below as the value of γ .

The pipeline strength related safety factor K for each defective cross section is found, using GPRL and the corresponding value of burst pressure, using the following expression:

$$K = \frac{P_f(t_\gamma)}{P_{op}}, \quad (7.32)$$

where t_γ is the defect GPRL obtained using formula (7.31); $P_f(t_\gamma)$ is the burst pressure at time t_γ obtained using one of internationally recognized pipeline design codes; P_{op} is the pipeline operating pressure.

Thus, estimates of each defect SF are obtained, in terms of burst pressure, which corresponds to GPRL found at $\gamma = 90\%$. This permits estimating the minimal SF as obtained by the developed Markov model.

The calculation results, averaged over the number of defects $N = 3372$, are listed in Table 7.2 and in Figs. 7.8, 7.9, 7.10, 7.11 and 7.12.

According to Table 7.2 the defects GPRLs at $\gamma = 90\%$ correspond to average SF value ranges from 1.5 to 2.0. In all cases the standard deviation of these SF is less than 0.03 (1.5–2.0% of their mean value).

According to [2], the pipeline design SF K_d ranges from 1.64 to 3.42. Figure 7.13 shows the estimated SF values of 3327 defects under consideration which correspond to the above GPRL, assessed via the developed Markov model. Vertical lines in Fig. 7.13 denote the span of SF values; dots denote the SF mean values.

Hence, the SFs of pipeline defective cross sections obtained with GPRL at gamma $\gamma = 90\%$ are within the design values as specified by the Pipeline Design Codes (except for B31G) [2].

Table 7.2 Statistical characteristics of safety factors of defects which correspond to gamma-percent residual life (GPRL) at $\gamma = 90\%$

Pipeline design code	Sample mean, years	Sample standard deviation, years	Minimum and maximum values
B31G	1.51	0.1	1.39; 1.53
B31Gmod	1.67	0.02	1.48; 1.69
Battelle	1.98	0.02	1.75; 2.01
DNV	2.03	0.02	1.78; 2.05
Shell92	1.84	0.03	1.57; 1.87

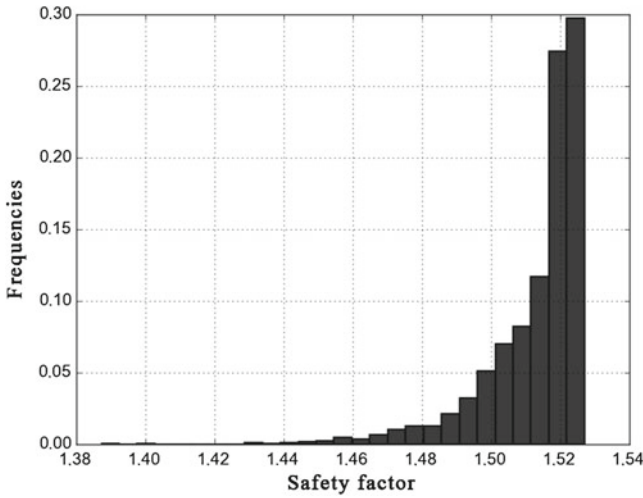


Fig. 7.8 Histogram of SF of defects, which correspond to GPRL at $\gamma = 90\%$ (B31G code)

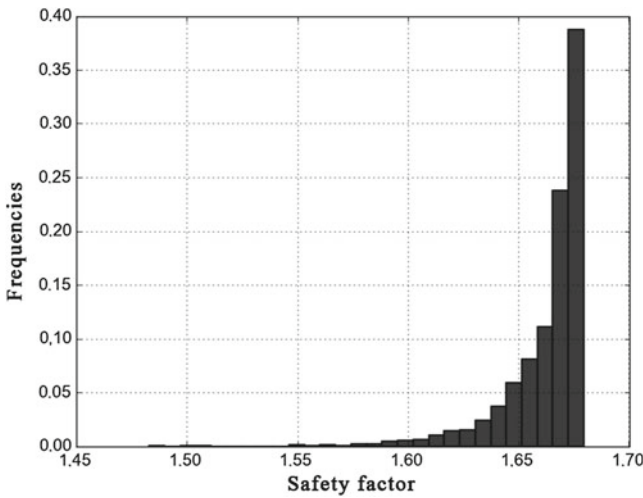


Fig. 7.9 Histogram of SF of defects, which correspond to GPRL at $\gamma = 90\%$ (B31Gmod code)

7.5.5 Algorithm for Assessing the Pipeline GPRL and the Probability of the Defects Failure Pressure Being in One of the Given States

Consider the algorithm of applying the above Markov model of residual strength degradation to the case from Sect. 7.5.4 for a pipeline cross section with a defect of

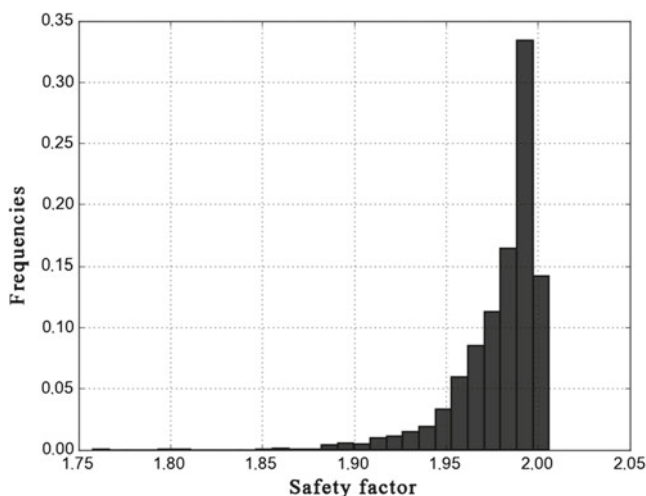


Fig. 7.10 Histogram of SF of defects, which correspond to GPRL at $\gamma = 90\%$ (Battelle code)

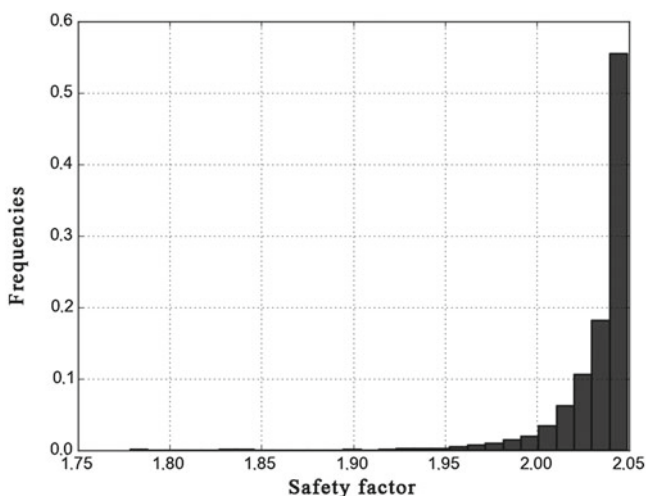


Fig. 7.11 Histogram of SF of defects, which correspond to GPRL at $\gamma = 90\%$ (DNV code)

the “metal loss” type with parameters given in Table 7.3. The pipeline parameters are given in Sect. 7.5.4.

Based on estimates of true sizes of 3327 defects depths and lengths, identified and sized through ILI diagnostics, the growth rates of defects are calculated by formula (9.8) with probability 0.95. They are found to be equal to $a_d = 0.20$ mm/year for defect depth and $a_l = 2.34$ mm/year for defect length.

Consider the step-by-step degradation process of the residual strength of defective cross section when using the B31Gmod code, according to which (see Sect. 2.5) the

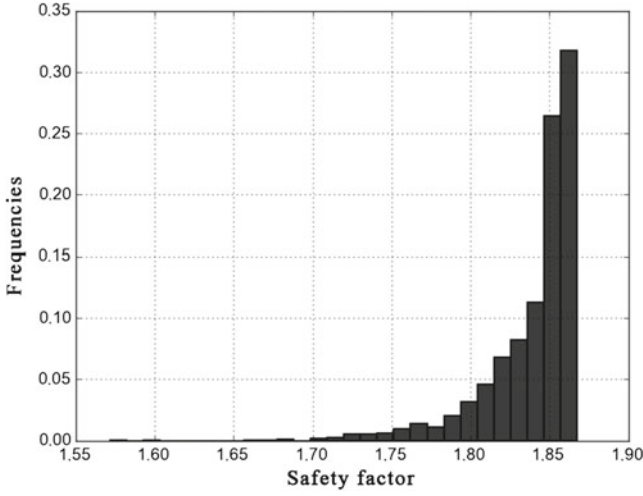


Fig. 7.12 Histogram of SF of defects, which correspond to GPRL at $\gamma = 90\%$ (Shell92 code)

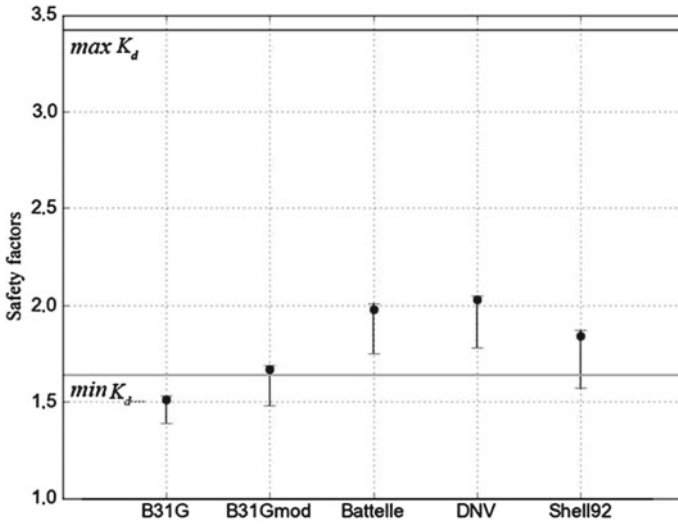


Fig. 7.13 SF of defects, which correspond to GPRL at $\gamma = 90\%$

burst pressure is calculated by formula

$$P_f = \frac{2wt (SMYS + 68.95 \text{ MPa})}{D} \cdot \frac{\left(1 - 0.85 \frac{d}{wt}\right)}{\left(1 - 0.85 \frac{d}{wt \cdot M_2}\right)}, \quad (7.33)$$

Table 7.3 Initial parameters of the most dangerous defects

Parameter	Symbol	Value, mm
<i>Parameters of defect #1</i>		
Depth	d_{01}	2.25
Length	l_{01}	226.00
<i>Parameters of defect #2</i>		
Depth	d_{02}	5.62
Length	l_{02}	70.00

where M_2 is the Folias factor, which has the form

$$M_2(t) = \begin{cases} \sqrt{1 + \frac{0.6275 \cdot l^2}{D \cdot wt} - \frac{0.003375 \cdot l^4}{(D \cdot wt)^2}}, & l \leq 7.07 \sqrt{D \cdot wt}, \\ \frac{0.032 \cdot l^2}{D \cdot wt} + 3, & l > 7.07 \sqrt{D \cdot wt}. \end{cases}$$

Step 1. Formation of intervals for BP of defects. Calculate by formula (7.33) the BP value for each defect at initial moment of time $t = 0$:

$$P_{f_1}(0) = 15.49 \text{ MPa}, P_{f_2}(0) = 13.73 \text{ MPa},$$

where $P_{f_1}(0)$ is the BP at moment of time $t = 0$ for defect #1, $P_{f_2}(0)$ is the same for defect #2.

Divide the span of BP change into $M = 10$ nonoverlapping intervals. The first interval (failure condition) is defined as $(0; P_{op}] = (0; 6.40]$. The length ΔI of the other nine equal size intervals is found by dividing the value of the expression $P_f(0) - P_{op}$ by the number of states (intervals):

$$\Delta I_1 = 0.91 \text{ MPa}, \Delta I_2 = 0.73 \text{ MPa},$$

Table 7.4 Intervals of defects burst pressure

Interval #	Intervals boundaries, MPa	
	Defect #1	Defect #2
10	(0.00; 6.40]	[0.00; 6.40)
9	(6.40; 7.31]	[6.40; 7.13)
8	(7.31; 8.23]	[7.13; 7.86)
7	(8.23; 9.14]	[7.86; 8.59)
6	(9.14; 10.06]	[8.59; 9.32)
5	(10.06; 10.97]	[9.32; 10.06)
4	(10.97; 11.89]	[10.06; 10.79)
3	(11.89; 12.80]	[10.79; 11.52)
2	(12.80; 13.72]	[11.52; 12.25)
1	(13.72; 14.63]	[12.25; 12.98)

Table 7.5 Predictive probability of finding burst pressures of defects in each state

Interval #	Probability of finding burst pressure of defects in each state at time t					
	Defect #1			Defect #2		
	$t = 1$	$t = 2$	$t = 3$	$t = 1$	$t = 2$	$t = 3$
1	7.43×10^{-1}	5.49×10^{-1}	4.04×10^{-1}	5.89×10^{-1}	3.40×10^{-1}	1.93×10^{-1}
2	2.21×10^{-1}	3.29×10^{-1}	3.66×10^{-1}	3.12×10^{-1}	3.67×10^{-1}	3.17×10^{-1}
3	3.29×10^{-2}	9.88×10^{-2}	1.66×10^{-1}	8.24×10^{-2}	1.98×10^{-1}	2.61×10^{-1}
4	3.26×10^{-3}	1.98×10^{-2}	5.02×10^{-2}	1.45×10^{-2}	7.10×10^{-2}	1.43×10^{-1}
5	2.43×10^{-4}	2.96×10^{-3}	1.14×10^{-2}	1.92×10^{-3}	1.91×10^{-2}	5.90×10^{-2}
6	1.44×10^{-5}	3.55×10^{-4}	2.06×10^{-3}	2.03×10^{-4}	4.13×10^{-3}	1.94×10^{-2}
7	7.17×10^{-7}	3.55×10^{-5}	3.12×10^{-4}	1.79×10^{-5}	7.42×10^{-4}	5.33×10^{-3}
8	3.05×10^{-8}	3.05×10^{-6}	4.04×10^{-5}	1.35×10^{-6}	1.14×10^{-4}	1.26×10^{-3}
9	1.13×10^{-9}	2.28×10^{-7}	4.58×10^{-6}	8.95×10^{-8}	1.54×10^{-5}	2.58×10^{-4}
10	3.86×10^{-11}	1.62×10^{-8}	5.07×10^{-7}	5.55×10^{-9}	2.06×10^{-6}	5.64×10^{-5}

where ΔI_1 is the length of the first nine intervals for defect #1; ΔI_2 is the same for defect #2.

Obtained intervals (states) for the defects under consideration are shown in Table 7.4.

Step 2. Assessment of predictive probabilities for defects BP being in each state. Using formulas (7.25) calculate the probability of finding defects BP in each state for three future moments of time $t = 1, 2, 3$ years. The obtained results are shown in Table 7.5.

Step 3. Assessment of defects GPRL. By formulas (7.31) estimate the GPRL of defects at $\gamma = 90\%$. For defect #1 it is equal to 16.4 years, and for defect #2 it is 10 years.

7.6 Method of Assessing Pipeline System POF Using Markov Processes

Consider the problem of evaluating reliability of a pipeline with multiple actively growing defects of arbitrary size, using Markov models of pure birth (Sect. 7.4) and pure death (Sect. 7.5).

The generalized models (PBMP and PDMP) of PS degradation processes of the corrosion growth type and burst pressure reduction type are constructed for a set of defects, which are discovered, identified and sized by ILI tools in a specific pipeline section. Fitting and calibrating of the model is performed using actual ILI data. The method is implemented by analyzing the behavior in time of the whole set of defects which were found in a certain section of the pipeline. In this sense, the

method transforms the set of quantities which describe the defects growth and residual strength reduction into a random process.

Evaluation of the pipeline POF with defects can be made using the above PBMP and PDMP. The probability of finding the depth of defects and their burst pressure in the last state is, actually, the probability of failure of the whole pipeline as a system:

- when using MPPB the probability of finding defects depths *in the last, conditional failure state*, which is equal to $(k \cdot wt; wt]$, is the PS *conditional probability of failure according to the “leak” criterion*.
- when using MPPD the probability of finding the burst pressure of defective cross section (PS with defects) *in the last, conditional failure, state*, which is equal to $(P_{op}; P_a]$, is the *conditional probability of failure* of the specific defect (PS with defects), *according to the “rupture” criterion*.

Implementation of the method is shown in Figs. 7.14 and 7.15, which visualize the movement of the probability mass in time for growing defects using MPPB method. It can be seen that the probability mass is moving from left to right over time, accumulating in the last, conditional failure, state. The probability of finding defects depths (see Fig. 7.14) and burst pressure (see Fig. 7.15) in the last state is the POF of the whole PS with defects by the “leak” and “rupture” criterion respectively. This POF is one of the two components needed for risk assessment of operating PS, because risk is POF multiplied by the consequences of failure.

The constructed Markov models of pure birth (death) allow assessing the probability of finding the whole set of depths and burst pressures of defects in any of the possible states, the probability of their transition from one state to another, and allow determining the conditional pipeline POF and, on this basis, assessing its integrity and operational risk.

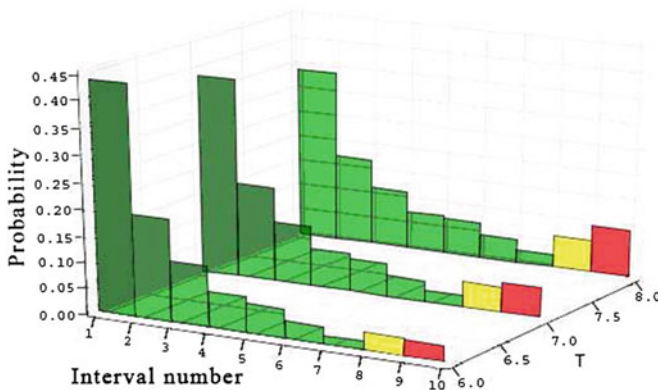


Fig. 7.14 Probability mass movement (PBMP method) for times $t = 6, 7, 8$ years

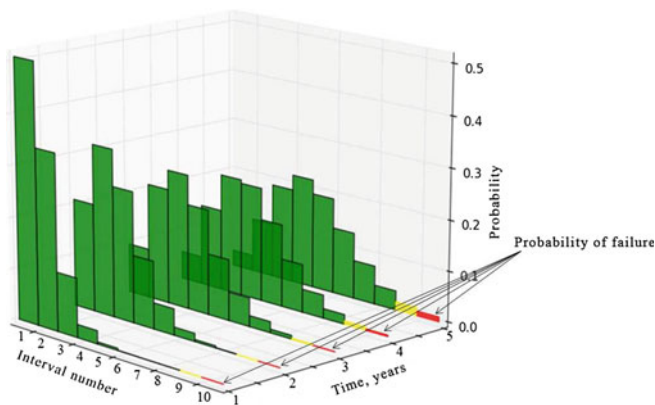


Fig. 7.15 Probability mass movement (PBMP method) for times $t = 1, 2, \dots, 5$ years

7.7 Optimization of the Timing for Performing Maintenance/Repair Work on a Pipeline System

The above Markov models allow determining optimal timing of the next in-line inspection (ILI) or maintenance/repair [6, 7, 9].

The essence of the method proposed below is in minimizing the total cost function for keeping pipeline in safe operation. It has the form

$$S(\tau_{or}) = C_0 P_M(\tau_{or}) + \frac{\tau_d}{\tau_{or} + \tau_r} C_{ILI}, \quad (7.34)$$

where τ_{or} is the design life (or remaining life) of the pipeline; τ_d is the design life (or remaining life) of the pipeline; τ_r is the average time needed to perform the maintenance/repair/rehabilitation (these numbers vary for different companies); C_{ILI} is the cost of in-line inspection or direct assessment of the pipeline; C_0 is the total cost of pipeline failure; $P_M(\tau_{or})$ is the conditional probability that the defects depth (burst pressure) are in the last (failure) state at moment of time τ_{or} , determined by using the pure birth (death) Markov process. The parameter C_0 includes following costs of: maintenance (repair, renewal), downtime, elimination/mitigation of environmental damage, all types of fines, etc.

The relationship $\tau_d/(\tau_{or} + \tau_r)$ is the frequency of maintenance/repair. Expression $\tau_d C_{ILI}/(\tau_{or} + \tau_r)$ is the amount of expenditures required to perform maintenance/repair; $C_0 P_M(\tau_{or})$ is the conditional probable loss due to pipeline failure for the cases when the depth or burst pressure of defects are in the last (failure) state.

The optimal period between the inspections/repairs can be found as the minimum of the total cost function (7.34) with respect to τ_{or} :

$$\tau_{or} : S(\tau_{or}) \rightarrow \min_{\tau_{or}}.$$

Function $S(\tau_{or})$ is continuous and differentiable at any $\tau_{or} : d(\tau_{or}) < wt$, where $d(\tau_{or})$ is the defect depth at time τ_{or} , wt is the pipe wall thickness. Hence

$$S'_{\tau_{or}} = -\frac{\tau_d}{(\tau_{or} + \tau_r)^2} C_{ILI} + P'_M(\tau_{or}) C_0 = 0 \quad (7.35)$$

where $P'_M(\tau_{or})$ is the derivative of function $P_M(\tau_{or})$ with respect to τ_{or} .

Thus, optimal timing of diagnostics/control and maintenance/repair τ_{or} is determined by numerical solution of equation (7.35).

Maintenance/inspection of the pipeline makes sense when the cost of services is less than cost of failure. The optimal time for the next pipeline diagnostics, depending on the ratio C_{ILI}/C_0 is shown in Fig. 7.16. It can be seen that when this ratio tends to zero, the optimal time for conducting the next inspection rapidly decreases. Therefore, it is very important to correctly quantify all the components of risk of pipeline failure.

The above model allows optimizing the timing of the next diagnostics and maintenance/ repair, taking into account the Markov description of defects parameters growth and degradation of pipeline residual strength.

Example 7.7.1 Calculate the optimal time for conducting repair of defective pipeline cross sections for the case described in Sect. 7.5.1.

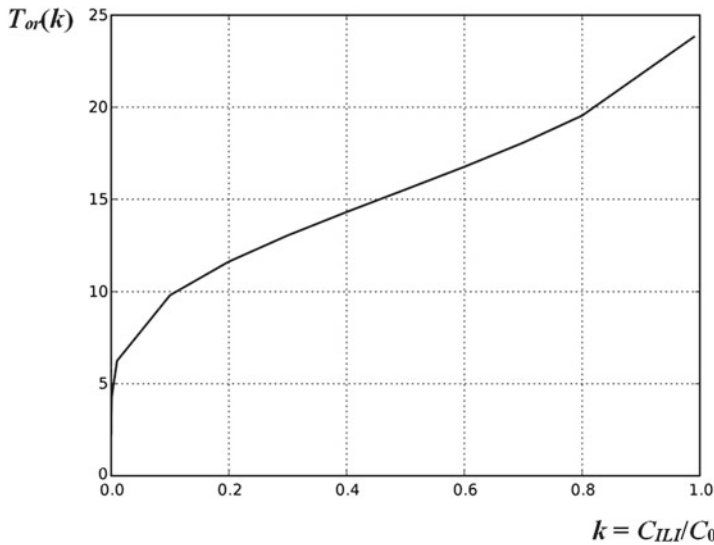


Fig. 7.16 Optimal time for the next inspection depending on ratio C_{ILI}/C_0

Let the cost of the consequences of pipeline failure be $C_0 = 10^6$ virtual monetary units (m.u.), cost of ILI $C_{ILI} = 250 \times 10^3$ m.u. The pipeline was in operation for $\tau_d = 26$ years, the average duration of ILI and repair $\tau_r = 0.1$ years. Numerical solution of the equation (7.35) with regard to τ_{or} gives the optimal time for repair of the defect #1 = 16.5 years and for defect #2 = 9.7 years.

7.8 Pipeline System Entropy

Preliminary considerations. If the state of a physical system is known in advance, obviously, it would not make sense to monitor its condition. The data accumulated via monitoring is meaningful only if the current state of the system is not known in advance. Having this in mind, consider a physical system with some stochastic properties (in our case, a pipeline) which state is known with a degree of uncertainty, which may randomly be in one state or another, as an object, from which data is being gathered.

Consider a stochastic physical system X , which can be in a finite set of states: $x_1, x_2, \dots, x_n$ with probabilities $P_1, P_2, \dots, P_n$, where P_i is the probability that the system X is in state x_i . In this case, obviously $\sum_{i=1}^n P_i = 1$.

The entropy H_X of system X is the sum of products of probabilities of various system states and the logarithm of these probabilities [10]:

$$H_X = - \sum_{i=1}^n P_i \log_a P_i. \quad (7.36)$$

Entropy H_X has a number of important properties: (1) It is equal to zero when the system can be found only in one state (its probability being equal to unity), while all other states are impossible (their probabilities equal to zero). In this case the information about the system is completely predictable; (2) Its entropy has a maximum, if the system can be found in several states, when the states are equiprobable (all probabilities are equal, and the uncertainty is maximal); (3) Entropy is additive—when several systems are combined into one, the entropy of the composite system is equal to the sum of entropies of the elements which form the whole system.

According to [10], the logarithm in (7.36) may be taken at any base $a > 1$. A change of base is equivalent to simple multiplication of entropy by a constant, and the choice of the base is equivalent to choosing a particular unit of entropy. For simplicity, in further calculations the natural logarithm is used.

7.8.1 Pipeline System Entropy Generated by Degradation of the Residual Strength of Corrosion-Type Defects

In Sect. 7.5 it was shown that the burst pressure of a pipeline cross section with defect can only monotonically decrease and move, at random times, from an i th state only to the $(i + 1)$ th with probability $P_i(t)$.

Entropy as a function of time, *generated by the degradation process* taking place in a cross section of the pipeline with a growing corrosion defect which may fail by the “rupture” type of failure is calculated using the formula

$$H_d(t) = - \sum_{j=1}^M P_j(t) \ln [P_j(t)], \quad (7.37)$$

where $P_j(t)$, calculated by (7.25), is the probability that the RV BP of defective cross section in the j th state at the moment of time t .

Assuming that the defects are independent, their failure pressures are also independent. In the considered format all residual strengths of defective pipe cross sections are RVs, which evolve in time. Therefore, entropy of the pipeline as a system with n defective cross sections, can be calculated as

$$H_p(t) = \sum_{i=1}^n H_{d_i}(t) = - \sum_{i=1}^n \sum_{j=1}^M P_{ij}(t) \ln [P_{ij}(t)], \quad (7.38)$$

where n is the number of defects; $P_{ij}(t)$ is the probability calculated using Eq. (7.25) that the RV BP of i th defect is in the j th state at time t .

According to the properties of entropy, it is equal to zero, when any one probability is equal to unity, and all the other probabilities are zero. It occurs at the initial time $t = 0$ (see initial conditions 7.19) and at the moment of time when $P_M(t) = 1$ (probability of finding the failure pressure in the last, conditional failure, state). Entropy takes its maximum value when all probabilities $P_i(t)$ are the same. After reaching the maximum value, entropy begins to monotonically decrease to zero, which happens at the moment of time when $P_M(t) = 1$. Hence, entropy can serve as a *diagnostic tool suitable for early diagnostics and as a precursor to pipe failure*.

7.8.2 Entropy Analysis of a Pipeline and Its Defective Cross Sections

Construct a graph of entropy change depending on possible values of burst pressure. Consider the previously described 325 mm diameter pipeline with 9 mm wall thickness, made out of steel which specified minimum yield strength is 245 MPa, ultimate

tensile strength is 410 MPa, and the operating pressure is 6.4 MPa. Use all five design codes for calculating residual strength of the PS.

Obviously, the failure pressure of any defect will be somewhere between the operating pressure P_{op} and the failure pressure of an ideal pipe (without defects) P_0^f , determined by formula

$$P_0^f = \frac{2wt \cdot \sigma_f}{D}.$$

Figure 7.17 shows the entropy of the considered pipeline as a function of the failure pressure.

Failure pressure decreases over time due to defect growth down to the operating pressure P_0^f (failure state). Hence, in Fig. 7.17 entropy changes *from right to left*, from P_0^f to P_{op} . The vertical lines on the left denote the values of P_{op} and the maximum safe operating pressure P_s , calculated using the safety factor K :

$$K = \frac{P_f(t)}{P_{op}} \Rightarrow P_s(t) = K \cdot P_{op}.$$

In this case $K = 1.4$, $P_s = 8.96$ MPa.

Figure 7.17 shows that the maximum value of entropy is invariant; being independent of the design code used, but is reached at different values of failure pressure. The same conclusion can be made for the size and growth rate of defects, because the values of BP from P_0^f to P_{op} cover the entire set of possible values of failure pressure of pipeline defects—from the moment of the defects formation to the failure condition.

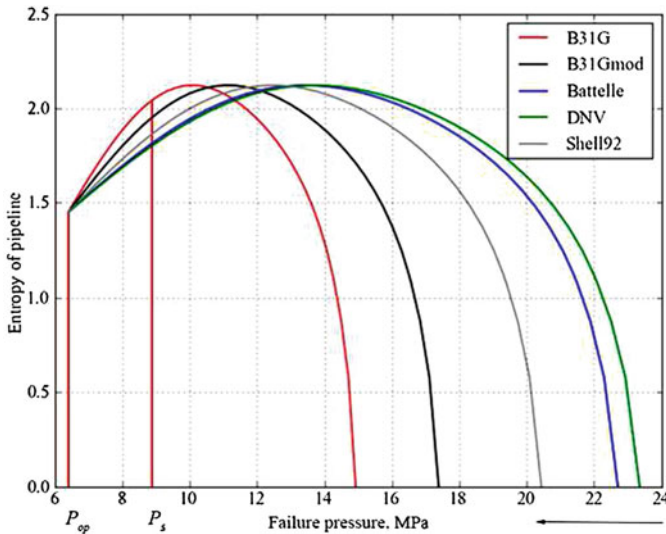


Fig. 7.17 Pipeline entropy as function of possible values of defects burst pressure

Maximum of entropy for the considered pipeline is 2.12 and is reached at 10.09 MPa for the B31G code; 11.16 MPa for the B31Gmod code; 12.47 MPa for the Shell92 code, 13.44 MPa for the Battelle code and 13.72 MPa for the DNV code. Moreover, the entropy value at the time of failure ($BP = P_{op}$) is equal to 1.45, and is also invariant in respect to used design codes.

Now consider one of the defects of the pipeline in consideration which depth is 10 % wt and length is 100 mm. Assume the growth rate of the defect depth a_d is equal to 0.3 mm/year, and the growth rate of defect length a_l is 3 mm/year. Estimate the time needed for the defect to reach its conditional critical and limit states:

- times t_{dp} , t_{df} for the defect depth to reach respectively 80 % (critical state) and 100 % of the pipe wall thickness (limit state—leak type failure);
- time t_s for the defect failure pressure to reach the value of maximum safe operating pressure (MSOP) (critical state—rupture type failure);
- time t_f for the defect failure pressure to reach the value of operating pressure (limit state—rupture type failure).

Construct for this defect its entropy as a function of time and mark on the entropy curve the times of occurrence of the above critical and limit states. The obtained results are shown in Figs. 7.18, 7.19, 7.20, 7.21, 7.22 and in Table 7.6. Vertical dashed lines correspond to the conditional rupture type failure, and the solid lines—to the leak type failure of the defect.

According to Figs. 7.18, 7.19, 7.20, 7.21, 7.22 and Table 7.6, the times of occurrence of the deterministic critical and limit states of the defect are located soon after

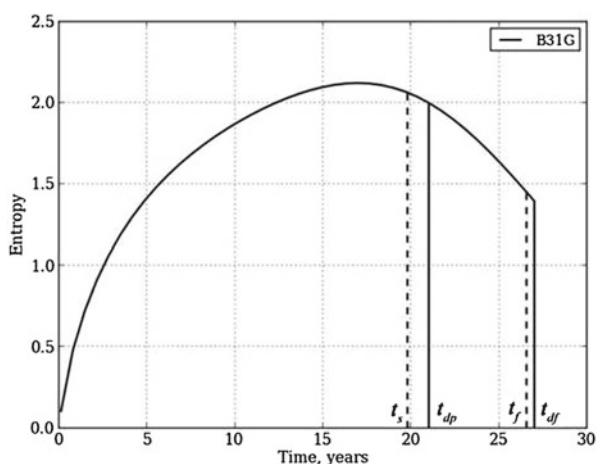


Fig. 7.18 Entropy, critical and limit state moments of time for the defective cross section as a function of time (according to the B31G code)

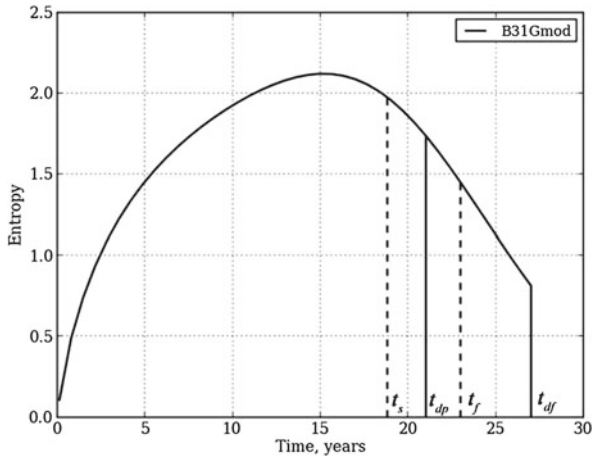


Fig. 7.19 Entropy, critical and limit state moments of time for the defective cross section as a function of time (according to the B31Gmod code)

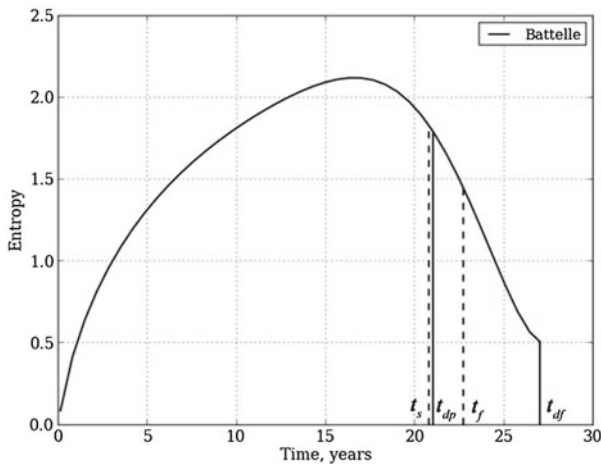


Fig. 7.20 Entropy, critical and limit state moments of time for the defective cross section as a function of time (according to the Battelle code)

the time entropy reaches its maximum value. This opens the possibility of using entropy analysis (the *entropy index—maximum entropy point*) for *early diagnostics of the pipeline critical condition*.

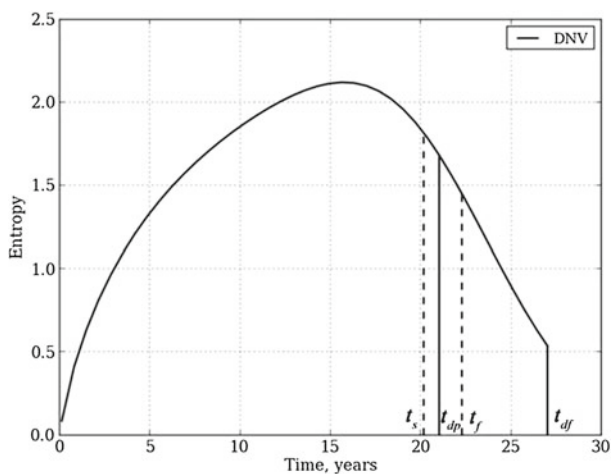


Fig. 7.21 Entropy, critical and limit state moments of time for the defective cross section as a function of time (according to the DNV code)

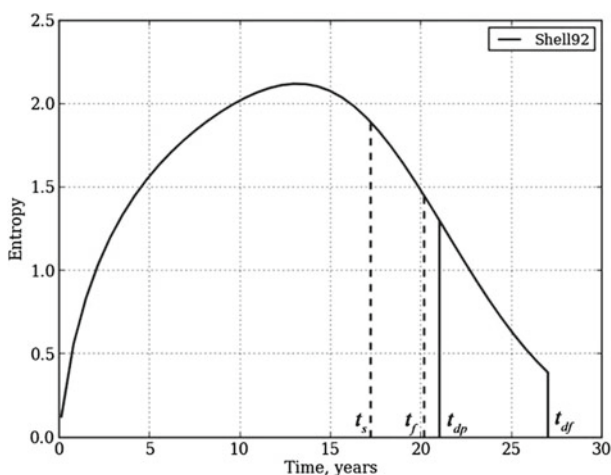


Fig. 7.22 Entropy, critical and limit state moments of time for the defective cross section as a function of time (according to the Shell92 code)

Calculate entropy of the whole pipeline, considering it as a system of six sections with defects, which depths are correspondingly: 10, 20, 30,...,60 %wt, using formula (7.38). Assume that the growth rate of defects depths a_d is equal to 0,5 mm/year and the growth rate of their lengths a_l – 5 mm/year. The calculated results are shown in Fig. 7.23, according to which *maximum entropy of the whole pipeline system* is

Table 7.6 Comparison of time of occurrence (years) of critical limit states of the defect and the time of reaching maximum entropy

Pipeline design code	t_{dp}	t_{df}	t_s	t_f	Time of reaching maximum entropy
B31G	21.00	26.99	19.79	26.55	16.22
B31Gmod			18.79	22.97	14.56
Battelle			20.77	22.69	16.19
DNV			20.14	22.26	15.34
Shell92			17.19	20.16	12.49

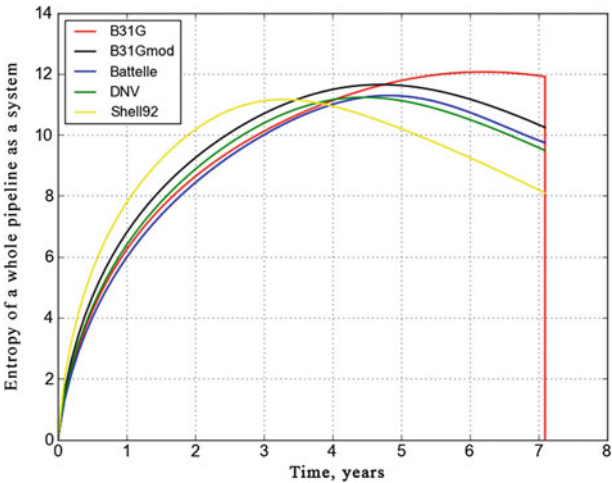


Fig. 7.23 Entropy of the whole pipeline system (using all the five pipeline design codes)

not invariant with respect to used design codes. This can be explained by that system entropy is defined as the sum of partial entropies of individual pipeline cross sections, each of which generates entropy at its own rate.

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Chapter 8

Method of Assessing the Probabilistic Characteristics of Crack Growth Under the Joint Influence of Random Loads and Different Types of Corrosion Processes

This chapter describes an algorithm of pipeline remaining life assessment with stress corrosion (SC) type cracks under conditions of cyclical load impact using nonlinear fracture mechanics and the crack growth criterion. The description presents:

- a pipeline segment reliability assessment correction algorithm under the SC conditions for three different results (outcomes) of the segment's inspection;
- an algorithm of reliability parameters recalculation on the basis of Bayesian network methodology;
- characteristics of the probability distribution of random pipeline parameters, taking into account new information gathered in the process of inspection.

The described algorithms can be used for:

- assessing main pipeline safe operation in the presence of:
 1. single corrosion crack;
 2. multiple, deep longitudinal SC cracks;
- predicting critical crack sizes and assessing pipeline remaining life, taking into account interaction (merger) of SC cracks;
- determining the influence of the operating pressure or variations of pipe material mechanical properties on the predicted pipeline remaining life;
- calculating a pipeline's remaining life statistical characteristics using the simulation Monte Carlo method;
- correcting pipeline reliability assessment, taking into account three possible results of diagnostics:
 1. crack was not detected;
 2. crack detected, but not measured;
 3. crack detected and measured;

- updating (based on Bayesian network) pipeline reliability and the PDFs of its random parameters given sequential and parallel connection of its segments, taking into account new information gathered during inspection;
- drafting the inspection plans between repairs.

8.1 Residual Lifetime Assessment of a Gas Pipeline Segment with Longitudinal SC Type Cracks Under Constant Pressure

8.1.1 Algorithm for the Case of a Single Longitudinal Crack

Assume that a gas pipeline segment has a SC type defect with known effective or maximal depth b_0 and semi-length a_0 (Fig. 8.1). It is assumed that in the process of operation the gas pressure p in the pipeline is constant.

It is also assumed that the shape of a crack in the loaded pipe remains semi-elliptical; moreover, the ratio of the ellipse's semi-axes does not change, i.e., $b_0/a_0 = b/a = \text{const}$. Here b and a are the current values of the depth and half-length of the crack.

The remaining life calculation for the pipe segment with the external longitudinal crack is performed using an algorithm based on the J -integral concept, when assessing pipeline integrity with localized corrosion areas.

The validity of the underlying model of the algorithm and justification of its application in real-life conditions are discussed in [6]. J -integral characterizes the rate of change of the potential energy of a body with a crack with the change of its length. According to [5, 6], the full value of the J -integral, composed of the elastic (J_e) and the plastic (J_p) components:

$$J = Q_f \cdot F_{Sf} \cdot b \cdot \sigma \left[\frac{\sigma \pi}{E} + f(n_1) \varepsilon_p \right], \quad (8.1)$$

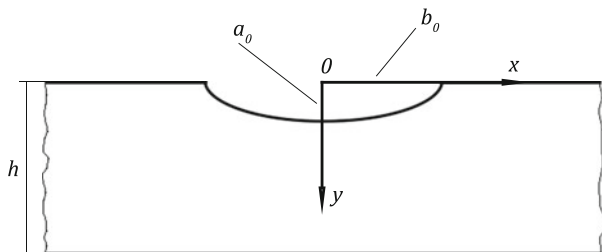


Fig. 8.1 Pipeline segment with an external semielliptical surface SC crack

where the ellipse-form coefficient

$$Q_f = 1.6260 - 1.4795(b/2a) - 6.3428(b/2a)^2 + 10.261(b/2a)^3,$$

the free surface coefficient

$$F_{sf} = \begin{cases} [(2h/\pi b) \tan(\pi b/2h)]^{1/2} & 0 < b/h < 0.95; \\ 2.918 & 0.95 \leq b/h \leq 1.00; \end{cases}$$

$$f(n_1) = [3.85(1/n_1)^{1/2}(1 - n_1) + \pi n_1](1 + n_1),$$

the local hoop stress

$$\sigma = \frac{R_1^2 \cdot p}{R_2^2 - R_1^2} \left(1 + \frac{R_2^2}{(R_1 + h - b)^2} \right),$$

where ε_p is the plastic deformation; k_0 and n_1 are the characteristics of pipe material and coefficients of equation $\sigma = k_0 \cdot \varepsilon_p^{n_1}$ that combines the stresses with the plastic deformations; E is the Young's modulus; $h = R_2 - R_1$ is the pipe wall thickness; R_2 and R_1 are the external and internal radii of the pipe.

Main stages of the algorithm for assessing remaining life of a pipe segment with a single crack.

1. *Estimate the critical depth of a pipeline crack.* As a first step, calculate the critical crack depth b_{cr} at a given inner pressure p (which corresponds to the predicted pipe fracture). The problem is solved by the following iterations:

- calculate the value of J -integral ($J^{(0)}$) at $b = b_0$ using formula (8.1);
- increase crack depth by increment Δb , so that $b_1 = b_0 + \Delta b$ and calculate, according to (8.1), the corresponding value of ($J^{(1)}$). For long cracks, following [5], it is assumed that $a = \text{const}$;
- compare the determined value of $J^{(1)}$ with fracture toughness J_c (determined experimentally on samples). If $J_c - J^{(1)} \leq \varepsilon$ (ε is the preset accuracy), then it is assumed that $b_{cr} = b_1$, $a_{cr} = b_{cr} \frac{a_0}{b_0}$. Otherwise, move to the next value $b_2 = b_1 + \Delta b$ and repeat calculations until, at some m -th step, the condition $J_c - J^{(m)} \leq \varepsilon$ is met. Then $b_{cr} = b_m$.

If the predicted critical crack size is larger than the thickness h of the pipe wall, then value h is assumed as b_{cr} , since this size corresponds to pipe leak [5].

2. *Calculation of the remaining life of a pipeline segment with a crack.*

Case 1. It is assumed that from experiment or field observations the SC rate is known, $v_p = \text{const}$. In this case, the following relation is valid:

$$\frac{db}{dt} = v_p. \quad (8.2)$$

Then the remaining life T_p of pipe segment with SC crack can be easily calculated as the time required for the defect to grow from the initial to the final size [8]. Separation of variables in Eq. (8.2) and integration produces

$$T_p = (b_{cr} - b_0) / v_p. \quad (8.3)$$

It should be noted that the assessment (8.3) is rather approximate. In reality it is necessary to take into account the nonuniformity of the crack growth rate (CGR) from the initial to the final size, using the crack propagation law.

Case 2. $v_p \neq \text{const.}$

According to [5, 6], in case SC crack depth growth is characterized by function J :

$$\frac{db}{dt} = GJ^g, \quad (8.4)$$

where G and g are the parameters depending on pipe material and the environment [2, 3].

Assume that values of parameters G and g are determined in a special experiment. Then, separation of variables in Eq. (8.4) and integration of both parts produces following assessment of remaining life of the pipe with a crack:

$$T_p = G^{-1} \int_{b_0}^{b_{cr}} [J(b)]^{-g} db.$$

8.1.2 Algorithm for Accounting for the Interaction of Multiple Longitudinal Cracks

General approach. If in a pipeline segment more than one defect was detected, it is necessary to study their interaction, since small longitudinal defects, as they grow in time, may merge to form long surface defects, and cause pipeline fracture [7, 8]. In this connection, the model described in Sect. 8.1.1 for assessing the remaining life of a pipeline segment was upgraded and extended for the case of interaction of multiple defects [4, 7]. The upgraded model presumes a joint study of long and deep surface defects. This approach is summarized as follows.

For each of the cracks (considered as a single isolated semielliptical crack with the effective area equal to the effective area of the defect) the J -integral value is determined. Then all its values are determined for all possible combinations of semielliptical cracks with the effective areas equal to the effective areas of the combined cracks. A single crack or a combination of cracks with the largest value of J will then be considered the predicted cause of pipeline fracture.

An example of assessing interaction of two semielliptical cracks with equal semi-axes on the basis of the described approach is considered in [7].

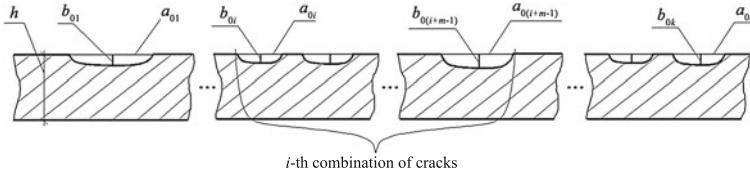


Fig. 8.2 Pipeline section with multiple semielliptical cracks

Algorithm for assessing remaining life of a pipeline segment with accounting of interaction of multiple SC type cracks. Based on the general approach in what follows an algorithm is described for calculating the remaining life of a pipeline segment with arbitrary number of SC cracks.

Consider the case (see Fig. 8.2), of a pipeline section with k ($k > 1$) longitudinal cracks with initial parameters (a_{0j}, b_{0j}) , $j = 1, \dots, k$, divided by spaces S_l ($l = 1, \dots, k - 1$), as given by direct measurements, which in general are RVs.

Main steps of the pipeline remaining life assessment algorithm are as follows:

1. Define, using the algorithm of Sect. 8.1.1, the individual values of the J -integral (J_j) for each given j -th crack.
2. Define values of $J_{int}^{(im)}$ that correspond to the interaction (merging) of the i -th combination of m adjacent cracks (see Fig. 8.2):

$$J_{int}^{(im)} = J_{i, \dots, (i+m-1)}, \quad i = 1, \dots, (k - (m - 1)); \quad m = 2, \dots, k.$$

The sizes $(a_{int}^{(im)}, b_{int}^{(im)})$ of the resulting semielliptical crack when m cracks of the i th combination fuse into one, are defined as in [7]. Namely, the area which is embraced by the resulting crack profile is taken as being equal to the sum of the areas embraced by the profiles of all cracks, which took part in the merger:

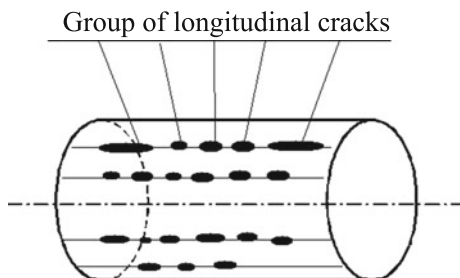
$$\begin{aligned} a_{int}^{(im)} &= a_{0(i+m-1)} + \sum_{j=i}^{i+m-2} (a_{0j} + S_j/2); \\ b_{int}^{(im)} &= \frac{\sum_{j=1}^{i+m-1} a_{0j} b_{0j}}{a_{int}^{(im)}}. \end{aligned} \quad (8.5)$$

3. Compare each of the defined values of $J_{int}^{(im)}$ with all other J_j ($j = 1, \dots, k$). Reveal all possible r combinations of q_r adjacent cracks, for which $J_{int}^{(rq_r)} > J_j$ for all $j = 1, \dots, k$. Select from them the ξ th combination of r_ξ adjacent cracks, for which $J_{int}^{(\xi r_\xi)} = \max_r J_{int}^{(rq_r)}$. Development of this ξ th combination of r_ξ adjacent cracks is then predicted as the cause of pipe failure.

Residual lifetime in this case is assessed by considering the pipe with a single crack, which parameters are defined by Eq. (8.5).

In the opposite case (if no r combinations of cracks are found, for which $J_{int}^{(rq_r)} > J_j$ for every $j = 1, \dots, k$), the maximal value of J -integral for single cracks is assessed

Fig. 8.3 Scheme of grouping of multiple SC cracks



as: $J_\eta = \max_j J_j$, ($j = 1, \dots, k$). Here the most possible cause of pipe rupture is established as the development of the η th single crack, and the remaining life is assessed as in Sect. 8.1.1.

In general case, when the pipe segment has multiple SC cracks (Fig. 8.3), they can be divided into separate groups, each of which unites cracks that are positioned along a line parallel to the longitudinal pipe axis. The above algorithm is applicable to each such group. At the same time, it is possible to solve problems of the cracks interaction in each group and make assessment of the remaining life of pipe segments with this group of cracks. The smallest of them is then taken as the assessment of the pipeline segment remaining life.

8.1.3 Numerical Cases

Example 8.1.1 Assessment of remaining life of a gas pipeline segment with SC cracks, without accounting for their interaction.

Consider a main gas pipeline segment with multiple longitudinal cracks. Pipeline material is 17G10C grade steel. Assume that ILI gave that maximal initial SC crack depth is b_0 and length is a_0 .

Define, using the algorithm described in Sect. 8.1.1, the minimal critical depth b_{cr} and the minimal remaining life T_r for an existing main gas pipeline with a single crack (a_0, b_0) for the initial parameters, as presented in Table 8.1.

The maximal SCC rate $v_p = 6 \times 10^{-4}$ m/year (0.024 inch/year) is taken as in [4]. Maximal initial crack depth $b_0 = 3 \times 10^{-3}$ m. The minimal value of the critical fracture toughness $J_c = 6 \times 10^4$ J/m² is taken from experimental results [11] for grade steel 17G10C.

Preliminarily, behavior of the J function with crack growth was investigated for different values of initial crack sizes. It was found that, in all cases, the value of J practically does not change as the length of the crack grows up to the size of $a > 0.2$ m. Because of this, in all further analysis it was assumed that $a = \text{const} = 0.2$ m.

Results of the calculations are given in Fig. 8.4. According to results of the analysis, the minimal value T_r of the remaining life of a pipeline with one SC crack

Table 8.1 Initial data for the problem of assessing gas pipeline remaining life under SCC conditions

Parameter		Designation	Value	Measurement unit
Radius	Ext.	R_2	0.71	m
	Int.	R_1	0.6949	m
Operating pressure		p	5 and 6	MPa
Exponent of the $\sigma \sim \varepsilon_p$ relation		n_1	0.119	–
Critical fracture toughness value		J_c	6×10	$\frac{kJ}{m^2}$
Maximal SCC rate		v_p	6×10^{-4}	m/year

significantly depends on the value of internal pressure in the pipe. When the operating pressure $p = 5$ MPa, the assessment of remaining life of a pipeline with an initial crack with $b_0 = 3 \times 10^{-3}$ m and semi-length a_0 that changes from 10^{-2} m to 25×10^{-2} m, is the interval of 19.8–18.5 years (see Fig. 8.4a). At the operating pressure of 6 MPa the residual lifetime drops to 16.2–14.7 years (see Fig. 8.4b).

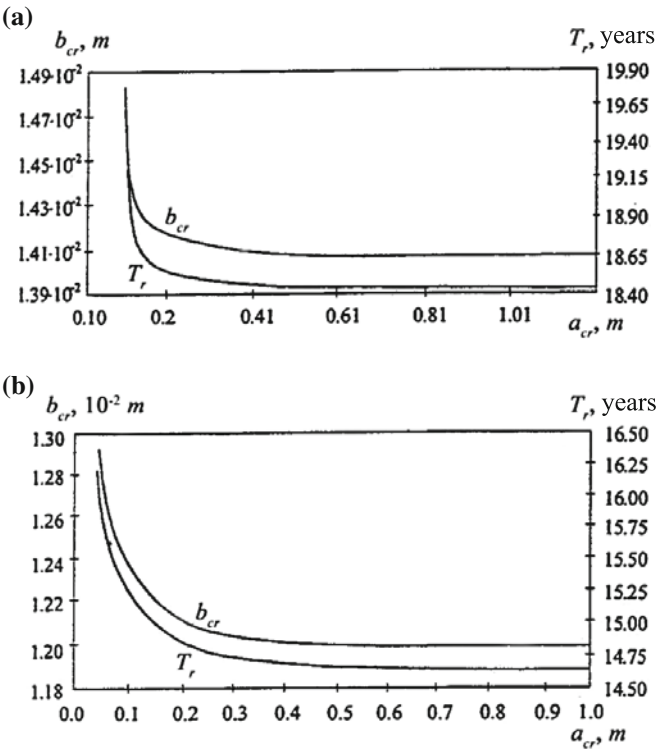


Fig. 8.4 Prognosis of the minimal critical crack depth b_{rc} and of the remaining life T_r as a function of critical crack semi-length a_{cr}

Table 8.2 Results of predicting merger of two cracks

b_{01}/h	s/a_{01}	$J_1, \text{J/m}^2$	$J_{12}, \text{J/m}^2$	$a_{12}, 10^{-1} \text{ m}$	$b_{12}, 10^{-3} \text{ m}$
0.1	0.03	2011.08	2011.35	1.0075	1.04988
0.2	0.06	4027.39	4033.62	1.0150	2.9754
0.3	0.10	6095.57	6102.89	1.0250	4.4195
0.4	0.14	8279.41	8285.65	1.0350	5.8357
0.5	0.17	10,678.89	10,697.03	1.0425	7.2422
0.6	0.19	13,472.19	13,505.41	1.0475	8.6492
0.7	0.19	17,028.43	17,093.49	1.0475	10.091
0.8	0.17	22,302.80	22,336.22	1.0425	11.588
0.9	0.10	33,094.45	33,332.59	1.0250	13.259

Example 8.1.2 Assessment of interaction of two longitudinal SC cracks.

Consider a main gas pipeline section with two longitudinal semielliptical cracks with initial sizes (a_{01}, b_{01}) and (a_{02}, b_{02}) located at a distance s from each other. Operating pressure $p = 5 \text{ MPa}$.

Solution of the interaction problem is conducted using the algorithm described in Sect. 8.1.2.

The numerical calculus was performed for the case of two equal-size cracks with following parameters: $a_{01} = a_{02} = 5 \times 10^{-2} \text{ m}$; $b_{01} = b_{02}$ is a variable fraction of pipe web thickness h ; s is a variable fraction of crack semi-length a_{01} . Other initial data are given in Table 8.1. Results of the calculation are given in Table 8.2 and Fig. 8.5. The graph is built as follows. Assume, that $b_{01}/h = 0.2$, $s/a_{01} = 0.1$ and calculate J_{12}, J_1, J_2 . If the condition of interaction (merger) of cracks ($J_{12} > J_i, i = 1, 2$) is met, incrementally increase s/a_{01} (for instance, assume $s/a_{01} = 0.2$) and repeat calculation of J_{12}, J_1, J_2 etc., until the condition of cracks interaction for the preset b_{01}/h is met. Plot the obtained point on the graph and move to the next value b_{01}/h , etc.

The results of calculations for an operating pipeline segment with two identical in size longitudinal cracks separated by distance s , define the area of change of the initial cracks parameters, where their interaction is excluded (the area above the curve in Fig. 8.5). In the case of shallow cracks $b_{01} = 0.1h$, the merger of cracks does not occur even when the distance between them is relatively small $s/a_{01} > 0.03$. Cracks with larger initial depth $b_0 = 0.2\text{--}0.6h$ will not interact, if the relative distance s/a_{01} between them will increase from 0.06 to 0.19. Deep cracks with $b_{01} = 0.6\text{--}0.7h$ will not merge if the distance between them satisfies the condition $s/a_{01} > 0.19$. But for deeper cracks with $b_0 = 0.7\text{--}0.9h$ the relative distance s/a_{01} between them, which excludes their interaction, according to Fig. 8.5, decreases from 0.19 to 0.1. This can be explained by the fact that, starting from some depth, the SC cracks start to interact differently (this has yet to be checked experimentally).

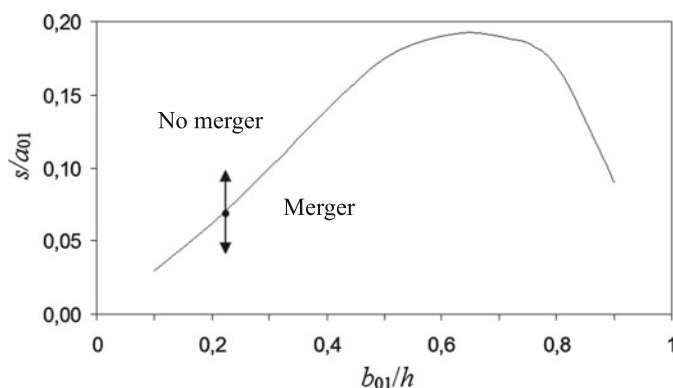


Fig. 8.5 Prognosis of merger of two equal (a_{01} ; b_{01}) cracks, separated by distance s

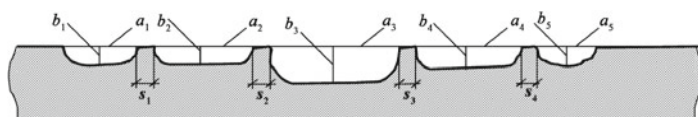


Fig. 8.6 A gas pipeline section with 5 SC cracks

Example 8.1.3 Remaining life assessment of pipeline with multiple SC cracks, taking into account their interaction.

Consider a pipeline section under operating pressure $p = 5$ MPa with five longitudinal cracks (Fig. 8.6) which initial parameters are given in Table 8.3, and other parameters are taken from Table 8.1.

Interaction of different combinations of adjacent cracks is assessed using the algorithm described in Sect. 8.1.2. Values of the J-integral J_j , ($j = 1, \dots, 5$) of different combination of adjacent cracks are calculated for each of the five cracks separately, as well as the values of J_{int} that correspond to their interaction. According to results of calculus (see Table 8.3), the most probable cause of pipeline failure would be development of a crack formed by merger of two initial cracks—the third and the fourth. Indeed, the maximal value of $J_{int} = J_{34} = 6.37 \text{ kJ/m}^2$, which exceeds all of the individual values of J_j ($j = 1, \dots, 5$), is related to the crack formed by the above-mentioned two cracks. Parameters of the resulting crack are: $a_{int} = a_{34} = 2.85 \times 10^{-2} \text{ m}$; $b_{int} = b_{34} = 4.46 \times 10^{-3} \text{ m}$ (see Table 8.3). The next step is to calculate, using the above algorithm of Sect. 8.1.1, the remaining life for the pipeline with a single SC crack (a_{int} , b_{int}) and the minimal critical crack depth, on the condition that the maximal SCC rate $v_p = 6 \times 10^{-4} \text{ m/year}$. The calculation gives $b_{cr} = 1.43 \times 10^{-2} \text{ m}$ and remaining life $T_p = 16.46$ years.

Table 8.3 Results of solving the problem for a gas pipeline segment with five cracks

#	Initial cracks parameters			Interaction of cracks														
				Two					Three					Four				
	J			a_{int}	b_{int}	J_{int}			a_{int}	b_{int}	J_{int}			a_{int}	b_{int}	J_{int}		
						J_{12}	J_{23}	J_{34}			J_{123}	J_{234}	J_{345}			J_{1234}	J_{2345}	J_{12345}
1	8.0	2.7	1.0	3.1	20.5	3.1	4.4	—	—	—	5.8	—	—	49.5	3.9	5.8	—	58.0
2	12.0	3.6	1.0	4.4	24.5	4.5	—	—	—	—	—	6.1	—	49.5	4.0	—	6.0	—
3	12.0	5.7	1.0	5.9	28.5	4.5	—	—	—	—	—	—	6.2	—	—	—	—	—
4	16.0	3.7	1.0	4.9	24.5	3.6	—	—	—	—	—	—	—	—	—	—	—	—
5	8.0	3.7	—	3.8	—	—	—	—	—	—	—	—	—	—	—	—	—	—

Note Measurements units $a, b, a_{int}, b_{int}, s - 10^{-3}$ m; $J, J_{int} - \text{kJ/m}^2$

8.2 Residual Life Time of a Gas Pipeline with a Single Longitudinal SC Crack Under Cyclic Internal Pressure

Calculation algorithm. Consider a main gas pipeline segment with a single longitudinal SC crack (see Fig. 8.1). During operation, the inner gas pressure p changes cyclically from the minimal ($p_{\min}$) to its maximal ($p_{\max}$) values. Normally, pipeline segments closest to a gas booster station are subject to such impacts. Assume, as in Sect. 8.1.1, that the crack shape under load remains semielliptical and the ellipse's semi-axes ratio does not change: $b_0/a_0 = b/a = \text{const}$.

The crack behavior under conditions of cyclical load impact is described by the Paris' equation [12]:

$$\frac{db}{dn} = C (\Delta K)^n, \quad (8.6)$$

where N is the number of load cycles; C and n are the experimentally determined characteristics of the materials; $\Delta K = K_{I\max} - K_{I\min}$ ($K_{I\max}$ and $K_{I\min}$ are the maximal and the minimal stress intensity factors SIF of the cycle for a tensile crack at $p = p_{\max}$ and $p = p_{\min}$, respectively).

Assessment of the remaining life N_p of pipeline segment with a crack, taking into account its depth growth from the initial size b_0 to the critical b_{cr} may be obtained by integrating Eq. (8.6):

$$N_p = C^{-1} \int_{b_0}^{b_{cr}} (\Delta K)^{-n} db. \quad (8.7)$$

According to [12], it is possible to make an approximate calculation of the SIF K_I for semielliptical crack in a pipe via functions K_{i0} ($i = 1, 2$), representing, respectively, the SIF of tensile and bending stresses of an infinite plate with thickness h , equal to pipe wall thickness, with a semielliptical crack with stresses $\sigma'_h = -\sigma_h(y)$ at its faces. In this case the linearized (by plate thickness) hoop stresses in an intact pipe will be

$$\sigma_h(y) = A_1 y + B_1. \quad (8.8)$$

Parameter K_I in the deepest point of the semielliptical crack, with the current lengths a and b of the large and small semi-axes, are determined by formula

$$K_I = K_{10}(\varepsilon_1, \varepsilon_2) \Phi_1(\varepsilon_3) + K_{20}(\varepsilon_1, \varepsilon_2) \Phi_2(\varepsilon_3), \quad (8.9)$$

where

$$K_{i0} = C_i \sqrt{\pi b / Q_1} F(\varepsilon_1, \varepsilon_2);$$

$$C_1 = A_1 h / 2 + B_1;$$

$$C_2 = -A_1 h H_1 / 2;$$

$$\begin{aligned}
Q_1 &= 1 + 1.464\varepsilon_1^{1.65}; \\
\Phi_1(\varepsilon_3) &= 1 + 5\pi\varepsilon_3\sqrt{3(1-\mu^2)}/32; \\
\Phi_2(\varepsilon_3) &= 1 - (1 + 2\mu + 5\mu^2)\pi\varepsilon_3\sqrt{3(1-\mu^2)}/[32(1-\mu)(3+\mu)]; \\
\varepsilon_1 &= b/a; \\
\varepsilon_2 &= b/h; \\
h &= R_2 - R_1; \\
R_2, R_1 &- \text{correspondingly the inner and outer pipe radii}; \\
\varepsilon_3 &= 2a^2/(R_2^2 - R_1^2); \\
F(\varepsilon_1, \varepsilon_2) &= (H_2 + H_3\varepsilon_2^2 + H_4\varepsilon_2^4); \\
H_1 &= 1 - (1.22 + 0.12\varepsilon_1)\varepsilon_2 + (0.55 - 1.05\varepsilon_1^{0.75} + 0.47\varepsilon_1^{1.5})\varepsilon_2^2; \\
H_2 &= 1.13 - 0.09\varepsilon_1; \\
H_3 &= -0.54 + 0.89/(0.2 + \varepsilon_1); \\
H_4 &= 0.5 - (0.65 + \varepsilon_1)^{-1} + 14(1 - \varepsilon_1)^{24}; \\
H_5 &= 1 - 0.34\varepsilon_2 - 0.11\varepsilon_1\varepsilon_2.
\end{aligned}$$

Parameters A_1 and B_1 in formula (8.8) for the assumed in Fig. 8.1 system of coordinates in case of external crack in a pipe are determined on the condition of the least deviation from the initial stresses under linearization. Incidentally, under the constant value of the main vector of the initial and the linearized stresses, as well as their equality in the inner pipe surface, obtain

$$A_1 = \frac{2pR_2}{R_2^2 - R_1^2}, \quad B_1 = \frac{p(R_1^2 + R_2^2 - 2R_2h)}{R_2^2 - R_1^2}.$$

Critical crack depth parameter b_{cr} in Eq. (8.7) is determined similarly [8], but by using another fracture criterion, formulated on the basis of linear fracture mechanics, namely:

$$K_{fc} - K_{I\max} \leq \varepsilon. \quad (8.10)$$

Here K_{fc} is the cyclic fracture toughness [12], determined experimentally on material samples, and ε is the given approximation accuracy.

Calculation b_{cr} is performed by iterations in several steps:

1. at $b = b_0$, $a = a_0$ and $p = p_{\max}$ calculate the corresponding value of $K_{I\max} = K_{I\max}^{(0)}$ using formula (8.9);
2. introduce an increment Δb and at $b_1 = b_0 + \Delta b$ again calculate $K_{I\max} = K_{I\max}^{(1)}$, according formula (8.9);

Table 8.4 Initial data

Parameter		Symbol	Value	Measurement units
Young modulus		E	2.1×10^5	MPa
Poisson coefficient		μ	0.26	–
Pipe radius	Ext.	R_2	0.71	m
	Int.	R_1	0.6949	m
Gas pressure in pipe		$p_{\max}$	5; 7.5	MPa
		$p_{\min}$	4; 3; 2; 1	MPa
Paris law		C	3.1×10^{-8}	$\frac{m^{(3n+2)/2}}{(MN)^n}$
Parameters		n	2.33	–
Gas pressure pulse frequency		f	8760	Cycle/year

3. check, whether the condition (8.10) is met. If it is, assume $b_{cr} = b_1$, $a_{cr} = b_{cr} \frac{a_0}{b_0}$. Otherwise, move to the next value $b_2 = b_1 + \Delta b$ and repeat calculations of $K_{I\max}$ etc., until at a certain m th step $K_{I\max}^{(m)} - K_{fc} \leq \varepsilon$.

If the critical crack size is predicted to be larger than the thickness h of the pipe wall, then it is assumed that h is b_{cr} , since this size corresponds to a pipe leak.

Example 8.2.1 Consider a main pipeline segment with SC type cracks. Gas pumping pressure changes cyclically from $p_{\min}$ to $p_{\max}$ with given frequency f . Pipe material is steel 17 G1S-U. Assume that from inspection results, the maximal initial depth b_0 of cracks and the corresponding to it half-length a_0 are known.

Determine, using the described above algorithm, the minimal remaining pipe life under the SCC conditions at input parameters from Table 8.4. Consider two variants of the initial parameters for the maximal crack: $a_0 = 3 \times 10^{-3}$ m, $b_0 = 1 \times 10^{-3}$ m and $a_0 = 1 \times 10^{-2}$ m, $b_0 = 3 \times 10^{-3}$ m. They correspond well with results [6] obtained from real-life pipelines inspections with maximal initial defect depth not more than 20 % of the pipe wall thickness.

Frequency f was assumed as 1 cycle/hour. The Paris equation parameters were taken from experimental data [14] for steel 17 GS.

Due to lack of K_{fc} data for pipe material its calculation value was taken as the maximal (at $N = 0$) value of the critical value of SIF K_I under static load. The latter can be determined [1] knowing the fracture toughness of the material: $K_{Ic} = \sqrt{\frac{EJ_c}{1-\mu^2}}$. Here E and μ are elastic modulus and Poisson coefficient, respectively, for the pipeline material. Minimal fracture toughness value for the pipe material $J_c = 6 \times 10^4$ J/m² was taken from experimental data [11] for steel 17 G1S.

Behavior of SIF functions $K_{I\max}$ and $K_{I\min}$ depending on cracks depth was studied (Fig. 8.7). Graphs of these functions are nonlinear; moreover, the degree of nonlinearity grows with growth of b .

Under the cyclical load $p_{\max} = 5$ MPa, $p_{\min} = 4$ MPa the initial crack in the pipe $a_0 = 1 \times 10^{-2}$ m, $b_0 = 3 \times 10^{-3}$ m grows from b_0 to $b_{cr} = h$, which increases $K_{I\max}$

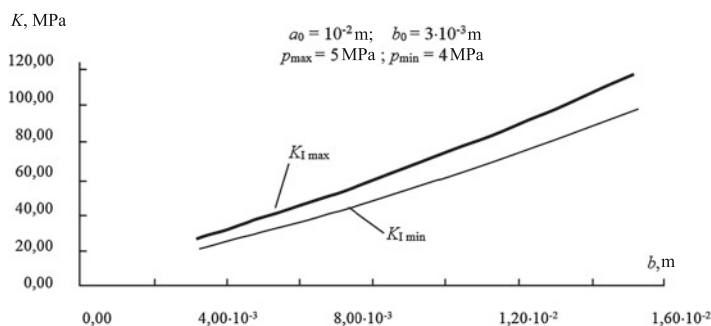


Fig. 8.7 Growth of functions $K_{I\max}$ and $K_{I\min}$ with growth of pipe crack depth

Table 8.5 Minimal remaining life N_p of a pipeline segment with maximal initial SC type crack $a_0 = 3 \times 10^{-3}$ m, $b_0 = 1 \times 10^{-3}$ m under cyclical gas loading

$p_{\max}$, MPa	$p_{\min}$, MPa	b_{cr} , m	N_p , cycles	$T_p = N_p/f$, years
5	4	h	6207	0.71
	3		1234	0.14
	2		480	0.05
	1		246	0.03
7.5	4	1.3×10^{-2}	330	0.04
	3		184	0.02
	2		115	0.01
	1		77	0.01

from 24 to 98 MPa, and $K_{I\min}$ from 19 to 67 MPa. Thus, the range of SIF of ΔK cycle changes under these conditions from 5 to 31 MPa (6.2 fold growth).

The results of calculation of the minimal remaining life N_p of a pipeline under the SCC conditions, according to the criterion of maximal crack growth from the initial to the critical size, for various characteristics of loading cycles, are presented in Tables 8.5, 8.6 and in Figs. 8.8, 8.9.

In both cases, the remaining life N_p of a pipeline segment decreases significantly with the growth of inner pressure amplitude (at fixed $p_{\max}$). For a pipe segment with a shallow initial SC type crack $a_0 = 3 \times 10^{-3}$ m, $b_0 = 1 \times 10^{-3}$ m, the change of $p_{\min}$ from 4 to 1 MPa results in a decrease of T_p :

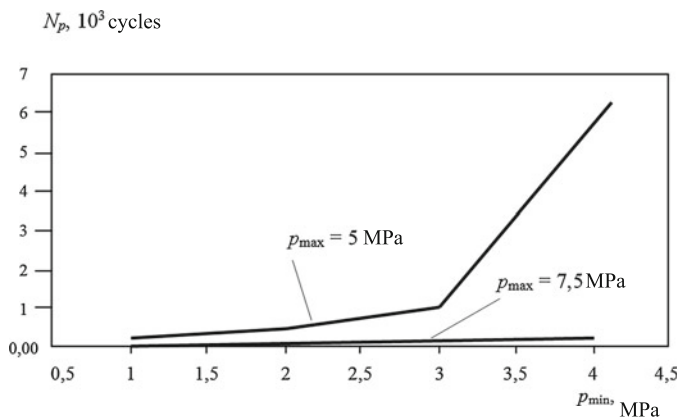
- at $p_{\max} = 5$ MPa—from 0.71 to 0.03 year;
- at $p_{\max} = 7.5$ MPa—from 0.038 to 0.009 year.

In case of a large initial crack ($a_0 = 1 \times 10^{-2}$ m, $b_0 = 3 \times 10^{-3}$ m) a drop of $p_{\min}$ from 4.8 to 1 MPa will result in a significant reduction of the remaining life T_p :

- at $p_{\max} = 5$ MPa—from 11.92 to 0.01 year;
- at $p_{\max} = 7.5$ MPa—from 1.338 to 0.003 year.

Table 8.6 Minimal remaining life of a pipeline with maximal initial SC type crack $a_0 = 10^{-2}$ m, $b_0 = 3 \times 10^{-3}$ m

$p_{\max}$, MPa	$p_{\min}$, MPa	b_{cr} , m	N_p , cycles	$T_p = N_p/f$, years
5	4.8	h	104,459	11.92
	4.5		12,352	1.41
	4		2457	0.28
	3		489	0.06
	2		190	0.02
	1		97	0.01
7.5	7	1.3×10^{-2}	11,724	1.34
	6		907	0.10
	4		126	0.01
	3		70	0.01
	2		44	0.01
	1		30	0.00

**Fig. 8.8** Minimal remaining life of pipeline segment N_p with maximal initial SC type crack $a_0 = 3 \times 10^{-3}$ m, $b_0 = 1 \times 10^{-3}$ m under various cyclical pressure parameters

8.3 Implementation of the Most Important Sampling Method for Assessing Pipeline POF with a Single SC Type Crack

While solving problems of fracture probability of a pipe with cracks, it is necessary to find the integral value in a rather complex domain. Such integration in an analytical form is often impossible and the only practical way to solve the problem is to use the method of statistical tests (Monte Carlo method). However, its direct use requires great computing time, even when rather powerful computers are used. To address

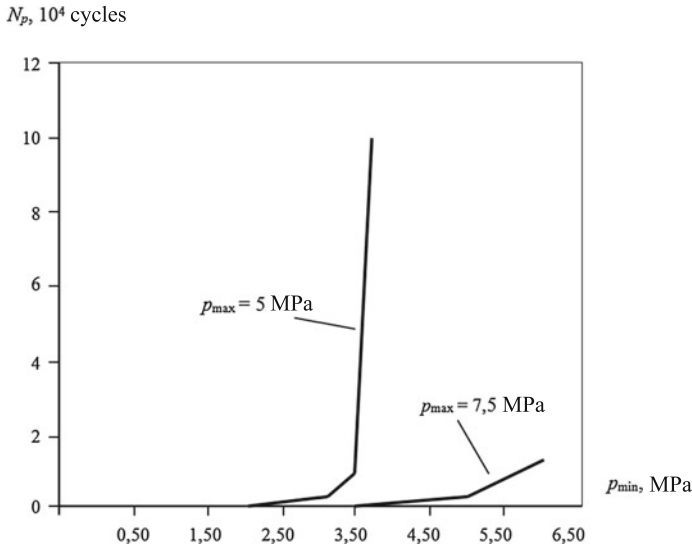


Fig. 8.9 Minimal remaining life of pipeline segment N_p with maximal initial SC type crack $a_0 = 10^{-2}$ m, $b_0 = 3 \times 10^{-3}$ m under various cyclical pressure parameters

this problem the so-called “important sampling method” [13] was developed. We illustrate it on a practical example.

The time independent probability of failure can be given as

$$P_f = \int_{R^n} I(\mathbf{x}) f_x(\mathbf{x}) d\mathbf{x}, \quad (8.11)$$

where $\mathbf{x}$ is some n -dimensional random vector in space R^n ; $f_x(\mathbf{x})$ is the probability density function of vector $\mathbf{x}$; $I(\mathbf{x})$ is the indicator function, defined as

$$I(x) = \begin{cases} 1, & \text{if } g(\mathbf{x}) \leq 0, \\ 0, & \text{if } g(\mathbf{x}) > 0 \end{cases}$$

where $g(\mathbf{x})$ is the limit state function.

(a) Integral (8.11) may be approximated by a sum, using direct Monte Carlo modeling, by generating n_s samples x_i , $i = 1, 2, \dots, n_s$, according to distribution $f_x(\mathbf{x})$:

$$\hat{P}_f = \frac{1}{n_s} \sum_{i=1}^{n_s} I[x_i].$$

In this case, the standard error equals

$$\varepsilon_{MS} = \frac{1}{n_S \cdot \hat{P}_f} \sqrt{n_S \left(\hat{P}_f - \hat{P}_f^2 \right)}.$$

(b) To improve calculation of P_f accuracy at given n_S , the important sampling method (ISM) is used. Main idea of this method is that the samples are generated not according to the distribution $f_x(\mathbf{x})$, but according to a new PDF $p_w(\mathbf{x})$, under which a larger number of samples is generated in the fracture domain, where the product $I(\mathbf{x}) \cdot f_x(\mathbf{x})$ has maximal values. In this case, integral (8.11) may be written as

$$P_f = \int_{R^n} \frac{I[\mathbf{x}] \cdot f_x(\mathbf{x})}{p_w(\mathbf{x})} p_w(\mathbf{x}) d\mathbf{x}.$$

Assuming further that samples x_i ($i = 1, \dots, n_S$) are generated according to distribution $p_w(\mathbf{x})$, assessment of P_f may be approximated by a sum with following weight contribution (WC) coefficients:

$$P'_f = \frac{1}{n_S} \sum_{i=1}^{n_S} I[x_i] w'_i,$$

where the WC coefficients are determined by formulas

$$w'_i = \frac{w_i}{\sum_{i=1}^{n_S} w_i},$$

$$w_i = \frac{f_x(x_i)}{p_w(x_i)}.$$

In case the samples are generated by a different PDF $\{p_w^{(j)}(\mathbf{x}), j = 1, \dots, n_h\}$, approximation of P_f is performed differently:

$$\hat{P}_f = \frac{1}{n_S} \sum_{j=1}^{n_h} \sum_{i=1}^{n_h} I[x_i^{(j)}] w_{ij},$$

$$w_{ij} = \frac{f_x(x_i^{(j)})}{p_w^j(x_i^{(j)})}.$$

(c) For reliability assessment, the adapted method (AM) of ISM is more efficient. It consists in continuous upgrading of the obtained set of sampling distributions, in

accordance with certain rules, on the basis of the latest available information about the statistical characteristics of the optimum sampling distribution $p_{opt}(\mathbf{x})$.

Main stages of the AM ISM algorithm using iteration procedure are as follows.

1. Assign:

- joint distribution density functions $f_x(\mathbf{x})$ of independent RVs;
- statistical distribution characteristics $f_x(\mathbf{x})$: mathematical expectation, standard deviation, correlation matrix;
- limit state function $g(\mathbf{x}, n)$, where n is the number of vector $\mathbf{x}$ coordinates;
- number of distributions n_s , to be generated for each distribution; maximal number of samples n_h ;
- coefficient $S (\geq 1)$ and the calculation error ε_{AIS} .

2. Generate random vector samples $X = [X^{(1)}, X^{(2)}, \dots, X^{(m)}]$ with given distributions of RVs:

$$x_l = [x_l^{(1)}, x_l^{(2)}, \dots, x_l^{(m)}], \quad l = 1, 2, \dots, n_h.$$

3. Iteration process:

- (a) calculate, at $i = 1$ statistics for the first approximation of the desired distribution $p^{(1)}(\mathbf{x})$:

$$\hat{m}_{(1)}^{(j)} = m^{(j)}, \hat{\sigma}_1^{(j)} = S \cdot \sigma^{(j)}, \quad j = 1, \dots, n,$$

where $m^{(j)}, \sigma^{(j)}, S$ are preset;

- (b) generate, for the current number $x_{l,i}^{(j)}$ of samples, according to normal distribution law with parameters $\hat{m}_i^{(j)}, \hat{\sigma}_i^{(j)}$ ($l = 1, \dots, n; j = 1, \dots, n$);
- (c) calculate the multivariate Gaussian distribution $p^{(i)}(x_{l,i})$ value;
- (d) calculate the joint distribution density function value for RV $f_x(x_{l,i})$. Here $f_x(x) = f_1(X^{(1)}) \cdot f_2(X^{(2)}) \dots f_n(X^{(n)})$, where $f_j(X^{(j)})$ are partial density distributions of RVs $X^{(j)}, j = 1, \dots, n$;
- (e) calculate the limit function $g(x_{l,i})$ value;
- (f) determine the value of the indicator function $I(x_{l,i})$;
- (g) calculate

$$w_{lK} = \frac{I[x_{l,K}] f_x(x_{l,K})}{\sum_{q=1}^i p^{(q)}(x_{l,K})};$$

- (h) calculate

$$w'_{lK} = \frac{w_{lK}}{\sum_{K=1}^i \sum_{l=1}^{n_s} w_{lK}};$$

- (i) determine the first approximation of fracture probability

$$P_f^{(1)} = \frac{1}{n_S} \sum_{l=1}^{n_S} I[x_{l,1}] \cdot w_{l1}^*;$$

$$w_{l1}^* = \frac{f_x(x_{l,1})}{p^{(1)}(x_{l,1})};$$

(j) calculate statistics for the $(i+1)$ -th approximation of $p^{(i+1)}(x_{l,i+1})$:

$$\hat{m}_{(i+1)}^{(j)} = \sum_{K=1}^i \sum_{l=1}^{n_S} x_{l,K}^{(j)} w'_{l,K}, j = 1, \dots, n;$$

$$\left\{ \hat{\sigma}_{(i+1)}^{(j)} \right\}^2 = \sum_{K=1}^i \sum_{l=1}^{n_S} \left(x_{l,K}^{(j)} - \hat{m}_K^{(j)} \right)^2 w'_{l,K};$$

(k) assess $P_f^{(i+1)}$ in the $(i+1)$ -th approximation:

$$P_f^{(i+1)} = \frac{1}{n_S} \cdot \sum_{K=1}^{i+1} \sum_{l=1}^{n_S} I[x_{l,K}] w_{lK}^*;$$

$$w_{lK}^* = \frac{f_x(x_{l,K})}{\sum_{q=1}^{i+1} p^{(q)}(x_{l,K})};$$

(l) assess the calculation error:

$$\varepsilon_{AIS} = \frac{1}{n_S \cdot P_f^{(i+1)}} \sqrt{\sum_{K=1}^{i+1} \sum_{l=1}^{n_S} I[x_{l,K}] (w_{lK}^*) - n_S \left(P_f^{(i+1)} \right)^2};$$

(m) compare ε_{AIS} with the pre-given accuracy ε^{giv} .

If $\varepsilon_{AIS} < \varepsilon^{giv}$, then fracture probability equals $P_f^{(i)}$. Otherwise, a transition from i to $(i+1)$ is performed and calculations return to point (b), etc., until the solution converges. The obtained value is compared with the assessment by the direct Monte Carlo method (formula (8.1)).

Example 8.3.1 Assess the probability of fracture of a gas pipeline section with an external crack at different periods of its operation, taking into account the random nature of the initial crack depth (b_0), gas pumping pressure (p) and fracture toughness (J_c). Additional input data are given in Tables 8.7 and 8.8. PDFs of the RV and computation algorithms are presented in Table 8.9.

Considering sequentially moments of time $K \cdot \Delta T, K = 1, 2, \dots; \Delta T$ is the time increment, receive fracture probability $P_f^{(K)}$ for a pipe segment with initial

Table 8.7 Input data for random parameters

Stochastic parameters	Notation of RV	PDF	Distribution	ME $m^{(j)}, j = 1, 2, 3$	SD $\sigma^{(j)}, j = 1, 2, 3$	MU
b_0	$X^{(1)}$	$f_1(X^{(1)})$	Normal	3×10^{-3}	$m^{(1)}/6$	m
p	$X^{(2)}$	$f_2(X^{(2)})$	Raleigh	5	$\frac{m^{(2)}}{\sqrt{\pi/2}}$	MPa
J_c	$X^{(3)}$	$f_3(X^{(3)})$	Normal	6×10^4	$m^{(3)}/6$	J/m ²

Note ME is the mathematical expectation; SD is the standard deviation; MU is the measurement unit

Table 8.8 Additional input data

Parameter	Symbol	Parameter values	
		AIS method	Monte Carlo method
Number of coordinates of vector x	n	3	3
Maximal number of PDF samples	n_h	i	i
Number of samples, generated for each PDF in the procedure	n_s	300; 500; 700	900
Coefficient	S	2	1
Calculus error	ε^{giv}	0.01	0.01

crack depth $b_0^{(K)} = b_0 + K \cdot V_K \cdot \Delta T$ and half-length $a_0^{(K)} = (a_0 + K \cdot V_K \cdot \Delta T) \frac{a_0}{b_0}$, where V_K is the SC rate. Having sequentially solved these problems, obtain a series of points $P_f^{(K)} \sim K \Delta T$, which form the fracture probability curve.

8.4 Updating Reliability Assessment of Pipeline in SCC Condition Using ILI Results

This section describes a procedure of correction fracture probability assessment for a pipe segment with an SC type crack using ILI data. Three possible inspection results are considered:

1. no cracks were detected;
2. cracks were detected but not measured;
3. cracks were detected and measured.

The algorithms of POF $P_f(T)$ assessment correction for a pipe segment with cracks at various options of inspection results are shown in Table 8.10. In the process of calculation of probabilities listed in Table 8.10, modified indicator functions are used (see Table 8.11).

In Table 8.11, the following notations were used: b_d is the minimal detectable crack size depending on the selected measurement tool; B is the crack depth measured during inspection T_{ins} ; $b_{T_{ins}}$ is the estimated crack depth at time of inspection; $J(T)$

Table 8.9 Random values modeling

Distribution	PDF	Distribution parameters	Moments	Algorithm of obtaining realizations of RVs
Normal	$f(x) = \begin{cases} \frac{1}{x \cdot \sigma \cdot \sqrt{2\pi}} \exp \left[-\frac{(\ln x - m)^2}{2\sigma^2} \right], & x > 0 \\ 0, & x \leq 0 \end{cases}$	m, σ	$m_{xx}^2 = e^{(\sigma^2+2m)}$ $D_x = \sigma_x^2 = e^{(\sigma^2+2m)} \times [e^{\sigma^2} - 1]$	$x = \exp \{ \sigma \eta + m \}$ (η – Gaussian RV (0, 1), i.e., with zero mean and unit variance)
Raleigh	$f(x) = \begin{cases} \frac{x}{\sigma_x^2} \exp \left[-\frac{x^2}{2\sigma_x^2} \right], & x > 0 \\ 0, & x \leq 0 \end{cases}$	$\sigma > 0$	$m_x = \sigma \sqrt{\frac{\pi}{2}},$ $D_x = \sigma_x^2 = \sigma^2 \left(2 - \frac{\pi}{2} \right)$	$x = \sigma \sqrt{-2 \ln r}$ (r – uniformly distributed [0, 1] RV)
Normal	$f(x) = \frac{1}{\sigma_x \sqrt{2\pi}} \exp \left[-\frac{(x-m_x)^2}{2\sigma_x^2} \right]$	m_x, σ_x	$-\infty < m_x < +\infty$ $D_x = \sigma_x^2, \sigma_x > 0$	$x = m_x + \sigma_x \left[\sum_{i=1}^{12} r_i - 6 \right]$ (η_i – realizations of uniformly distributed RV $r[0, 1]$)

Note Realizations η and r are obtained by random numbers generator

Table 8.10 Updating pipe fracture probability assessment using ILI

#	Inspection result at time T_{in}	Updated assessment of fracture probability inspection results $P_{f,K}(T)$
1	No cracks were detected	$\frac{P(b_{T_{ins}} \leq b_d \cap J_c - J(T) \leq 0)}{P(b_{T_{ins}} \leq b_d)}$
2	Cracks were detected but not measured	$\frac{P(b_{T_{ins}} \geq b_d \cap J_c - J(T) \leq 0)}{P(b_{T_{ins}} \geq b_d)}$
3	Cracks were detected and their depths measured	$\frac{P[J_c - J(T) \leq 0 \cap b_{T_{ins}} - B \leq b^{(2)}] - P[J_c - J(T) \leq 0 \cap b_{T_{ins}} - B \leq b^{(1)}]}{P[b_{T_{ins}} - B \leq b^{(2)}] - P[b_{T_{ins}} - B \leq b^{(1)}]}$

is the value of the J -integral at the current moment T (is calculated as shown in Sect. 8.1.1, at $b(T) = V_p T$, $a(T) = b(T) a_0 / b_0$, where a_0, b_0 are the initial crack sizes, and V_p is the SCC rate); $b^{(1)}$ and $b^{(2)}$ are close to zero depth values.

Example 8.4.1 Perform updating fracture probability of pipe segment with a crack using inspection data (Table 8.12). Assume that B, b_d are random values with known PDFs and parameters (see Table 8.12). RVs are modeled according to the scheme shown in Table 8.9.

In this case, the updating of fracture probability is performed using formula from Table 8.10, referring to the inspection result at the moment T_{ins} as “crack detected and its depth determined.” Performing calculation, obtain an updated value of $P_{f,cor}^0$. Similarly, considering pipeline operation moments $T_l = T_{ins} + l \cdot \Delta T, l = 1, 2, \dots$, it is possible to update the assessments of fracture probability $P_{f,cor}^0$ using corresponding inspection data.

8.5 Updating Reliability Assessment of a Pipeline with SCC Cracks Using the Bayesian Network Approach

Traditionally Bayesian network is used for assessing the POF of a system, utilizing available experimental data. If via inspection new information is received about the system state, then it is possible to correct the previous reliability predictions, as well as the statistical characteristics of random parameters using the Bayesian network (BN) machinery [9, 10].

8.5.1 Sequential Connection of Pipeline Segments

Consider a segment of gas pipeline operating under SCC conditions. Represent it in the form of sequentially connected segments with SC type cracks. This type of

Table 8.11 Indicator function modifications in the process of probabilities calculation

#	Probability $P(\dots)$	Modified indicator function $I_m [\dots]$
1	$P(b_{T_{ins}} \leq b_d \cap J_c - J(T) \leq 0);$	$\begin{cases} 1, & \text{if } b_{T_{ins}} \leq b_d \cap J_c - J(T) \leq 0; \\ 0, & \text{if } \begin{cases} b_{T_{ins}} \leq b_d \cap J_c - J(T) \leq 0; \\ \text{or} \\ b_{T_{ins}} > b_d \end{cases} \end{cases}$
2	$P(b_{T_{ins}} \leq b_d);$	$\begin{cases} 1, & \text{if } b_{T_{ins}} \leq b_d; \\ 0, & \text{if } b_{T_{ins}} > b_d \end{cases}$
3	$P(b_{T_{ins}} \geq b_d \cap J_c - J(T) \leq 0);$	$\begin{cases} 1, & \text{if } b_{T_{ins}} \geq b_d \cap J_c - J(T) \leq 0; \\ 0, & \text{if } \begin{cases} b_{T_{ins}} \geq b_d \cap J_c - J(T) > 0; \\ \text{or} \\ b_{T_{ins}} < b_d \end{cases} \end{cases}$
4	$P(b_{T_{ins}} \geq b_d);$	$\begin{cases} 1, & \text{if } b_{T_{ins}} \geq b_d; \\ 0, & \text{if } b_{T_{ins}} < b_d \end{cases}$
5	$P[J_c - J(T) \leq 0 \cap b_{T_{ins}} - B \leq b^{(1)}];$	$\begin{cases} 1, & \text{if } J_c - J(T) \leq 0 \cap b_{T_{ins}} - B \leq b^{(1)}; \\ 0, & \text{if } \begin{cases} J_c - J(T) \leq 0 \cap b_{T_{ins}} - B > b^{(1)}; \\ \text{or} \\ J_c - J(T) > 0 \end{cases} \end{cases}$
6	$P[J_c - J(T) \leq 0 \cap b_{T_{ins}} - B \leq b^{(2)}];$	$\begin{cases} 1, & \text{if } J_c - J(T) \leq 0 \cap b_{T_{ins}} - B \leq b^{(2)}; \\ 0, & \text{if } \begin{cases} J_c - J(T) \leq 0 \cap b_{T_{ins}} - B > b^{(2)}; \\ \text{or} \\ J_c - J(T) > 0 \end{cases} \end{cases}$
7	$P(b_{T_{ins}} - B \leq b^{(1)});$	$\begin{cases} 1, & \text{if } b_{T_{ins}} - B \leq b^{(1)}; \\ 0, & \text{if } b_{T_{ins}} - B > b^{(1)} \end{cases}$
8	$P(b_{T_{ins}} - B \leq b^{(2)});$	$\begin{cases} 1, & \text{if } b_{T_{ins}} - B \leq b^{(2)}; \\ 0, & \text{if } b_{T_{ins}} - B > b^{(2)} \end{cases}$

system fails in case of fracture of any one of its segments. In further discussion limit the pipeline representation by two segments each of which has one surface crack (Fig. 8.10).

Denote the segments state via A and B , respectively, and the state of the whole system as C . In the process of analysis, each component may assume only one of the two values: 1—fracture; 0—survival.

Assume that the probabilistic information about the pipe segments is set by random characteristics:

Fig. 8.10 Pipe segments with the most dangerous cracks

Table 8.12 Additional input data after pipe segment inspection

#	Parameter	Symbol	DV	RV		m, σ	Numerical value
				Symbol	PDF		
1	Minimal threshold crack size	b_d	–	$X^{(4)}$	$f_4(X^{(4)})$ (Lognormal)	m_{b_d}	$0.2 \times 10^{-3} \text{ m}$
						σ_{b_d}	$m_{b_d}/6 \text{ m}$
2	Crack depth measured during inspection	B	–	$X^{(5)}$	$f_5(X^{(5)})$ (Lognormal)	m_b	$5 \times 10^{-3} \text{ m}$
						σ_B	$m_B/6 \text{ m}$
3	Values of crack depth close to zero	$b^{(1)}$	DV	–	–	–	$0.01 \cdot B \text{ m}$
		$b^{(2)}$	DV	–	–	–	$0.015 \cdot B \text{ m}$
4	Number of coordinates of vector $\mathbf{x}$	n	DV	–	–	–	5
5	Time of inspection	T_{ins}	DV	–	–	–	5 years
6	Time increment	ΔT	DV	–	–	–	0.5 years

Note DV is the deterministic value; m, σ —are correspondingly the mathematical expectation and SD of RV

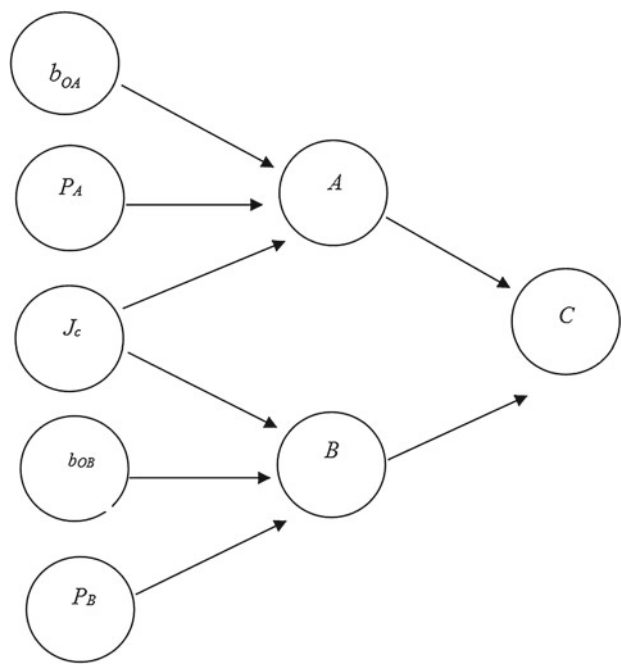


Fig. 8.11 Bayesian network for a given system

Table 8.13 Conditional probability $P(C/A, B)$ in a serial system

	A = 1	A = 0
B = 1	1.0	1.0
B = 0	1.0	0.0

- initial sizes of crack depths b_{OA}, b_{OB} ;
- gas pressure p_A, p_B ;
- critical value of J -integral for the pipe material J_c .

Build a Bayesian network for nodes A, B , and C . A Bayesian network is the graphic representation of probabilistic causal dependence between the variables and the information flow in the model [9].

Build a three-node BN (Fig. 8.11) with three variables A, B , and C , which characterize the state of separate parts and the system as a whole.

Node C is a dependent one (according to classification [9]—a child), and has conditional probability functions $P(C/A, B)$, which characterize the state of the two adjacent nodes (Table 8.13).

Demonstrate that in this case, nodes A and B are not independent.
Indeed, assume that the fracture of part A occurs under condition $J_c - J^{(A)} \leq \varepsilon$, and of part B , when $J_c - J^{(B)} \leq \varepsilon$. Here $J^{(A)}, J^{(B)}$ are the respective values of the J -integral for pipe segments with initial cracks b_{OA}, b_{OB} , and gas pressures p_A, p_B .

Further, consider several levels of danger with the corresponding limit conditions. For instance, the three levels of danger ε ; $\varepsilon_1 = 0, 8\varepsilon$ and $\varepsilon_2 = 0.7\varepsilon$, will correspond to limit conditions $J_c - J \leq \varepsilon$; $J_c - J \leq 0.8\varepsilon$ and $J_c - J \leq 0.7\varepsilon$.

It can be seen that there is a statistical correlation between states A and B , since their limit states include a common random variable, namely, J_c . This means that nodes A and B are not independent, even if the fractures in them occur simultaneously. Consequently, the BN structure, consisting of the three nodes A , B , and C , must be updated, in order to include in it a dependence, caused by the correlation of limit states. With this purpose introduce additional (root) nodes, so that obtained scheme contains all input random variables.

Assume further that all the considered random values are independent. For additional nodes, a table of prior RV distribution functions must be established.

Now discuss different variants of the new information about the state of the system as a whole and of its individual parts.

(a) If destruction of the system is detected, then the probability of fracture of its separate parts, as well as PDFs of respective random variables may be corrected.

For instance, the probability of part A fracture equals

$$P(A = 1 | C = 1) = \frac{P(J_c - J^{(A)} \leq \varepsilon)}{P(C = 1)}.$$

Here $P(C = 1)$ denotes the fracture probability of the pipe as a whole, and is determined by expression:

$$P(C = 1) = P(J_c - J^{(A)} \leq \varepsilon) + P(J_c - J^{(B)} \leq \varepsilon) + P\left[(J_c - J^{(A)} \leq \varepsilon) \cap (J_c - J^{(B)} \leq \varepsilon)\right].$$

In this case values $J^{(A)}$ and $J^{(B)}$ at a given moment of time T (for known initial crack parameters, gas pressure and SCC rate) may be calculated as described in Sect. 8.1 and [10].

Probability of part B fracture is determined in a similar way:

$$P(B = 1 | C = 1) = \frac{P(J_c - J^{(B)} \leq \varepsilon)}{P(C = 1)}.$$

For random value b_{OA} the modified distribution function will be:

$$\begin{aligned} P(b_{OA} \leq b_A; C = 1) = & P\left[J_c - J^{(A)} \geq \varepsilon \cap J_c - J^{(B)} \leq \varepsilon \cap b_{OA} \leq b_A\right] \\ & + P\left[J_c - J^{(A)} \leq \varepsilon \cap J_c - J^{(B)} \geq \varepsilon \cap b_{OA} \leq b_A\right] \\ & + P\left[J_c - J^{(A)} \leq \varepsilon \cap J_c - J^{(B)} \leq \varepsilon \cap b_{OA} \leq b_A\right]. \end{aligned}$$

Similar formulas may be written also for other RV b_{OB} , $J_c p_A$ and p_B .

(b) If information about fracture of part B , is available, it is possible to correct characteristics for part A :

$$P(A = 1 | B = 1) = \frac{P(A = 1, B = 1)}{P(B = 1)} = \frac{P(J_c - J^{(A)} \leq \varepsilon \cap J_c - J^{(B)} \leq \varepsilon)}{P(J_c - J^{(B)} \leq \varepsilon)}.$$

Similarly, it is possible to correct distributions for J_c and p_A .

(c) In case of part A fracture, characteristics for part B are corrected as

$$P(B = 1 | A = 1) = \frac{P(J_c - J^{(B)} \leq \varepsilon \cap J_c - J^{(A)} \leq \varepsilon)}{P(J_c - J^{(A)} \leq \varepsilon)}.$$

(d) Information about fracture of any of the pipe parts may also be used for correcting fracture probability of the whole system

$$P(C = 1 | B = 1) = \frac{P(C = 1, B = 1)}{P(B = 1)} = \frac{P(B = 1)}{P(B = 1)} = 1,$$

$$P(C = 1 | A = 1) = 1.$$

8.5.2 Parallel Connection of Pipeline Segments

If the pipeline system has parallel segments (Fig. 8.12), then this system fails only if both segments fail. In this case, in addition to statistical dependence, as demonstrated for a sequential system, it is necessary to account for the whole set of possible sequences of defects failure. Namely, for the considered system there are three fracture sequences:

- first fails part A , then part B ;
- first fails part B , then part A ;
- parts A and B fail simultaneously.

It should be noted that failure of one part of the system changes POF of the other part.

In order to take into account multiple fracture sequences, it is possible to use the BN from Fig. 8.11, supplemented by additional information about the fracture sequences probability represented in Table 8.14, where $A = 1$ and $B = 1$ are POF

Fig. 8.12 Layout diagram of parallel pipeline segments

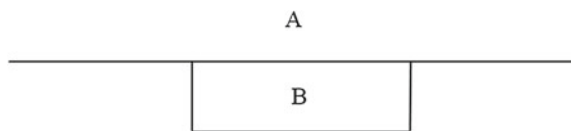


Table 8.14 Conditional system failure probability $P(C | A, B)$ depending on the state of parallel system components

	$A = 0$	$A = 1$
$B = 0$	0	$P(B_{(A)} = 1 A = 1, B = 0)$
$B = 1$	$P(A_{(B)} = 1 B = 1, A = 0)$	1

of pipe parts reckoned from the intact system; $A_{(B)}$ is the modified state of A after failure of B ; $B_{(A)}$ is the modified state of B after failure of A .

In accordance with Table 8.14:

$$\begin{aligned} P(C = 1 | A = 0, B = 1) &= P(A_{(B)} = 1 | B = 1, A = 0), \\ P(C = 1 | A = 1, B = 0) &= P(B_{(A)} = 1 | A = 1, B = 0). \end{aligned}$$

In this case, for instance, the first formula means that the POF of the system ($C = 1$) under condition of the primary failure of B , equals the probability of failure of A after failure of B , since, by definition, in case of a parallel system, $C = 1$ means both parts failed.

Assess in accordance with this condition, reliability of a system which consists of two parallel pipe segments.

When the system is intact, the limit states are expressed by formulas:

$$\begin{aligned} \text{for } A = 1 : J_c - J^{(A, p_A)} &\leq \varepsilon, \\ \text{for } B = 1 : J_c - J^{(B, p_B)} &\leq \varepsilon. \end{aligned} \quad (8.12)$$

The modified (after failure of one of the parts) states are described by different limit states:

$$\begin{aligned} A_B = 1 : J_c - J^{(A, p)} &\leq \varepsilon, \\ B_A = 1 : J_c - J^{(B, p)} &\leq \varepsilon. \end{aligned} \quad (8.13)$$

In formulas (8.12), (8.13) $J^{(A, p_A)}$, $J^{(B, p_B)}$ and $J^{(A, p)}$, $J^{(B, p)}$ denote, respectively, values of the J-integral for segments A and B under pressures p_A , p_B and p in these segments and in the unbranched part of the pipe, correspondingly.

Thus, considering jointly the BN in Fig. 8.11, Table 8.14 of conditional probabilities and conditions (8.12), (8.13) of limit states for each component, we obtain

$$\begin{aligned} P(C = 1) &= P\left(J_c - J^{(A, p_A)} \leq \varepsilon \bigcap J_c - J^{(B, p_A)} \leq \varepsilon\right) \\ &+ P\left[\left(J_c - J^{(A, p)} \leq \varepsilon\right) \bigcap \left(J_c - J^{(A, p_A)} \geq \varepsilon\right) \bigcap \left(J_c - J^{(B, p_B)} \leq \varepsilon\right)\right] \\ &+ P\left[\left(J_c - J^{(B, p)} \leq \varepsilon\right) \bigcap \left(J_c - J^{(A, p_A)} \leq \varepsilon\right) \bigcap \left(J_c - J^{(B, p_B)} \geq \varepsilon\right)\right]. \end{aligned}$$

$$P(C = 1 | B = 1) = \frac{p(J_c - J^{(A, p)} \leq \varepsilon \cap J_c - J^{(A, p_A)} \geq \varepsilon)}{p(J_c - J^{(B, p_b)} \leq \varepsilon)} + \frac{p(J_c - J^{(A, p_A)} \leq \varepsilon \cap J_c - J^{(B, p_b)} \leq \varepsilon)}{p(J_c - J^{(B, p_b)} \leq \varepsilon)}.$$

Similarly, it is possible to write $P(C = 1 | A = 1)$.

All probabilities in Sects. 8.5.1 and 8.5.2 may be calculated by the standard Monte Carlo method or with the help of AM ISM (see Sect. 8.3).

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Chapter 9

Methodology of Predictive Maintenance of Pipelines

Practical predictive maintenance (and repair) methodology for pipeline systems (described in this book) is based on the theory of the two-(multilevel) policy of managing reliability of mechanical systems proposed in [1], for various conditional and physical (real-life) failure criteria.

The main criterion of physical failure for pipelines is loss of integrity, which is the key parameter in the problem, remaining life and safety assessment.

The main problem for ensuring the integrity and safety of pipelines operation is *predicting their future technical condition*, on the basis of which the period of their safe operation and time before occurrence of the critical state is determined.

This chapter describes the predictive maintenance methodology, which consists of: (1) assessing the time of occurrence of the warning, critical and limit states of the PS, (2) assessment of their POF, depending on the types of defects, loads, and impacts on the basis of available information about multiple heterogeneous defects. We move on to description of this methodology.

9.1 Method for Assessing the Time of Occurrence of Critical and Limit States of a Pipeline with Corrosion-Type Defects

Assume that as a result of in-line inspection of a pipe segment two types of defects were detected: “metal loss” and “laminations”. Consider a comprehensive assessment method of the time of occurrence of the critical and limit states, using various failure criteria.

At the first stage the set of defects detected during inspection is divided into subsets according to their type to be analyzed separately. Since existing ILI methods

do not produce the true values of the measured defects parameters, as they contain intrinsic measurement errors, at the second stage the obtained ILI tool measurements are updated.

If results of additional diagnostic control (verification) are available, the ILI data calibration method described in Sect. 4.5 may be used for updating the defects parameters. Otherwise, the MEs are accounted for with the help of technical specifications of the used measurement tools. In some cases, when the ME values are unknown, a certain tolerance, which is a function of MEs, is added to each measurement.

After updating sizes of the defects, it is possible to assess the time of occurrence of the critical and/or the limit state, according to the set of deterministic and probability criteria presented in Table 9.1. Those criteria permit assessing the probabilities and times of occurrence of *warning*, *alarm (critical)*, or *physical failure*, and, hence, can be used to provide for pipeline safety. They ensure the required awareness level of the decision makers (DMs) about the current danger of the PL operation, or trigger various procedures for its maintenance, depending on the technical policy adopted by the pipeline operator.

The deterministic criteria from Table 9.1 are the physical criteria since they either trigger specific pipe safety recovery actions, or describe actual loss of integrity (leak or rupture). A warning failure (critical state) triggers actions of the respective diag-

Table 9.1 Criteria for assessment of the critical and the limit states of the defective PS segments occurrence

#	Used criteria	Description of criteria
<i>Deterministic criteria</i>		
1	$d(t) = k_d \cdot wt$	The depth of the most dangerous defect $d(t)$ is equal to $k_d \cdot 100\%$ of the pipe wall thickness wt . Defect reaches its warning/alarm limit state criteria (pre-leak condition)
2	$d(t) = wt$	The depth of the most dangerous defect $d(t)$ is equal to the pipe wall thickness wt . Defect reaches its physical limit state criteria (leak)
3	$P_a(t) = P_{op}$	The safe maximal operating pressure $P_a(t)$ is equal to the operating pressure P_{op} . Defect reaches its alarm limit state criteria (preburst condition)
4	$P_f(t) = P_{op}$	The failure pressure $P_f(t)$ is equal to the operating pressure P_{op} . Defect reaches its physical limit state criteria (burst)
<i>Probabilistic criteria</i>		
5	$POF = Q_l$	Probability of failure of the pipeline with defect is equal to the ultimate permissible POF Q_l . Defect reaches its probabilistic limit state criteria (ultimate permissible POF Q_l)
6	$E_{\max}$	Entropy indicator (maximum entropy point). Defect reaches its physical limit state
7	t_γ	Gamma-percent residual life time of the pipe segment as given by the Markov pure death process. Defect considered to have reached its physical longevity
8	τ_{or}	Optimal repair timing for defect repair, as given by the Markov pure death process. Defect reached its conditional failure state

nostic or repair service, which are performed taking into account existence of a rather significant time lag for their performance without the occurrence of a real danger (pipe leak or rupture). This time lag may be used by a PS operator for careful planning and performing of all the required repair and recovery actions, without a particular hurry. The time of occurrence of a physical limit state of defect triggers, in the general case, immediate repair and recovery procedures, since in this case there is much less (or zero, in case of the pipe integrity loss) time before the actual failure occurrence.

Unlike the planned preventive repair/maintenance, which is a complex of organizational and technical actions performed in accordance with the planned schedule, the proposed methodology is not a set of planned actions, but is a predictive description of the development of a sequence of events in the emergency situation on a PS, according to the chosen failure criteria. In fact, this is the concept of operating a pipeline “according to its current condition”. Based on this prognosis, the proposed methodology allows organizing various economically efficient PS integrity support actions.

Since a pipeline is a system of elements (segments with defects) connected sequentially, failure of even of one of its elements results in failure of the whole system. Hence, the times of occurrence of critical and limit state of all pipeline defects, according to criteria of Table 9.1, serve as assessments of the pipeline system residual life, i.e., the “weak link” principle is utilized. In fact, the proposed above methodology is a synthesis of methods described in previous chapters.

We provide a detailed description of criteria of Table 9.1.

Assessment of the time required for a defect to affect part of the pipe wall thickness. To do this, it is necessary to assess the predicted defect size values. Assuming their linear growth in time (see formulas 9.4), the time required for a defect to eat up part or all of the pipe wall thickness may be calculated by formula

$$t = \frac{k_d \cdot wt - d_0}{a_d},$$

where k_d is the factor of conditional defect failure by the warning/alarm limit state criteria (pre-leak condition) which may equal 0.6, 0.7, 0.8, depending on the corrosivity of the product being transported, pipeline class, etc., or 1.0 for the case of the physical limit state; d_0 is the defect depth at time of inspection; a_d is the rate of defect depth growth, which may be assessed using methods described in Sect. 9.2.

Assessment of failure pressure in pipeline segments with defects is performed by one of the methodologies for residual strength assessment described in Sect. 2.5.

To assess the predicted value of failure pressure $P_f(t)$ at time t , it is necessary to use formulas which describe the predicted defect parameters, e.g., formulas (9.4). To determine the time for the failure pressure to reach the operating pressure value, the equation of criterion #4 from Table 9.1 is numerically solved for time t .

For the lamination-type defects failure pressure assessment is possible only after they are reduced to surface defects of the “metal loss” type.

The laminations are caused by the steel and pipe manufacturing technology, and may also appear during pipeline operation. According to [2, 3], laminations can be

further classified as metallurgical laminations, hydrogen-induced cracking (HIC), nonmetallic inclusions, and so on.

The laminations, even though they are not corrosion-caused defects, could be reduced to surface defects of the type of “metal loss” according to JSC “Gasprom” industry code based on theoretical and experimental research [2, 3].

Models of converting laminations to surface “loss of metal” type defects and calculating the thickness of converted defect layer of pipe metal, for not long laminations, when the defect length $l \leq 0.2D$, are shown in Fig. 9.1, where d is thickness of detected lamination, d^* is thickness of the converted defect (it is used further as defect depth); l is the length of lamination along the pipe axis; wt is the pipe wall thickness, wt_r is the residual pipe wall thickness.

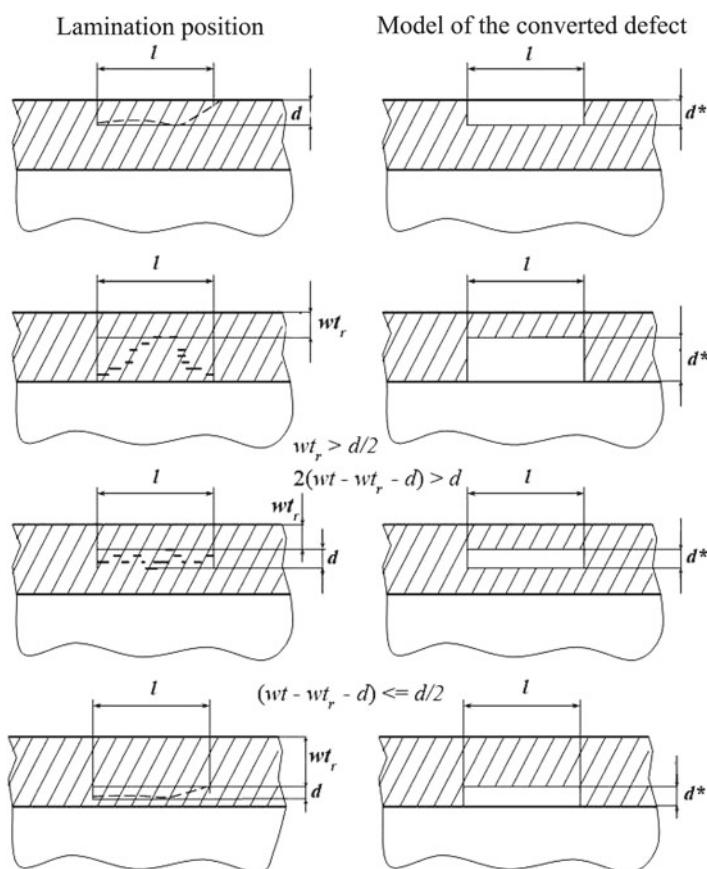


Fig. 9.1 Location of the laminations and models of their conversion to the surface “loss of metal” type defects [2, 3]

According to Fig. 9.1, for all cases, except one (see last case in Fig. 9.1), the converted thickness of lamination is equal to the detected lamination, hence, conversion is not required.

For long laminations ($l > 0.2D$) that do not surface, the depth of the converted defect is

$$d^* = d_l + 0.5d_a,$$

where d_a is the lamination thickness along the pipe axis; d_l is the lamination thickness across pipe circumference.

For long laminations ($l > 0.2D$) which appear on the surface of the pipe wall (and transported product penetrates the pipe wall), and its length along the pipe axis is l_a the depth of the converted defect is calculated by formula

$$\begin{aligned} d^* &= d_l + d_a - 0.5d_a \left(1 - \frac{l_a}{l}\right) \left(1 - \frac{l_\phi}{l}\right), \quad l_\phi < D, \\ d^* &= d_l + d_a, \quad l_\phi \geq D, \end{aligned}$$

where l_ϕ is the length of lamination along pipe circumference.

If a long lamination ($l > 0.2D$) appears on the pipe wall surface (but transported product does not penetrate the pipe wall), and its length along the pipe axis is l_a the depth of the converted defect layer is calculated by formula

$$d^* = d_l + d_a - 0.5d_a \left(1 - \frac{l_a}{l}\right).$$

For pipelines *transporting noncorrosive products*, the lamination thickness d_l and length l_ϕ across pipe circumference, which appear on the pipe wall surface, are limited by inequalities

$$\begin{aligned} d_l &\leq 0.4 \text{ wt}, \\ 0.4 \text{ wt} &\leq d_l \leq 0.6 \text{ wt}. \end{aligned} \tag{9.1}$$

In the first case of formula (9.1) the length l_ϕ should not exceed 1/3 of pipe circumference; in the second case the l_ϕ should not exceed 1/6 length of pipe circumference.

For pipelines *transporting corrosive products*, the lamination thickness d_l and length l_ϕ over pipe circumference, which appear on the surface of the pipe wall, are limited by inequalities

$$\begin{aligned} d_l &\leq 0.2 \text{ wt}, \\ 0.2 \text{ wt} &\leq d_l \leq 0.4 \text{ wt}. \end{aligned} \tag{9.2}$$

In the first case of formula (9.2) the length l_ϕ should not exceed 1/6 of length over the pipe circumference; in the second case the l_ϕ should not exceed 1/12 of pipe circumference.

For the hydrogen induced cracking, the thickness of converted defective metal layer of the pipe wall is defined by formula

$$d^* = d + (wt - wt_r - d) \left(0.3 + 1.4 \frac{l_\varphi}{D} \right), \quad l_\varphi < \frac{D}{2},$$

$$d^* = d + wt_r, \quad l_\varphi \geq \frac{D}{2}.$$

For the “pipe wall lamination” type defects, after converting them to the surface “loss of metal” type defects, assessment of the rupture pressure is performed using codes from Sect. 2.5, considering them as “loss of metal” defects [2, 3].

Safe maximum operating pressure (SMOP) of the defective cross section of a pipeline can be calculated using the safety factor by formula

$$P_a(t) = \frac{1}{K} P_f(t), \quad (9.3)$$

where $P_f(t)$ is the failure pressure assessed using one of the world wide accepted codes: B31G [4], B31Gmod [5], Shell92 [6], DNV [7], PCORRC (Battelle) [8], described in Sect. 2.5; K is the strength safety factor with respect to the rupture type of failure

$$K = \frac{P_f}{P_{op}}.$$

Russian pipelines operator companies, e.g., JSC “Gasprom” introduce their own industry strength safety factors, depending on the category of defects (not dangerous, potentially dangerous, and dangerous) [2, 3, 9]:

- *dangerous defects* require repair as soon as possible. For pipelines transporting hydrogen sulfide-containing substances, the surface defects are dangerous, with the residual wall thickness less than 40 % of the nominal wall thickness and with SF smaller than for potentially dangerous defects;
- *potentially dangerous defects* are not included in the category of dangerous, but have sizes, which exceed the requirements of applicable codes. These defects require external inspection and planned preventive maintenance;
- *not dangerous defects* neither affect the strength capacity of a pipe nor require any external inspection or repair. This group includes surface pipe metal anomalies acceptable under applicable codes, and inner metallurgical defects.

The potential danger of defective section of a pipeline, which transports *corrosive products*, is estimated using following strength safety factors [2, 3, 9]:

1. for dangerous defects $K \leq 0.6K^* + 0.4$;
2. for potentially dangerous defects $0.6K^* + 0.4 < K < K^*$;
3. for not dangerous defect $K \geq K^*$.

Under the conditions (1)–(3) K^* is the allowed strength safety factor, determined according to the applicable code, by formula

$$K^* = \sigma_s / [\sigma],$$

where σ_s is the stress, which corresponds to appearance of flow stress at the defect tip, i.e., stress, which exceeds the steel yield strength, but is slightly lower than the tensile strength; $[\sigma]$ is the design stress according to BR [10] depending on the pipeline functional application and the designated safety factor.

For a pipeline, transporting *noncorrosive products*, the potential danger of the defective section is estimated using following strength safety factors:

1. for dangerous defects $K \leq 0.7K^* + 0.3$;
2. for potentially dangerous defects $0.7K^* + 0.3 < K < K^*$;
3. for not dangerous defect $K \geq K^*$.

In most real-life cases the SMYS according to pipe design codes, batch certification data, or mechanical tests results, are assumed to be the plastic flow stress values.

The assumed design stress value according to BR is normally the minimum value of the two (see Sect. 6.5.1):

$$[\sigma] = \min \left\{ \frac{UTS \cdot m}{k_1 k^*}; \frac{SMYS \cdot m}{k_2 k^*} \right\}.$$

According to [11–14], pipeline companies introduce safety factors depending on the type of pipeline (subsea or land), pipeline location class, depending either on population density, or on the number of surrounding structures, and the utilized fracture pressure calculation methodology. British code PD 8010 [14] was designed for marine (subsea) pipelines; American codes B31.4 [11]—for land pipelines transporting hydrocarbon products; B31.8 [13]—for land gas pipelines; Canadian codes CSA Z662 [12]—for ground oil and gas pipelines.

Factor K is the warning factor, signaling possible defect failure and need of repair, which renders the failure conditional.

The Estimated Repair Factor is defined as

$$ERF(t) = \frac{P_{op}}{P_a(t)}.$$

If for the pipe cross section in consideration with a defect $ERF(t) \geq 1$, the defect is subject to immediate repair.

To determine the time needed for the acceptable operating pressure of the defective pipe segment to reach the operating pressure value, criterion #3 equation from Table 9.1 is numerically solved for time t .

Deterministic criteria (#1–4) from Table 9.1 may be conveniently represented graphically in one figure in the form of the so-called “express assessment” of the defects danger [2, 3, 9]. This express assessment is based on safety factors described above and allows accounting for the two possible “leak” and “rupture” failure scenarios. For this purpose the graphs are built, which limit the sizes of pipeline defects and allow making quick decisions on further pipeline operation, as well as perform

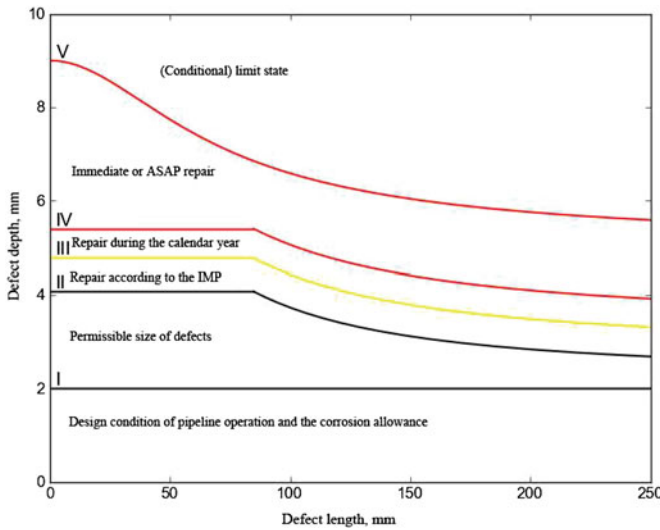


Fig. 9.2 Graphical representation of zones of the parameters of defects with varying levels of their potential danger (for pipeline with $wt = 9$ mm)

classification of the potential danger of the pipeline's defects, depending on their position relative to the graphs (see Fig. 9.2).

Line I is the boundary for Zone I which is comprised of pipeline design operational conditions, and allowance for corrosion (10 or 20 % wt).

Line II is produced by step-by-step calculations of SMOP using formula (9.3) up to the value of OP P_{op} (as designed or planned) for a pipeline by changing the length and depth of the defect, respectively, in 1 and 0.05 mm increments. In this case, the pipeline operating pressure is allowed with a design safety factor of $K = K^*$, as related to failure pressure.

Line III is produced by step-by-step calculations of SMOP for the defective section of the pipeline, up to a value at which the failure pressure is $P_f(t)$ which is $K = [0.8K^* + 0.2]$ times more than the OP of a pipeline, by changing, correspondingly, the length and depth of the defect in 1.00 and 0.05 mm increments.

Line IV is produced by step-by-step calculations of MAOP, up to the value of OP, by changing the length and depth of the defect and utilizing the safety factor K , which restricts the limit sizes of the potentially dangerous defects.

Line V is produced by step-by-step calculations of the failure pressure $P_f(t)$, up to the value of OP, while changing the length and depth, i.e., determining the defect size which can cause pipeline failure at the OP and $K = 1$.

The horizontal zones, which restrict the limit depth of defects, are produced by carrying over the point from Line IV (correspond to 60 or 80 % of pipe wall thickness) to the Lines II and III.

Depending on the location of ILI data on the graphs, the conditions of further pipeline operation or repair of defective cross sections are determined:

- *Zone #1* contains the corrosion allowance and the design permitted conditions of the pipeline;
- *Zone #2* contains permissible size of defects for the case when pipeline is operated under “normal” conditions, which provide for effective electrochemical and inhibitor protection;
- *Zone #3* contains potentially dangerous defects. Defect should be repaired according to the IMP, if the defect is below the yellow Line III, and during the calendar year, if the defect is above the yellow Line III;
- *Zone #4* contains dangerous defects, which should be repaired immediately or ASAP;
- *Zone #5* is the conditional failure area depending on the used design code (pipeline limit state).

In order to use probabilistic failure criteria it is necessary to use corresponding probabilistic methods of design.

The POF assessment is performed with the updated and calibrated Gram–Charlier–Edgeworth series method described in Sect. 6.3, or any other suitable method (Sorm, MC).

To be able to use criterion #5 from Table 9.1 it is necessary to know the maximum allowed failure probability values Q_l . Table 9.2 shows the values of these probabilities tied to pipeline safety classes, taking into account both the risk of fatalities (injuries), and the environmental and economic consequences of a failure.

To determine the time needed for the maximum allowable probability of failure to reach the value designated for criterion #5 from Table 9.1 the equation is numerically solved for time t , and POF is determined by formula (6.15).

Entropy parameter. Maximum entropy point (criterion #6 from Table 9.1) for a single defective pipe segment is determined by formula (7.37).

Assessment of gamma-percentile residual life is performed by formula (7.25) on the basis of PDMP described in Sect. 7.5.

Optimum time for repairing a defect is calculated by formula (7.35) based on PDMP (see Sect. 7.5).

Table 9.2 Maximum allowed failure probability values for oil and gas pipelines depending on their safety class

Safety class	Ultimate permissible POF, km/year
Low	10^{-4}
Normal	10^{-5}
High	10^{-6}
Very high	10^{-7}

9.2 Different Approaches to Assessing the Rate of Defect Parameter Growth

Corrosion rates (CRs) for defect parameters are playing a crucial role in creating an optimal integrity management plan for production pipelines (well piping, inter-field pipes, cross-country flow lines, and facility piping) with a thinning web and/or growing defects. CRs are indispensable when assessing the remaining strength, POF and reliability of a production piping/pipeline with defect(s), and permit assessing the time to reach an ultimate permissible POF, a limit state, or time to actual failure of the leak/rupture type. The CRs are also needed when creating a risk-based pipeline inspection (RBI) plan, which is at the core of a sound IMP. This paragraph briefly describes the state of the art and current problems in consistent assessing CR parameters using different mathematical models of corrosion growth currently introduced to pipeline industry. The possible sources and the needed quality of direct assessment (DA) and ILI to construct comprehensive CR models are listed and formulated.

Any type of analysis of the future state of a pipeline, like residual strength, POF, etc., is based on the predicted sizes of the defects, which were detected during ILI or DA. If the rate of the depth and length of a corrosion defect change are close to linear in time, then the defect parameters at time t can be assessed using the following formula:

$$\begin{aligned} d(t) &= d_0 + a_d \cdot t, \\ l(t) &= l_0 + a_l \cdot t, \end{aligned} \quad (9.4)$$

where d_0 , l_0 are the depth and the length of the defect at the time of performing the ILI; a_d , a_l are, correspondingly, the corrosion rates in the radial and the longitudinal directions.

Deterministic case. Traditionally, it is presumed that the corrosion rate (CR) are constant values.

For the case when results of two sequential ILI are available, the CRs are defined as the difference between the corresponding parameters of the defects, as given by the first and second ILI, divided by the time between these ILIs:

$$CR = \frac{p_L - p_P}{t_L - t_P}, \quad (9.5)$$

where p_P , p_L are, correspondingly, the parameters of the defect as measured during the last and the previous ILIs; t_P , t_L are the times of conducting, correspondingly, the previous and the last ILI.

To compensate for measurement errors of the defects parameters in the process of assessment of their growth rate, the measured defect parameter tolerance is used, which is obtained from the specifications of the employed ILI tool:

$$CR = \frac{(p_L + tol_L) - (p_P + tol_P)}{t_L - t_P},$$

where tol_L , tol_P are the employed MI tolerance for the defect parameter during the last and the previous ILIs correspondingly. For example, the MFL tool tolerance, with regard to corrosion defect depth measurement, is $\pm 10\%$ of pipe wall thickness.

If results of only one ILI are available, then the CR is defined according to the formula

$$CR = \frac{p}{\tau_d} \quad \text{or} \quad CR = \frac{p + tol}{\tau_d},$$

where p is the measured defect parameter; τ_d is the time of the pipeline operation before the ILI; tol is the tolerance for the defect parameter in accordance with the employed MI.

Stochastic case. In real-life CRs are RVs. We consider several approaches to defect parameters growth rate as a random value.

The first approach is the method of projecting future defect parameter sizes, taking into account the conventionally maximum rate of their development [3]. This assessment implies that the total number n of defects, detected as a result of ILI, is distributed in accordance with the two-parameter Weibull law (with parameters α and β).

The maximal defect depth, which is possessed or exceeded by the $(1 - \gamma)$ -th portion of the total number of defects found during the ILI, is defined according to following formula (expression for the Weibull PDF quantile)

$$p_{\max \gamma} = \alpha (-\ln(1 - \gamma))^{\frac{1}{\beta}}. \quad (9.6)$$

The Weibull PDF parameters can be assessed by numerical solution of the following system of equations:

$$\begin{cases} \alpha = \left(\frac{\sum_{i=1}^n p_i^\beta}{n} \right)^{\frac{1}{\beta}}, \\ \frac{1}{\beta} + \frac{1}{n} \sum_{i=1}^n \ln p_i - \frac{\sum_{i=1}^n p_i^\beta \ln p_i}{\sum_{i=1}^n p_i^\beta} = 0, \end{cases}$$

where p_i is the parameter of i -th defect; n is the total number of defects.

In the case when the distribution of the defect set is normal or approximately normal, the depth of the defect, with probability γ , is assessed using the formula for the normal distribution quantile

$$p_{\max \gamma} = \Phi(\gamma) \sigma_d + \bar{p}, \quad (9.7)$$

where $\Phi(\gamma)$ is the inverse of the standard normal CDF; $\bar{p}$ is the sample average of the defects depth; σ_p^2 is the sample standard deviation of the defects depth.

If results of two sequential ILs are available, then the maximal CR, with a probability of γ , is defined by formula:

$$a_{\max \gamma} = \frac{p_{\max \gamma L} - p_{\max \gamma P}}{t_L - t_P},$$

where $p_{\max \gamma P}$, $p_{\max \gamma L}$ are the maximal depths of the defects, as defined by formula (9.6) or (9.7) for the previous (P) and the last (L) ILI correspondingly.

If results of only one ILI are available, then the maximal CR, with probability γ , is defined by formula:

$$a_{\max \gamma} = \frac{p_{\max \gamma}}{\tau_d}, \quad (9.8)$$

where τ_d is the net time of pipeline operation before the time of conducting the ILI.

Second approach. It is used for assessment of corrosion rate for each defect separately. Since the measurements of the defects parameters have errors, which makes them random values, the corrosion rate will also be a random value, with parameters

$$M[CR] = M\left[\frac{p_L - p_P}{t_L - t_P}\right] = \frac{M[p_L] - M[p_P]}{t_L - t_P}, \quad (9.9)$$

$$D[CR] = D\left[\frac{p_L - p_P}{t_L - t_P}\right] = \frac{D[p_L - p_P]}{(t_L - t_P)^2}, \quad (9.10)$$

where M is the mathematical expectation; D is the variance; p_P , p_L are the defect parameters, determined during the last and the previous ILIs correspondingly; t_P , t_L is the time of the ILI runs correspondingly.

If both ILIs were performed with one and the same tool, the mathematical expectation (9.9) can be written as

$$M[CR] = \frac{M[p_{tr}(t_L) + \varepsilon(t_L) - p_{tr}(t_P) - \varepsilon(t_P)]}{t_L - t_P} \quad (9.11)$$

$$= M[CR_{tr}] + \frac{M[\varepsilon_L] - M[\varepsilon_P]}{t_L - t_P}, \quad (9.12)$$

where $p_{tr}(t_L)$, $p_{tr}(t_P)$ are the assessments of true defect parameter sizes during the previous and the last ILI correspondingly; $\varepsilon(t_L)$, $\varepsilon(t_P)$ are the random MEs during the previous and the last ILI correspondingly; $M[CR_{tr}]$ is the mathematical expectation of the true corrosion rate.

Formula (9.11) demonstrates that assessment of mathematical expectation of corrosion rate is unbiased only in the case when the average ME during both ILIs is equal to zero or had identical values.

In the general case the corrosion rate variance (9.10) is calculated by formula

$$\begin{aligned} D[CR] = D[CR_{tr}] &+ \frac{D[\varepsilon(t_P)]}{(t_L - t_P)^2} + \frac{D[\varepsilon(t_L)]}{(t_L - t_P)^2} + 2cov\left[CR_{tr}, \frac{\varepsilon(t_L)}{(t_L - t_P)}\right] \\ &- 2cov\left[CR_{tr}, \frac{\varepsilon(t_P)}{(t_L - t_P)}\right] - 2cov\left[\frac{\varepsilon(t_L)}{(t_L - t_P)}, \frac{\varepsilon(t_P)}{(t_L - t_P)}\right]. \end{aligned} \quad (9.13)$$

If MEs are independent of each other or of the true defect parameters values, and if one and the same MI was used, then the ME variance in both cases is the same, and the expression (9.13) assumes the form

$$D[CR] = D[CR_{tr}] + \frac{2D[\varepsilon(t_p)]}{(t_L - t_p)^2}$$

where

$$D[CR_{tr}] = D[CR] - \frac{2D[\varepsilon(t_p)]}{(t_L - t_p)^2}.$$

The two latter expressions demonstrate that the MEs increase the true corrosion rate variance.

In real-life cases the defect sizes in (9.9) and (9.10) are considered to be RVs with mathematical expectation equal to their true value assessment, their variances are determined using the methodology described in Sect. 4.5, or in accordance with the ILI tool readings and the ILI tool ME variance, calculated on the basis of the specified ILI tool tolerance. For instance, in the process of measuring the “metal loss” type of defect with a HRMFL tool, the defect depth tolerance is $\pm 10\%$ of the pipe wall thickness wt at 80 %-th confidence level. Hence, taking into account that the MEs are normally distributed, the ILI tool ME standard deviation for the defect measurement equals

$$SD = \frac{0.1 \, wt}{1.28}.$$

If the measurements are independent of each other and one and the same ILI tool is used, formula (9.10) assumes the form

$$D[CR] = \frac{2SD^2}{(t_L - t_p)^2}.$$

In case results of only one ILI are available, formulas (9.9) and (9.10) shall be rewritten as

$$M[CR] = \frac{M[p]}{\tau_d},$$

$$D[CR] = \frac{D[p]}{\tau_d^2}.$$

The probability density function and the integral function of the defect parameter growth rate may be determined using the convolution formula for two RVs. In other words, PDF $f_{CR}(x)$ and CDF $F_{CR}(x)$ are determined by formulas

$$\begin{aligned}
 f_{CR}(x) &= \frac{1}{t_L - t_P} \int_{-\infty}^{\infty} f_{p_L}(x+y) f_{p_P}(y) dy, \\
 F_{CR}(x) &= \frac{1}{t_L - t_P} \int_{-\infty}^x dz \int_{-\infty}^{\infty} f_{p_L}(z+y) f_{p_P}(y) dy,
 \end{aligned} \tag{9.14}$$

where $f_{p_L}(x)$ is PDF of RV p_L , $f_{p_P}(x)$ is PDF of RV p_P .

According to [15] the formula (9.14) can be rewritten as

$$F_{CR}(x) = \frac{1}{t_L - t_P} \int_{-\infty}^{\infty} F_{p_L}(x+y) dF_{p_P}(y) = \frac{1}{t_L - t_P} \int_{-\infty}^{\infty} F_{p_L}(x+y) f_{p_P}(y) dy,$$

where $F_{p_L}(x)$ is CDF of RV p_L , $F_{p_P}(x)$ is CDF of RV p_P .

9.3 Assessment of Corrosion Rates for Developing RBIs and IMPs for Production Pipelines

Since corrosion or, in general, deterioration of pipelines is a stochastic time dependent process, the best way to assess pipeline state is to monitor the growth of its defects and/or thinning of its web. Currently, the pipeline industry is using such methods as electric resistivity probes (ERP), corrosion samples (CS), and weight loss coupons (WLC) to define the CR for pipelines which transport extremely corrosive substances, or are located in a corrosive environment. Additionally, inhibitors are used to bring the CR to an acceptable level. In this setting the most reliable methods which permit assessment of CRs with needed accuracy and consistency, are probabilistic methods.

This section describes a practical method of predicting the probabilistic growth of the defect parameters using the readings of separated in time different DA or ILI measurements, using the two-level control policy [1]. The procedure of constructing the PDFs of the defect parameters as functions of time, linear/nonlinear CR growth, and the initial size of the defects is presented. Their use when creating an RBI plan and IMP based on time-dependent reliability of pipelines with defects is demonstrated in two illustrative cases—a production pipeline carrying crude oil, and a pipeline subject to internal CO_2 corrosion.

Internal pipeline corrosion (CO_2 , H_2S corrosion, etc.) can lead to an enormous loss of oilfield production. The Alaska's pipeline failure accident (due to internal corrosion) caused a 200,000 gallon, 1.9 acre oil spill. This led to a shutdown of oil field productions and an 8% decrease of U.S. domestic crude oil production [16].

Time-dependent failure mechanisms as related to production pipelines include corrosion, wear, high/low cycle fatigue, and SCC. The common sense defense against these types of failures is basically an inspection system, which is a statistically

described process since no inspection technique is perfect and no inspection is entirely accurate. In the case of pipeline inspections there are numerous difficulties which spring from the limited capability of the inspection methods and the human factor when performing such inspections.

Production pipelines can experience multiple internal degradation threats, among them [17]: CO_2 corrosion (sweet corrosion); microbiologically influenced corrosion (MIC); under-deposit corrosion (UDC); galvanic corrosion; preferential weld corrosion; hydrogen sulfide (H_2S) corrosion (sour corrosion); oxygen (O_2) corrosion; flow-assisted corrosion; solid erosion and erosion corrosion; acid corrosion; SCC, the latter minor in occurrence. In the three-phase oil system CO_2 corrosion is most prevalent with the possibility of flow-assisted CO_2 . In some injection systems for produced water it would be UDC, and for sea water it would be UDC and MIC. These are very difficult damage types to detect/manage, because they cause small diameter pittings. The small pipe diameter of production pipelines is hard to diagnose due to the physical limits of the currently used iridium radiography, and can be very resource intensive for ultrasonic inspections, which require removing of the insulation. The external piping corrosion threats would be: corrosion under insulation; below grade cased piping; submerged/buried piping; sea spray exposure. Corrosion rates (CRs) are key element in constructing predictive maintenance technology for pipelines and creating optimal IMP for pipelines with growing defects.

CRs are indispensable when assessing the remaining strength, POF of a pipeline with defects, and permit assessing the time to reaching an ultimate permissible POF, a limit state, or time to actual failure of the leak/rupture type.

In this section two types of corrosion of production pipelines are considered: (1) small diameter pittings occurring at any azimuth, and (2) internal types of corrosion (erosion corrosion, flow-assisted CO_2 corrosion, etc.), which lead to uniform thinning of the pipe web. The predicted failure pressure (P_{fi}) should not exceed the maximum operating pressure ($MAOP_i$), expected at each i -th defect's location.

The operational acceptability of each i th defect is determined (following the Pipeline Operators' Forum recommendations) by its ERF .

Consistent and accurate assessments of CRs for the pipe wall and defect parameters are the key elements which play a crucial role in creating an optimal risk-based inspection (RBI) plan and a consistent integrity management plan (IMP) for the production pipelines.

A new stochastic model of corrosion-type defect growth/(wall thinning) due to internal or external aggressive environment is presented. The new methodology of constructing the PDFs of the defect parameters as functions of time, linear/nonlinear CR growth, and their initial size is described. This methodology can be used when assessing pipeline residual strength, residual life, and POF.

There are significant complications in gathering the needed data for assessing the CRs:

- Initial thicknesses of the mill pipes are often poorly known;
- Ultrasonic thickness measurements can have significant systematic and random errors;

- Other nondestructive diagnostic methods currently used when inspecting production pipelines are mostly qualitative;
- The data collected has to be statistically sufficient and cleansed of electronic noise and faulty data (i.e., when the pipes were reported as getting thicker between measurements);

Given these issues the collected data can eventually be used to construct a consistent and lean IMP plan based on the concept of predictive maintenance for production pipelines using the proposed two-level control policy method.

9.3.1 *CO₂ Type Corrosion Control Strategies*

Carbon steel (CS) is the predominant construction material for the production pipelines, but their corrosion resistance is rather poor. Hence, controlling *CO₂* corrosion during oil production is essential for the use of carbon steel. One of the most common oilfield corrosion control strategies (CCS) can be described by the verbal formula [18]

$$CCS = CS + CA + CI + CM. \quad (9.15)$$

The *corrosion allowance* (CA) is an additional wall thickness, which is deliberately added during design of the pipeline to the wall thickness required for operational pressure to achieve the designed service life [19]. The CA can be determined knowing the desired pipeline service life time and predicted corrosion rate, which requires reliable corrosion prediction model which accounts for and integrates past field experience. The correctly chosen CA value permits assuring pipeline integrity and saving unnecessary costs [20].

If the predicted CR is high enough (usually, 8 mpy and higher) to require corrosion allowance over the predetermined limit (usually, 8 mm), a *corrosion inhibitor* should be considered to reduce the CR. According to NACE, a corrosion inhibitor is a substance which retards corrosion when added to an environment in small concentrations (*ppm*). Injection of a corrosion inhibitor is the most widely used internal pipeline corrosion control method, as it is economical, highly effective, and easily implemented. Injection can be administered continuously or in batches, depending on field location, conditions, and solubility of the inhibitor. *Corrosion monitoring* (CM) is the last component in internal pipeline CCS—corrosion control strategy (management). The field fluids and operating conditions may vary with time during the production life. Hence, operators and corrosion engineers need to know the effectiveness of applied corrosion control methods. CM describes how corrosive the fluids are, and at what rate steel has been corroded. The essential data collection includes flow rate, pressure, temperature, fluid analysis (pH, acid gas compositions, ferrous ion count, etc.) [21].

Some techniques are available for *direct corrosion rate measurements*, such as WLC, CS, electrical resistance (ER) probes, and linear polarization resistance (LPR) probes. Each of the above corrosion monitoring techniques has some limitations, which come down to poor accuracy. Thus a special effort should be taken to filter out all the electronic noise from the raw data, keeping in mind that ERP and the like data reflect the stochastic influence of the environment over time only at each specific location in the pipe. For more on this see [22].

To compensate for poor accuracy, several different monitoring techniques are used simultaneously in oilfields. The corrosion monitoring data accrued in this fashion does not only give an early warning of corrosion problems, but also helps to provide information for creating risk-based inspection plans and IMP for the future, and identifying possible causes of corrosion failure.

The basic failure problem associated with *pipe thinning* is shown in Figs. 9.5, 9.6, 9.7 and 9.8. Here it is assumed that a mill pipe with an initial thickness t_0 , which is a RV, is subject to a random constant thinning rate v_{th} . The pipeline will not actually fail due to rupture until the piping thickness is t_f . This value can be obtained using the design code which was used when the pipeline was designed, taking the safety factor $SF = 1$. In accordance with the two-level policy of reliability control [1, 23] we introduce the warning level t_w and the alarm level t_a of pipeline thickness/defect depth (see Figs. 9.5, 9.6, 9.7 and 9.8). In general, these levels are initially unknown. They can be found using the optimization procedure where the pipeline operation cost is a function of these levels. To produce valid results using this approach we need to gather actual data on CRs from different types of corrosion coupons and samples, coupled with verification using UT measuring instruments, and corresponding regression analysis. This topic is beyond the scope of this book. Below the warning and the alarm levels are determined using some common sense principles. **The initial thickness t_0 .** When ordered according to the standards, mill pipes are delivered with a range of thicknesses falling within a tolerance range typically $\pm(2-5)\%$. Conducted special measurements show that the actual pipe thickness tends to be at the high end of the permitted tolerance range. **The warning level thickness t_w ,** at which point the maintenance crew will be alerted to perform some specified action (i.e., create a schedule for the next inspection, etc.), is calculated using the following equation:

$$t_w = t_f + v_{th}kb_j, \quad (9.16)$$

where t_f is failure (burst type) thickness as defined by pipeline design codes with safety factor $=1.0$ mm; v_{th} is thinning rate, mm/year; b is the assumed interval between inspections, years, and k is the number of inspection intervals to be allowed for warning (usually, no less than two). Because v_{th} is a RV, t_w is also a RV.

Alarm-level thickness is the thickness that is a signal triggering immediate repair. Thus, for the leak type of failure, the alarm-level thickness would be $t_a = 0.8t$ (t —design value of pipeline thickness).

Failure-level thickness is the thickness of the pipe at rupture as determined by the corresponding design code (with $SF = 1$).

The repair/replacement thickness. API 581 uses a rough probabilistic approach based on keeping the POF below certain levels. Appendix O of RP [24] assumes that the likelihood of failure is 1 when $kbv_{th}/t_0 = 1$, i.e., when the leak occurs. The objective is thus to keep the ratio kbv_{th}/t_0 low. For expensive failures, API 581 [24] suggests that $[kbv_{th}/t_0]$ be kept below 0.35. In other words, 65 % of the pipe life will be lost. With yearly highly accurate inspections the kbv_{th}/t_0 can be raised close to unity losing only a small percentage of life. The amount of pipe life lost will also depend on how v_{th} is estimated. In this book a conservative 5 % (95 %) confidence interval is used.

9.3.2 Economics of ILI and DA for Production Pipelines

A comprehensive risk-based approach to pipeline inspection includes economics of inspection. The introduction of economics into the assessment and decision-making process is performed using risk analysis to balance the very large cost of pipeline leaks and ruptures, the smaller but still significant cost of ILI and DA and patch repairs, and the cost of complete replacement of a mill pipe, a pipe segment, or the full pipeline. Currently, most of the published approaches [24–28] assume that the risk of various failures has to be kept below certain arbitrary levels. The ratio (cost of inspection)/(cost of production pipeline failure) can vary anywhere from 1/10 to 1/10,000 and more. If there is a large population of similar pipes in a production pipeline system which requires a significant cost to inspect, this will definitely affect maintenance decision.

9.3.3 State of the Art in RBI and Corrosion Rate Assessment for Production Pipelines

Risk-based approaches are increasingly used in the art of decision-making in engineering. Risk is defined as being conditional probability of failure times consequences of failure $R = CPOF \cdot CF$, and is eventually measured in \$\$\$/year.

Simplified risk-based inspection guidelines have been created by ASME [25] and API [24]. The EU has created the RIMAP program (Risk-Based Inspection and Maintenance Procedures) which defines in detail the technical content of risk-based approaches [27]. It also shows how to integrate risk-based approach with the day-to-day operation of assets [26]. According to [24], RBI is an integrated risk management tool, which provides a methodology for determining the optimum combination of inspection methods and frequencies. API 581 [24] has introduced a systematic and simple approach for likelihood and failure consequence analysis.

For likelihood analysis, API 581 [24] has in the following way categorized all the factors, which influence failure frequencies:

$$F_{adj} = F_{gen} \cdot F_E \cdot F_M, \quad (9.17)$$

where F_{adj} is the adjusted frequency; F_{gen} is the generic failure frequency from a compilation of available production pipeline failure frequencies; F_M is the management systems evaluation factor (a measure of the company's management effectiveness); F_E is the asset modification factor, the product of the following four subfactors:

- Technical module subfactor ("TMSF"), which depends on the modes of deterioration experienced by the pipeline and the effectiveness of inspections;
- Universal SF (covers conditions that affect all the assets, e.g., seismic activity);
- Mechanical SF (accounts for characteristics of construction such as complexity and construction design code);
- Process SF (includes factors influenced by the pumping process and its stability).

For consequence analysis, API 581 [24] has introduced four major factors: flammable, toxic, environmental damage, and business interruption. In the pipeline industry, in most cases, environmental damage and business interruption are by far the two dominant effects.

The pipeline industry has not as yet embraced the RBI approach in every day operation of pipelines.

9.3.4 CR Assessments for Production Pipelines

The quality of statistical CR assessment depends on large numbers of environmental and operational factors. First, data alignment should be performed with accurate accounting for the segmentation strategy (pipeline segments or zones of similar statistical characteristics), coating effectiveness (field/plant applied coatings), CP effectiveness within a specific distance from the pipeline (rectifiers or anode beds), ROW topography (water accumulation at low points), etc.

The best approach to assessing corrosion rates for defect growth and pipe web thinning is by measuring the defects' depth/length and web thickness over a period of years. Even given this there are a number of technical and statistical problems in collecting, analyzing, and extrapolating this data. The methods for assessing the CRs of well piping, cross-country flow lines, and facility piping differ.

Cross-country flow lines are the largest diameter pipelines among the production pipelines. Their diameters permit using ILI for their diagnostics, and verification of its results. Depending on the number of conducted ILI, one or two ILI data sets can be used for assessing the CRs. The methodology of CR assessments for these types of pipelines was described in detail in [29].

The well piping and facility piping have much smaller diameters, and have no pig launchers and receivers. These obstacles currently do not allow their ILI. For

these pipelines which transport extremely corrosive substances, or are located in a corrosive environment, some DA methods are used to define the CR for pipelines, among them UT measurement instruments, ERP, CS, and WLC.

Systematic error and random error in measurement. Commercially available ultrasonic thickness measurement equipment has a resolution of 0.01 mm. Nevertheless, the measurement error (ME) of the UT tool can have a systematic error = 0.5 mm [50 (!) times its resolution], the SD = 0.4 mm (40 times its resolution), and the 95 % confidence that the ME is less than 1.2 mm (120 times its resolution!).

Thickness of a pipeline subject to erosion /corrosion cannot increase over time. Hence, every data which indicates that some of the corroded pipes became thicker with time, (obviously, due to some systematic or human error) is false and should be erased from the collected data.

The data related to field pipelines, censored in the above way, should be processed using the EIV regression analysis, treating the gathered data separately for each type of pipeline system and generic environment. Analysis of available literature shows that the average thinning rate for production lines can be in the range from 0.05 mm/year (2 mpy, when using inhibitors) to 0.50 mm/year (20 mpy) and, in extreme cases, up to 250 mpy. For more on this, see [19].

9.3.5 Posing the Production Pipeline CR Assessment Problem

It is clear from the above that consistent and accurate assessment of CR as a RV is the key element in a sound IMP. In this context below a comprehensive method is described of assessing the PDFs of CRs, using the data from continuous monitoring of pipe thinning or defect growth.

Consider the size of a corrosion defect (for clarity reasons its depth $a(t)$ is considered further down) to grow in time. This process is described by a differential equation, as proposed in [1]:

$$\frac{da(T)}{dT} = Ka^n(T) \quad (9.18)$$

$a(T)$ is a certain function of the independent variable T , which, at time $T = T_0$ takes the given initial value $a(t_0) = a_0$, K, n are some empirical coefficients derived from observations and/or experiments. It is required, using the results of a single or a sequence of ILI, DA, or data from ERP, CS, WLC, and knowing the time elapsed since the commissioning of the pipeline, to define the consistent statistical values of the CRs of the pipeline defects. The problem comes down to defining the PDF of the corrosion depth, $a(t)$ which is a function of the RV a_0 at any arbitrary moment of time $T \in [T_0, T_*)$, T_* is the depth of prediction in time.

9.3.6 The Stochastic Solution of Assessing the CR for Production Pipelines

Assume that $a(t)$ is a bijection function, then the PDF $f[a(t)]$ for $a(t)$ is of the form [29]:

$$f[a(t)] = f\{a_0[a(t)]\} \left| \frac{da_0}{da(t)} \right|.$$

In the case when $a(t)$ is not bijection, it is necessary to divide the range of a_0 into intervals, in which the $a(t)$ will be bijection. Variants of constructing $f[a(t)]$ for different initial data are given in Table 9.3.

Case #1 (see Table 9.3). For any arbitrary moment of time $t \in [t_0, T)$ the transformation of a_0 into $a(t)$ is described by a linear operator:

$$a(t) = a_0 \exp[K(t - t_0)]. \quad (9.19)$$

After expressing a_0 from (9.19), inserting the result into $f(a_0)$ and multiplying the right-hand part of this PDF by the derivative with respect to $a(t)$:

$$\left| \frac{da_0}{da(t)} \right| = \frac{1}{\exp[K(t - t_0)]}.$$

Table 9.3 Initial data for designing PDFs for different types of CRs and $a(t)$

Type of function $a(t)$	Case	PDF of the initial defect depth $a(t_0) = a_0$ (RV)	Parameters of Eq. (9.18)	
			K	n
Linear	1	Exponential $f(a_0) = \lambda \exp(-\lambda a_0)$, $a_0 \in [0, a_{0max}]$, λ is known	Const	1
	2	Lognormal $f(a_0) = \frac{1}{a_0 \sqrt{2\pi d^2}} \exp\left[-\frac{(\ln a_0 - b)^2}{2d^2}\right]$, b and d^2 —(the average) and d^2 (the variance) are known	Const	1
	3	Arbitrary	Const	1
Nonlinear	4	Arbitrary	Const	$n < 0$
	5	Arbitrary	Const	$0 < n < 1$ $n > 1$
	6	Arbitrary	Const	Const
	7	Arbitrary	RV	RV

(Where the left-hand part is the absolute value of the transformation Jacobian), one obtains the PDF of $a(t)$:

$$f[a(t)] = \frac{\lambda}{\exp[K(t-t_0)]} \cdot \exp\left\{-\frac{\lambda a(t)}{\exp[K(t-t_0)]}\right\}.$$

Case #2 (see Table 9.3). Knowing for an arbitrary a_0 the dependencies between m , σ^2 and parameters b , d^2 , define the mean m_t and the variance σ_t^2 of the function $a(t)$ from the following system of equations:

$$\begin{aligned} \exp[K(t-t_0)] \cdot m &= \exp\left(b_t + \frac{d_t^2}{2}\right); \\ \exp[2K(t-t_0)] \cdot \sigma^2 &= [\exp(d_t^2) - 1] \exp(2b_t + d_t^2). \end{aligned}$$

The final result will be

$$\begin{aligned} f[a(t)] &= \frac{1}{a(t) \cdot \sqrt{2\pi \ln\left(\frac{\sigma^2}{m^2} + 1\right)}} \\ &\times \exp\left(-\frac{\left\{\ln \frac{a(t)}{\exp[K(t-t_0)]} - \left[K(t-t_0) + \ln m - \frac{1}{2} \ln\left(\frac{\sigma^2}{m^2} + 1\right) + 1\right]\right\}^2}{2 \ln\left(\frac{\sigma^2}{m^2} + 1\right)}\right). \end{aligned}$$

Case #3 (see Table 9.3). The solution of this case can be conducted in the following steps: (1) Count the number M of known parameters in the function $f(a_0)$; (2) Take M central moments of the PDF for $f(a_0)$; (3) Multiply each central moment by the linear multiplier in the corresponding power; (4) Solve the system of equations as related to the M unknown parameters; (5) Insert the obtained M parameters and $a_0 = \phi[a(t)]$ into the expression for $f(a_0)$, then multiply the right-hand side by the derivative $\left|\frac{da_0}{da(t)}\right|$ and for any arbitrary moment of $t \in [t_0, T]$ define the PDF $f[a(t)]$. Following this algorithm it is possible to construct the PDF $f[a(t)]$ also for cases 4, 5, 6.

Case #7. Parameters a_0 , k , n in Eq. (9.18) are RVs with known PDFs $f_a(a_0)$, $f_k(k)$, $f_n(n)$ on the sets of values of $a_0 \in A$, $m \in M$, $n \in N$. The general solution of Eq. (9.18), solved in relation to any of the parameters a_0 , k , n (i.e., as related to k), will take the form:

$$f[a(t)] = \int_N \int_A f_k \left[\frac{a(t)^{-n+1} - a_0^{-n+1}}{t} \right] f_a(a_0) f_n(n) \left| \frac{(-n+1)a(t)^{-n}}{t} \right| da_0 dn. \quad (9.20)$$

Integration is performed in the following limits: $N \in [0, \infty)$, $A \in [0, \infty)$.

Example. For the exponential PDF of a_0 : $f(a_0) = \lambda \exp(-\lambda a_0)$, $\lambda = 1$. If $t_0 = 0$, $K = 1$, $n = 1$, then solution (9.18) is defined as $a(t) = \exp t$. Taking $a_{0\min} = 0$, $a_{0\max} = 5$ (mm) and $t = 1$ (year) one obtains $a(t=1)_{\min} = a_{0\min} \exp 1 = 0$; $a(t=1)_{\max} = a_{0\max} \exp 1 \approx 13.6$ and so on, for each moment of time $t_2, t_3, \dots$

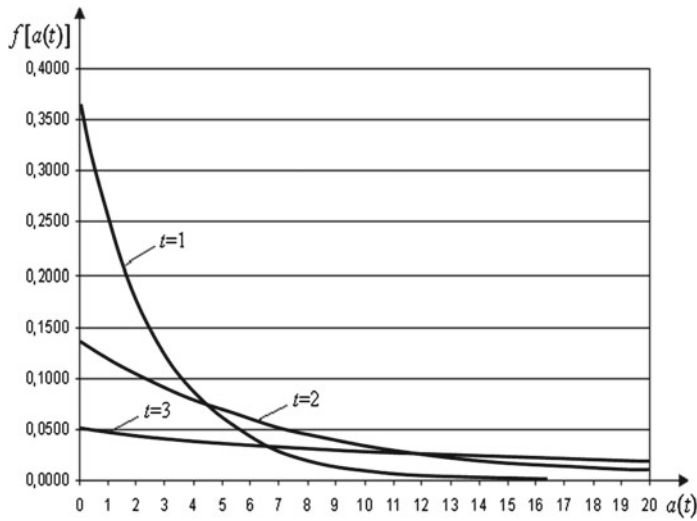


Fig. 9.3 The change in time of the exponential pdf for defect depth growth

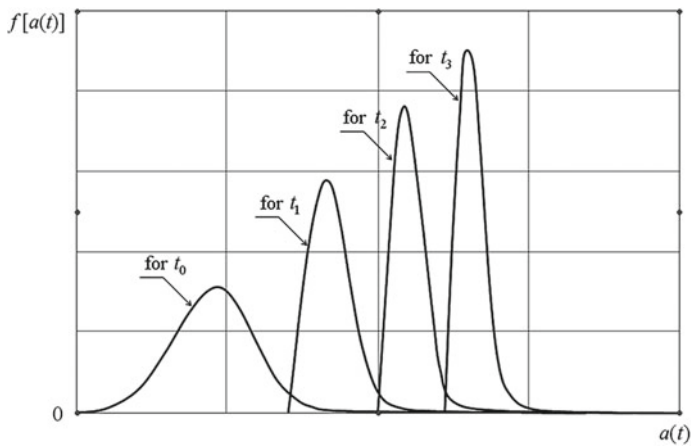


Fig. 9.4 The change in time of the Weibull pdf for defect depth growth

The constructed PDFs are shown in graphical form in Fig.9.3. The corresponding solution for the case of Weibull PDF is given in Fig.9.4.

9.3.7 Two Illustrative Case Studies of Production Pipelines

In order to illustrate implementation of the above approach to constructing a sound RBI, assessing the remaining life of production pipelines, and producing a consistent IMP, two illustrative cases are presented below.

The first case deals with pipelines subjected to uniform corrosion which affects the pipe wall causing its *thinning*. The initial data needed for calculations is given in Tables 9.4 and 9.5.

The warning level of pipe web thickness was introduced as $wt(t) = w$, $w = (wt - a)/2$ is the half of the difference between the thickness as given by the B31Gmod code, with $SF = 0.72$, and the design thickness (which includes the CA component). The alarm level was taken as $w(t) = a$, where a is the design thickness of the pipe web, according to B31Gmod, and the failure level was $wt(t) = f$ (f is the pipe wall thickness at rupture type failure, with $SF = 1$). For each combination of RVs (wt , v_{rc}) the time to reach the corresponding levels of web thickness was calculated, using the Monte Carlo simulation method. Each set of data (ten thousand arrival times) was analyzed; histograms were plotted, and the arrival times' quantiles of the orders 0.05; 0.5; and 0.95 were found.

The time span between the quantile of the 0.05 order and the quantile of the 0.5 order, and the time span between the latter and the quantile of 0.95 order were also assessed. Statistical characteristics of the arrival time (AT) for the three levels of pipe web thickness when the CR is distributed according to the Weibull PDF with mean = 0.05 mm (2 mpy—a permissible CR with inhibitors used) and different coefficients of variations (COV) is given in Table 9.6 and Figs. 9.5, 9.6, 9.7 and 9.8.

Table 9.4 Initial data for DVs

Parameter	Value
Diameter D , mm	200
SMYS, MPa	358
Operating pressure P_{op} , MPa	5.0
Class location	1
Number N of modeling each RV	10,000
Quantile orders, p	0.05, 0.5, 0.95

Table 9.5 Initial data for RVs

Parameter	Mean	COV	PDF
Design pipe web thickness wt , mm	$a * +3$ mm	—	—
Initial pipe web thickness wt_0 , mm	100 % wt	0.02	Lognormal
Corrosion rate v_{rc} , mm/year	0.05, 0.125, 0.25	0.1, 0.2, 0.3, 0.5	Weibull, Lognormal

* Design pipe wall thickness determined according to the B31Gmod code; 3 mm = corrosion allowance (CA)

Table 9.6 Statistical characteristics of the arrival time for the three levels of pipe web thickness (CR PDF Weibull with mean = 0.05 mm/year, COV = Var)

Level	M	S	q_1	q_2	q_3	$q_2 - q_1$	$q_3 - q_2$
Variation coefficient (COV) = 0.1							
Warning	30.3	4.1	25.0	29.7	37.7	12.7	8.0
Alarm	60.6	7.4	51.7	59.2	73.8	22.1	14.6
Failure	72.8	8.8	62.3	71.1	88.5	26.2	17.5
Variation coefficient (COV) = 0.2							
Warning	31.5	8.4	22.2	29.7	47.6	25.4	17.9
Alarm	63.1	16.4	45.3	59.3	94.0	48.7	34.7
Failure	75.8	19.7	54.5	71.2	112.7	58.2	41.5
Variation coefficient (COV) = 0.3							
Warning	34.1	18.3	19.7	29.9	60.8	41.2	31.0
Alarm	68.2	36.0	39.9	59.9	121.7	81.9	61.9
Failure	81.9	43.1	48.0	71.8	146.3	98.3	74.4
Variation coefficient (COV) = 0.5							
Warning	44.6	58.7	15.6	31.7	108.4	92.8	76.7
Alarm	89.2	116.2	31.3	63.4	216.7	185.3	153.3
Failure	107.1	139.3	37.6	76.2	261.2	223.6	185.0

Note M is the sample mean; S is the sample SD; q_1 is the quantile of order 0.05; q_2 is the quantile of order 0.5 (median); q_3 is the quantile of order 0.95

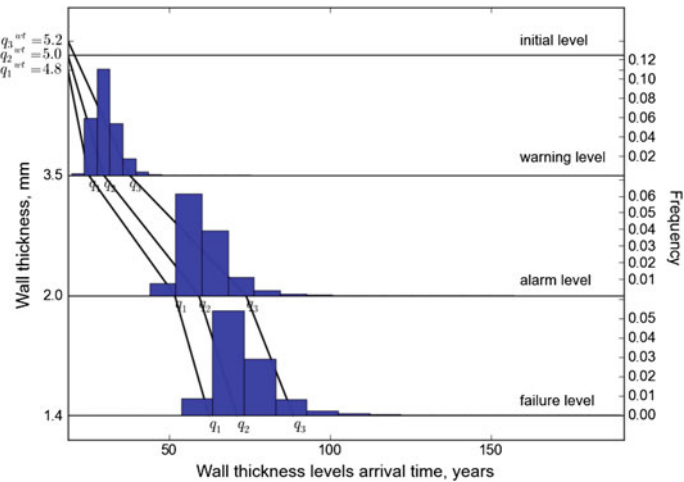


Fig. 9.5 Histograms of ATs (CR PDF Weibull with mean = 0.05 mm/year, COV = 0.1)

Statistical characteristics of the arrival times ATs for the three levels of pipe web thickness when the CR is distributed according to the Lognormal PDF with mean = 0.05 mm/year and different coefficients of variations (COV) are given in Table 9.7 and Figs. 9.9, 9.10 and 9.11. Comparison of Tables 9.6 and 9.7 leads to following

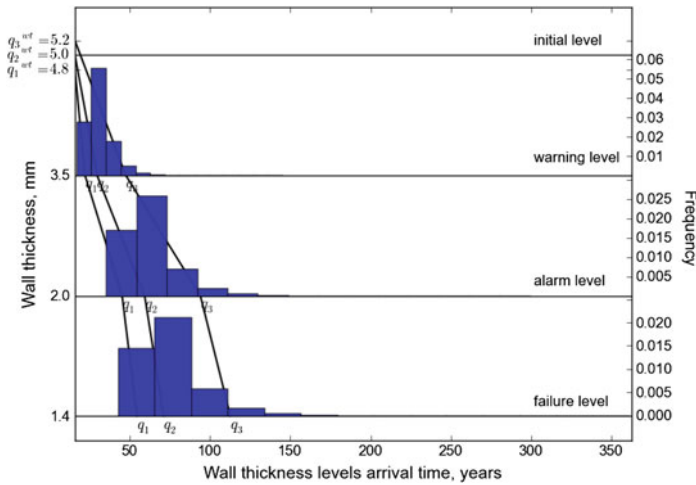


Fig. 9.6 Histograms of ATs (CR PDF Weibull with mean = 0.05 mm/year, COV = 0.2)

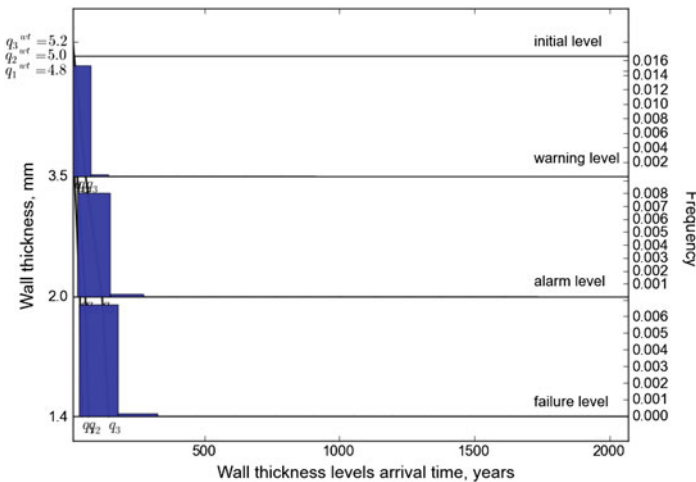


Fig. 9.7 Histograms of ATs (CR PDF Weibull with mean = 0.05 mm/year, COV = 0.3)

conclusions: When the COV is small (0.1–0.2) the difference of arrival times’ parameters as calculated for both types of PDFs is small; but with COV growing the discrepancy becomes drastically different. This shows that at big fluctuations of the RV it is essential to accurately assess to which type of PDF the CR belongs to Figs. 9.5, 9.6, 9.7, 9.8, 9.9, 9.10, and 9.11, clearly show that with time the scatter of the corresponding arrival times (ATs) increases. Hence, it is prudent not to go with the mean (or the median, although it is slightly more conservative) values of the ATs, but use the order 0.05 quantile of the AT instead.

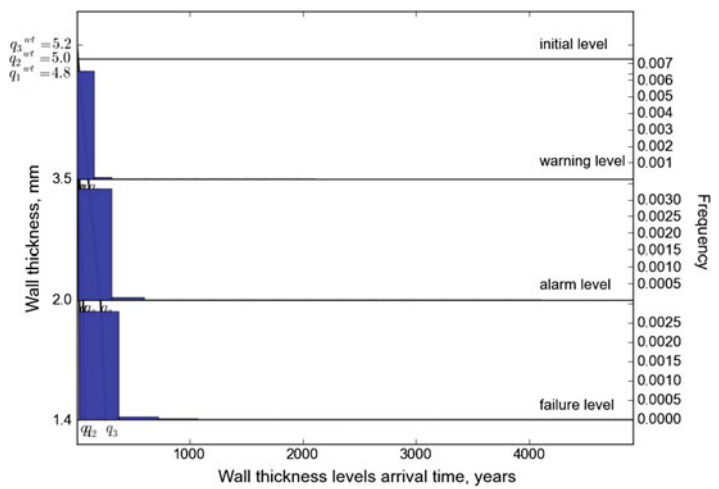


Fig. 9.8 Histograms of ATs (CR PDF Weibull with mean = 0.05 mm/year, COV = 0.5)

Table 9.7 Statistical characteristics of the arrival time for the three levels of pipe web thickness (CR PDF lognormal with mean = 0.05 mm/year, COV = Var)

Level	<i>M</i>	<i>S</i>	<i>q</i> ₁	<i>q</i> ₂	<i>q</i> ₃	<i>q</i> ₂ − <i>q</i> ₁	<i>q</i> ₃ − <i>q</i> ₂
Variation coefficient (COV) = 0.1							
Warning	30.2	3.6	24.7	30.1	36.5	11.8	6.5
Alarm	60.5	6.3	50.9	60.3	71.5	20.6	11.2
Failure	72.7	7.5	61.2	72.4	85.8	24.5	13.4
Variation coefficient (COV) = 0.2							
Warning	31.2	6.6	21.6	30.5	42.9	21.3	12.4
Alarm	62.4	12.6	44.0	61.0	85.0	41.0	24.0
Failure	74.9	15.1	53.0	73.3	102.1	49.1	28.8
Variation coefficient (COV) = 0.3							
Warning	32.7	10.0	19.2	31.3	51.3	32.1	20.1
Alarm	65.4	19.6	38.9	62.7	101.9	63.0	39.2
Failure	78.6	23.4	46.6	75.4	122.1	75.5	46.7
Variation coefficient (COV) = 0.5							
Warning	37.4	19.1	15.2	33.2	74.5	59.3	41.2
Alarm	74.9	37.9	30.6	66.7	148.3	117.7	81.6
Failure	90.0	45.5	36.8	80.1	178.0	141.2	97.8

Note *M* is the sample mean; *S* is the sample SD; *q*₁ is the quantile of order 0.05; *q*₂ is the quantile of order 0.5 (median); *q*₃ is the quantile of order 0.95

The results of calculations performed for the case when the CR has a Lognormal PDF with a mean of 0.125 mm (5 mpy) is given in Table 9.8. From this table it can be seen that the values of the ATs in this case roughly follow the median of the CRs.

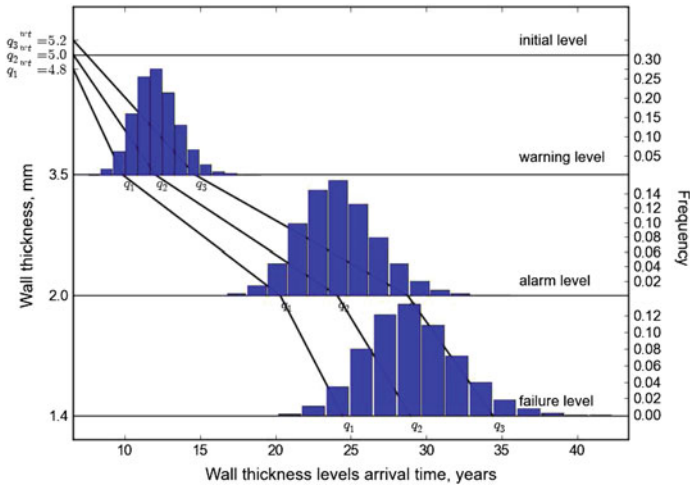


Fig. 9.9 Histograms of ATs (CR PDF lognormal with mean = 0.05 mm/year, COV = 0.1)

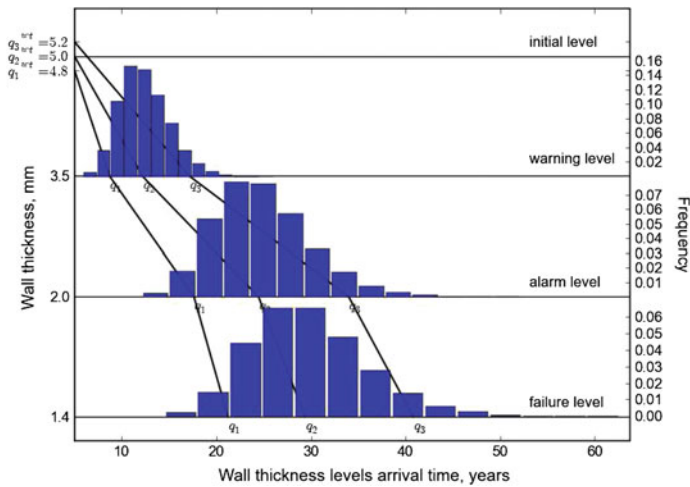


Fig. 9.10 Histograms of ATs (CR PDF lognormal with mean = 0.05 mm/year, COV = 0.2)

The time difference between the adjacent ATs indicates the time available *to create a state of awareness* for the maintenance crew about the current state of the pipeline and create a sound RBI plan and IMP, taking into account the cost components of maintenance versus failure cost [1, 30, 31].

The second case considered in this paper is related to pitting type defects' depth propagation in time due to CO_2 type corrosion. The initial data are the same as in the first case (see Tables 9.4 and 9.5), except for the CR. The web itself in this case is not thinning; the CR is related exclusively to the pitting defect depth

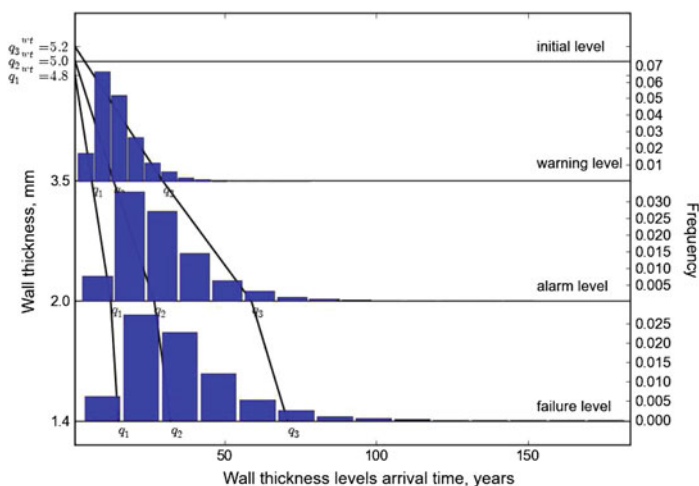


Fig. 9.11 Histogram of ATs (CR PDF lognormal with mean = 0.05 mm/year, COV = 0.5)

Table 9.8 Statistical characteristics of the arrival time for the three levels of pipe web thickness (CR PDF lognormal with mean = 0.125 mm/year, COV = Var)

Level	M	S	q_1	q_2	q_3	$q_2 - q_1$	$q_3 - q_2$
Variation coefficient (COV) = 0.1							
Warning	12.1	1.6	10.0	11.9	15.0	5.0	3.1
Alarm	24.3	2.9	20.7	23.8	29.5	8.8	5.7
Failure	29.2	3.4	25.0	28.5	35.3	10.3	6.8
Variation coefficient (COV) = 0.2							
Warning	12.7	3.7	8.9	11.8	19.3	10.5	7.5
Alarm	25.4	7.3	18.1	23.7	38.4	20.3	14.8
Failure	30.5	8.7	21.8	28.4	46.1	24.3	17.7
Variation coefficient (COV) = 0.3							
Warning	13.7	7.0	7.9	12.0	24.5	16.7	12.5
Alarm	27.4	13.9	16.0	24.0	48.9	33.0	24.9
Failure	32.9	16.6	19.2	28.8	58.9	39.7	30.1
Variation coefficient (COV) = 0.5							
Warning	17.9	23.3	6.3	12.5	44.3	38.0	31.7
Alarm	35.9	46.3	12.6	25.2	88.3	75.7	63.1
Failure	43.1	55.6	15.1	30.2	105.6	90.5	75.4

Note M is the sample mean; S is the sample SD; q_1 is the quantile of order 0.05; q_2 is the quantile of order 0.5 (median); q_3 is the quantile of order 0.95

$d(t) = d_0 + v_{rc}t$. The initial defect depth wt_0 , mm, is assumed to be a normal RV with mean = $0.3wt$. The warning level is introduced as $0.7wt$, the alarm level is $0.8wt$. Results of calculation for the case when CR PDF is Lognormal with mean

Table 9.9 Statistical characteristics of the arrival times for the three levels of defect depths (CR PDF lognormal, mean = 0.25 mm/year, COV = Var)

Level	M	S	q_1	q_2	q_3	$q_2 - q_1$	$q_3 - q_2$
Variation coefficient (COV) = 0.1							
Warning	16.2	1.7	13.5	16.1	19.2	5.7	3.1
Alarm	20.2	2.1	16.9	20.1	23.9	7.0	3.9
Failure	28.3	3.0	23.7	28.1	33.5	9.7	5.3
Variation coefficient (COV) = 0.2							
Warning	16.7	3.4	11.7	16.3	22.8	11.1	6.5
Alarm	20.8	4.2	14.7	20.4	28.5	13.8	8.1
Failure	29.2	5.9	20.6	28.6	39.8	19.2	11.3
Variation coefficient (COV) = 0.3							
Warning	17.4	5.2	10.3	16.7	27.0	16.7	10.3
Alarm	21.8	6.5	12.9	20.9	33.8	20.8	12.9
Failure	30.5	9.1	18.1	29.3	47.3	29.2	18.0
Variation coefficient (COV) = 0.5							
Warning	20.1	10.1	8.3	17.9	39.8	31.5	21.9
Alarm	25.1	12.6	10.3	22.4	49.8	39.5	27.4
Failure	35.2	17.6	14.5	31.4	69.7	55.2	38.3

Note M is the sample mean; S is the sample SD; q_1 is the quantile of order 0.05; q_2 is the quantile of order 0.5 (median); q_3 is the quantile of order 0.95

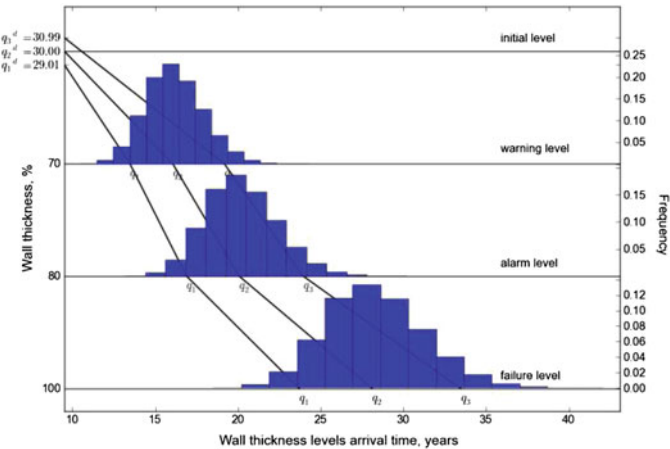


Fig. 9.12 Histogram of ATs for the three levels of defect depths (CR PDF lognormal, mean = 0.25 mm/year, COV = 0.1)

$d = 0.25$ mm/year (10 mpy) are given in Table 9.9 and Figs. 9.12, 9.13 and 9.14. The general behavior of the corrosion process resembles the case of web thinning, but it can be observed that the arrival times for the leak-type failure are larger than in the

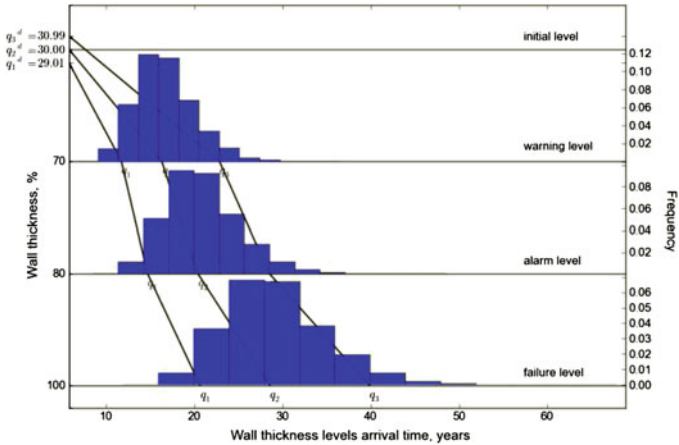


Fig. 9.13 Histogram of ATs for the three levels of defect depths (CR PDF lognormal, mean = 0.25 mm/year, COV = 0.2)

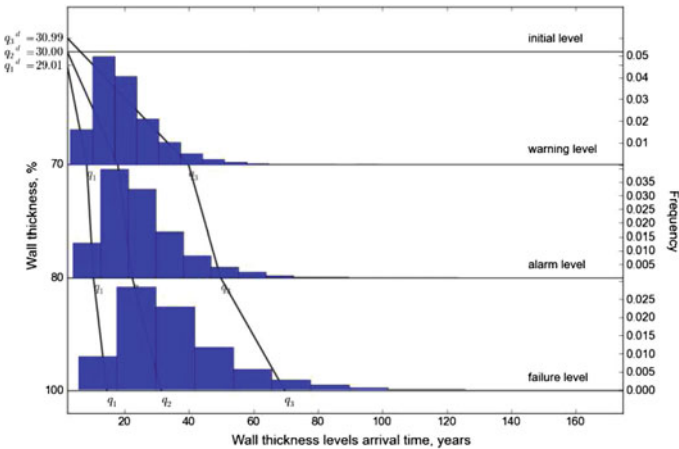


Fig. 9.14 Histogram of ATs for the three levels of defect depths (CR PDF lognormal, mean = 0.25 mm/year, COV = 0.5)

previous case. Here, again, the quantile of the 0.05 order is recommended for assessing the times to different levels of defect depths. The breakthrough in the accuracy of CR assessments lies in conducting special statistical analysis of data collected simultaneously by different type of measurement instruments on the same pipeline.

9.4 Some Results of Real-Life Pipeline Segments Analysis

Example 9.4.1 The analysis was performed for a subsea pipeline connecting a sea platform with California coast. Parameters of this pipeline are shown in Table 9.10.

As a result of the ILI performed in August 2005, 22 external defects of “metal loss” type were detected, ILI of 2008 detected 69 external “metal loss” defects.

Assessment of corrosion rate. For the purposes of analysis, two cases are considered when the corrosion rate of an individual defect is a deterministic value (formulas (9.5) were used for assessment), and when it was a random value (formulas (9.9) and (9.10) were used). For defects not detected in the course of the previous ILI, in accordance with NACE (National Association of Corrosion Engineers) recommendations [32], the assumed rate of corrosion was 0.016 in/year (0.41 mm/year), and the variance was determined by formula (9.10).

The prognosis of defects depths and lengths. The prediction of defects depths and lengths at time t are defined by formulas (9.4) using the calculated above corrosion rates. The prognosis is 5 years deep, which is the depth of prediction generally accepted in the pipeline industry. Consider six defects with largest depths ($\leq 39\% wt$), whose parameters are given in Table 9.11. The predicted depths of these defects are shown in Fig. 9.15.

In Fig. 9.15 the vertical lines define the overall tolerance of the ILI tool, defect depth $\pm$ tolerance ($tol = 15\% wt$). It can be seen that the most dangerous is defect #3. At the current corrosion rate, even without accounting for the tolerance, already in 2011 (research was carried out in 2007) the depth of this defect will be equal

Table 9.10 Initial data

Notation	Value
Pipe diameter D , mm	324.0
Pipe wall thickness wt , mm	12.7
$SMYS$, psi	42,000 and 52,000
MAOP P_{op} , psi	1037
Tolerance for defects depth tol , % wt	$\pm 15\% wt$
Safety factor K	1.39

Note 1 psi = 6895 Pa

Table 9.11 Most dangerous six anomalies as per 2008 ILI

ID #	Depth, % wt	Length, mm	Width, mm
1	39.0	56.9	70.4
2	40.9	71.9	101.6
3	56.1	80.8	117.1
4	38.4	35.8	70.4
5	45.0	98.8	211.1
6	0.58	187.5	5.8

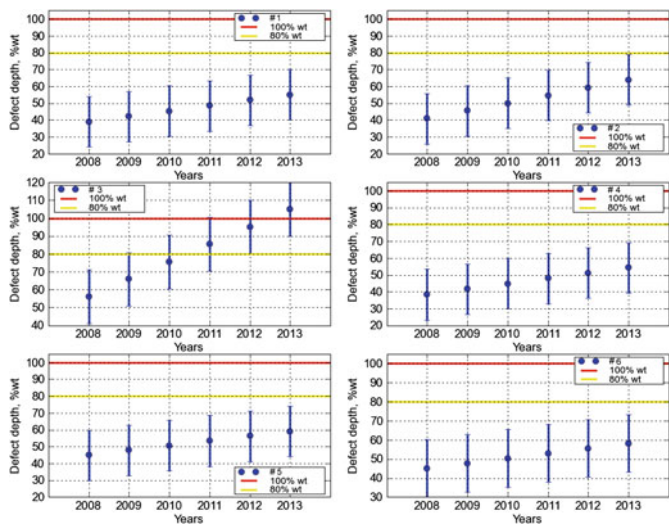


Fig. 9.15 Predicted defect depths of top six anomalies

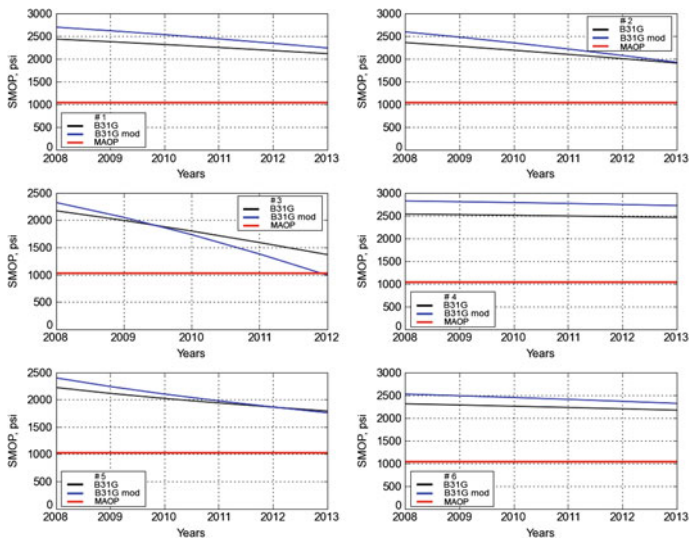


Fig. 9.16 Predicted SMOP for six deepest anomalies (1 psi = 6895 Pa)

to 80 % wt, and in 2013 will be equal to pipe wall thickness. The defect #2, with accounting for the ILI tool tolerance, will be 80 % wt only in 2013. All other defects, even with accounting for the tolerance, still will be in 2013 below the 80 % wt mark.

The prediction of pipeline residual strength. The prediction of SMOP $P_a(t)$ at time t is defined by formula (9.3) using the B31G and B31Gmod codes. In Fig. 9.16

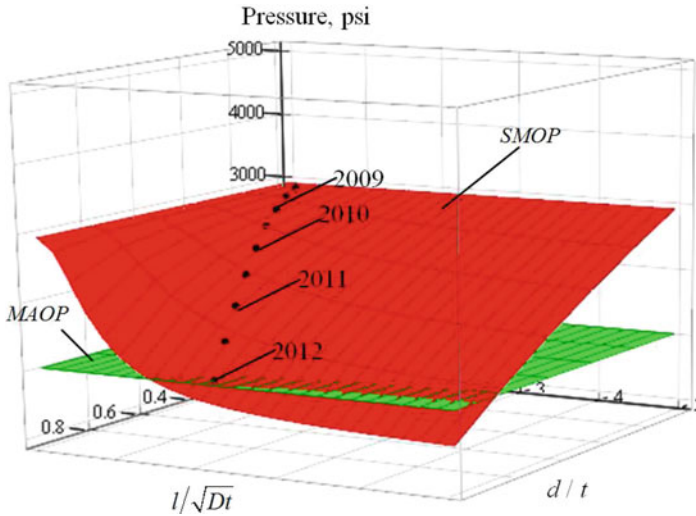


Fig. 9.17 The SMOP P_{op} and MAOP P_a surface according to B31G mod code and the degradation trajectory for the most dangerous defect of the pipeline (1 psi = 6895 Pa)

the predicted values of SMOP are presented, calculated for the defects being considered.

In Fig. 9.17 the surfaces of SMOP $P_a(t)$ and MAOP P_{op} for the pipeline in consideration are constructed. SMOP is built as a function of two variables: dimensionless defect's depth and length. The black dots on the figures represent the SMOP of the most dangerous defect #3, depending on the prognosis time t . The last dot (farthest from the origin) corresponds to the moment of time $t = 4$ years (2012). It is below the plane of P_{op} and indicates that the predicted failure of this defect in 2012 was conditional. Hence, before this moment it is necessary to either decrease P_{op} or repair the defect.

Prediction of pipeline POF. The assessment is conducted using the G-C-E method for the cases when the CRs are deterministic and RVs. In the second case the variance of the corrosion growth rate $\frac{2D}{9} \approx 0.5$ mm (see formula 9.10) for all the defects. Here the ILI ME variance, when measuring defect depth, $D = (tol/1.28)^2 \approx 2.22$ mm. Other initial data are considered as RVs and their parameters are given in Table 9.12. The found parameters of the corrosion rates for the six most deep defects are given in Table 9.13, and the results of prediction—in Table 9.14. According to them, the condition that the ultimate permissible POF is 10^{-7} km/year and with the present corrosion rate, the defect #3 will need repair already after 1 year after the last inspection (in 2009, the research was carried out in 2007), the defect #5—after 2 years (in 2010).

Residual time to pipeline repair/failure criteria. The pipeline residual life assessments are given in Table 9.15 for the most dangerous defect #3, in chronological order, starting from the moment of conducting the last ILI.

Table 9.12 Pipeline parameters considered as normal distribution RVs

Symbol	Mathematical expectation	COV
wt , mm	12.70	0.02
D , mm	323.90	0.02
$SMYS$, psi	42,000 or 52,000	0.07
P_{op} , psi	1037.00	0.10

Table 9.13 Corrosion rate parameter of the six most deep defects (in both cases variance is 0.5 mm^2)

Defect number	Average value of the radial corrosion rate, mm	Average value of the longitudinal axis corrosion rate, mm
1	0.4	8.0
2	0.6	10.0
3	12.0	119.0
4	0.4	0.4
5	0.4	272.0
6	0.3	0.4

Table 9.14 Predicted POF values of pipe cross sections with defect

Defect number	Years				
	2009	2010	2011	2012	2013
1	0.00	4.31×10^{-14}	3.82×10^{-9}	8.67×10^{-6}	7.50×10^{-4}
2	8.66×10^{-15}	1.41×10^{-9}	1.03×10^{-5}	1.51×10^{-3}	1.96×10^{-2}
3	8.02×10^{-7}	3.88×10^3	1.16×10^{-1}	3.70×10^{-1}	1.00
4	0.00	0.00	0.00	0.00	1.44×10^{-15}
5	2.01×10^{-9}	6.75×10^{-6}	8.80×10^4	1.15×10^{-2}	4.56×10^{-2}
6	3.33×10^{-15}	7.77×10^{-12}	1.38×10^{-8}	3.75×10^{-6}	1.60×10^{-4}

Figure 9.18 is a visualization of Table 9.15. It turns out that the most sensitive criterion is, obviously, 10^{-7} , using the B31Gmod code. All criteria related to specific values of POF using different design codes serve as *warning* and *alarm* levels of pipeline safety. They provide needed awareness for the DMs, or trigger different actions, depending on the engineering principles utilized by the Operator. The last three criteria in Table 9.15 are physical criteria, because they describe triggered actions or actual loss of containment by the pipeline. The warning level leads to activity which is ruled by the fact that there is a relatively large amount of time before advancement of a leak or rupture, which may be used by the Operator to plan and carefully execute necessary actions. The alarm level triggers, in general, more fast activity because the time to actual failure is much shorter.

The actual spill (physical failure) triggers a disaster scenario, in which every single moment counts. For the three described above cases the cost of the same activities dramatically differ, depending on the time that is available to perform the needed actions.

Table 9.15 Times needed for the most dangerous defect to reach the conditional residual life according to different probabilistic and deterministic criteria

Used criteria	Predicted conditional time for reaching criteria
POF of pipe cross section with defect = 10^{-7} (B31Gmod)*	Jul 2009
POF of pipe cross section with defect = 10^{-7} (B31G)*	Aug 2009
POF of pipe cross section with defect = 10^{-6} (B31Gmod)*	Sep 2009
POF of pipe cross section with defect = 10^{-5} (B31Gmod)*	Nov 2009
POF of pipe cross section with defect = 10^{-6} (B31G)*	Dec 2009
POF of pipe cross section with defect = 10^{-5} (B31G)*	Mar 2010
Defect depth = 80 % wt	Feb 2011
$P_a = P_{op}$ (B31Gmod)	Jul 2012
Defect depth = 100 % wt	Feb 2013

* Defect and pipeline parameters are RVs

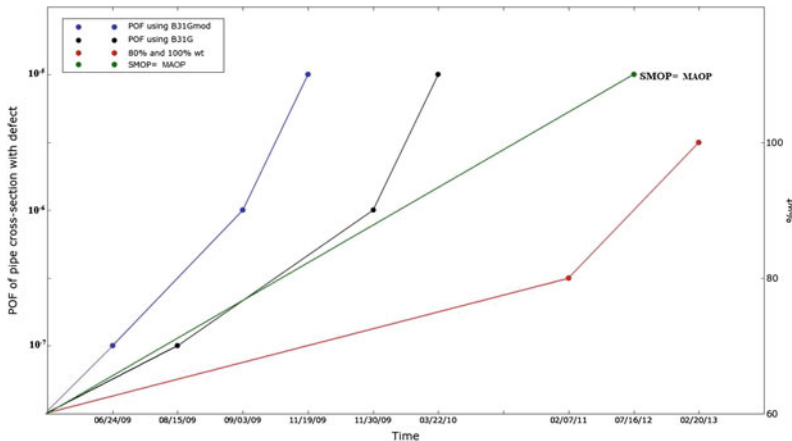


Fig. 9.18 Times for conducting prescribed maintenance actions or time to failure for the most dangerous defect, according to different criteria

Example 9.4.2 A pipeline section 11 km long, located on Russian territory. The pipeline parameters and other initial data necessary for analysis are presented in Table 9.16.

ILI was carried out in 2005, which resulted in finding 3384 defects of the “loss of metal” type and 11 defects of the “pipe wall lamination” type. A small part of the defects was verified.

In the first stage of analysis, using the methodology described in Sect. 4.5, estimates of the true sizes of the depths of the verified and nonverified defects were

Table 9.16 Initial data for calculus

Parameter	Value
Outer diameter D , mm	325.0
Pipe wall thickness wt , mm	9.0
Pipe material $SMYS$, MPa	245.0
Operating pressure P_{op} , MPa	6.4
Safety coefficient related to allowable stresses n_k	1.67
Form coefficient k_f when using B31Gmod code	$k_f = 0.67$ (for outer defects) $k_f = 1.00$ (for inner defects)
Tolerance for defects depths (ILI ME), mm	10 % $wt = 0.9$

calculated and used in further analysis. In the second stage of analysis, the defects of “pipe wall lamination” type were converted to the surface defects of the “loss of metal” type by the method described above.

The failure pressure is estimated using the B31Gmod code with the different coefficients of defect shape k_f , which is equal 0.67 for external defects and 1.0 for internal defects.

Ranking defects according their level of danger. In this stage of analysis, the express assessment of the level of defects danger was performed, results of which are presented in Figs. 9.19, 9.20 and 9.21.

According to Figs. 9.19 and 9.20 three defects of the “loss of metal” type must be repaired within 1 year after ILI, as these defects are located between Lines III and

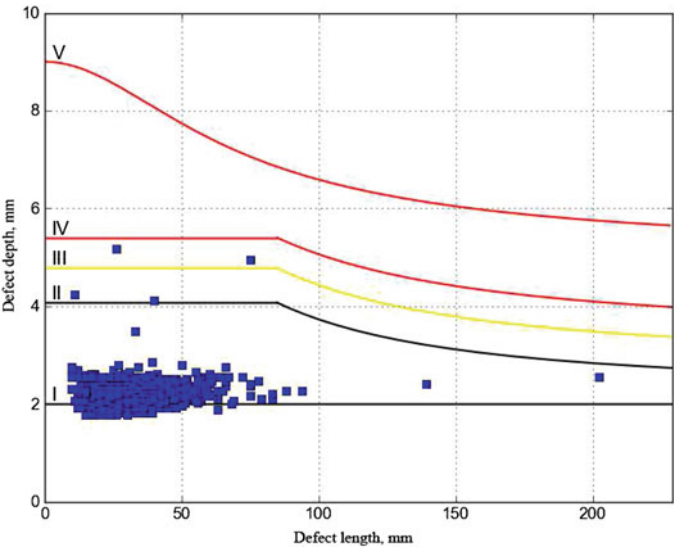


Fig. 9.19 Express assessment of the danger level of internal “loss of metal” type defects

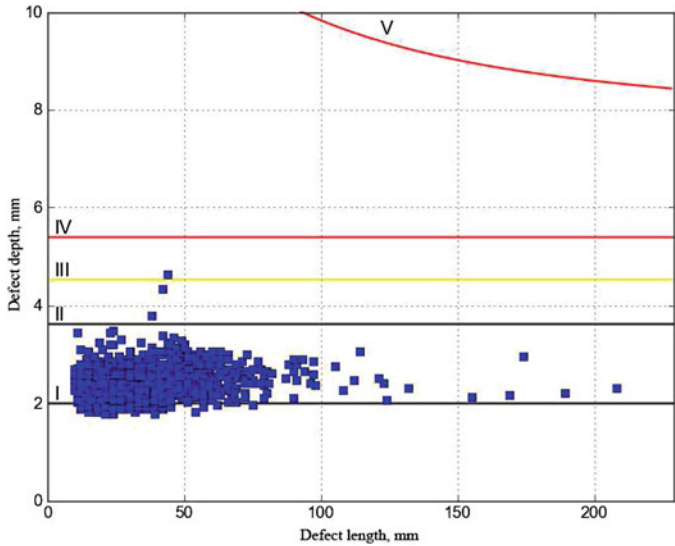


Fig. 9.20 Express assessment of the danger level of internal “loss of metal” type defects

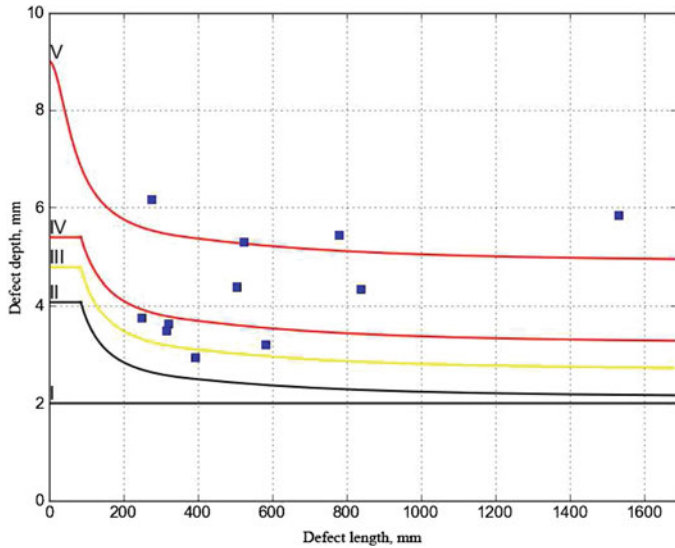


Fig. 9.21 Express assessment of the danger level of “pipe wall lamination” type defects

IV; and four defects located between Lines II and III should be repaired according to the IMP.

Out of the lamination type defects, according to Fig. 9.21 six defects should be repaired ASAP; four defects must be repaired within 1 year after ILI, as these defects

Table 9.17 Maximal defect depth and length and the maximal corrosion rate, with probability γ

Defect parameters	Maximal CR for defect parameters, mm/year	Maximal size of defect parameters, mm
Length	0.11	2.72
Depth	2.34	60.96

are located between Lines III and IV; and one defect, located between the Lines II and III, should be repaired according to the IMP.

Prediction of future defect sizes. The rates of growth of the length and depth of defects of the “loss of metal” type were found using their conditional maximal growth (see Sect. 9.2). The calculation was performed using probability $\gamma = 0.95$. The pipeline operation time prior to the last ILI is 26 years ($\tau_d = 26$).

The obtained assessments of the maximal defect depth and length, which is possessed or exceeded by the $(1 - \gamma)$ th portion of the total number of defects found during the ILI, and the maximal CR $a_{\max \gamma}$ with the probability γ , are given in Table 9.17.

Assessment of residual life. Using the assessments of the defects growth rate for each i th defect of the metal loss type, the residual life is defined by the formula:

$$\tau_i^r = \frac{d_i^{III} - d_i}{a_{\max \gamma}}, \quad (9.21)$$

where d_i^{III} is the maximum allowable depth of i th defect d_i , defined by line III of the express assessment of the defects danger; $a_{\max \gamma}$ is the maximal CR with probability γ , assessed on the previous step.

Note that the calculation of the residual life by this formula is made for the current length of the defect. Thus, its growth in time is not taken into account. The calculation results are presented in Table 9.18 and Fig. 9.22, according to which the residual life of nine defects is less than 10 years.

Predictive express assessment of the defects danger level. Using the assessments of the defects growth rate, the predictive express assessment was carried out of the defects danger level, whose remaining life time is less than 10 years (see Table 9.18). The calculation is performed for ten future moments of time $t = 1, 2, \dots, 10$ years. The results are shown in Figs. 9.23 and 9.24.

According to the obtained results one defect will require immediate repair after 2 years since the last ILI; one defect—after 4 years; one defect—after 6 years; and one defect—after 9 years. These defects will be dangerous in terms of loss of pipeline integrity by the “leak” type failure, because their depths, growing, outcross the horizontal red Line IV (60 % wt).

Gamma-percent residual life of the pipeline. Excluding from Table 9.18 all the defects which are subject to immediate repair, and repair within 1 year after the ILI, the gamma-percent pipeline residual life is equal 8.67 years, with the next ILI to be

Table 9.18 Residual life of the pipeline defective cross sections (assessments of true sizes of defects depths were used)

Defect #	Assessment of true size of defect depth, mm	Length, mm	Type of defect	Residual life, years
1	4.9	75.0	Internal	0.0
2	4.6	44.0	External	0.0
3	5.2	26.0	Internal	0.0
4	4.3	42.0	External	1.9
5	4.2	11.0	Internal	5.3
6	4.1	40.0	Internal	6.3
7	3.8	38.0	External	7.0
8	2.6	202.0	Internal	8.7
9	3.5	24.0	External	10.0

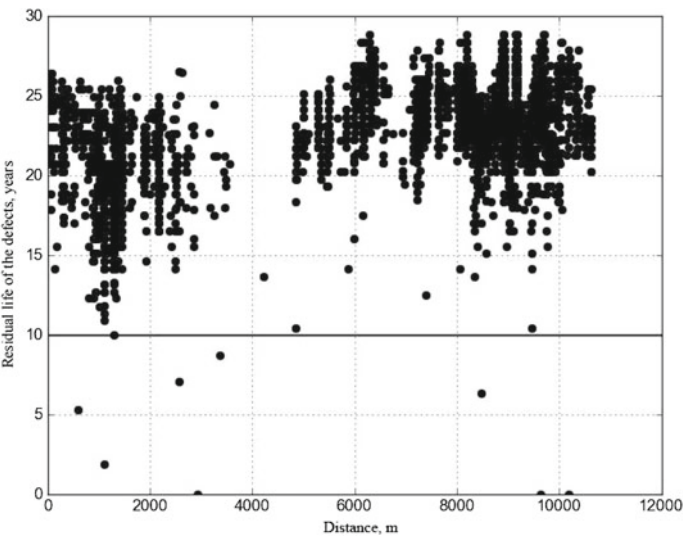


Fig. 9.22 Residual life of the pipeline defective cross sections (assessments of true sizes of defects depths were used)

performed after 7.67 years. It is recommended to execute the next ILI after 6 years (in 2011, the research was carried out in 2007) since the last ILI.

Map of defective pipeline segments. On the basis of performed analysis the defects which had to be repaired within the 10-year period after the ILI were identified, see Table 9.19. Based on this table a map of defects repair was made (Fig. 9.25).

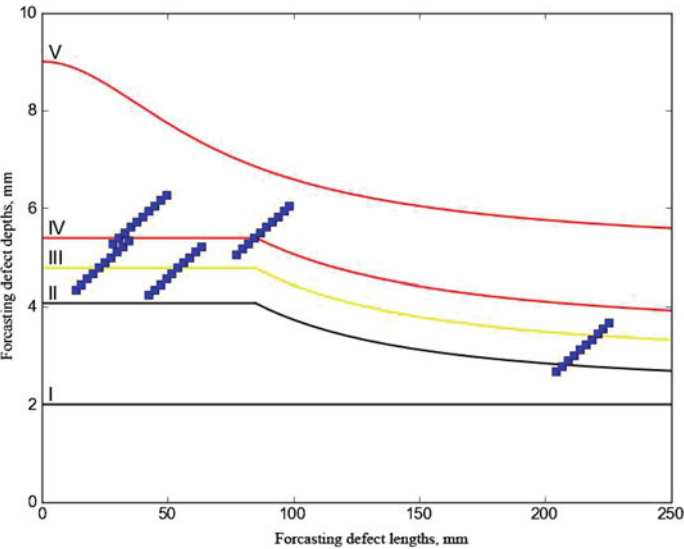


Fig. 9.23 Predicted express assessment of the danger level of internal defects of the “loss of metal” type

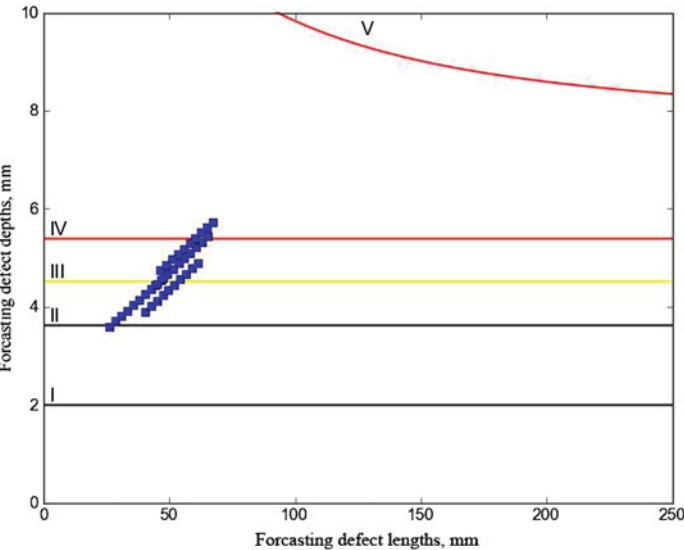


Fig. 9.24 Predicted express assessment of the danger level of external “loss of metal” type defects

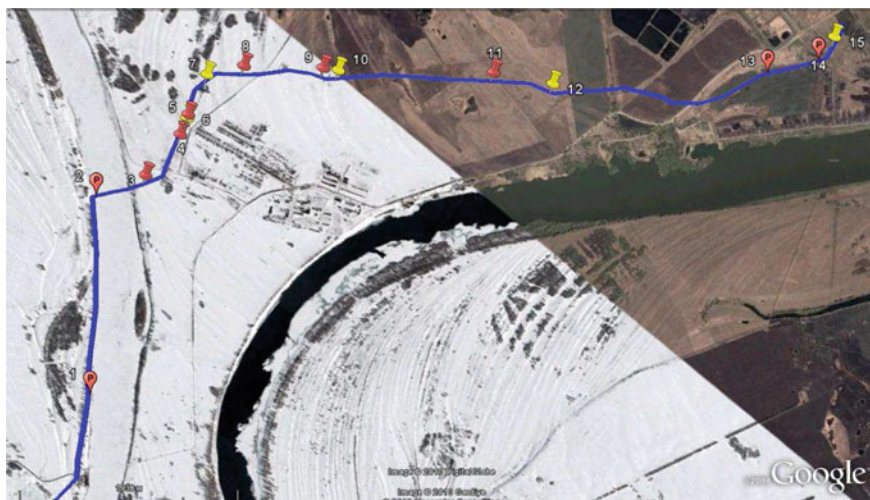


Fig. 9.25 Map of defects repair for the nearest 10 years after the ILI

In the map the sign  marks “metal loss” type of defects, and the sign  the “lamination” defects.

Summing up, the following conclusions may be made:

- the proposed methodology gives pipeline operators a convenient tool for drafting and implementing optimum integrity management plan (IMP) for each particular pipe using diagnostics results;
- pipeline operator using the proposed technique receives all necessary information in the required format. This allows making an informed decision on the choice of the warning, critical, or limit state (failure) criteria for initiation of the respective actions on a pipeline in a given situation (diagnostics, continued monitoring, maintenance, or repair of pipeline segments);
- knowledge of the time to occurrence of a certain type of warning, critical, or limit state allows minimizing pipeline maintenance and repair costs without jeopardizing its integrity. In fact, this is a well-founded prognosis of the most probable sequence of events, as it develops into an emergency situation on a pipeline.

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Conclusion

A new approach to the solution of interdisciplinary problems of pipeline diagnostics and reliability is demonstrated. The problem under study is considered holistically and represented as a chain of problems, each of which may, in general, be a subject of a separate study by some fundamental, applied or engineering science. In this format the desired solution is obtained by solving this sequence of problems in such a way that the solution of the first problem is an “entry” (input data) for the second problem, etc., until the “output” of the last problem in the sequence produces the desired result. Despite transparent formulation of this problem, its implementation is not trivial and requires significant efforts, since the solution of each preceding problem has to meet the metrics for the next one, and be represented in a corresponding form, which in itself is quite difficult.

Given this formulation, the solution of the stated interdisciplinary problem used all practically applicable achievements of modern science, which gives hope that the obtained results would most comprehensively and correctly reflect the essence of the problem under study.

The authors hope that, in general, the book is a good illustration of the fact that, quoting J.W von Goethe: “*All theory, dear friend, is dry, but the golden tree of life springs ever green*”, or in other words, there is nothing more practical than a good theory.

We hope that the book will draw the attention of everyone who is interested in studying and providing the integrity and safety of pipeline systems for different purposes, and is able to use the achievements of fundamental and applied research in their everyday operations.

The breakthrough results presented in the book may, in our opinion, serve as a basis for the development of innovative pipeline transportation technologies of the twenty-first century, both in the area of diagnostics and monitoring, and in the area of ensuring integrity, reliability and safety of pipeline systems and similar critical infrastructures.