\Modelling mechanical properties of GTAW welds of commercial titanium alloys
Transactions of the Nonferrous Metals Society of China, Vol. 15, 2005, 70--74.
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Modeling mechanical properties of welds in plates of commercial titanium alloys

Y. H. Wei, H.K.D.H Bhadeshia and T. Sourmail

Abstract strength, ductility and hardness were modeled for multi-pass welds deposited by gas tungsten arc welding in plates of commercial titanium alloys. Models are developed for analysis and prediction those mechanical properties by applying artificial neural network (ANN). The input parameters of the neural network are alloy compositions and heat treatment conditions and the output of the neural network are mechanical properties of the weld metal of titanium alloys, namely ultimate tensile strength (UTS), yield strength, elongation, reduction of the area and hardness. The titanium alloys used in the paper include commercially pure titanium, alpha or near-alpha titanium, alpha-beta titanium and beta or near-beta titanium.

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1. Introduction

Titanium metal is finding many uses because of the advantages it offers in strength-to-weight ratio, corrosion and erosion resistance, high temperature strength, fatigue strength, creep resistance and cryogenic properties. Fabricators are concerned with the weldability of many alloys from which they may design for a particular application. They especially concern what factors influence the mechanical properties and how they work in order to optimize welding procedure design. Corresponding researches have been conducted for many years to provide some basic design facts concerned with the strength and toughness properties of weld metal of the major commercial titanium alloys [1-19]. Even a few empirical models have been developed to predict some mechanical properties of weld metal for commercially pure titanium [20-21], but there are few empirical models available for predicting mechanical properties of weld metal for the titanium alloys. The advent of neural network provides an effective way to model welding phenomenon and predict and analyze mechanical properties [22]. The usefulness and effectiveness of the neural network models have been already proved by many research works [23-26]. However, most of these neural network models for mechanical properties mainly deal with steel welding and there are few such kinds of models for titanium welding. Therefore, this paper will develop neural network models for prediction and analysis of mechanical properties of weld metal of titanium alloys.

2. Experimental Conditions [19]

The materials used in welding were classified into the four major titanium alloy types: commercially pure, alpha or near alpha, alpha-beta and beta or near-beta. Filler metals for welding each plate were made from the same material as the plate so that the weld metal and base metal compositions were the same in any welded plate.

Welds were made with the gas tungsten-arc welding process using dcsp power. Welded plates of each alloy were tested in two conditions: as-welded and stress-relieved (SR). The SR condition consisted of heating at 1100F for 2 hr and air cooling. A vacuum annealing treatment was used for reducing the hydrogen contents of filler metal strips and plates of several alloys before welding and the specimens were tested as welded which was called VAAW.

All-weld metal tensile specimens 0.250 in. diameter, were machined from the saw-cut blanks which had the full thickness of weld reinforcement and were 0.75 to 1.0 in. wide by 3.0 in. long with the weld located longitudinally alone the center.

Rockwell C hardness tests were made on a 2.25 in. wide cross section slice from each welded alloy in the as-welded and SR conditions.

Chemical analyses for oxygen and hydrogen were made on weld metal from a fracture face of the room temperature broken impact specimens of each test series.

3. Neural Network Model

3.1 Basic principle of neural network

A neural network is a general method of regression in which linear or non-linear functions are fitted to experimental data. The basic unit in the neural network is neurons which are connected to each other by links known as synapses, associated with each synapse there is a weight factor. The standard feed forward networks used in this work consist of 2 layers of neurons interconnected as described in Fig. 1.

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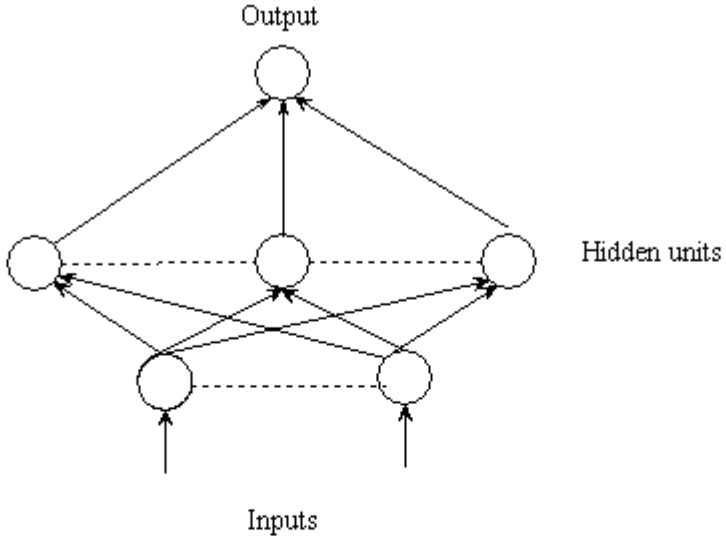


Fig. 1 the feedforward network used in the work

These networks are also referred to as three layers network which are the input nodes, the hidden units and the output node. The inputs x_i (compositions, post welding heat treatment and tested temperatures) defines the input nodes, and the mechanical property e.g. ultimate tensile strength defines the output node. The relationship between the input nodes and output nodes are determined by functions as equation (1) and (2).

$$h_j = \tanh\left(\sum_j w_{ij} x_j + \theta_j\right) \tag{1}$$

$$y = \sum_i w_i h_i + \theta \tag{2}$$

where xj are the j variables on which the output y depends, w_i, w_{ij} are weights and θj, θ are bias and i is the number of hidden nodes.

Equation (1) is non-linear, in the present case a tangent function, which defines the relationship between the hidden layer and the input nodes. The flexibility of the non-linear function scales with the number of the hidden nodes.

Equation (2) performs a linear combination of each hidden nodes so as to get an output.

The above functions combined with a set of weights and bias, and inputs define the neural network. To make the output and inputs fit well, the network has to be trained during which the weights and bias have to be changed systematically until the best-fit reaches.

3.2 Model description

The schematic model of the neural network for modeling mechanical properties of welds is shown in Fig. 2.

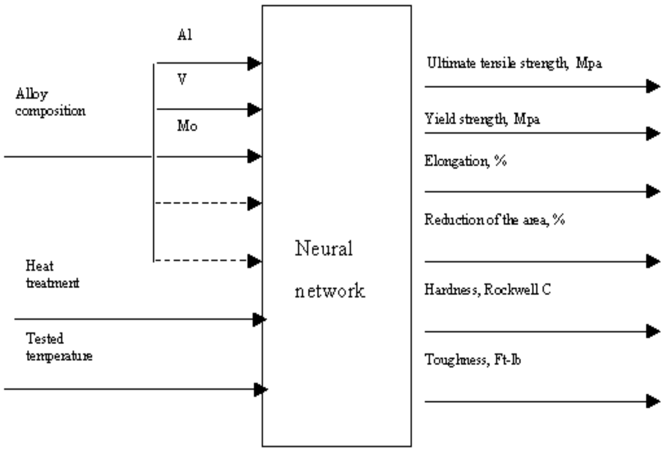


Fig.2 Schematic model of the neural network for modeling mechanical properties of welds

As shown in the Fig. 2, the input of the model includes chemical compositions, heat treatment and tested temperature and the output model includes 5 most important mechanical properties namely ultimate tensile strength, tensile yield strength, elongation, reduction of area, hardness and toughness. The toughness models will be introduced in the following paper.

Chemical composition includes the most commonly used alloying elements, namely Al, V, Cr, Mo, Sn, Ni, Zr, Cu, Cb, Ta, Mn, Si, C, Fe, H, O and N. Among them, hydrogen and oxygen are from welded metal and other chemical compositions are from base metal as received. The post weld heat treatment is digitized with 1 and 0 which represent stress relief and as welded respectively. When VAAW is used, the hydrogen in welded metal usually decreases so the influence of VAAW has been taken into consideration by the content of hydrogen. Therefore, VAAW could be treated as welded.

There are about 20 variables are considered as input parameters including chemical compositions and post welding heat treatment. Analysis of input parameters in one of the databases is shown in Table 1 which is used for UTS models. The data distribution for each parameter in UTS models is attached in appendix A.

Table 1. Analysis of the input parameters used for training and testing model of UTS

Input element	Minimum	Maximum	Mean	Standard deviation
Aluminum (Wt%)	0	7.3	3.5373	2.676
Vanadium (Wt%)	0	15.7	2.2745	3.6917
Chromium (Wt%)	0	11.1	0.4333	1.9962
Molybdenum (Wt%)	0	4.1	0.4894	1.0802
Tin (Wt%)	0	5.9	0.2961	1.0134
Nickel (Wt%)	0	1.5	0.066	0.280
Zirconium (Wt%)	0	14.2	0.4667	2.1051
Copper (Wt%)	0	0.76	0.0149	0.1059
Columbium (Wt%)	0	2.6	0.3137	0.7631
Tantalum (Wt%)	0	1.3	0.1490	0.3636
Manganese (Wt%)	0	7.6	0.3092	1.3005

Silicon (Wt%)	0	0.27	0.0063	0.0381
Carbon (Wt%)	0	0.04	0.0211	0.0076
Iron (Wt%)	0.02	5.1	0.2571	0.8007
Hydrogen (p.p.m)	7	258	54.5980	35.1816
Nitrogen (Wt%)	0.04	0.14	0.0113	0.020
Oxygen (Wt%)	0.063	0.630	0.1567	0.1181
Stress relief treatment	0	1	0.3725	0.4859

3.3 Neural network training

Neural networks are usually trained by minimizing an error function as equation (3):

$$M(w) = \beta E_D + \alpha E_w \tag{3}$$

$$E_D = \frac{1}{2}\sum_j (t_j - y_j)^2$$

$$E_W = \frac{1}{2}\sum_j w_j^2$$

Where E_D is the overall error, and E_W the regulariser which are used to force the newwork to use small weights as described in equation (3). α and β control parameters which largely influence the complexity of the model. t_j is the target (experimental data of mechanical property) for the set of inputs x_j , while yj is the corresponding networks output.

The algorithm used to train the networks has been written by D.J.C. Mackay. It implements a particular learning method using Bayesian statistics to infer the most probable distribution for weights given the data, instead of calculating sets of weights [23]. The error bars therefore become large when data are sparse or locally noisy.

In this context, a very useful measure is the log predictive error (LPE) as shown in equation (4), because the penalty for making a wild prediction is reduced if the wild prediction is accompanied by appropriately large error bars [23].

$$LPE = \sum_j \left[\frac{1}{2}(t_j - y_j)^2 / \sigma_j^2 + \log\left(\sqrt{2\pi}\sigma_j\right) \right] \tag{4}$$

where σ_j is related to the uncertainty of fitting for the set of inputs x_j.

Notes that the bigger the LPE is the better the model is.

Because of the great flexibility of the functions used in the network, there is a possibility of overfitting data. The solutions are implemented to solve this problem. The first is contained in the algorithm, i.e. the complexity parameters α and β are inferred from the data, therefore allowing automatic control of the model complexity. The second resides in the training method. The experimental data is divided into two sets, a training dataset and a test dataset. The training dataset is used to train models with different hidden units and test dataset is used to test the models and make predictions.

Fig. 3 and Fig. 4 show the test error and LPE of the elongation model, and Fig. 5 shows the predictions with both the training dataset and test dataset.

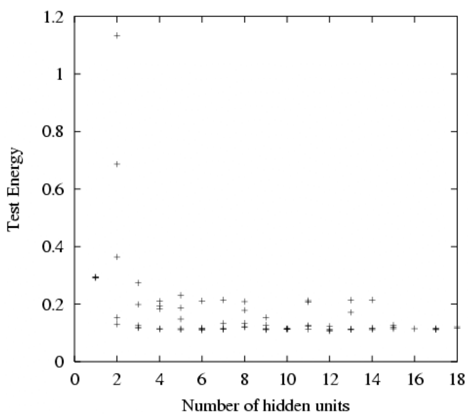


Fig 3 the test error of elongation model

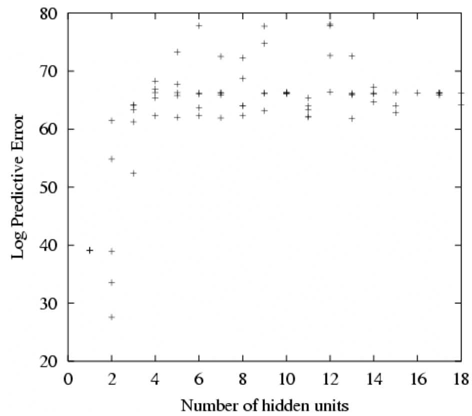
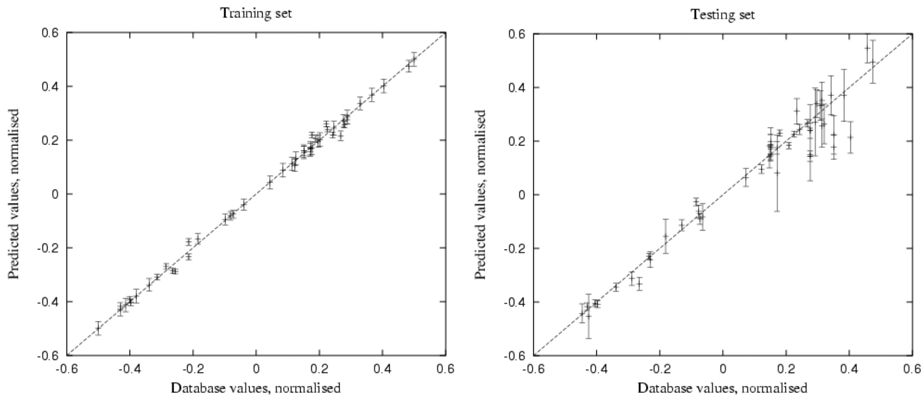


Fig. 4 LPE of elongation model



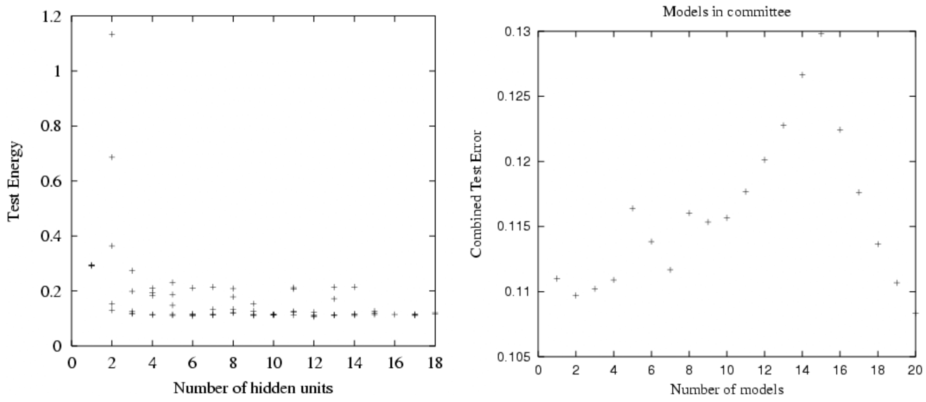
(a) Predicted with trained dataset (b) predicted with testing dataset

Fig 5. Predicted yield strength from the neural network versus values for training and testing

As shown in Fig.3 and Fig.4, the test error becomes smaller and LPE becomes bigger as model becomes more complex. Fig. 5 demonstrates the fitness of the models. Predictions with trained dataset are normally accurate than those predicted with test dataset.

As mentioned above, the complexity of a model depends on its number of hidden units. Therefore, models with different numbers of hidden units will give different predictions. These models are then ranked according to how they perform on unseen data (test data set). Most of time, a combination of the best models namely a committee performs better than a single model. To determine the optimum number of models to use in a committee, the combined error presents a minimum which corresponds to the optimum number of models to be used.

Fig. 6 is an example of the test error of models and the combined errors of committee of models of Elongation



(a) The test error of single model (b) combined error of a committee

Fig. 6 an example of the test error of models and the combined errors of committee of models

As shown in Fig.6, when 2 models are used the combined test error is the minimum for elongation models.

4. Prediction with the models

4.1 Predictions with UTS model

After the models have been trained they can be used in many ways, among them, prediction of mechanical properties of titanium welds can be made and the trend of their changes and the predicted error bands can be shown clearly and the corresponding mechanical properties can been stored in the special files too. Due to the limit of page, only UTS model is cited as an example for predictions. The average of each composition is used and as-welded test condition is chosen to make the following predictions, as shown in Fig. 7.

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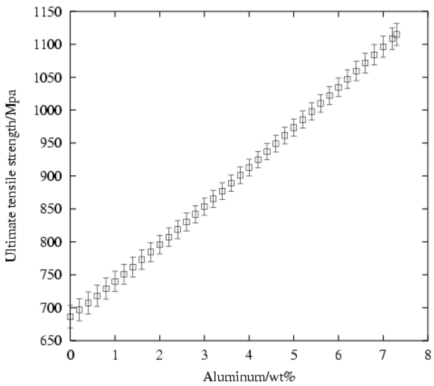
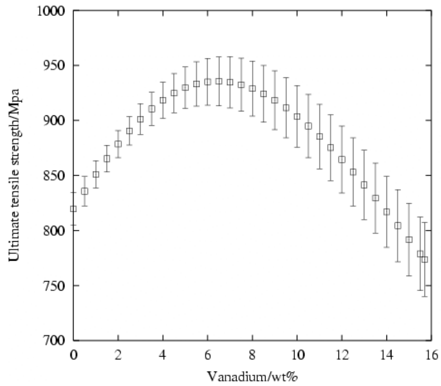
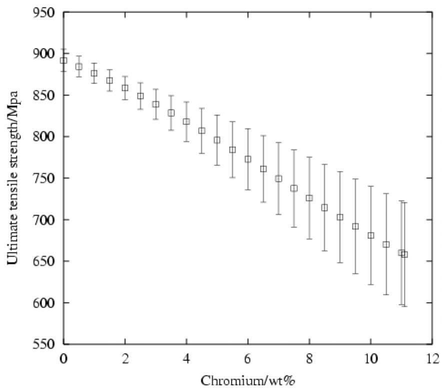


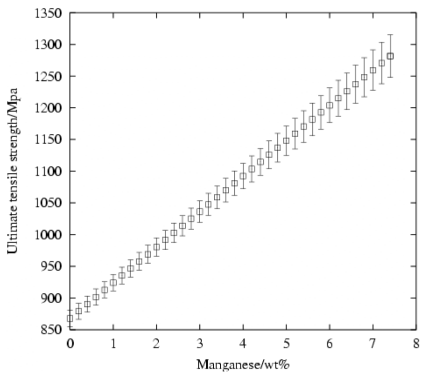
(a) Aluminum



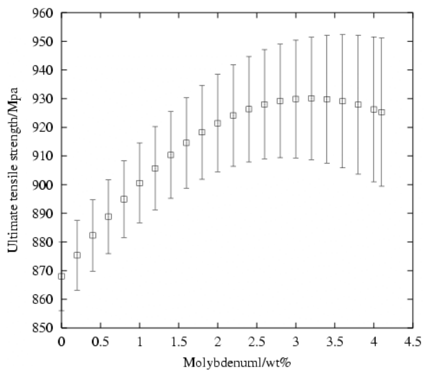
(b) Vanadium



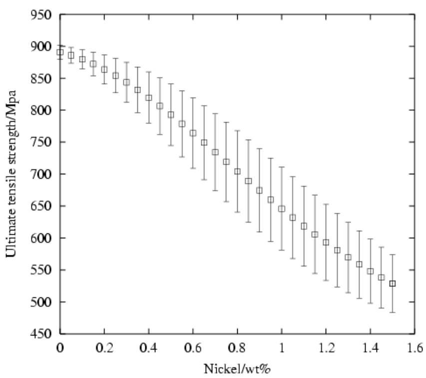
(c) Chromium



(d) Manganese



(e) Molybdenum



(f) Nickel

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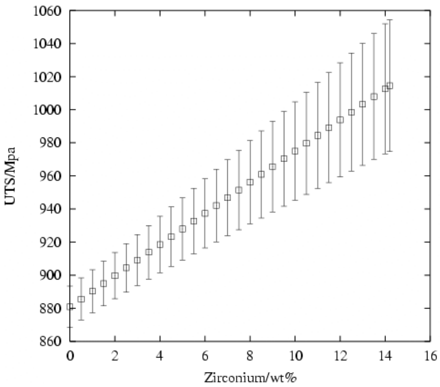
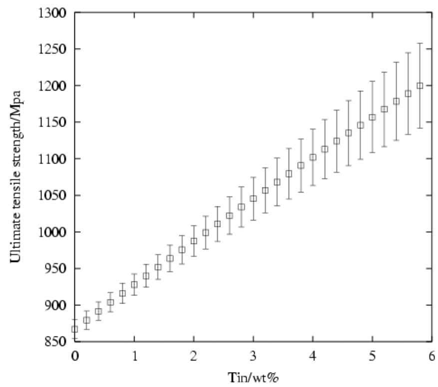
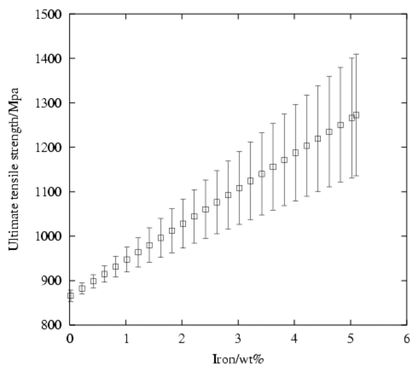


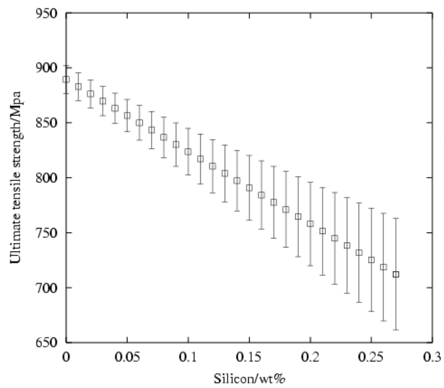
(g) Zirconium



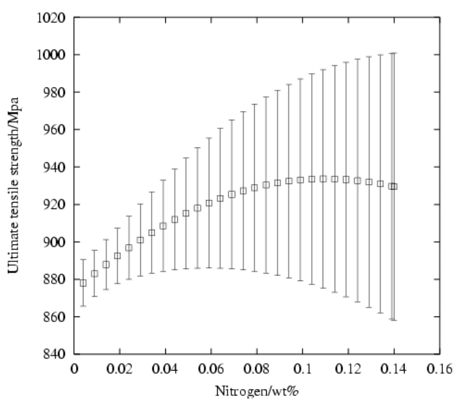
(h) Tin



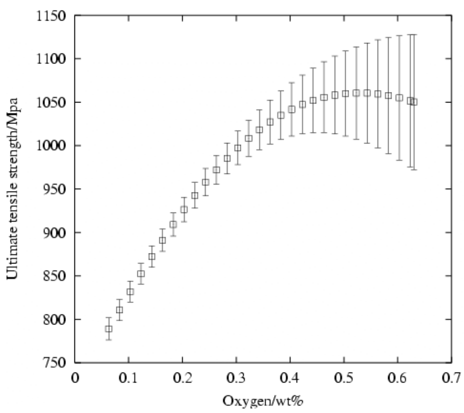
(i) Iron



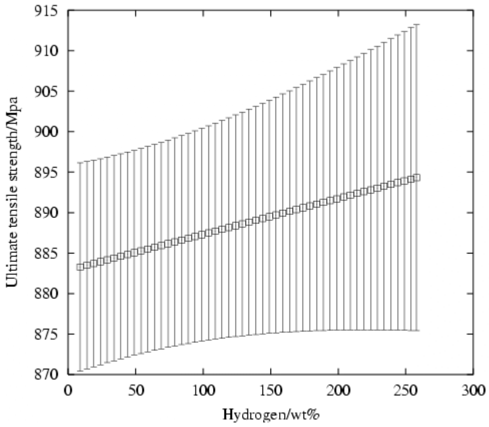
(j) Silicon



(k) Nitrogen



(l) Oxygen



(m) Hydrogen

Fig.7 the predictions made with the UTS model based on neural network

As shown in Fig. 7, the influences of variables on the ultimate tensile strength can be divided three parts: increasing UTS, decreasing UTS and increasing first then decreasing UTS. Among them, aluminum, manganese, molybdenum, zirconium, tin, iron, nitrogen, oxygen and hydrogen will increase the UTS with their contents increasing in the material. Chromium, nickel and silicon will decrease the UTS with increasing their contents in the material. Only vanadium has different influences on the UTS with different contents. When vanadium is less 6.5 the UTS will increase with more vanadium. When vanadium is greater then 6.5 the UTS will decrease with more vanadium.

4.2 Predictions with all models for different kinds of titanium alloys

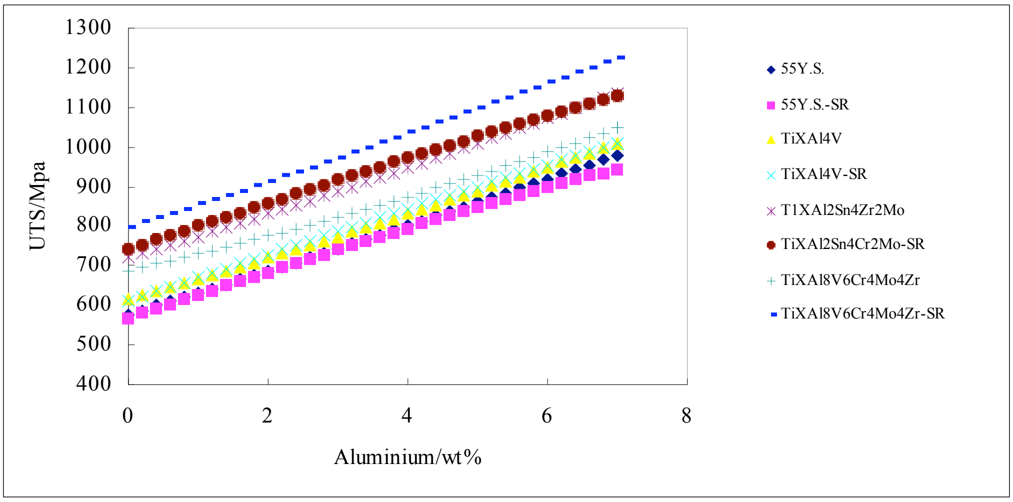
Different titanium alloys are chosen to predict mechanical properties for aluminum and vanadium which are the most important alloys. At the same time the influence of tested conditions (as-welded and SR) is covered. To make the figures clear the error bands are omitted. Different kinds of titanium alloys are used to make predictions and their compositions are listed in table 2.

Table 2 Titanium alloys and their compositions used in predictions

Alloy	Type	Al (%)	V (%)	Cr (%)	Mo (%)	Zr (%)	Sn (%)	Fe (%)	C (%)	O (%)	N (%)	H (ppm)
55 Y.S.	CP	0	0	0	0	0	0	0.28	0.02	0.192	0.006	42
Ti6A14V	α+β	6.3	4.2	0	0	0	0	0.16	0.02	0.11	0.010	53
Ti6A12Sn4Zr2Mo	α	6.0	0	0	2.0	4.0	2.0	0	0.02	0.10	0.03	50
Ti3A18V8Cr4Mo4Zr	β	3.4	8.2	5.8	4.0	3.9	0	0.17	0.02	0.090	0.011	21

4.2.1 Aluminum

The influence of aluminum on the mechanical properties of welded metal of titanium are shown in Fig. 8 (a) to (g) according to the neural network models.



(a) UTS model

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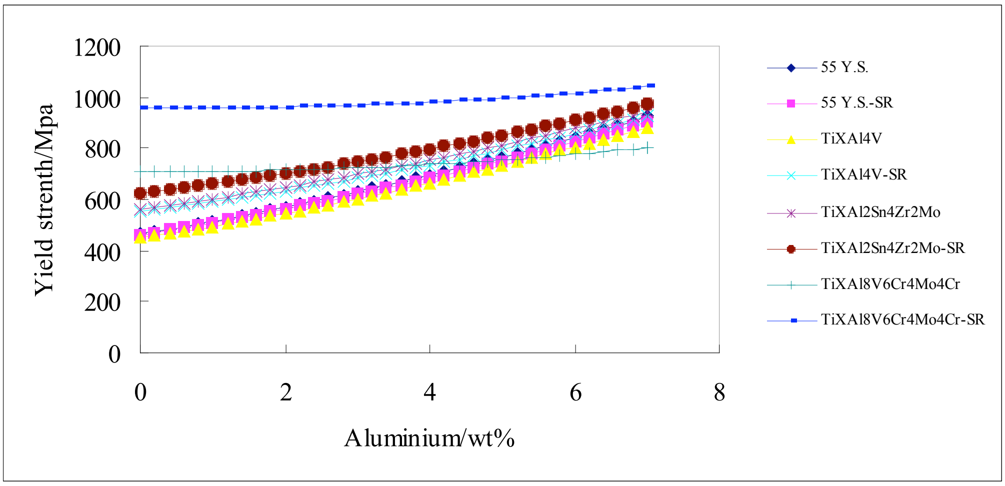
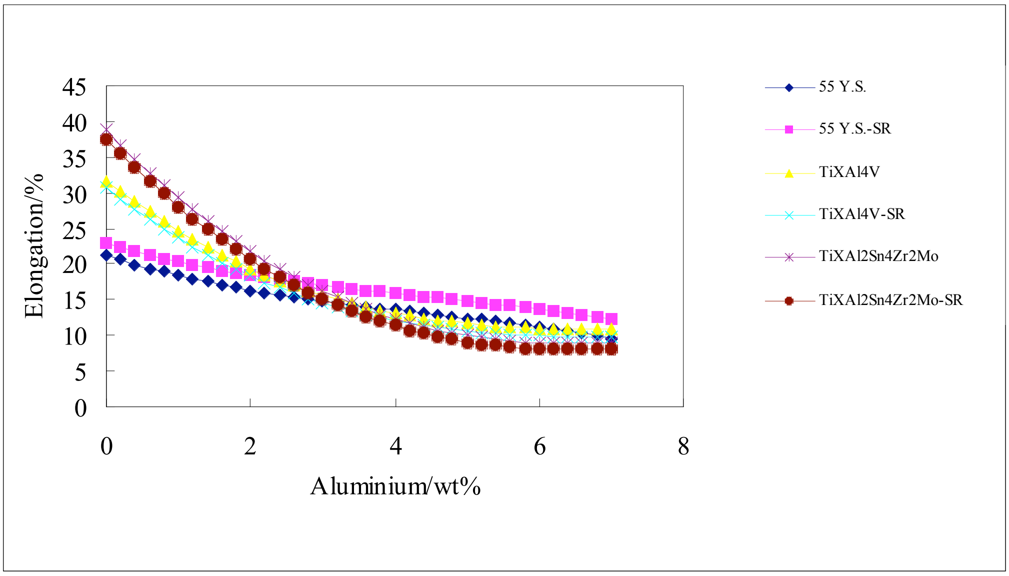
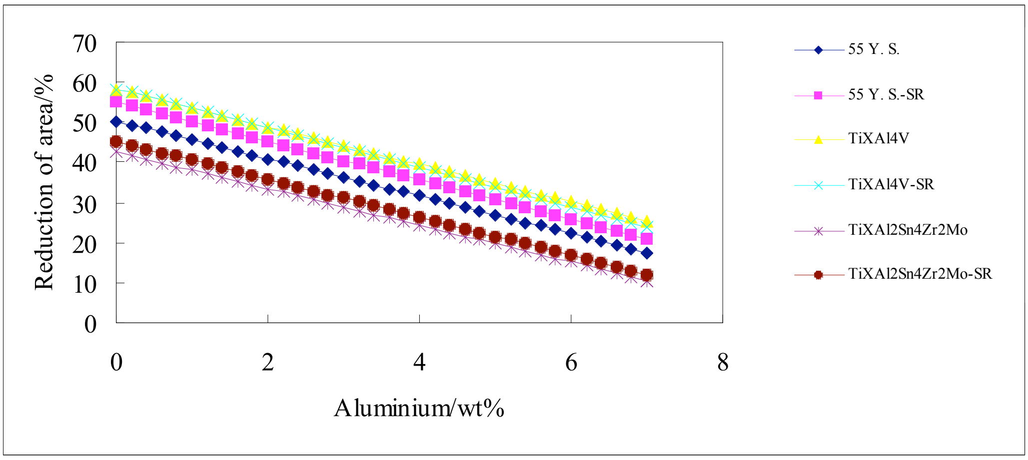


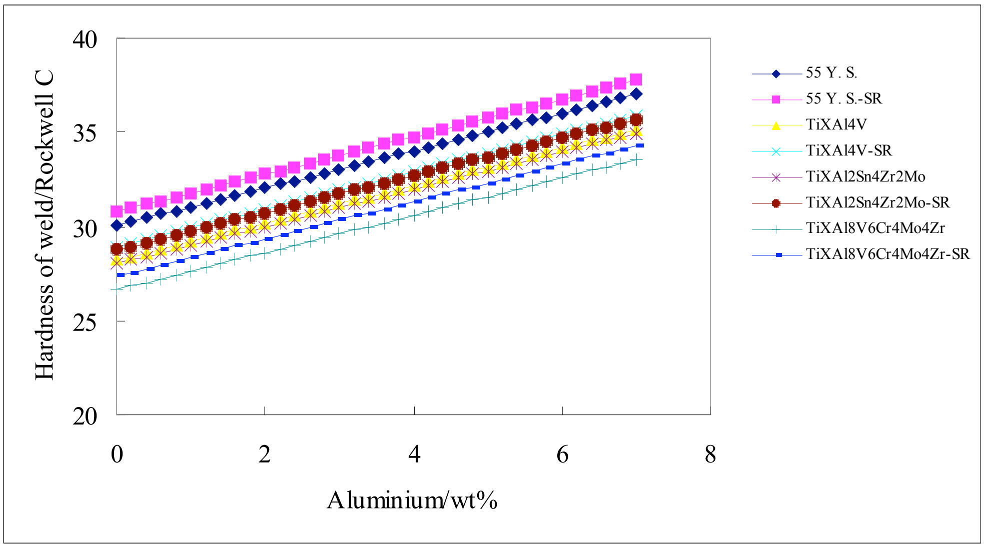
(b) Yield strength model



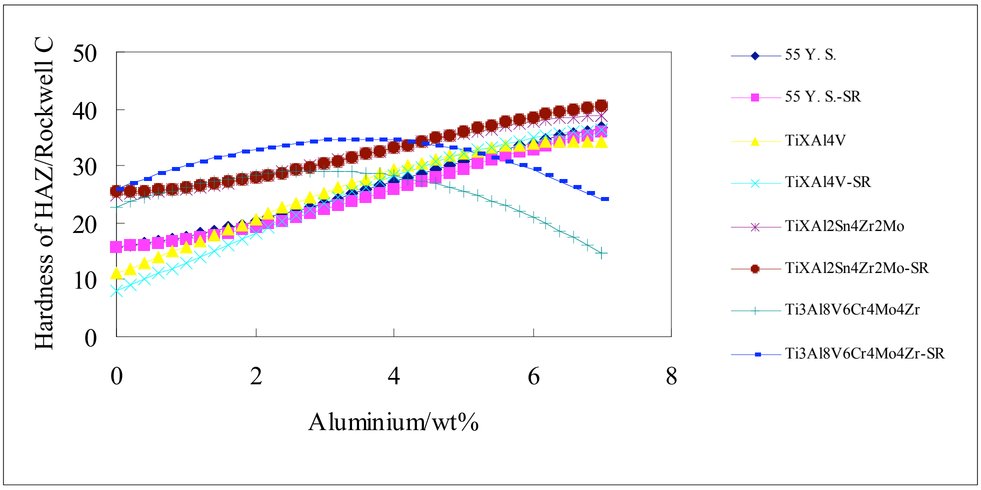
(c) Elongation model



(d) Reduction of area



(f) Hardness of weld



(g) Hardness of HAZ

Fig.8 neural network predictions for the influence of aluminium content the mechanical properties for different titanium alloy system

From the simulated results in Fig.8, it can be concluded that with increasing aluminium content the ultimate tensile strength, yield strength and the hardness both in weld and HAZ increase except that the HAZ hardness of titanium TiXAl8V6Cr4Mo4Zr increases when the aluminium content is less than 3.0 and drops after that. the elongation and reduction of the area drop dramatically with increasing content of aluminium. These results accord very well with the neural network predictions for influence of the aluminium on the mechanical properties for the titanium TiXAlXV [27].

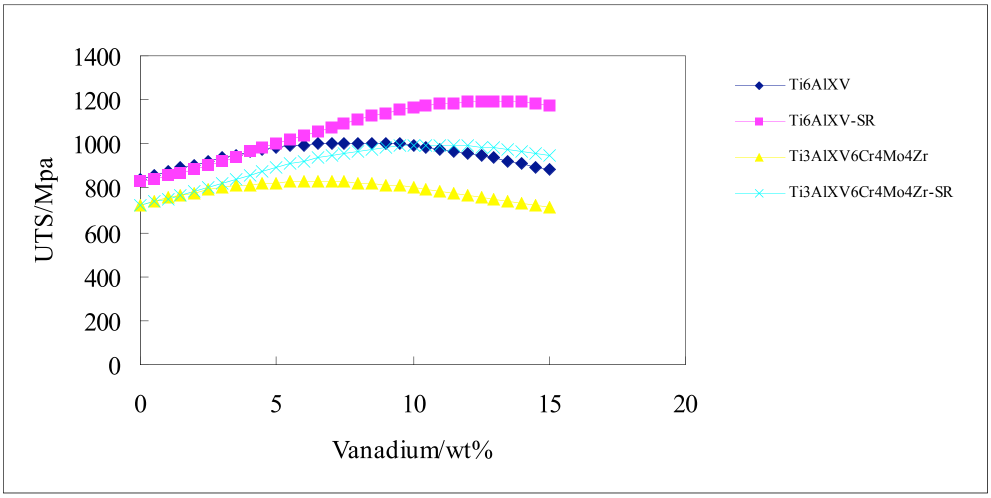
As mentioned above, welded plates of each alloy were tested in either as-welded or stress-relieved. The influences of the tested conditions can be found in Fig. 8 too. There are no obvious influences of the tested conditions on the ultimate tensile strength of weld metals of 55 Y.S, TiXAl4V and TiXAl2Sn4Zr2Mo, however, the UTS of TiXAl8VCr4Mo4Zr tested in stress-relieved conditions is much greater than that tested in as-welded conditions. Compared with as welded, the yield strength of weld metal of pure titanium 55 Y.S doesn't change much when they are tested in condition of SR while the yield strength of weld metal of TiXAl4V, TiXAl2Sn4Zr2Mo and TiXAl8VCr4Mo4Zr increases to different extents, among them, the biggest increase is obtained for TiXAl8VCr4Mo4Zr. The elongation and ROA for pure titanium 55 Y.S. increase appreciably while the elongation and ROA of the other titanium alloys drop a little when tested in the SR condition than that as welded as shown Fig. 8 (c) and (d).

The hardness of weld increases for all titanium alloys if they are tested in SR conditions than tested as welded conditions, which is as demonstrated in Fig.8 (e)

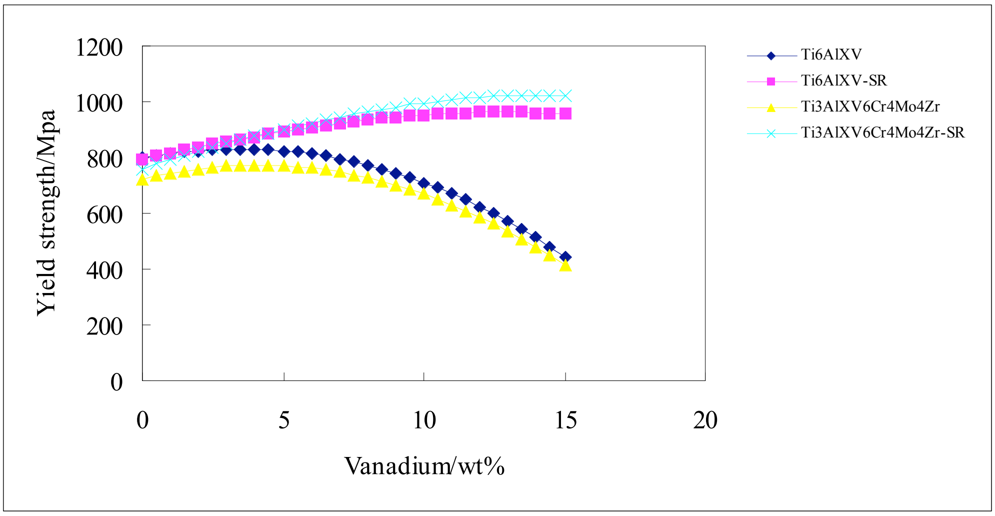
As shown in Fig.8 (f), the hardness of HAZ of TiXAl8VCr4Mo4Zr.increases while others change little when tested in SR condition compared with as-welded test condition.

4.2 Vanadium

The influence of Vanadium on the mechanical properties of welded metal of titanium is shown in Fig. 9 (a) to (f) according to the neural network models.



(a) UTS model



(b) Yield strength model

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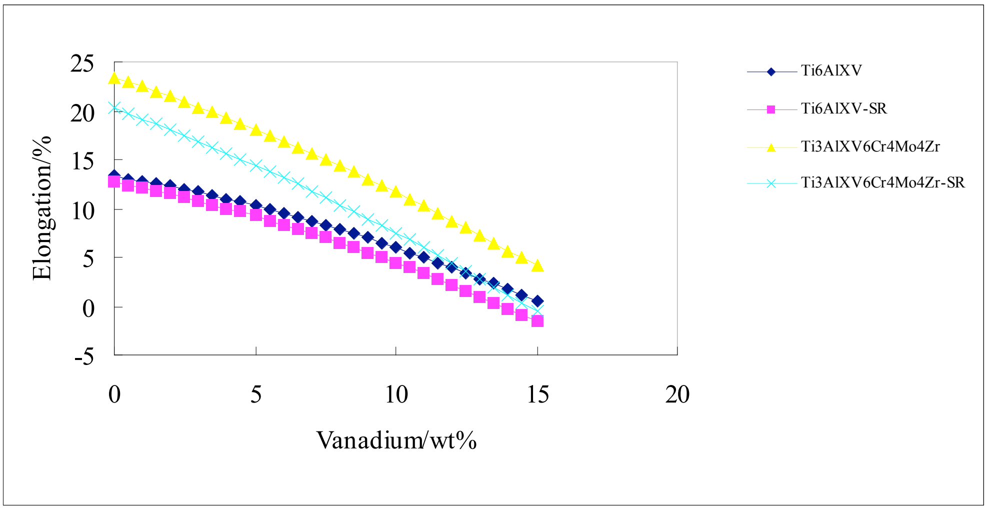
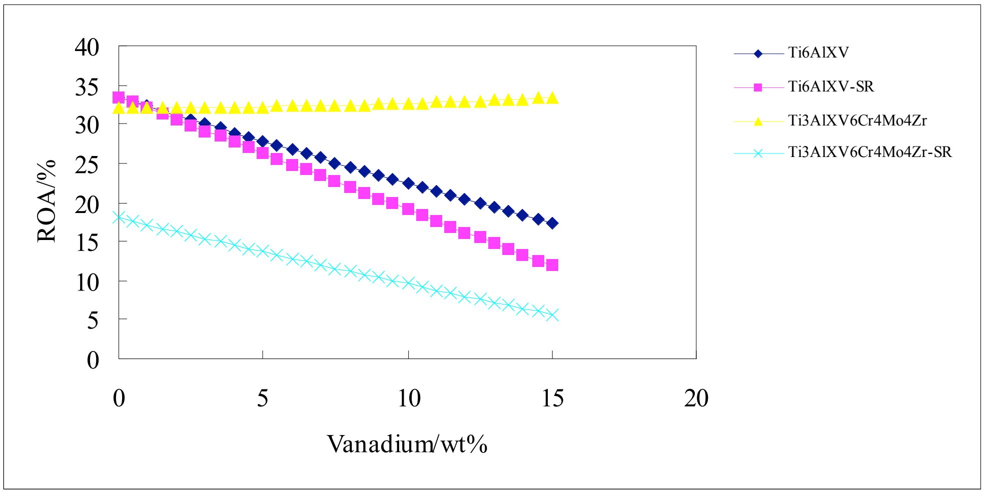
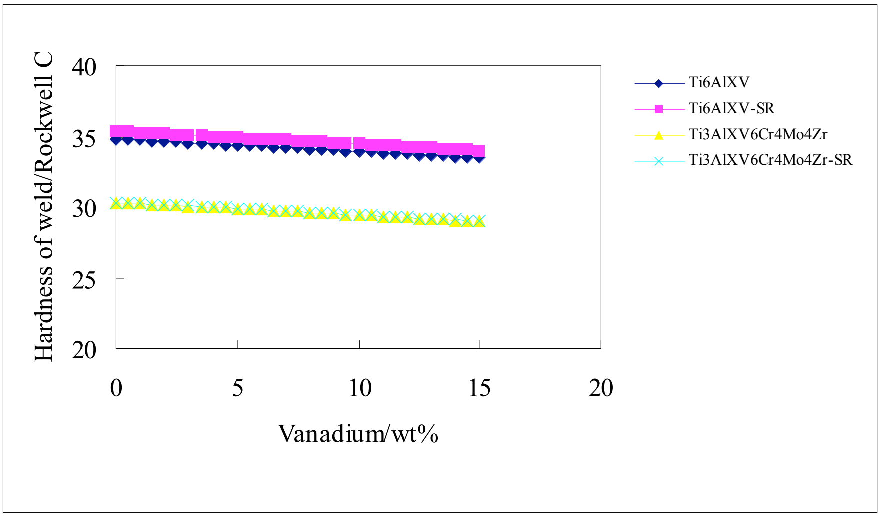


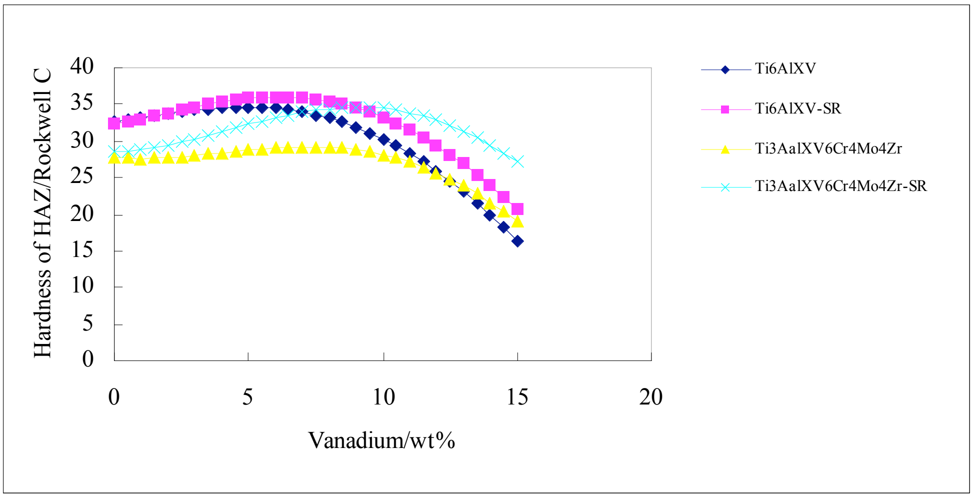
(c) Elongation model



(d) ROA model



(e) Hardness of weld



(f) Hardness of HAZ

Fig.9 neural network predictions for the influence of vanadium content the mechanical properties for different titanium alloy system

As shown in Fig. 9, the vanadium just like aluminium has strong effect on the mechanical properties of titanium weld metal. Firstly, with increasing vanadium, the tensile strength increases in both tested conditions and yield strength increases only in SR tested condition. In as-welded tested condition, the yield strength increases with more vanadium before it reaches 5% and begins to decreases after it. Secondly, elongation and the reduction of the area decrease with increasing vanadium content. Thirdly, the hardness of weld drops appreciably when vanadium increases while the hardness in HAZ increases firstly then decreases.

From Fig. 9, the effect of the tested conditions can also be found. The tensile strength, yield strength and the HAZ hardness which are tested in SR conditions are greater than those tested as-welded conditions for titanium Ti6AlXV, Ti3AlXV6Cr4Mo4Zr. The elongation and the reduction of the area tested in SR conditions are smaller than those tested as-welded condition. The hardness of weld doesn't change much between those two tested conditions.

Conclusion

The UTS, yield strength, elongation and ROA of weld metal of titanium alloys have been modeled with neural network. The models were analyzed and applied for different kinds of titanium alloys. The results show that the models are reasonable and accord well with previous research work.

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Appendix A Data distributions of UTS model

\Modelling mechanical properties of GTAW welds of commercial titanium alloys
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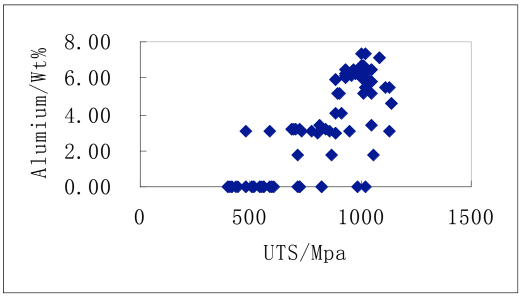

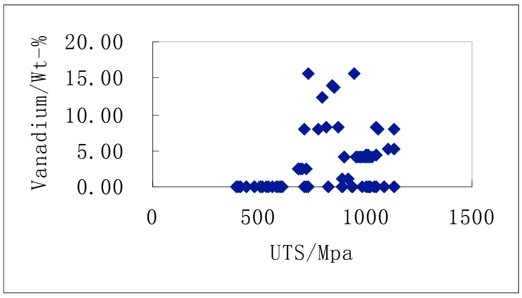

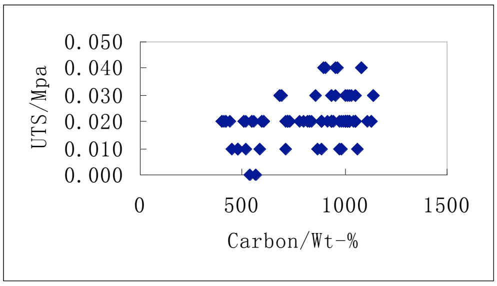

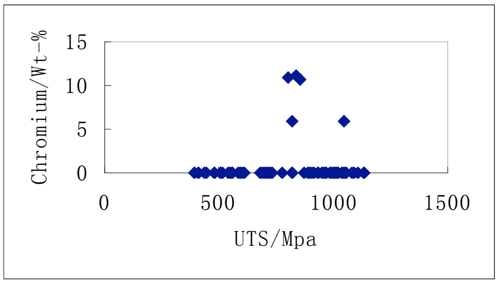

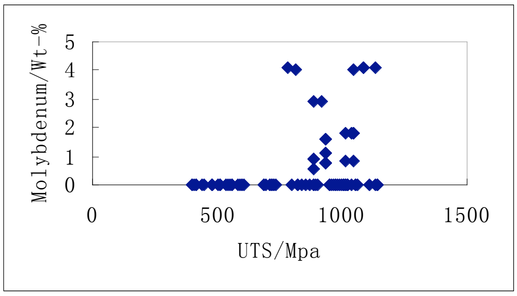

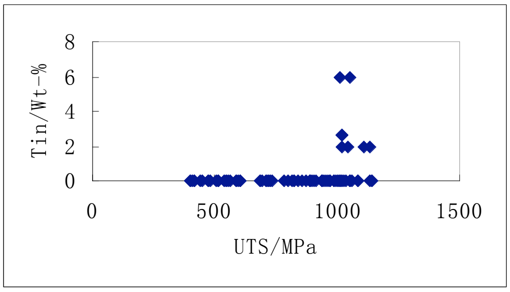

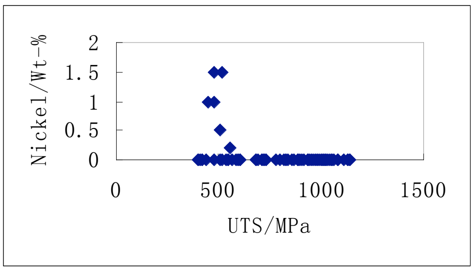

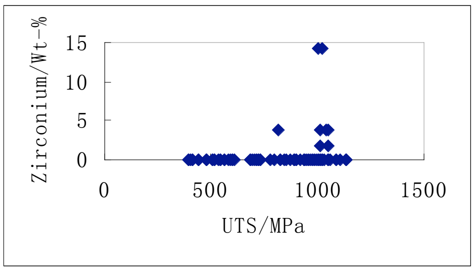

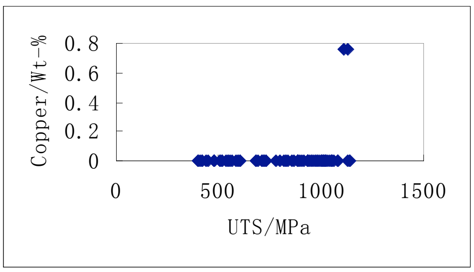

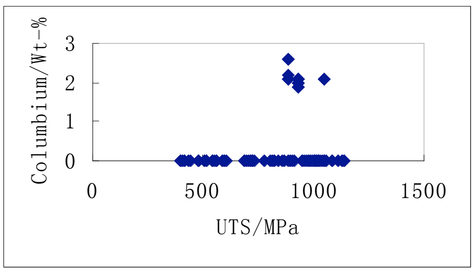

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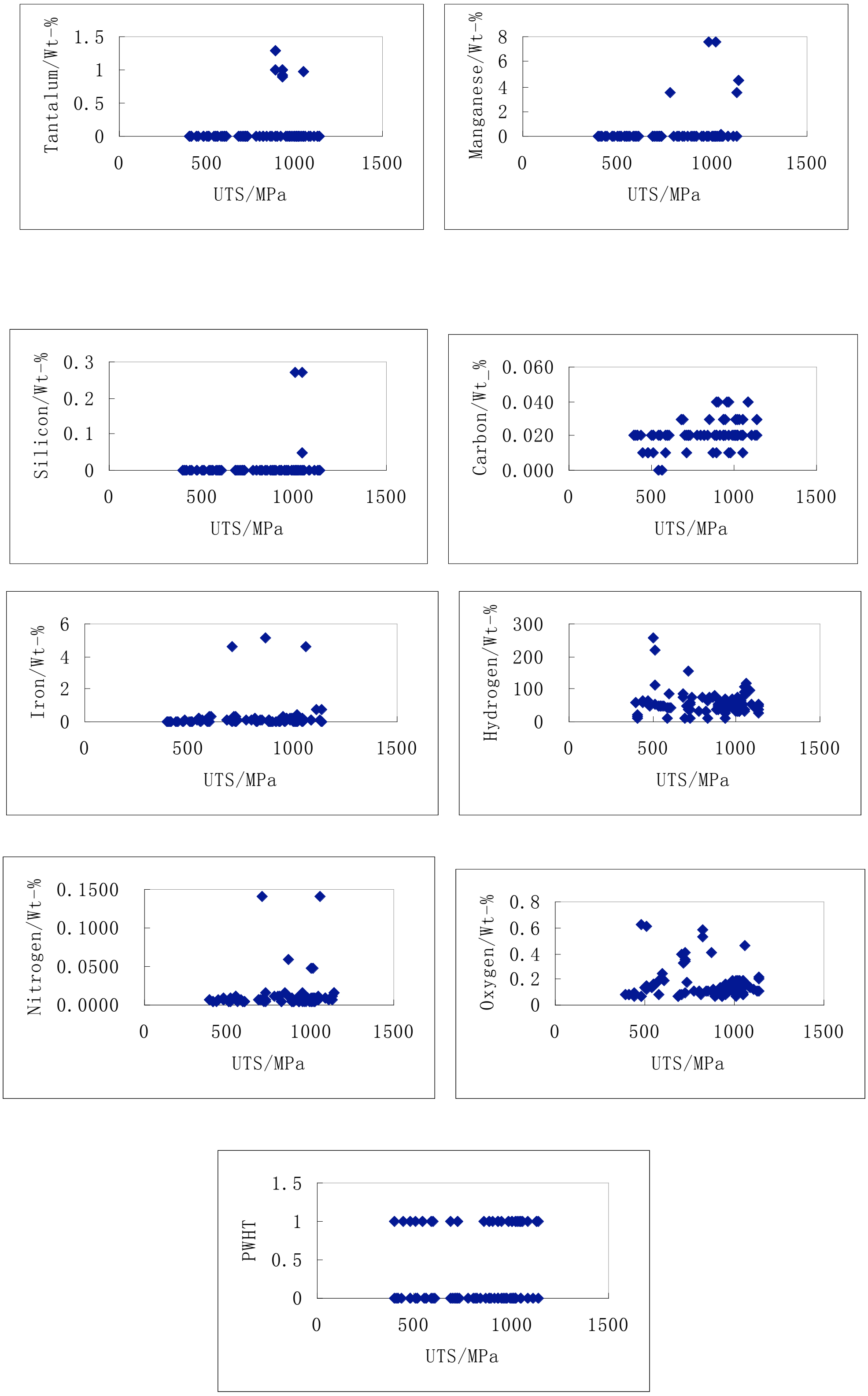

Database distributions