

ENERGY ESTIMATING AND MODELING METHODS

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GENERAL CONSIDERATIONS

THE ENERGY requirements and fuel consumption of HVAC systems have a direct impact on the cost of operating a building and an indirect impact on the environment. This chapter discusses methods for estimating energy use for two purposes: modeling for the design of buildings and HVAC systems and associated design optimization (**forward modeling**); and modeling the energy use of existing buildings for establishing baselines and calculating retrofit savings (**inverse modeling**).

FORWARD AND INVERSE MODELS

A mathematical **model** is a description of the behavior of a system. It is made up of three components (Beck and Arnold 1977):

1. **Input variables** (statisticians call these regressor variables while physicists refer to them as forcing variables), which act on the system. Note that there are two types of such variables: controllable by the experimenter, and such uncontrollable variables as climate.
2. **System structure and parameters/properties**, which provide the necessary physical description of the system (for example, thermal mass or mechanical properties of the elements).
3. **Output** (or response or dependent) variables, which describe the reaction of the system to the input variables. Energy use is often a response variable.

The science of mathematical modeling as applied to physical systems involves determining the third component of a system when the other two components are given or specified. We can broadly differentiate between two distinct categories of modeling, the choice of which is dictated essentially by the objective or purpose behind the investigation (Rabl 1988).

Forward or Classical Approach. The objective is to predict the output variables of a specified model with known structure and known parameters when subject to specified input variables. In order to ensure accuracy of prediction, the models have tended to become increasingly complex, especially with the advent of cheap and powerful computing power. This approach presumes detailed knowledge not only of the various natural phenomena affecting system behavior but also of the magnitude of various interactions (e.g., effective thermal mass, heat and mass transfer coefficients, etc.). The main advantage of this approach is that the system need not be physically built in order to predict its behavior. Thus, this approach

is ideal in the preliminary design and analysis stage and is most often employed as such.

Forward modeling as applied to building energy use begins with a physical description of the building system or component of interest. For example, we define the building geometry, geographical location, physical characteristics (such as wall material and thickness), type of equipment and operating schedules, type of HVAC system, building operating schedules, plant equipment, etc. The peak and average energy use of such a building can then be predicted or simulated by the forward simulation model. The primary benefits of this method are that it is based on sound engineering principles usually taught in colleges and universities and consequently has gained widespread acceptance by the design and professional community. Major government-developed simulation codes, such as BLAST, DOE-2, and EnergyPlus, are based on forward simulation models. [Figure 1](#) is a flow chart that illustrates the ordering of the analysis that is typically performed by a building energy simulation program.

Inverse or Data-Driven Approach. In this case, the input and output variables are known and measured, and the objective is to determine a mathematical description of the system and to estimate the system parameters. In contrast to the forward approach, the inverse approach is relevant to the case when the system has already been built and actual performance data are available for model development and/or identification. Two types of performance data can be used: nonintrusive and intrusive. **Intrusive data** are gathered under conditions of certain predetermined or planned experiments on the system in order to elicit system response under a wider range of system performance than would have occurred under normal system operation. Such performance data allow for more accurate model specification and identification. When constraints on system operation do not permit such tests to be performed, the model must be identified from **nonintrusive data** obtained under normal operation.

The inverse modeling approach often allows identification of system models that are not only simpler to use but that are more accurate predictors of future system performance than forward models. The inverse approach arises in many fields, such as physics, biology, engineering, and economics. Although several monographs, textbooks, and even specialized technical journals are available in this area, the approach has not been widely adopted in energy-related curricula and has yet to diffuse in a significant and pervasive manner (as has the forward approach) into the building professional community.

The preparation of this chapter is assigned to TC 4.7, Energy Calculations.

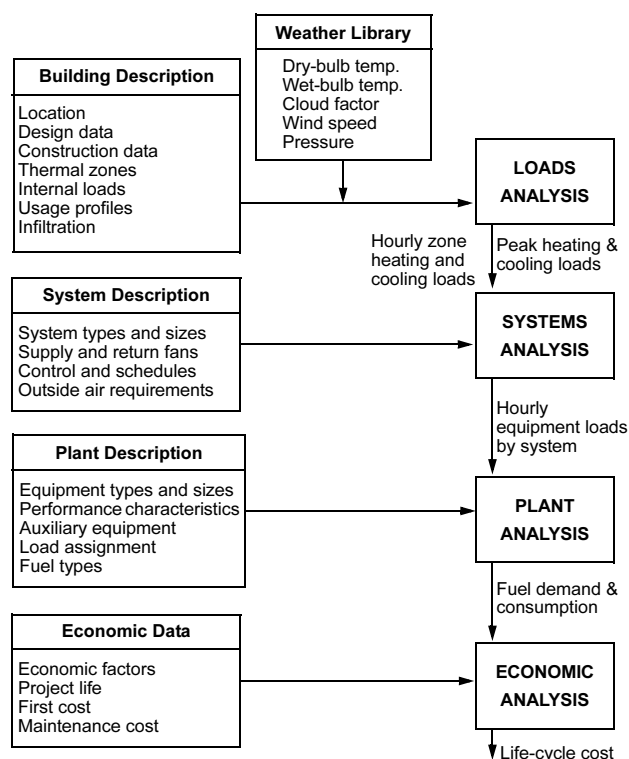


Fig. 1 Flow Chart for Building Energy Simulation Program
(Ayres and Stamper 1995)

CHARACTERISTICS OF MODELS

Forward Models

Although the procedures for estimating energy requirements vary considerably in their degree of complexity, they all have three common elements: the calculation of (1) space load, (2) secondary equipment load, and (3) primary equipment energy requirements. Here, secondary refers to equipment that distributes the heating, cooling, or ventilating medium to conditioned spaces, while primary refers to central plant equipment that converts fuel or electric energy to heating or cooling effect. A major distinction is made between **steady-state** methods (based on degree-days or temperature bins) and **dynamic** methods (e.g., based on transfer functions).

The first step in calculating energy requirements is to determine the **space load**, which is the amount of energy that must be added to or extracted from a space to maintain thermal comfort. The simplest procedures assume that the energy required to maintain comfort is only a function of the outdoor dry-bulb temperature. More detailed methods consider solar effects, internal gains, heat storage in the walls and interiors, and the effects of wind on both building envelope heat transfer and infiltration. [Chapters 28](#) and [29](#) discuss load calculation in detail.

While energy calculations are similar to the heating and cooling load calculations used to size equipment, they are not the same. Energy calculations are based on average use and typical weather conditions rather than on maximum use and worst-case weather. Currently, the most sophisticated procedures are based on hourly profiles for climatic conditions and operational characteristics for a number of typical days of the year or on 8760 h of operation per year.

The second step translates the space load to a **load on the secondary equipment**. This can be a simple estimate of duct or piping losses or gains or a complex hour-by-hour simulation of an air system, such as variable air volume with outdoor-air cooling. This step must include the calculation of all forms of energy required by the

secondary system (i.e., electrical energy to operate fans and/or pumps, as well as energy in the form of heated or chilled water).

The third step calculates the fuel and energy required by the **primary equipment** to meet these loads and the peak demand on the utility system. It considers equipment efficiencies and part-load characteristics. It is often necessary to keep track of the different forms of energy, such as electrical, natural gas, or oil. In some cases, where calculations are required to assure compliance with codes or standards, these energies must be converted to source energy or resource consumed, as opposed to energy delivered to the building boundary.

Often, energy calculations lead to an economic analysis to establish the cost-effectiveness of conservation measures (ASHRAE *Standard* 90.1). Thus, thorough energy analysis provides intermediate data, such as time of energy usage and maximum demand, so that utility charges can be accurately estimated. Although not part of the energy calculations, estimated capital equipment costs should be included in such an analysis.

Complex and often unexpected interactions can occur between the systems or between various modes of heat transfer. For example, radiant heating panels impact the space loads by raising the mean radiant temperature in the space (Howell and Suryanarayana 1990). As a result, the air temperature can be lowered while maintaining comfort. Compared to a conventional heated air system, radiant panels create a greater temperature difference from the inside surface to the outside air. Thus, conduction losses through the walls and roof increase because the inside surface temperatures are greater. At the same time, the heating load due to infiltration or ventilation decreases because of the reduced indoor air to outdoor air temperature difference. The infiltration rate may also decrease because the reduced air temperature difference reduces the stack effect.

Inverse Models

The inverse model has to meet requirements very different from the forward model. The inverse model can only contain a relatively small number of parameters because of the limited and often repetitive information contained in the performance data. (For example, building operation from one day to the next is fairly repetitive.) The inverse model is thus a much simpler model that contains fewer terms representative of aggregated or macroscopic parameters (e.g., overall building heat loss coefficient and time constants). Since the model parameters are deduced from actual building performance, it is much more likely to accurately capture the as-built system performance, thus allowing more accurate prediction of future system behavior under certain specific circumstances. Performance data collection and model formulation need to be appropriately tailored for the specific circumstance, which often requires a higher level of skill and expertise of the user. In general, inverse models are less flexible than forward models in evaluating energy implications of different design and operational alternatives, and so they are not a substitute in this regard.

To better understand the uses of inverse models, consider some of the questions that a building professional may ask about an existing building whose energy consumption is known (Rabl 1988):

- How does the consumption compare with design predictions (and, in case of discrepancies, are they due to anomalous weather, to unintended building operation, to improper operation, or to other causes)?
- How would the consumption change if the thermostat settings, ventilation rates, or indoor lighting levels were changed?
- How much energy could be saved by retrofits to the building shell, changes to air handler operation from CV to VAV, or changes in the various control settings?
- If the retrofits are implemented, can one verify that the savings are due to the retrofit and not to other causes (e.g., the weather)?
- How can one detect faults in HVAC equipment and optimize control and operation?

All the above questions are better addressed by the inverse approach. The forward approach could also be used, for example, by going back to the blueprints of the building and of the HVAC system, and repeating the analysis performed at the design stage while using actual building schedules and operating modes. This, however, is tedious and labor-intensive, and materials and equipment often perform differently under as-built conditions than as specified. Tuning the forward simulation model is often awkward and labor intensive, although it is still an option (as adopted in the calibrated inverse approach).

CHOOSING AN ANALYSIS METHOD

The most important step in selecting an energy analysis method is to match the method capabilities with project requirements. The method must be capable of evaluating all design options with sufficient accuracy to make correct choices. The following factors apply generally (Sonderegger 1985):

- **Accuracy.** The method should be sufficiently accurate to allow correct choices. Because of the many parameters involved in energy estimation, absolutely accurate energy prediction is not possible (Waltz 1992).
- **Sensitivity.** The method should be sensitive to the design options being considered. The difference in energy use between two choices should be accurate.
- **Versatility.** The method should allow the analysis of all options under consideration. When different methods must be used to consider different options, an accurate estimate of the differential energy use cannot be made.
- **Speed and cost.** The total time (gathering data, preparing input, calculations, and analysis of output) to make an analysis should be appropriate to the potential benefits gained. With greater speed, more options can be considered in a given time. The cost of analysis is largely determined by the total time of analysis.
- **Reproducibility.** The method should not allow so many vaguely defined choices that different analysts would get completely different results (Corson 1992).
- **Ease of use.** This impacts both on the economics of analysis (speed) and the reproducibility of results.

ASHRAE *Standard* 140, Method of Test for the Evaluation of Building Energy Analysis Computer Programs, has been developed to identify and diagnose differences in predictions that may possibly be caused by algorithmic differences, modeling limitations, or coding errors.

Selecting Energy Analysis Computer Programs

The selection of a building energy analysis program depends on its application, the number of times it will be used, the experience of the user, and the hardware available to run it. The first criterion is the capability of the program to deal with the application. For example, if the effect of a shading device is to be analyzed on a building that will also be shaded by other buildings part of the time, the capability of analyzing detached shading is an absolute requirement, regardless of any other factors.

Because almost all manual methods are now implemented on a computer, the selection of an energy analysis method is the selection of a computer program. Today, all well-known programs run on microcomputers. However, the cost of the computer facilities and the software itself are typically a small part of running a building energy analysis. The major costs are the cost of learning to use the program and the cost of using it. Major issues that influence the cost of learning a program include (1) complexity of the input procedures, (2) quality of the user's manual, and (3) availability of a good support system to answer questions. As the user becomes more experienced, the cost of learning becomes less important, but the need to obtain and enter a complex set of input data will continue to consume the

time of even an experienced user until such data are readily available in electronic form compatible with simulation programs.

The **complexity of input** is largely influenced by the availability of default values for the input variables. Default values can be used as a simple set of input data when detail is not needed or when the building design is very conventional, but additional complexity can be supplied when needed. Secondary defaults, which can be supplied by the user, are also useful in the same way. Some programs allow the user to specify a level of detail. Then the program requests only the information appropriate to that level of detail, using default values for all others.

The **quality of the output** is another factor to consider. Reports should be easy to read and uncluttered. The titles and headings should be unambiguous. Units should be stated explicitly. The user's manual should explain the meanings of the data presented. Graphic output can be very helpful. In most cases, simple summaries of overall results are the most useful, but very detailed output is needed for certain studies and also for debugging program input during the early stages of an analysis.

Before a final decision is made, manuals for the most suitable programs should be obtained and reviewed, and, if possible, demonstration versions of the programs should be obtained and run. During this last part of the selection process, support from the software supplier should be tested. The availability of training should be considered when choosing a more complex program.

The **availability of weather data** and the availability of a weather data processing subroutine or program are major features of a program. Some programs include subroutine or supplementary programs that allow the user to create a weather file for any site for which weather data is available. Programs that do not have this capability must have weather files for various sites created by the program supplier. In that case, the available weather data and the terms on which the supplier will create new weather data files must be checked.

Auxiliary capabilities, such as economic analysis and design calculations, are a final concern in selecting a program. An economic analysis may include only the ability to calculate annual energy bills from utility rates, or it might extend to calculations or even to life-cycle cost optimization. An integrated program may save time because some input data will have been entered already for other purposes.

The results of computer calculations should be accepted with caution, as the software vendor does not accept responsibility for the correctness of calculations or the use of the program. A manual calculation should be run to develop a good understanding of the underlying physical processes and building behavior. In addition, the user should (1) review the computer program documentation to determine what calculation procedures are used, (2) compare the results with manual calculations and measured data, and (3) conduct sample tests to confirm that the program delivers acceptable results.

Tools for Energy Analysis

The most accurate methods for calculating building energy consumption are the most costly because of their intense computational requirements and the needed expertise on the part of the designer or analyst. Simulation programs that assemble component models into system models and then exercise those models with weather and occupancy data are preferred by experts for determining energy use in buildings. This chapter provides descriptions of methods to model heating and cooling loads, including heat flow through building foundations, and methods to model the performance of secondary and primary HVAC equipment. The chapter continues with information about system-level modeling.

Often, energy consumption at a system or whole-building level must be estimated quickly to study trends, compare systems, or study building effects such as envelope characteristics. For these purposes, simpler methods may be used. Degree-day and bin methods are two

Table 1 Classification of Analysis Methods For Building Energy Use

Method	Forward	Inverse			Comments
		Empirical or Black-Box	Calibrated Simulation	Physical or Gray-Box	
Steady-State Methods					
Simple linear regression (Kissock et al. 1998, Ruch and Claridge 1991)	—	X	—	—	One dependent parameter, one independent parameter. May have slope and y-intercept.
Multiple linear regression (Dhar 1995, Dhar et al. 1998, 1999a,b, Katipamula et al. 1998, Sonderegger 1998)	—	X	—	—	One dependent parameter, multiple independent parameters.
Modified degree-day method	X	—	—	—	Based on fixed reference temperature of 18.3°C.
Variable-base degree-day method, or 3-P change point models (Fels 1986, Reddy et al. 1997, Sonderegger 1998)	X	X	—	X	Variable base reference temperatures.
Change point models: 4-P, 5-P (Fels 1986, Kissock et al. 1998)	—	X	—	X	Uses daily or monthly utility billing data and average period temperatures.
ASHRAE bin method and inverse bin method (Thamilseran and Haberl 1995)	X	X	—	—	Hours in temperature bin times load for that bin.
ASHRAE TC 4.7 modified bin method (Knebel 1983)	X	—	—	—	Modified bin method with cooling load factors.
Multistep parameter identification (Reddy et al. 1999)	—	—	—	X	Uses daily data to determine overall heat loss and ventilation of large buildings.
Dynamic Methods					
Thermal network (Sonderegger 1977, Rabl 1988, Reddy 1989)	X	—	—	X	Uses equivalent thermal parameters (inverse mode).
Response factors (Stephenson and Mitalas 1967, Mitalas and Stephenson 1967, Mitalas 1968, Kusuda 1969)	X	—	—	—	Tabulated or as used in simulation programs.
Fourier analysis (Shurcliff 1984, Subbarao 1988)	X	—	X	X	Frequency domain analysis convertible to time domain.
ARMA model (Subbarao 1986, Rabl 1988, Reddy 1989)	—	—	—	X	Autoregressive Moving Average model.
PSTAR (Subbarao 1988)	X	—	X	X	Combination of ARMA and Fourier series, includes loads in time domain.
Modal analysis (Bacot et al. 1984, Rabl 1988)	X	—	—	X	Building described by diagonalized differential equation using nodes.
Differential equation (Rabl 1988)	—	—	—	X	Analytical linear differential equation.
Computer simulation: DOE-2, BLAST (Norford et al. 1994, Haberl and Bou-Saada 1998, Manke et al. 1996)	X	—	X	—	Hourly simulation programs with system models.
Computer emulation (HVACSIM+, TRNSYS) (Clark 1985, Klein et al. 1994)	X	—	—	—	Subhourly simulation programs.
Artificial neural networks (Kreider and Wang 1991, Kreider and Haberl 1994)	—	X	—	—	Connectionist models.

simpler approaches described in the chapter. Finally, the chapter addresses inverse models in detail.

Table 1 classifies methods for analyzing building energy use as forward or inverse and steady-state or dynamic. The U.S. Department of Energy maintains an up-to-date listing of building energy software with links to other sites that describe energy modeling tools: www.eren.doe.gov/buildings/tools_directory/

COMPONENT MODELING AND LOADS

CALCULATING SPACE SENSIBLE LOADS

Calculating instantaneous space sensible load is a key step in any building energy simulation. The **heat balance method** and the **weighting factor method** are two methods used for these calculations. A third method, the **thermal network method**, while not widely used, shows promise.

The **instantaneous space sensible load** is the rate of heat flow into the space air mass. This quantity, sometimes called the cool-

ing load, differs from heat gain in that heat gain usually contains a radiative component that passes through the air and is absorbed by other bounding surfaces. Instantaneous space sensible load is entirely convective; even loads from internal equipment, lights, and occupants enter the air by convection from the surface of such objects or by convection from room surfaces that have absorbed the radiant component of energy emitted from these sources. However, some adjustment must be made when radiant cooling and heating systems are evaluated because some of the space load is offset directly by radiant transfer without convective transfer to the air mass.

For equilibrium, the instantaneous space sensible load must match the heat removal rate of the conditioning equipment. Any imbalance in these rates changes the energy stored in the air mass. Customarily, however, the thermal mass (heat capacity) of the air itself is ignored in an analysis, so that the air is always assumed to be in thermal equilibrium. Under these assumptions, the instantaneous space sensible load and the rate of heat removal are equal in magnitude and opposite in sign.

The weighting factor method and the heat balance method use conduction transfer functions (or their equivalents) to calculate transmission heat gain or loss. The principal difference is in the methods used to calculate the subsequent internal heat transfers to the room. Experience with both methods has indicated largely the same results, provided the weighting factors are determined for the specific building under analysis.

Heat Balance Method

The heat balance method for calculating net space sensible loads is more fundamental than the weighting factor method. Its development relies on the first law of thermodynamics (conservation of energy) and the principles of matrix algebra. Because it requires fewer assumptions than the weighting factor method, it is also more flexible. However, the heat balance method requires more calculations at each point in the simulation process, using more computer time. The weighting factors used in the weighting factor method are determined with a heat balance procedure. Although not necessary, linearization is commonly used to simplify the radiative transfer formulation.

The heat balance method allows the net instantaneous sensible heating and/or cooling load to be calculated on the space air mass. Generally, a heat balance equation is written for each enclosing surface, plus one equation for room air. This set of equations can then be solved for the unknown surface and air temperatures. Once these temperatures are known, they can be used to calculate the convective heat flow to or from the space air mass. The heat balance method is developed in [Chapter 29](#) for use in design cooling load calculations, so a fuller description is omitted here. However, one fundamental difference is that the heat balance procedure described in [Chapter 29](#) is aimed at obtaining the design cooling load for a fixed zone air temperature. For building energy analysis purposes, it is preferable to know the actual heat extraction rate.

This may be determined by recasting [Equation \(36\) of Chapter 29](#) so that the system heat transfer is determined simultaneously with the zone air temperature. The system heat transfer is the rate at which heat is transferred to the space by the system. Although this can be done by simultaneously modeling the zone and the system (Taylor et al. 1990, 1991), it is convenient to make a simple, piecewise-linear representation of the system known as a control profile. This usually takes the form

$$q_{sysj} = a + bt_{aj} \quad (1)$$

where

q_{sysj} = system heat transfer at time step j , W

a, b = coefficients that apply over a certain range of zone air temperatures

t_{aj} = zone air temperature at time step j , °C

The system heat transfer q_{sysj} may be considered positive when heating is provided to the space and negative when cooling is provided. It is equal in magnitude but opposite in sign to the zone cooling load, as defined in [Chapter 29](#), when the zone air temperature is fixed.

Substituting Equation (1) into [Equation \(36\) of Chapter 29](#) and solving for the zone air temperature,

$$t_{aj} = \frac{a + \sum_{i=1}^N A_i h_{ci} t_{si,j} + \rho c V_{infilj} t_{oj} + \rho c V_{ventj} t_{vj} + q_{c,intj}}{-b + \sum_{i=1}^N A_i h_{ci} + \rho c V_{infilj} + \rho c V_{ventj}} \quad (2)$$

where

t_{aj} = zone air temperature at time step j , °C

N = number of zone surfaces

A_i = area of i th surface, m²

h_{ci} = convection coefficient for i th surface

$t_{si,j}$ = surface temperature for i th surface at time step j , °C

ρ = density, kg/m³

c = specific heat of air, J/(kg · K)

V = volumetric flow rate of air, m³/s

t_{oj} = outdoor air temperature at time step j , °C

t_{vj} = ventilation air temperature at time step j , °C

$q_{c,intj}$ = sum of the convective portions of all internal heat gains at time step j , W

The zone air heat balance equation [Equation (2)] must be solved simultaneously with the interior and exterior surface heat balance equations [[Equations \(35\) and \(34\)](#)] described in [Chapter 29](#). Also, it is necessary to determine the correct temperature range to use the proper set of a and b coefficients. This may be done iteratively. Once the zone air temperature is found, the actual system heat transfer rate may be found directly from Equation (1).

Beyond the treatment of the system heat transfer, there are a few other considerations that may be important in building energy analysis programs. These include simulations over periods as long as a year, treatment of radiant cooling and heating systems, treatment of interzone heat transfer, modeling of convection heat transfer, and modeling of radiation heat transfer.

The heat balance method presented in [Chapter 29](#) assumes the use of a single design day. When utilized in a building energy analysis program, it is most commonly used with a year's worth of design weather data. In this case, the first day of the year is usually simulated several times until a steady-periodic response is obtained. Then, each day is simulated sequentially, and, where needed, historical data for surface temperatures and heat fluxes from the previous day are utilized.

When radiant cooling and heating systems are evaluated, the radiant source should be identified as a room surface. The calculation procedure considers the radiant source in the heat balance analysis. Therefore, the heat balance method is preferred over the weighting factor method for evaluating radiant systems. Strand and Pedersen (1997) have described the implementation of heat-source conduction transfer functions, which may be used for modeling of radiant panels, into a heat balance-based building simulation program.

In principle, the heat balance method described above extends directly to multiple spaces, with heat transfer between zones. In this case, some surface temperatures will appear in the surface heat balance equations for two different zones. In practice, however, the size of the coefficient array required for solving the simultaneous equations becomes prohibitively large, and the solution time excessive. For this reason, many programs solve only one space at a time and assume that the adjacent space temperatures are either the same as the space in question or some assigned, constant value. Other approaches may remove this limitation (Walton 1980).

Relatively simple exterior and interior convection models may be used for design cooling load calculation procedures. However, it may be desirable to use more sophisticated exterior convection models (Cooper and Tree 1973, Fracastoro et al. 1982, Melo and Hammond 1991, Walton 1983, Yazdani and Klems 1993) that incorporate the effects of wind speed, wind direction, surface orientation, etc. Likewise, a number of more detailed interior convection correlations have been published for use in buildings (Alamdari and Hammond 1982, 1983; Altmayer et al. 1983; Bauman et al. 1983; Bohn et al. 1984; Chandra and Kerestecioglu 1984; Khalifa and Marshall 1990; Spitler et al. 1991; Walton 1983).

Also, more detailed models of exterior long-wave radiation transfer [e.g., Cole (1976) and Walton (1983)] and interior long-wave radiation transfer have been implemented in detailed building

simulation programs. See Carroll (1980), Davies (1988), Kamal and Novak (1991), Steinman et al. (1989), and Walton (1980) for further discussion of interior radiation heat transfer models.

Weighting Factor Method

The weighting factor method of calculating instantaneous space sensible load represents a compromise between simpler methods, such as a steady-state calculation, that ignore the ability of building mass to store energy, and more complex methods, such as complete energy balance calculations. With this method, space heat gains at constant space temperature are determined from a physical description of the building, ambient weather conditions, and internal load profiles. Along with the characteristics and availability of heating and cooling systems for the building, space heat gains are used to calculate air temperatures and heat extraction rates. This discussion is in terms of heat gains, cooling loads, and heat extraction rates. Heat losses, heating loads, and heat addition rates are merely different terms for the same quantities, depending on the direction of the heat flow.

The weighting factors represent Z-transfer functions (York and Cappiello 1982, Kerrisk et al. 1981). The Z-transform is a method for solving differential equations with discrete data. Two groups of weighting factors are used: heat gain and air temperature.

Heat gain weighting factors represent transfer functions that relate space cooling load to instantaneous heat gains. A set of weighting factors is calculated for each group of heat sources that differ significantly in (1) the relative amounts of energy appearing as convection to the air versus radiation, and (2) in the distribution of radiant energy intensities on different surfaces.

Air temperature weighting factors represent a transfer function that relates room air temperature to the net energy load of the room. The weighting factors for a particular heat source are determined by introducing a unit pulse of energy from that source into the room's network. The network is a set of equations that represents a heat balance for the room. At each time step (1 h intervals), including the initial introduction, the energy flow to the room air represents the amount of the pulse that becomes a cooling load. Thus, a long sequence of cooling loads can be generated from which the weighting factors are calculated. Similarly, a unit pulse change in room air temperature can be used to produce a sequence of cooling loads.

A two-step process is used to determine the air temperature and heat extraction rate of a room or building zone for a given set of conditions. First, the room air temperature is assumed to be fixed at some reference value. This reference temperature is usually chosen as the average air temperature expected for the room over the simulation period. Instantaneous heat gains are calculated based on this constant air temperature. Various types of heat gains are considered. Some, such as solar energy entering through windows or energy from lighting, people, or equipment, are independent of the reference temperature. Others, such as conduction through walls, depend directly on the reference temperature.

A space sensible cooling load for the room, defined as the rate at which energy must be removed from the room to maintain the reference value of the air temperature, is calculated for each type of instantaneous heat gain. The cooling load generally differs from the instantaneous heat gain because some energy from the heat gain is absorbed by walls or furniture and stored for later release to the air. At an hour θ , the calculation uses present and past values of the instantaneous heat gain ($q_\theta, q_{\theta-1}$), past values of the cooling load ($Q_{\theta-1}, Q_{\theta-2}, \dots$), and the **heat gain weighting factors** ($v_0, v_1, v_2, \dots, w_1, w_2, \dots$) for the type of heat gain under consideration. Thus, for each type of heat gain q_θ , the cooling load Q_θ is calculated as

$$Q_\theta = v_0 q_\theta + v_1 q_{\theta-1} + \dots - w_1 Q_{\theta-1} - w_2 Q_{\theta-2} \dots \quad (3)$$

The heat gain weighting factors are a set of parameters that quantitatively determine how much of the energy entering a room is stored and how rapidly the stored energy is released during later hours. Mathematically, the weighting factors are parameters in a Z-transfer function relating the heat gain to the cooling load.

These weighting factors differ for different heat gain sources because the relative amounts of convective and radiative energy leaving various sources differ and because the distribution of radiative energy can differ. The heat gain weighting factors also differ for different rooms because room construction influences the amount of incoming energy stored by walls or furniture and the rate at which it is released. Sowell (1988) showed the effects of 14 zone design parameters on zone dynamic response. After the first step, the cooling loads from various heat gains are added to give a total cooling load for the room.

In the second step, the total cooling load is used—along with information on the HVAC system attached to the room and a set of **air temperature weighting factors**—to calculate the actual heat extraction rate and air temperature. The actual heat extraction rate differs from the cooling load (1) because, in practice, the air temperature can vary from the reference value used to calculate the cooling load or (2) because of HVAC system characteristics. The deviation of the air temperature t_θ from the reference value at hour θ is calculated as

$$t_\theta = 1/g_0 + [(Q_\theta - ER_\theta) + P_1(Q_{\theta-1} - ER_{\theta-1}) + P_2(Q_{\theta-2} - ER_{\theta-2}) + \dots - g_1 t_{\theta-1} - g_2 t_{\theta-2} - \dots] \quad (4)$$

where ER_θ is the energy removal rate of the HVAC system at hour θ , and $g_0, g_1, g_2, \dots, P_1, P_2, \dots$ are the air temperature weighting factors, which incorporate information about the room, particularly the thermal coupling between the air and the storage capacity of the massive elements.

Tables of values of weighting factors for typical building rooms are presented in the table below. One of the three groups of weighting factors, for light, medium, and heavy construction rooms, can be used to approximate the behavior of any room. Some automated simulation techniques allow weighting factors to be calculated specifically for the building under consideration. This option improves the accuracy of the calculated results, particularly for a building with an unconventional design. McQuiston and Spitler (1992) provided electronic tables of weighting factors for a large number of parametrically defined zones.

Normalized Coefficients of Space Air Transfer Functions

Room Envelope Construction	g_0^*	g_1^*	g_2^*	P_0	P_1
	W/(m ² ·K)			Dimensionless	
Light	+9.54	−9.82	+0.28	1.0	−0.82
Medium	+10.28	−10.73	+0.45	1.0	−0.87
Heavy	+10.50	−11.07	+0.57	1.0	−0.93

Two assumptions are made in the weighting factor method. First, the processes modeled are linear. This assumption is necessary because heat gains from various sources are calculated independently and summed to obtain the overall result (i.e., the superposition principle is used). Therefore, nonlinear processes such as radiation or natural convection must be approximated linearly. This assumption does not represent a significant limitation because these processes can be linearly approximated with sufficient accuracy for most calculations. The second assumption is that system properties influencing the weighting factors are constant (i.e., they are not functions of time). This assumption is necessary because only one set of weighting factors is used during the entire simulation period. This assumption can limit the use of weighting factors in situations where important room properties vary during the calculation. Two examples are the distribution of

solar radiation incident on the interior walls of a room, which can vary hourly, and inside surface heat transfer coefficients.

When the weighting factor method is used, a combined radiative-convective heat transfer coefficient is used as the inside surface heat transfer coefficient. This value is assumed constant even though in a real room (1) the radiant heat transferred from a surface depends on the temperature of other room surfaces (not on the room air temperature) and (2) the combined heat transfer coefficient is not constant. Under these circumstances, an average value of the property must be used to determine the weighting factors. Cumali et al. (1979) have investigated extensions to the weighting factor method to eliminate this limitation.

Thermal Network Methods

Although implementations of the thermal network method vary, they all have in common the discretization of the building into a network of nodes, with interconnecting paths through which energy flows. In many respects, thermal network models may be considered a refinement of the heat balance method. Where the heat balance model generally uses one node for zone air, the thermal network method might use multiple nodes. For each heat transfer element (wall, roof, floor, etc.), the heat balance model generally has one interior surface node and one exterior surface node; the thermal network model may include additional nodes. Heat balance models generally use simple methods for distributing radiation from lights; thermal network models may model the lamp, ballast, and luminaire housing separately. Furthermore, thermal network models depend on a heat balance at each node to determine the node temperature and the energy flow between all connected nodes. The energy flows may include conduction, convection, short-wave radiation, and long-wave radiation.

For any mode of energy flow, a range of techniques may be used to model the energy flow between two nodes. Taking conduction heat transfer as an example, the simplest thermal network model would be a resistance-capacitance network (Sowell 1990). By refining the network discretization, the models become what are commonly thought of as finite difference or finite volume models (Clarke 1985, Lewis and Alexander 1990, Walton 1993).

Thermal network models generally use a set of algebraic and differential equations. In most implementations, the solution procedure is separated from the models so that, in theory, different solvers might be used to perform the simulation. In contrast, most heat balance programs and weighting factor programs interweave the solution technique with the models. Various solution techniques have been used in conjunction with thermal network models. Examples include graph theory combined with Newton-Raphson and predictor-corrector ordinary differential equation integration (Buhl et al. 1990) and the use of Euler explicit integration combined with sparse matrix techniques (Walton 1993).

Of the three zone models discussed, thermal network models are the most flexible and have the greatest potential for high accuracy. As a trade-off, they also require the most computation time, and, in current implementations, they require more user effort to take advantage of the flexibility.

GROUND HEAT TRANSFER

The thermal performance of building foundations, including guidelines for placement of insulation, is described in [Chapter 24](#) of this volume and [Chapter 43 of the ASHRAE Handbook—Applications](#). [Chapter 28](#) provides information needed to calculate transmission heat losses through slab foundations and through basement walls and floors. These calculations are appropriate for design loads but are not intended for estimating annual energy usage. This section provides simplified calculation methods suitable for energy estimates over time periods of arbitrary length.

The thermal performance of building foundations has been largely ignored. It is estimated that in the early 1970s, only 10% of the total energy use of a typical U.S. home was attributed to the heat transfer from its foundation (Labs et al. 1988). Since then, the thermal performance of above-grade building elements has improved significantly, and the contribution of ground-coupled heat transfer to total energy use in a typical U.S. home has increased. Shipp and Broderick (1983) estimated that the heat transfer from an uninsulated basement in Columbus, Ohio, can represent up to 67% of the total building envelope heating load.

Earth-contact heat transfer, rated at 1 to 3 EJ of energy annually in U.S. buildings, has an impact similar to infiltration on annual heating and cooling loads in residential buildings (Claridge 1988a). Adding insulation to building foundations is estimated to save up to 0.5 EJ of annual energy use in the U.S. (Labs et al. 1988).

Simplified Calculation Method for Slab Foundations and for Basements

A simplified design tool for calculating heat loss for slabs and basements is presented by modifying the design tool for slab-on-grade floors developed by Krarti and Chuangchid (1999). The proposed design tool is easy to use and requires straightforward input parameters with continuously variable values, including foundation size, insulation R-values, soil thermal properties, and indoor and outdoor temperatures. The simplified method provides a set of equations that are suitable for estimating the design, seasonal, and annual total heat loss of a slab or a basement as a function of a wide range of variables.

When the indoor temperature of the building is maintained constant, the ground-coupled heat transfer $q(\theta)$ varies with time according to the following equation:

$$q(\theta) = q_{mean} + q_{amp} \sin(\omega\theta + \phi) \quad (5)$$

where

q_{mean} = annual-mean heat loss/gain, W

q_{amp} = heat loss/gain amplitude, W

ϕ = phase lag between total slab heat loss/gain and soil surface temperature, s

ω = annual angular frequency ($\omega = 1.992 \times 10^{-7}$ rad/s)

θ = time, s

Equation (5) is convenient and flexible because it can be used to calculate the foundation heat loss/gain not only at any time but also at design conditions and for any time period (such as a heating season or 1 year). In particular, the design heat loss/gain load Q_{des} for a slab foundation is obtained as follows:

$$q_{des} = q_{mean} + q_{amp} \quad (6)$$

The parameters q_{mean} and q_{amp} are functions of such variables as building dimensions, soil properties, and insulation R-values. Expressions developed by nondimensional analysis allow the calculation of q_{mean} and q_{amp} .

The soil conductivity is normalized to form four parameters— U_o , G , H , and D :

$$U_o = \frac{k_s}{(A/P)_{eff,b}} \quad (7)$$

where

k_s = soil thermal conductivity, W/(m·K)

P = slab perimeter, m

A = slab area, m²

For mean calculations,

$$(A/P)_{eff,b,mean} = [1 + b_{eff}(-0.4 + e^{-H_b})](A/P)_b \quad (8)$$

For annual calculations,

$$(A/P)_{eff, b, amp} = (1 + b_{eff}e^{-H_b})(A/P)_b \quad (9)$$

where

$$H_b = \frac{(A/P)_b}{k_s R_{eq}} \quad (10)$$

$$b_{eff} = \frac{B}{(A/P)_b} \quad (11)$$

B = basement depth, m (0 m for slab)

$$G = k_s R_{eq} \sqrt{\frac{\omega}{\alpha_s}} \quad (12)$$

where

R_{eq} = equivalent thermal resistance for the entire slab, $m^2 \cdot K/W$
 α_s = soil thermal diffusivity, m^2/s

For uniform insulation configurations (placed horizontally beneath the slab floor),

$$R_{eq} = R_f + R_i \quad (13)$$

where

R_f = thermal resistance of the floor, $m^2 \cdot K/W$
 R_i = thermal resistance of insulation, $m^2 \cdot K/W$

For partial insulation configurations (both horizontal and vertical),

$$R_{eq} = \frac{R_f}{\left[1 - \left(\frac{c}{A/P} \frac{R_i}{R_i + R_f}\right)\right]} \quad (14)$$

where c = insulation length of slab, m.

$$H = \frac{(A/P)_{eff, b}}{k_s R_{eq}} \quad (15)$$

$$D = \ln \left[(1 + H) \left(1 + \frac{1}{H} \right)^H \right] \quad (16)$$

The effective heat-transfer coefficients for mean heat flow $U_{eff, mean}$ and heat-flow amplitude $U_{eff, amp}$, $W/m^2 \cdot K$, are

Table 2 Coefficients m and a for Slab-Foundation Heat Transfer Calculations

Insulation Placement	m	a
Uniform—Horizontal	0.40	0.25
Partial—Horizontal	0.34	0.20
Vertical	0.28	0.13

$$U_{eff, mean} = m U_o D \quad (17)$$

$$U_{eff, amp} = a U_o D^{0.16} G^{-0.6} \quad (18)$$

where the dimensionless coefficients m and a depend on the insulation placement configurations and are provided in [Table 2](#).

The annual-mean slab foundation and basement heat loss/gain can now be defined as

$$q_{mean} = U_{eff, mean} A (t_a - t_r) \quad (19)$$

where

t_a = annual average ambient dry-bulb temperature, $^{\circ}C$
 t_r = annual average indoor dry-bulb temperature, $^{\circ}C$

The heat loss/gain amplitude for slab foundations and basements is

$$Q_a = U_{eff, a} A t_{amp} \quad (20)$$

where t_{amp} = annual amplitude ambient temperature, K.

This simplified model for slab-foundation and basement heat flows provides accurate predictions when A/P is larger than 0.5 m. To illustrate the use of the simplified models, two examples are presented: one for a slab-on-grade floor for a building insulated with uniform horizontal insulation, and one for a basement structure insulated with uniform insulation.

Example 1. Calculation for Slab Foundations. Determine the annual mean and annual amplitude of total slab heat loss for the slab foundation illustrated in [Figure 2](#). The building is located in Denver, Colorado.

Solution:

Step 1. Provide the required input data.

Dimensions

Slab width = 10.0 m

Slab length = 15.0 m

Ratio of slab area to slab perimeter, $A/P = 3.0$ m

102 mm thick reinforced concrete slab, thermal resistance $R_f = 0.5 \text{ m}^2 \cdot K/W$

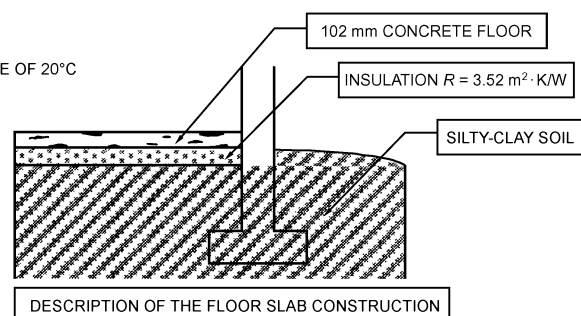
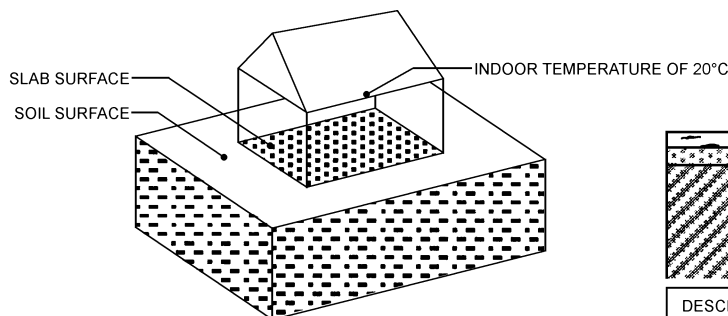


Fig. 2 Slab Foundation for Example 1

Soil Thermal Properties

Soil thermal conductivity $k_s = 1.21 \text{ W/m}\cdot\text{K}$
 Soil density $\rho = 700 \text{ kg/m}^3$
 Soil thermal diffusivity $\alpha_s = 5.975 \times 10^{-7} \text{ m}^2/\text{s}$

Insulation

Uniform insulation R-value $R_i = 3.52 \text{ m}^2\cdot\text{K/W}$

Temperatures

Indoor temperature $t_r = 20^\circ\text{C}$
 Annual average ambient temperature $t_a = 6.3^\circ\text{C}$
 Annual amplitude ambient temperature $t_{amp} = 20 \text{ K}$
 Annual angular frequency $\omega = 1.992 \times 10^{-7} \text{ rad/s}$

Step 2. Calculate q_{mean} and q_{amp} values.

The various normalized parameters are first calculated using Equations (7) through (18). Then, the annual mean and amplitude of the foundation slab heat loss/gain are determined using Equations (19) and (20).

$$U_o = \frac{k_s}{(A/P)} = \frac{1.21}{3.0} = 0.4033$$

$$H = \frac{(A/P)}{k_s R_{eq}} = \frac{3.0}{1.21(0.5 + 3.52)} = 0.6168$$

$$D = \ln \left[\left(1 + H \right) \left(1 + \frac{1}{H} \right)^H \right] = 1.0748$$

$$G = k_s R_{eq} \sqrt{\frac{\omega}{\alpha_s}} = 1.21(0.5 + 3.52) \sqrt{\frac{1.992 \times 10^{-7}}{5.975 \times 10^{-7}}} = 2.8086$$

Therefore,

$$q_{mean} = U_{eff, mean} A(t_r - t_a) = 0.4 \times 0.4033 \times 1.0748 \times 150 \times (20 - 6.3) = 356 \text{ W}$$

and

$$q_{amp} = U_{eff, amp} A t_{amp} = 0.25 \times 0.4033 \times 1.0748^{0.16} \times 2.8086^{-0.6} \times 150 \times 20 = 165 \text{ W}$$

Example 2. Calculation for Basements. Determine the annual mean and annual amplitude of total basement heat loss for a building located in Denver, Colorado.

Solution:**Step 1. Provide the required input data.****Dimensions**

Basement width = 10.0 m
 Basement length = 15.0 m
 Basement wall height $B = 1.5 \text{ m}$
 Basement slab and wall total area = 225.0 m^2
 Ratio of slab and wall area to slab and wall perimeter,
 $(A/P)_b = 3.629 \text{ m}$
 102 mm thick reinforced concrete slab, thermal resistance
 $R_f = 0.5 \text{ m}^2\cdot\text{K/W}$

Soil Thermal Properties

Soil thermal conductivity $k_s = 1.21 \text{ W/m}\cdot\text{K}$
 Soil thermal diffusivity $\alpha_s = 4.47 \times 10^{-7} \text{ m}^2/\text{s}$

Insulation

Uniform insulation R-value $R_i = 1.152 \text{ m}^2\cdot\text{K/W}$

Temperatures

Indoor temperature, $t_r = 22^\circ\text{C}$
 Annual average ambient temperature, $t_a = 10^\circ\text{C}$
 Annual amplitude ambient temperature, $t_{amp} = 12.7 \text{ K}$
 Annual angular frequency, $\omega = 1.992 \times 10^{-7} \text{ rad/s}$

Step 2. Calculate q_{mean} and q_{amp} values.

The normalized parameters are first calculated using Equations (7) through (18). Then the annual mean and amplitude of the basement heat loss are determined using Equations (19) and (20).

$$H_b = \frac{(A/P)_b}{k_s R_{eq}} = \frac{3.629}{1.21(0.5 + 1.152)} = 1.8155$$

$$b_{eff} = \frac{B}{(A/P)_b} = \frac{1.5}{3.629} = 0.4133$$

$$(A/P)_{eff, b, mean} = [1 + 0.4133(-0.4 + e^{-1.8155})] \times 3.629 = 3.2731$$

$$(A/P)_{eff, b, amp} = [1 + 0.4133 e^{-1.8155}] \times 3.629 = 3.8731$$

$$U_{o, mean} = \frac{k_s}{(A/P)_{eff, b, mean}} = \frac{1.21}{3.2731} = 0.3697$$

$$U_{o, amp} = \frac{k_s}{(A/P)_{eff, b, amp}} = \frac{1.21}{3.8731} = 0.3124$$

$$H_{mean} = \frac{(A/P)_{eff, b, mean}}{k_s R_{eq}} = \frac{3.2731}{1.21(0.5 + 1.152)} = 1.6374$$

$$H_{amp} = \frac{(A/P)_{eff, b, amp}}{k_s R_{eq}} = \frac{3.8731}{1.21(0.5 + 1.152)} = 1.9376$$

$$D_{mean} = \ln \left[\left(1 + H_{mean} \right) \left(1 + \frac{1}{H_{mean}} \right)^{H_{mean}} \right] = 1.7503$$

$$D_{amp} = \ln \left[\left(1 + H_{amp} \right) \left(1 + \frac{1}{H_{amp}} \right)^{H_{amp}} \right] = 1.8839$$

$$G = k_s R_{eq} \sqrt{\frac{\omega}{\alpha_s}} = 1.21(0.5 + 1.152) \sqrt{\frac{1.992 \times 10^{-7}}{4.47 \times 10^{-7}}} = 1.3344$$

Therefore,

$$q_{mean} = U_{eff, mean} A(t_a - t_r) = 0.4 \times 0.3697 \times 1.7503 \times 225 \times (22 - 10) = 699 \text{ W}$$

and

$$q_{amp} = U_{eff, amp} A t_{amp} = 0.25 \times 0.3124 \times 1.8839^{0.16} \times 1.3344^{-0.6} \times 225 \times 12.7 = 208 \text{ W}$$

Table 3 compares results of the simplified method presented here and the more exact interzone temperature profile estimation (ITPE) (Krarti 1994a, 1994b; Krarti et al. 1988a, 1988b).

Table 3 Example 2 Heat Loss per Unit Area for the Simplified and ITPE Methods

Method	Mean (q_{mean}), W	Amplitude (q_{amp}), W
Simplified	699	208
ITPE solution	658	212

SECONDARY SYSTEM COMPONENTS

Secondary HVAC systems generally include all elements of the overall building energy system between a central heating and cooling plant and the building zones. The precise definition depends heavily on the building design. A secondary system typically includes air-handling equipment, air distribution systems with the

associated ductwork, dampers, fans, and heating, cooling, and humidity conditioning equipment. Secondary systems also include the liquid distribution systems between the central plant and the zone and air-handling equipment, including piping, valves, and pumps.

While the exact design of secondary systems varies dramatically among buildings, they are composed of a relatively small set of generic HVAC components. These components include distribution components (e.g., pumps/fans, pipes/ducts, valves/dampers, headers/plenums, fittings) and heat and mass transfer components (e.g., heating coils, cooling and dehumidifying coils, liquid heat exchangers, air heat exchangers, evaporative coolers, steam injectors). Most secondary systems can be described by simply connecting these components to form the complete system.

Energy estimation through computer simulation often mimics the modular construction of secondary systems by using modular simulation elements [e.g. the ASHRAE *HVAC 2 Toolkit* (Brandemuehl 1993, Brandemuehl and Gabel 1994), the simulation program TRNSYS (Klein et al. 1994), and Annex 10 activities of the International Energy Agency]. To the extent that the secondary system consumes energy and transfers energy between the building and central plant, an energy analysis can be performed by characterizing the energy consumption of the individual components and the energy transferred among system components. In fact, few of the secondary components consume energy directly, except fans, pumps, furnaces, direct expansion air-conditioning package units with gas-fired heaters, and inline heaters. In this chapter, secondary components are divided into two categories: distribution components and heat and mass transfer components.

Fans, Pumps, and Distribution Systems

The distribution system of an HVAC system affects energy consumption in two ways. First, fans and pumps consume electrical energy directly, based on the flow and pressures under which the device operates. Ducts and dampers, or pipes and valves, and the system control strategies affect the flow and pressures at the fan or pump. Second, thermal energy is often transferred to (or from) the fluid due to heat transfer through pipes and ducts and due to the electrical input to fans and pumps. The analysis of system components should, therefore, account for both direct electrical energy consumption and thermal energy transfer.

Fan and pump performance are discussed in [Chapters 18](#) and [39](#) of the *ASHRAE Handbook—Systems and Equipment*. In addition, [Chapter 34](#) of this handbook covers pressure loss calculations for airflow in ducts and duct fittings. [Chapter 35](#) presents a similar discussion for fluid flow in pipes. While these chapters do not specifically focus on energy estimation, energy use is governed by the same performance characteristics and engineering relationships. Strictly speaking, performance calculations of the fan and air distribution systems in a building require a detailed pressure balance on the entire network. For example, in an air distribution system, the airflow through the fan depends on its physical characteristics, the operating speed, and the pressure differential across the fan. The pressure drop through the duct system depends on the duct design, the position of all dampers, and the airflow through the fan. The interaction between the fan and duct system results in a set of coupled, nonlinear algebraic equations. Models and subroutines for performing these calculations are available in the ASHRAE *HVAC 2 Toolkit* (Brandemuehl 1993).

While a detailed analysis of a distribution system requires flow and pressure balancing among the components, nearly all commercially available energy analysis methods approximate the effect of the interactions with part-load performance curves. This procedure eliminates the need to calculate pressure drop through the distribution system at off-design conditions. The part-load curves are often expressed in terms of a **power input ratio** as a function of the part-load ratio, defined as the ratio of part-load flow to design flow:

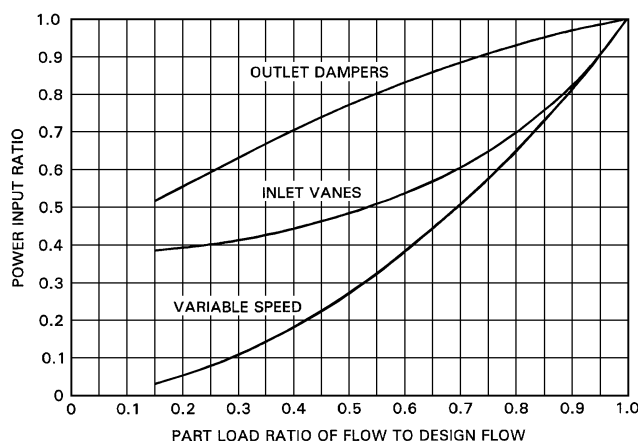


Fig. 3 Part-Load Curves for Typical Fan Operating Strategies

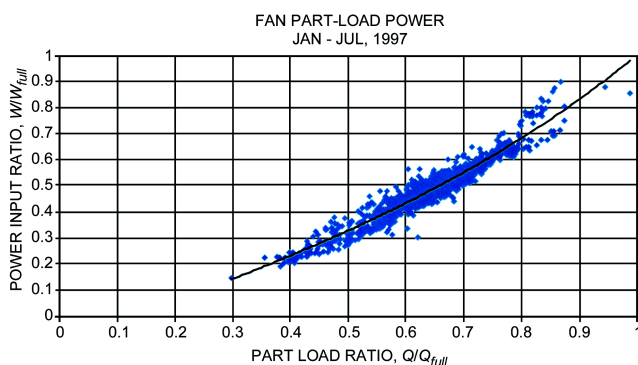


Fig. 4 Fan Part-Load Curve Obtained from Measured Field Data under ASHRAE 823-RP

$$\text{PIR} = \frac{W}{W_{\text{full}}} = f_{\text{plr}}\left(\frac{Q}{Q_{\text{full}}}\right) \quad (21)$$

where

PIR = power input ratio

W = fan motor power at part load, W

W_{full} = fan motor power at full load or design, W

Q = fan airflow rate at part load, m³/s

Q_{full} = fan airflow rate at full load or design, m³/s

f_{plr} = regression function, typically polynomial

The exact shape of the part-load curve depends on the effect of flow control on the pressure and fan efficiency and may be calculated using a detailed analysis or measured field data. [Figure 3](#) shows the relationship for three typical fan control strategies, as represented in a simulation program (York and Cappiello 1982). Within the simulation program, the curves are represented by polynomial regression equations. Models and subroutines for performing these calculations are also available in the ASHRAE *HVAC 2 Toolkit* (Brandemuehl 1993).

[Figure 4](#) shows an example of a similar curve for the part-load operation of a fan system in a monitored building (Brandemuehl and Bradford 1999). In this particular case, the fan system represents ten separate air handlers, each with supply and return fans, operating with variable-speed fan control to maintain a set duct static pressure. Notice that, although the shape of the curve is similar to the variable-speed curve of [Figure 3](#), the measured data for this particular system exhibit a more linear relationship between power and flow.

Heat transferred to the airstream due to fan operation increases the temperature of the air. While the shaft power of the fan has a direct effect on the heat transfer, motor inefficiencies also heat the air if the motor is mounted inside the airstream. For pumps, this contribution is typically assumed to be zero.

The following equation provides a convenient and general model to calculate the heat transferred to the fluid:

$$q_{fluid} = [\eta_m + (1 - \eta_m)f_{m,loss}]W \quad (22)$$

where

- q_{fluid} = heat transferred to the fluid, W
- $f_{m,loss}$ = fraction of the motor heat loss transferred to the fluid stream, dimensionless (= 1 if fan mounted in airstream, = 0 if fan mounted outside airstream)
- W = fan motor power, W
- η_m = motor efficiency

Heat and Mass Transfer Components

Secondary HVAC systems comprise such heat and mass transfer components as steam-based air-heating coils, chilled water cooling and dehumidifying coils, shell-and-tube liquid heat exchangers, air-to-air heat exchangers, evaporative coolers, and steam injectors. While these components do not consume energy directly, their thermal performance dictates the interactions between the building loads and the energy-consuming primary components (e.g., chillers, boilers). In particular, the performance of the secondary components determines the entering fluid conditions for primary components, which in turn determine the energy efficiencies of the primary equipment. Accurate energy calculations cannot be performed without appropriate models of the system heat and mass transfer components.

For example, the load on a chiller is typically described as the sum of zone sensible and latent loads, plus any heat gain from ducts, plenums, fans, pumps, and piping. However, the energy consumption of the chiller is determined not only by the load but also by the return chilled water temperature and flow rate. The return water condition is determined by the cooling coil performance and the part-load operating strategy of the air and water distribution system. The cooling coil might typically be controlled to maintain a constant leaving air temperature by modulating the water flow through the coil. In such a scenario, the cooling coil model must be able to calculate the leaving air humidity, leaving water temperature, and leaving water flow rate given the cooling coil design characteristics, entering air temperature and humidity, entering airflow, and entering water temperature.

Virtually all building energy simulation programs include, and require, models of heat and mass transfer components. In general, these models are relatively simple. While a coil designer might use a detailed tube-by-tube analysis of conduction and convection heat transfer and condensation on fin surfaces to develop an optimal combination of fin and tube geometry, an energy analyst is more interested in determining the changes in leaving fluid states as operating conditions vary during the year. In addition, the energy analyst is likely to have limited design data on the equipment and, therefore, requires a model with very few parameters that depend on equipment geometry and detailed design characteristics.

A typical approach to modeling heat and mass transfer components for energy calculations is based on an **effectiveness-NTU heat exchanger model** (Kays and London 1984). The effectiveness-NTU model is described in most heat transfer textbooks and is briefly discussed in [Chapter 3](#). It is particularly appropriate for describing the leaving fluid conditions when the entering fluid conditions and equipment design characteristics are known. In addition, this model requires only a single parameter to describe the characteristics of the exchanger—the overall transfer coefficient UA —which can be determined from limited design performance data.

Because the classical effectiveness methods were developed for sensible heat exchangers, they are used to perform energy calculations for a variety of sensible heat exchangers in HVAC systems. For typical finned-tube air-heating coils, the crossflow configuration with both fluid streams unmixed is most appropriate. The same configuration typically applies to air-to-air heat exchangers. For liquid-to-liquid exchangers, tube-in-tube equipment can be modeled as parallel or counterflow, depending on flow directions; and shell-and-tube equipment can be modeled as either counter- or crossflow, depending on the extent of baffling and the number of tube passes.

The energy analyst must determine the UA to describe the operations of a specific heat exchanger. There are typically two approaches to determine this important parameter: direct calculation and from manufacturers' data. Given detailed information about the materials, geometry, and construction of the heat exchanger, it is possible to apply fundamental heat transfer principles to calculate the overall heat transfer coefficient. An alternative to direct calculation, and the method most appropriate for energy estimation, is to use manufacturers' performance data or direct measurements of installed performance. In reporting the design performance of a heat exchanger, a manufacturer typically gives the rate of heat transfer under various operating conditions, with the operating conditions described in terms of entering fluid flow rates and temperatures. The effectiveness and UA can be calculated from the given heat transfer rate and entering fluid conditions.

Example 3. An energy analyst seeks to perform an evaluation of a hot water heating system that includes a hot water heating coil. The energy analysis program uses an effectiveness-NTU model of the coil and requires the UA of the coil as an input parameter. While detailed information on the coil geometry and heat transfer surfaces is not available, the manufacturer states that the 1-row hot water heating coil will deliver 240 kW of heat under the following design conditions:

Design Performance

- Entering water temperature $t_{hi} = 80^\circ\text{C}$
- Water mass flow rate = 5.0 kg/s
- Entering air temperature $t_{ci} = 20^\circ\text{C}$
- Air mass flow rate = 8.0 kg/s
- Design heat transfer $q = 240 \text{ kW}$

Solution: The solution proceeds by first determining the heat exchanger UA from the design data, and then using the UA to predict performance at the off-design conditions. The effectiveness-NTU relationships are used for both steps. The key assumption is that the UA is constant for both operating conditions. This example uses the nomenclature as described in [Chapter 3](#) in the section on Overall Heat Transfer.

- a) An examination of the flow rates and fluid specific heats allows calculation of the capacity rates C_h and C_c at design conditions and the capacity rate ratio Z .

$$C_h = (\dot{m}c_p)_h = (5.0)(4.195) = 20.97 \text{ kW/K}$$

$$C_c = (\dot{m}c_p)_c = (8.0)(1.007) = 8.05 \text{ kW/K}$$

$$C_{max} = C_h \quad C_{min} = C_c$$

$$Z = \frac{C_{min}}{C_{max}} = 0.384$$

- b) The effectiveness can be directly calculated from the heat transfer definition.

$$\varepsilon = \frac{(t_{co} - t_{ci})}{(t_{hi} - t_{ci})} = \frac{q/C_c}{(t_{hi} - t_{ci})} = \frac{240/8.05}{(80 - 20)} = 0.497$$

- c) The effectiveness-NTU relationships for a crossflow heat exchanger with both fluids unmixed allows calculation of the effectiveness in terms of the capacity rate ratio Z and the NTU [the relationships are available from most heat transfer textbooks and specifically can be found in Kays and London (1984)].

Given the effectiveness and capacity rate ratio, the NTU can be determined to be $NTU = 0.804$.

- d) The heat transfer UA is then determined from the definition of the NTU.

$$UA = C_{min}NTU = (8.05)(0.804) = 6.47 \text{ kW/K}$$

Application to Cooling and Dehumidifying Coils

The analysis of air-cooling and dehumidifying coils requires coupled, nonlinear heat and mass transfer relationships. These relationships form the basis for all HVAC components with moisture transfer, including cooling coils, cooling towers, air washers, and evaporative coolers. While the complex heat and mass transfer theory that is presented in many textbooks is often required for cooling coil design, simpler models based on effectiveness concepts are usually more appropriate for energy estimation. For example, the bypass factor is a form of effectiveness in the approach of the leaving air temperature to the apparatus dew-point, or coil surface, temperature.

While the effectiveness-NTU method is typically developed and applied in the analysis of sensible heat exchangers, it can also be used to analyze other types of exchangers such as cooling and dehumidifying coils that couple heat and mass transfer. By redefining the state variables, the capacity rates, and the overall exchange coefficient of these enthalpy exchangers, the effectiveness concept may be used to calculate heat transfer rates and leaving fluid states. For sensible heat exchangers, the state variable is temperature, the capacity is the product of mass flow and fluid specific heat, and the overall transfer coefficient is the conventional overall heat transfer coefficient. For cooling and dehumidifying coils, the state variable becomes moist air enthalpy, the capacity has units of mass flow, and the overall heat transfer coefficient is modified to reflect enthalpy exchange. This approach forms the basis for models by Threlkeld (1970), Elmahdy and Mitalas (1977), Braun (1988), and Brandemuehl (1993). The same principles also underlie the coil model described in [Chapter 21 of the ASHRAE Handbook—Systems and Equipment](#).

The effectiveness model is based on the observation that, for a given set of entering air and liquid conditions, the heat and mass transfer are bounded by thermodynamic maximum values. [Figure 5](#) shows the limits for leaving air states on a psychrometric chart. Specifically, the leaving chilled water temperature cannot be warmer than the entering air temperature and the leaving air temperature and humidity cannot be lower than the conditions of saturated moist air at the temperature of the entering chilled water.

[Figure 5](#) also shows that the performance of a cooling coil requires the evaluation of two different effectivenesses to identify the leaving air temperature and humidity. An overall effectiveness can be used to describe the approach of the leaving air enthalpy to the minimum possible value. An air-side effectiveness, related to the coil bypass factor, describes the approach of the leaving air temperature to the effective wet coil surface temperature.

The effectiveness analysis is accomplished for wet coils by establishing a common state variable for both the moist air and liquid streams. As implied by the lower limit of the entering chilled water temperature, this common state variable is the moist air enthalpy. In other words, all liquid and coil temperatures are transformed to the enthalpy of saturated moist air at the liquid or coil temperature. Changes in liquid temperature can similarly be expressed in terms of changes in saturated moist air enthalpy through a saturation specific heat $c_{p,sat}$ defined by the following:

$$c_{p,sat} = \frac{\Delta h_{l,sat}}{\Delta T_l} \quad (23)$$

Using the definition of Equation (23), the basic effectiveness relationships discussed in [Chapter 3](#) can be written as

$$q = C_a(h_{a,ent} - h_{a,lvg}) = C_l(h_{l,sat,lvg} - h_{l,sat,ent}) \quad (24)$$

$$q = \varepsilon C_{min}(h_{a,ent} - h_{l,sat,ent}) \quad (25)$$

$$C_a = \dot{m}_a \quad (26)$$

$$C_l = \frac{(\dot{m}c_p)_l}{c_{p,sat}} \quad (27)$$

$$C_{min} = \min(C_a, C_l) \quad (28)$$

where

q = heat transfer from air to water, kW

C = fluid capacity, kg/s

$\dot{m}_a$ = dry air mass flow rate, kg/s

$\dot{m}_l$ = liquid mass flow rate, kg/s

$c_{p,l}$ = liquid specific heat, kJ/(kg·K)

$c_{p,sat}$ = saturation specific heat, defined by Equation (23), kJ/(kg·K)

h_a = enthalpy of moist air, kJ/kg

$h_{l,sat}$ = enthalpy of saturated moist air at the temperature of the liquid, kJ/kg

The cooling coil effectiveness of Equation (25) is defined, then, as the ratio of moist air enthalpies in [Figure 5](#). As in the case of sensible heat exchangers, the effectiveness is also a function of the physical coil characteristics and can be obtained by modeling the coil as a counterflow heat exchanger. However, since the heat transfer calculations are performed based on enthalpies, the overall transfer coefficient must be based on enthalpy potential rather than temperature potential. The enthalpy-based heat transfer coefficient UA_h is related to the conventional temperature-based coefficient by the specific heat:

$$q = UA\Delta t = UA_h\Delta h$$

$$UA_h = \frac{UA\Delta t}{\Delta h} = \frac{UA}{c_p} \quad (29)$$

A similar analysis can be performed to evaluate the air-side effectiveness, which identifies the leaving air temperature. While the overall enthalpy-based effectiveness is based on an overall heat transfer coefficient between the chilled water and the air, the air-side effectiveness is based on a heat transfer coefficient between the coil surface and the air.

As with sensible heat exchangers, the overall heat transfer coefficients UA can be determined either from direct calculation from coil properties or from manufacturers' performance data. While a sensible heat exchanger is modeled with a single effectiveness and

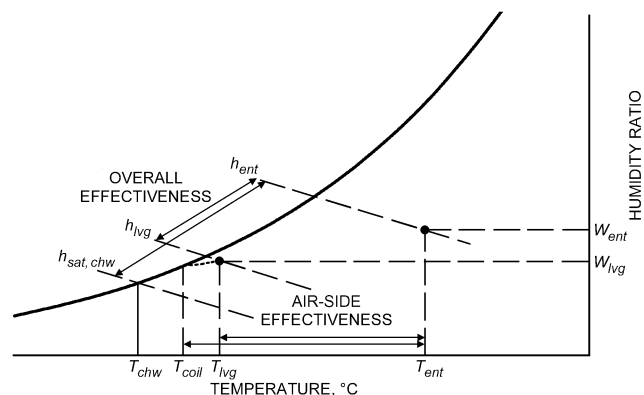


Fig. 5 Psychrometric Schematic of Cooling Coil Processes

can be described by a single parameter UA , a wet cooling and dehumidifying coil requires two parameters to describe the two effectivenesses shown in Figure 5. These two parameters are the internal and external UAs —one describes the heat transfer between the chilled water and the air-side surface through the pipe wall and the other between the surface and the moist air. These two parameters can be determined from the sensible and latent capacity of a cooling coil at a single rating condition. A significant advantage of the effectiveness-NTU method is that the component can be described with as little as one measured data point or one manufacturer's design calculation.

PRIMARY SYSTEM COMPONENTS

Primary HVAC systems consume energy and deliver heating and cooling to a building, usually through secondary systems. Primary equipment generally includes chillers, boilers, cooling towers, cogeneration equipment, and plant-level thermal storage equipment. In particular, primary equipment generally represents the major energy-consuming equipment of a building, so accurate characterization of building energy use relies on accurate modeling of primary equipment energy consumption.

Modeling Strategies

The energy consumption characteristics of primary equipment generally depend on equipment design, load conditions, environmental conditions, and equipment control strategies. For example, chiller performance depends on the basic equipment design features (e.g., heat exchange surfaces, compressor design), the temperatures and flow through the condenser and evaporator, and the methods for controlling the chiller at different loads and operating conditions (e.g., inlet guide vane control on centrifugal chillers to maintain leaving chilled water temperature set point). In general, these variables that dictate energy consumption vary constantly and require calculations on an hourly basis.

Regression Models. While many secondary components (e.g., heat exchangers, valves) are readily described by fundamental engineering principles, the complex nature of most primary equipment has discouraged the use of first-principle models for energy calculations. Instead, the energy consumption characteristics of primary equipment have traditionally been modeled using simple equations developed by regression analysis of manufacturers' published design data. Because published data are often available only for full-load design conditions, additional correction functions are used to correct the full-load data to part-load conditions. The functional form of the regression equations and correction functions takes many forms, including exponentials, Fourier series, and, most of the time, second- or third-order polynomials. The selection of an appropriate functional form depends on the behavior of the equipment. In some cases, energy consumption is calculated using direct interpolation from tables of data. However, this method often requires excessive data input and computer memory.

The typical approach to modeling primary equipment in energy simulation programs is to assume the following functional form for equipment power consumption:

$$P = \text{PIR} \times \text{Load} \quad (30)$$

$$\text{PIR} = \text{PIR}_{\text{nom}} f_1(t_a, t_b, \dots) f_2(\text{PLR})$$

$$C_{\text{avail}} = C_{\text{nom}} f_3(t_a, t_b, \dots) \quad (31)$$

$$\text{PLR} = \frac{\text{Load}}{C_{\text{avail}}}$$

where

P = equipment power, kW
 PIR = energy input ratio

PIR_{nom} = energy input ratio under nominal full-load conditions

Load = power delivered to the load, kW

C_{avail} = available equipment capacity, kW

C_{nom} = nominal equipment capacity, kW

f_1 = function relating full-load power at off-design conditions ($t_a, t_b, \dots$) to full-load power at design conditions

f_2 = fraction full-load power function, relating part-load power to full-load power

f_3 = function relating available capacity at off-design conditions ($t_a, t_b, \dots$) to nominal capacity

t_a, t_b = various operating temperatures that affect power

PLR = part-load ratio

The part-load ratio is defined as the ratio of the load to the available equipment capacity at given off-design operating conditions. Like the power, the available, or full-load, capacity will be a function of operating conditions.

The particular forms of the off-design functions f_1 and f_3 depend on the specific type of primary equipment. For example, for fossil-fuel boilers, full-load capacity and power (or fuel use) can be affected by the thermal losses to ambient temperature. However, these off-design functions are typically considered to be unity in most building simulation programs. For chillers, both capacity and power are affected by the condenser and evaporator temperatures. These two temperatures are often characterized in terms of their secondary fluids. For direct expansion air-cooled chillers, the operating temperatures are typically the wet-bulb temperature of the air entering the evaporator and the dry-bulb temperature of the air entering the condenser. For liquid chillers, the temperatures are usually the leaving chilled water temperature and the entering condenser water temperature.

As an example, consider the performance of a direct expansion (DX) packaged single-zone rooftop unit. The nominal rated performance of these units is typically given for an outdoor air temperature of 35°C and evaporator entering coil conditions of 26.7°C dry-bulb temperature and 19.4°C wet-bulb temperature. However, the performance changes as the outdoor temperature and entering coil conditions vary. To account for these effects, the DOE-2.1E simulation program expresses the off-design functions f_1 and f_3 with biquadratic functions of the outdoor dry-bulb temperature and the coil entering wet-bulb temperature.

$$f_1(t_{\text{wb,ent}}, t_{\text{oa}}) = a_0 + a_1 t_{\text{wb,ent}} + a_2 t_{\text{wb,ent}}^2 + a_3 t_{\text{oa}} + a_4 t_{\text{oa}}^2 + a_5 t_{\text{wb,ent}} t_{\text{oa}} \quad (32)$$

$$f_3(t_{\text{wb,ent}}, t_{\text{oa}}) = c_0 + c_1 t_{\text{wb,ent}} + c_2 t_{\text{wb,ent}}^2 + c_3 t_{\text{oa}} + c_4 t_{\text{oa}}^2 + c_5 t_{\text{wb,ent}} t_{\text{oa}} \quad (33)$$

The constants in Equations (32) and (33) are given in Table 4.

The fraction full-load power function f_2 represents the change in equipment efficiency at part-load conditions and depends heavily on the control strategies used to match load and capacity. Figure 6 shows several possible shapes of these functional relationships. (Notice that these curves are similar to the fan part-load curves of Figure 3.) Curve 1 represents equipment with constant efficiency, independent of load. Curve 2 represents equipment that is most efficient in the middle of its operating range. Curve 3 represents equipment that is most efficient at full load. Note that these types of curves apply to both boilers and chillers.

Table 4 Correlation Coefficients for Off-Design Relationships

Correlation	0	1	2	3	4	5
f_1	-1.063931	0.0306584	0.0001269	0.0154213	0.0000497	0.0002096
f_3	0.8740302	0.0011416	0.0001711	-0.002957	0.0000102	0.0000592

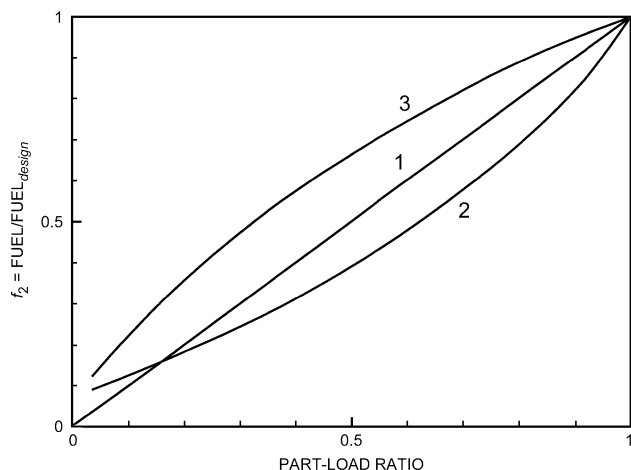


Fig. 6 Possible Part-Load Power Curves

First-Principle Models. As with the secondary components, engineering first principles can also be used to develop models of primary equipment. Lebrun et al. (1999), Gordon and Ng (1994, 1995), Gordon et al. (1995), and others have sought to develop such models in which unknown model parameters are extracted from measured or published manufacturers' data.

The energy analyst is often faced with choosing the appropriate model for the job. For example, a complex boiler model is not appropriate if the boiler in question operates at virtually constant efficiency. By similar arguments, a regression-based model might be appropriate when the user has a full dataset of reliable in-situ measurements of the plant. However, first-principle physical models generally have several advantages over pure regression models:

- Physical models allow confident extrapolation outside the range of available data.
- Regression is still required to obtain values for unknown physical parameters. However, the values of these parameters usually have physical significance. The engineer can capitalize on this significance to estimate default parameter values, diagnose errors in data analysis through checks for realistic parameter values, and even evaluate potential performance improvements.
- The number of unknown parameters is generally much smaller than the number of unknown coefficients in the typical regression model. For example, the standard ARI compressor model requires as many as 30 coefficients, 10 coefficients each for the regressions of capacity, power, and refrigerant flow. By comparison, a physical compressor model may have as few as four or five unknown parameters. As a result, the physical models require fewer measured data.
- Data on part-load operation of chillers and boilers are notoriously difficult to obtain. Part-load corrections often represent the greatest uncertainty in the regression models, while causing the greatest effect on annual energy predictions. By comparison, physical models of full-load operation often allow direct extension to part-load operation with little additional required data.

While physical models of primary HVAC equipment are generally based on fundamental engineering analysis and found in many HVAC textbooks, the models described here are specifically based on the work of Bourdouxhe et al. (1994a, 1994b, 1994c) in the development of the ASHRAE *HVAC 1 Toolkit* (Lebrun et al. 1999). The behavior of each elementary component is characterized by a limited number of physical parameters, such as heat exchanger heat transfer area or centrifugal compressor impeller blade angle. Values of these parameters are identified, or tuned, based on regression fits of overall performance compared to measured or published data.

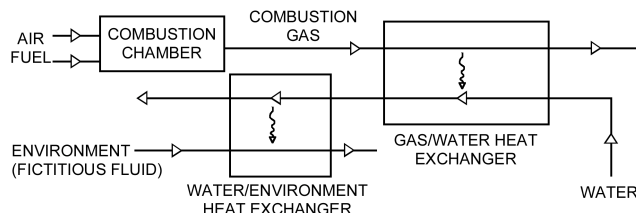


Fig. 7 Boiler Modeled with Elementary Components

While physical models are based on physical characteristics, the values obtained through a regression analysis of manufacturers' data are not necessarily representative of the actual measured values. Strictly speaking, the parameter values are regression coefficients with somewhat fictitious values, identified to minimize the error in overall system performance. In other words, errors in the fundamental models of the equipment are offset by over or underestimation of the parameter values.

Boiler Model

The thermal model of a water boiler operating in a steady-state regime is shown in Figure 7. It consists of an adiabatic combustion chamber and two heat exchangers. These three components interact through the following fluids: air, fuel, combustion gas, water, and a fictitious fluid representing the environment.

The adiabatic combustion chamber and the two heat exchangers can be modeled using classical thermodynamic principles. For example, the boiler heat exchangers can be described using effectiveness-NTU models. That is, knowing the flow rates and entering fluid temperatures, the heat transfer is calculated using a single overall heat transfer coefficient UA . For the water/environment heat exchanger, the environment is considered to be an isothermal reservoir and can be modeled as a fictitious fluid with infinite capacitance. The values of the overall heat transfer coefficients of the two heat exchangers are selected, or tuned to manufacturer's data, to represent the behavior of a particular boiler.

Most boilers are equipped with combustion control systems that vary fuel input to satisfy changing heating loads. The model of Figure 7 can reflect the physical effects of varying fuel, fluid flow, and stand-by losses to realistically show the degradation of performance at part-load operation. In addition, single-stage boilers with on-off control and two-stage boilers with two distinct firing rates can be modeled as "quasi-static" systems, where the cyclic operation is represented by a linear combination of two steady-state regimes.

Vapor Compression Chiller Models

Figure 8 shows a schematic of a vapor compression chiller. In this case, the components include two heat exchangers, an expansion valve, and a compressor with a motor and transmission. The components of a chiller are linked through the refrigerant. For energy estimating, a simplified approach is sufficient to represent the refrigerant as a "perfect" fluid with fictitious property values. That is, refrigerant liquid is modeled as incompressible, and vapor properties are described by ideal gas laws with effective average values of property parameters, such as specific heat.

Condenser and Evaporator Modeling. Both condensers and evaporators are modeled as classical heat exchangers. The two heat exchangers are each assumed to have a constant overall heat transfer coefficient. In addition, the models used in chiller systems suffer from one additional assumption—the refrigerant fluid is assumed to be isothermal for both heat exchangers, which effectively ignores the superheated and subcooled regions of the heat exchanger. The assumption of an isothermal refrigerant is particularly crude for the condenser, which sees very high refrigerant temperatures from the compressor discharge. The effect of the

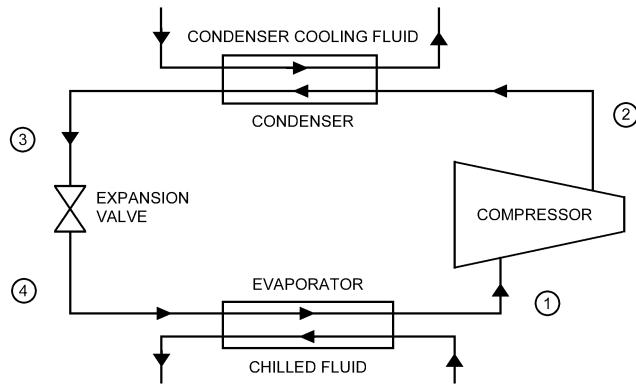


Fig. 8 Chiller Model Using Elementary Components

assumption is to significantly underestimate the mean temperature difference between refrigerant and water in the heat exchanger. Fortunately, this systematic error is compensated by a significant overestimate of the corresponding heat transfer coefficient.

General Compressor Modeling. The modeling of real compressors requires the description of many thermomechanical losses within the compressor. Such losses could include heat loss, fluid friction, throttling losses in valves, or motor and transmission inefficiencies. While some of these losses can be modeled within the compressor, others are too complex or unknown to describe in a model for energy calculations.

The general approach used here for compressor modeling is described in the Figure 9. The compressor is described by two distinct internal elements: an idealized internal compressor and a motor-transmission element to account for unknown losses. Schematically, the motor-transmission subsystem represents an inefficiency of energy conversion. The losses from these inefficiencies are assumed to heat the fluid prior to compression. Mathematically, it can be modeled by the following linear relationship:

$$W = W_{lo} + (1 + \alpha)W_{in} \quad (34)$$

where

W = electrical power for a hermetic or semihermetic compressor, or shaft power for an open compressor

W_{in} = idealized internal compressor power (depends on type of compressor)

W_{lo} = constant electromechanical loss

α = proportional power loss factor

W_{lo} and α are empirical parameters determined by performing a regression analysis on manufacturers' data. Other parameters are also required to model W_{in} , the idealized internal compressor power, depending on the type of compressor.

The following sections describe different modeling techniques for reciprocating, screw, and centrifugal compressors. Detailed modeling techniques are available in the ASHRAE *HVAC 1 Toolkit* (Lebrun et al. 1999) and associated references.

Modeling the Reciprocating Compressor. The conceptual schematic for a reciprocating compressor, for use with the general model, is shown in Figure 10. The refrigerant enters the compressor at state 1 and is heated to state 1a by the thermomechanical losses of the motor-transmission model in Figure 9. The refrigerant undergoes an isentropic compression process to state 2s, followed by a throttling process to the compressor discharge at state 2. The throttling valve is a simplified approach to model the known losses within the compressor due to pressure drops across the suction and discharge valves. Perhaps a more accurate model would include pressure losses at both the inlet and outlet of the compressor, but analysis of compressor data reveals that this simpler model is ade-

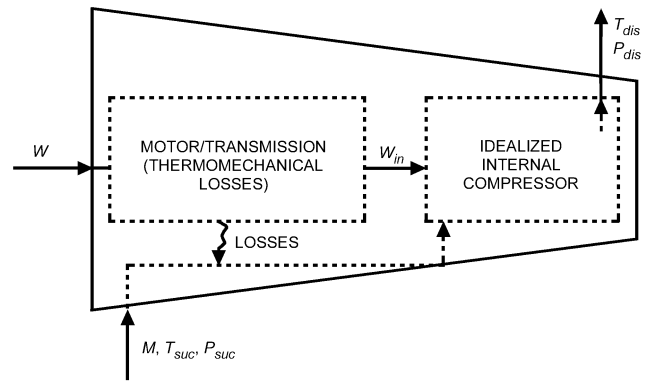


Fig. 9 General Schematic of Compressor

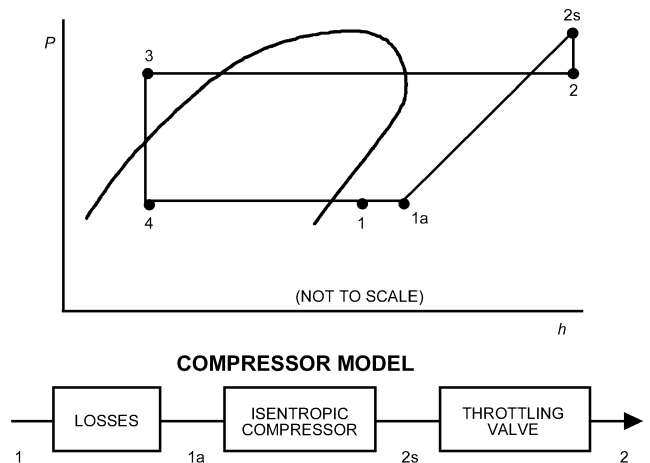


Fig. 10 Schematic of Reciprocating Compressor Model

quate for modeling of typical reciprocating compressors. In fact, many compressors can be adequately modeled with no throttling valve at all.

The refrigerant flow rate through the system must be determined to predict chiller and compressor performance. In general, volumetric flow depends on the pressure difference across the compressor. The compressor refrigerant flow rate is a decreasing function of the pressure ratio due to the re-expansion of the vapor in the clearance volume. With the refrigerant vapor modeled as an ideal gas, the volumetric flow rate is given by the following:

$$V = V_s \left[1 + C_f - C_f \left(\frac{P_{ex}}{P_{suc}} \right)^{1/\gamma} \right] \quad (35)$$

where

V = volumetric flow rate

V_s = swept volumetric flow rate (geometric displacement of the compressor)

C_f = clearance factor = $V_{clearance}/V_s$

P_{ex}/P_{suc} = cylinder pressure ratio

γ = specific heat ratio

V_s and C_f must be identified using data for the actual reciprocating compressor.

While the models discussed apply to full-load operation, Equation (35) is also valid at part-load conditions. However, the internal power use can be different at part load depending on the particular strategy for capacity modulation, such as on-off cycling, cylinder

unloading, hot-gas bypass, or variable-speed motor. In most cases, simple physical models can be developed to describe these methods, which generally vary the swept volumetric rate. Additional thermomechanical losses can also be modeled flow but often involve additional parameters. For example, the effect of cylinder unloading can be modeled by the following relationship:

$$W_{in} = W_{in,FL} + \left(1 - \frac{N_c}{N_{c,FL}}\right) W_{pump} \quad (36)$$

where

- N_c = number of cylinders in use
- $N_{c,FL}$ = number of cylinders in use in full-load regime
- W_{pump} = internal power of the compressor when all the cylinders are unloaded ("pumping" power)
- $W_{in,FL}$ = full-load power

The variable W_{pump} characterizes the part-load regime of the reciprocating compressor, and it is assumed to be constant throughout the entire part-load range.

In summary, a realistic physical model of a reciprocating compressor, covering both full-load and part-load operations, can be developed based on six parameters: the constant and proportional loss terms of the motor-transmission model W_{lo} and α , the swept volumetric flow rate V_s of the compressor cylinders, the cylinder clearance volume factor C_f , the fictitious exhaust valve flow area A_{ex} , and the zero-load pumping power of the unloaded compressor W_{pump} . The entire chiller can then be modeled with two additional parameters for the overall heat transfer coefficients of the condenser and evaporator.

Modeling of Other Compressors and Chillers. From a modeling perspective, the thermodynamic processes of a screw compressor are similar to those of a reciprocating compressor. Physically, the screw compressor transports an initial volumetric flow rate of refrigerant vapor to a higher pressure and density by squeezing it into a smaller space. A realistic physical model of a variable-volume-ratio, twin-screw compressor, covering both full-load and part-load operations, can be developed based on five parameters: the constant and proportional loss terms of the motor-transmission model of Equation (34), the swept volumetric flow rate of the compressor screw, the internal leakage area, and a pumped pressure differential for diverted flow at part-load (Lebrun et al. 1999). The entire chiller can then be modeled with two additional parameters for the overall heat transfer coefficients of the condenser and evaporator.

An idealized internal model of a centrifugal compressor, to be used in conjunction with Equation (34) and Figure 9, can be based on an ideal analysis of a single-stage compressor composed of an isentropic impeller and isentropic diffuser. In addition to the thermomechanical loss parameters of Equation (34), only three additional parameters are required by this centrifugal compressor model: the peripheral speed of the impeller, the inclination of the vanes at the impeller exhaust, and the impeller exhaust area.

The refrigerant cycle of an absorption chiller is the same as for a vapor compression cycle, except for the absorption-generation subsystem in place of the compressor. The absorption-generation subsystem includes an absorber, a steam-fired generator, a recovery heat exchanger, a pump, and a control valve. All components except the pump and control valve can be modeled as heat exchangers.

Cooling Tower Model

A cooling tower is used in primary systems to reject heat from the chiller condenser. The controls typically control the tower fans and pumps to maintain a desired water temperature entering the condenser. Like cooling and dehumidifying coils in secondary systems, the performance of a cooling tower has a strong influence on the energy consumption of the chiller. In addition, tower fans consume electrical energy directly.

Fundamentally, a cooling tower is a direct contact heat and mass exchanger. Equations describing the fundamental processes are given in Chapter 5 and in many HVAC textbooks. Chapter 36 of the *ASHRAE Handbook—Systems and Equipment* describes the specific performance of cooling towers. In addition, cooling tower performance subroutines are available in Lebrun et al. (1999) and Klein et al. (1994).

For energy calculations, cooling tower performance is typically described in terms of the outdoor wet-bulb temperature, the temperature drop of the water flowing through the tower (the range), and the difference between the leaving water temperature and the air wet-bulb temperature (the approach). While simple models assume constant range and approach, more sophisticated models use rating performance data to relate leaving water temperature to the outdoor wet-bulb temperature, water flow, and airflow. Simple cooling tower models, such as those based on a single overall transfer coefficient that can be directly inferred from a single tower rating point, are often appropriate for energy calculations.

SYSTEM MODELING

OVERALL MODELING STRATEGIES

In developing a simulation model for building energy prediction, two basic issues must be considered—(1) modeling of components or subsystems and (2) the overall modeling strategy. Modeling of components, which was discussed in the section on Component Modeling and Loads, results in sets of equations describing the individual components. The overall modeling strategy refers to the **sequence** and **procedures** used to solve these equations. The accuracy of results and the computer resources required to achieve these results depend on the modeling strategy.

In most building energy programs, the load models are executed for every space for every hour of the simulation period. (Practically all models use 1 h as the time step, which excludes any information on phenomena occurring in a shorter time span.) The load model is followed by running models for every secondary system, one at a time, for every hour of the simulation. Finally, the plant simulation model is executed again for the entire period. Each sequential execution processes the **fixed** output of the preceding step.

This procedure is illustrated in Figure 11. The solid lines represent data passed from one model to the next. The dashed lines represent information, usually provided by the user, about one model passed to the preceding model. For example, the system information consists of a piecewise-linear function of zone temperature that gives the system capacity.

Because of this loads-systems-plants sequence, certain phenomena cannot be modeled precisely. For example, if the heat balance method for computing loads is used, and some component in the system simulation model cannot meet the load, the program can only report the current load. In actuality, the space temperature should readjust until the load matches the equipment capacity, but this cannot be modeled because the loads have been precalculated and fixed. If the weighting factor method is used for loads, this problem is partially overcome, because loads are continually readjusted during the system simulation. However, the weighting factor tech-

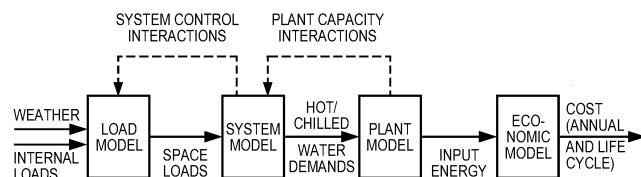


Fig. 11 Overall Modeling Strategy

nique is based on linear mathematics, and wide departures of room temperatures from those used during execution of the load program can introduce errors.

A similar problem arises in plant simulation. For example, in an actual building, as the load on the central plant varies the supply chilled water temperature also varies. This variation in turn affects the capacity of the secondary system equipment. In an actual building, when the central plant becomes overloaded, space temperatures should rise to reduce the load. However, in most energy estimating programs, this condition cannot occur; thus, only the overload condition can be reported. These are some of the penalties associated with decoupling of the load, system, and plant models.

An alternative strategy, in which all calculations are performed at each time step, is conceivable. Here the load, system, and plant equations are solved simultaneously at each time interval. With this strategy, unmet loads and imbalances cannot occur; conditions at the plant are immediately reflected to the secondary system and then to the load model, forcing them to readjust to the instantaneous conditions throughout the building. The results of this modeling strategy are superior to those currently available, although the magnitude and importance of the improvement are uncertain.

The principal disadvantage of the alternative approach, and the reason that it has not been widely used, is that it demands more computing resources. However, programs that, to one degree or another, implement simultaneous solution of the loads, system, and plant models have been developed by Clarke (1985), Park et al. (1985), Klein et al. (1994), and Metcalfe et al. (1995).

An economic model, as shown in Figure 11, calculates energy costs (and sometimes capital costs) based on the estimated required input energy. Thus, the simulation model calculates energy usage and cost for any given input weather and internal loads. By applying this model (i.e., determining output for given inputs) at each hour (or other suitable interval), the hour-by-hour energy consumption and cost can be determined. Maintaining running sums of these quantities yields monthly or annual energy usage and costs.

These models only compare design alternatives; a large number of uncontrolled and unknown factors usually rule out such models for accurate prediction of utility bills. For example, Miller (1980) found that the dynamics of control of components may have at least minor effects on predicted energy use. The section on Bibliography lists several models, which are also described in Walton (1983) and York and Cappiello (1981). Generally, the load models tend to be the most complex and time-consuming, while the central plant model is the least complex.

Because the detailed models are computationally intensive, several simplified methods have been developed. These methods include the degree-day method, the bin method, and correlation methods, and they are presented in the next two sections.

DEGREE-DAY AND BIN METHODS

Degree-day methods are the simplest methods for energy analysis and are appropriate if the building use and the efficiency of the HVAC equipment are constant. Where efficiency or conditions of use vary with outdoor temperature, the consumption can be calculated for different values of the outdoor temperature and multiplied by the corresponding number of hours; this approach is used in various **bin methods**. When the indoor temperature is allowed to fluctuate or when interior gains vary, models other than simple steady-state models must be used.

Even in an age when computers can easily calculate the energy consumption of a building, the concepts of degree-days and balance point temperature remain valuable tools. The severity of a climate can be characterized concisely in terms of degree-days. Also, the degree-day method and its generalizations can provide a simple estimate of annual loads, which can be accurate if the indoor temperature and internal gains are relatively constant and if the heating

or cooling systems operate for a complete season. For these reasons, basic steady-state methods continue to be important.

Balance Point Temperature

The balance point temperature t_{bal} of a building is defined as that value of the outdoor temperature t_o at which, for the specified value of the interior temperature t_i , the total heat loss q_{gain} is equal to the heat gain from sun, occupants, lights, and so forth.

$$q_{gain} = K_{tot}(t_i - t_{bal}) \quad (37)$$

where K_{tot} is the total heat loss coefficient of the building in W/K. For any of the steady-state methods described in this section, heat gains must be the average for the period in question, not for the peak values. In particular, solar radiation must be based on averages, not peak values. The balance point temperature is therefore obtained as

$$t_{bal} = t_i - \frac{q_{gain}}{K_{tot}} \quad (38)$$

Heating is needed only when t_o drops below t_{bal} . The rate of energy consumption of the heating system is

$$q_h = \frac{K_{tot}}{\eta_h} [t_{bal} - t_o(\theta)]^+ \quad (39)$$

where η_h is the efficiency of the heating system, also designated on an annual basis as the annual fuel use efficiency (AFUE), θ is time, and the plus sign above the bracket indicates that only positive values are to be counted. If t_{bal} , K_{tot} , and η_h are constant, the annual heating consumption can be written as an integral:

$$Q_{h, yr} = \frac{K_{tot}}{\eta_h} \int [t_{bal} - t_o(\theta)]^+ d\theta \quad (40)$$

This integral of the temperature difference conveniently summarizes the effect of outdoor temperatures on a building. In practice, it is approximated by summing averages over short time intervals (daily or hourly); the result is termed **degree-days** or **degree-hours**.

Annual Degree-Day Method

Annual Degree-Days. If daily average values of outdoor temperature are used for evaluating the integral, the degree-days for heating $DD_h(t_{bal})$ are obtained as

$$DD_h(t_{bal}) = (1 \text{ day}) \sum_{\text{days}} (t_{bal} - t_o)^+ \quad (41)$$

with dimensions of K·days. Here the summation is to extend over the entire year or over the heating season. It is a function of t_{bal} , reflecting the roles of t_i , heat gain, and loss coefficient. The balance point temperature t_{bal} is also known as the **base** of the degree-days. In terms of degree-days, the annual heating consumption is

$$Q_{h, yr} = \frac{K_{tot}}{\eta_h} DD_h(t_{bal}) \quad (42)$$

Heating degree-days or degree-hours for a balance point temperature of 18.3°C have been widely tabulated based on the observation that this has represented average conditions in typical buildings in the past. The 18.3°C base is assumed whenever t_{bal} is not indicated explicitly. The extension of degree-day data to different bases is discussed later.

Cooling degree-days can be calculated using an equation analogous to Equation (41) for heating degree-days as

$$DD_c(t_{bal}) = (1 \text{ day}) \sum_{\text{days}} (t_o - t_{bal})^+ \quad (43)$$

While the definition of the balance point temperature is the same as that for heating, in a given building its numerical value for cooling is generally different from that for heating because q_i , K_{tot} , and t_i can be different. According to Claridge et al. (1987), t_{bal} can include both solar and internal gains as well as losses to the ground.

Calculating cooling energy consumption using degree-days is more difficult than heating. For cooling, the equation analogous to Equation (42) is

$$Q_{c, yr} = \frac{K_{tot}}{\eta_h} DD_c(t_{bal}) \quad (44)$$

for a building whose K_{tot} does not change. That assumption is generally acceptable during the heating season, when windows are closed and the air exchange rate is fairly constant. However, during the intermediate or cooling season, heat gains can be eliminated, and the onset of mechanical cooling can be postponed by opening windows or increasing the ventilation. (In buildings with mechanical ventilation, this is called the **economizer** mode.) Mechanical air conditioning is needed only when the outdoor temperature extends beyond the threshold t_{max} . This threshold is given by an equation analogous to Equation (38), with the replacement of the closed window heat transmission coefficient K_{tot} by its value K_{max} for open windows:

$$t_{max} = t_i - \frac{q_{gain}}{K_{max}} \quad (45)$$

K_{max} varies considerably with wind speed, but a constant value can be assumed for simple cases. The resulting sensible cooling load is shown schematically in Figure 12 as a function of t_o . The solid line is the load with open windows or increased ventilation; the dashed line shows the load if K_{tot} were kept constant. The annual cooling load for this mode can be calculated by breaking the area under the solid line into a rectangle and a triangle, or

$$Q_c = K_{tot}[DD_c(t_{max}) + (t_{max} - t_{bal})N_{max}] \quad (46)$$

where $DD_c(t_{max})$ are the cooling degree-days for base t_{max} , and N_{max} is the number of days during the season when t_o rises above t_{max} .

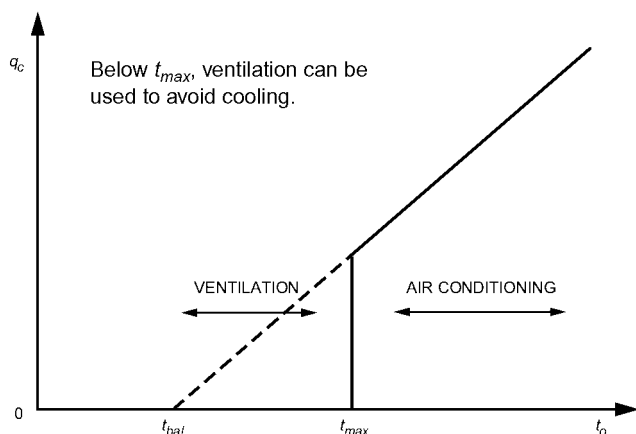


Fig. 12 Cooling Load as Function of Outdoor Temperature t_o

This is merely a schematic model of air conditioning. In practice, heat gains and ventilation rates vary, as does the occupant behavior in using the windows and the air conditioner. Also, in commercial buildings with economizers, the extra fan energy for increased ventilation must be added to the calculations. Finally, air-conditioning systems are often turned off during unoccupied periods. Therefore, cooling degree-hours better represent the period when equipment is operating than cooling degree-days because degree-days assume uninterrupted equipment operation as long as there is a cooling load.

Latent loads can form an appreciable part of a building's cooling load. The degree-day method can be used to estimate the latent load during the cooling season on a monthly basis by adding the following term to Equation (46):

$$q_{latent} = \dot{m} h_{fg} (W_o - W_i) \quad (47)$$

where

q_{latent} = monthly latent cooling load, kW

$\dot{m}$ = monthly infiltration (total airflow), kg/s

h_{fg} = heat of vaporization of water, kJ/kg

W_o = outdoor humidity ratio (monthly averaged)

W_i = indoor humidity ratio (monthly averaged)

The degree-day method assumes that t_{bal} is constant, which is not well satisfied in practice. Solar gains are zero at night, and internal gains tend to be highest during the evening. The pattern for a typical house is shown in Figure 13. As long as t_o always stays below t_{bal} , the variations average out without changing the consumption. But for the situation in Figure 13, t_o rises above t_{bal} from shortly after 10:00 A.M. to 10:00 P.M.; the consequences for energy consumption depend on the thermal inertia and on the control of the HVAC system. If this building had low inertia and if temperature control were critical, heating would be needed at night and cooling during the day. In practice, this effect is reduced by thermal inertia and by the dead band of the thermostat, which allows t_i to float.

The closer t_o is to t_{bal} , the greater the uncertainty. If the occupants keep the windows closed during mild weather, t_i will rise above the set point. If they open the windows, the potential benefit of heat gains is reduced. In either case, the true values of t_{bal} become uncertain. Therefore, the degree-day method, like any steady-state method, is unreliable for estimating the consumption during mild weather. In fact, the consumption becomes most sensitive to occupant behavior and cannot be predicted with certainty.

Despite these problems, the degree-day method (using an appropriate base temperature) can give remarkably accurate results for the annual heating energy of single-zone buildings dominated by losses

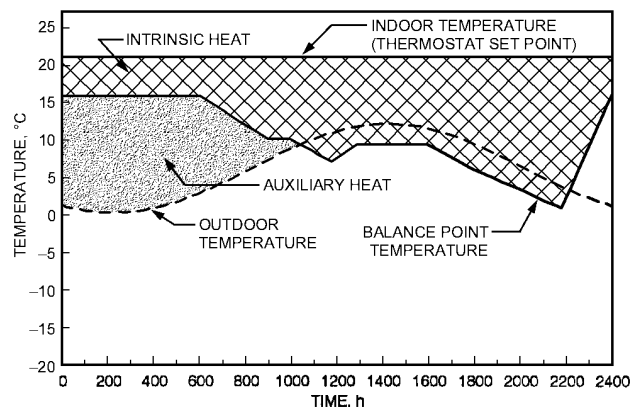


Fig. 13 Variation of Balance Point Temperature and Internal Gains for a Typical House
(Nisson and Dutt 1985)

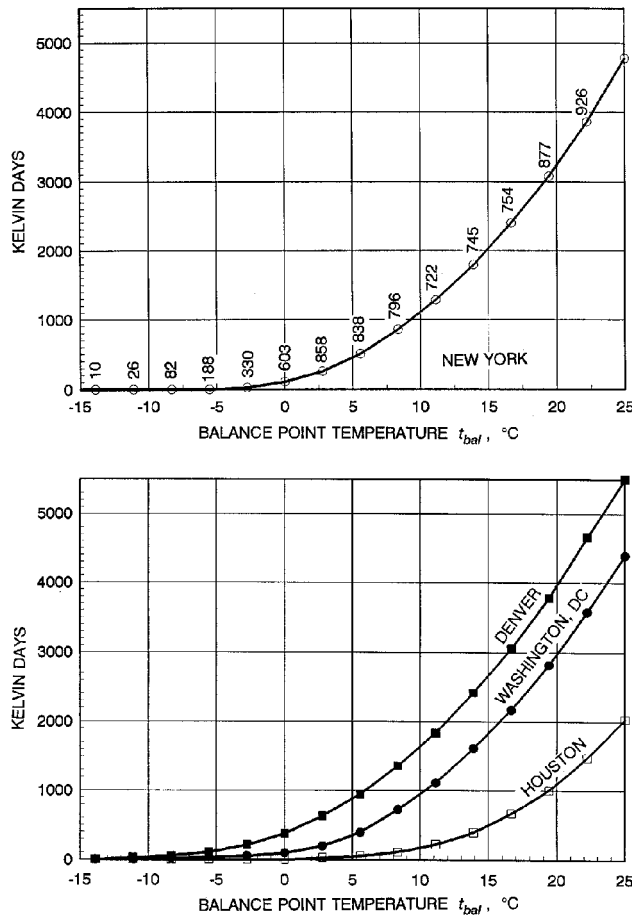


Fig. 14 Annual Heating Days $DD_h(t_{bal})$ as Function of Balance Temperature t_{bal}

through the walls and roof and/or ventilation. Typical buildings have time constants that are about 1 day, and a building's thermal inertia essentially averages over the diurnal variations, especially if t_i is allowed to float. Furthermore, the energy consumption in mild weather is small; hence, a relatively large error here has only a small effect on the total for the season.

Variable-Base Annual Degree-Days. The calculation of Q_h from degree-days $DD_h(t_{bal})$ depends on the value of t_{bal} . This value varies widely from one building to another because of widely differing personal preferences for thermostat settings and setbacks and because of different building characteristics. In response to the fuel crises of the 1970s, heat transmission coefficients have been reduced, and thermostat setback has become common. At the same time, the energy use by appliances has increased. These trends all reduce t_{bal} (Fels and Goldberg 1986). Hence, in general, degree days with the traditional base 18.3°C are not to be used.

Figure 14A shows how the heating degree-days vary with t_{bal} for a particular site, in this case, New York. The plot is obtained by evaluating Equation (41) with data for the number of hours per year during which t_o is within 2.8 K temperature intervals centered at 25°C, 22.2°C, 19.4°C, 16.6°C, ..., -13.9°C. The data for the number of hours in each interval, or **bin**, are included as labels in this plot. Analogous curves, without these labels, are shown in Figure 14B for three other sites: Houston, Washington, and Denver. If the annual average of t_o is known, the cooling degree-days to any base below $22 \pm 1.4^\circ\text{C}$ can also be found.

Seasonal Efficiency. The seasonal efficiency η_h of heating equipment depends on such factors as steady-state efficiency, sizing, cycling effects, and energy conservation devices. Sometimes it is much lower than and other times it is comparable to steady-state efficiency. Alereza and Kusuda (1982) developed expressions to estimate the seasonal efficiency for a variety of furnaces, if information on rated input and output is available. These expressions correlate seasonal efficiency with variables determined by using the equipment simulation capabilities of a large hourly simulation program and typical equipment performance curves supplied by the National Institute of Standards and Technology (NIST):

$$\eta = \frac{\eta_{ss} CF_{pl}}{1 + \alpha_D} \quad (48)$$

where

η_{ss} = steady-state efficiency (rated output/input)

α_D = fraction of heat loss from ducts

CF_{pl} = part-load correction factor

The dimensionless term CF_{pl} is a characteristic of the part-load efficiency of the heating equipment, which may be calculated as follows:

Gas Forced-Air Furnaces

With pilot

$$CF_{pl} = 0.6328 + 0.5738(RLC) - 0.3323(RLC)^2$$

With intermittent ignition

$$CF_{pl} = 0.7791 + 0.1983(RLC) - 0.0711(RLC)^2$$

With intermittent ignition and loose stack damper

$$CF_{pl} = 0.9276 + 0.0732(RLC) - 0.0284(RLC)^2$$

Oil Furnaces Without Stack Damper

$$CF_{pl} = 0.7092 + 0.6515(RLC) - 0.4711(RLC)^2$$

Resistance Electric Furnaces

$$CF_{pl} = 1.0$$

These equations are based on many annual simulations for the equipment. The dimensionless ratio RLC of building design load to the capacity (rated output) of the equipment is defined as follows:

$$RLC = \frac{BLC}{CHT} (t_{bal} - t_{od})(1 + \alpha_D)$$

where

BLC = building loss coefficient, W/K

t_{od} = outside design temperature, °C

CHT = capacity (rated output) of heating equipment, W

The building loss coefficient BLC can be defined as design-day heat loss/($t_{bal} - t_{od}$). The design-day heat loss includes both infiltration and ground losses. Duct losses as a percentage of the design-day heat loss are added via the factor $(1 + \alpha_D)$. RLC assumes values in the range 0 to 1.0, appropriate for typical cases when the heating equipment is oversized. Seasonal efficiency is also discussed by Chi and Kelly (1978), Parker et al. (1980), and Mitchell (1983).

Monthly Degree-Days

Many formulas have been proposed for estimating the degree-days relative to an arbitrary base when detailed data are not available. The basic idea is to assume a typical probability distribution of

temperature data, characterized by its average $\bar{t}_o$ and by its standard deviation σ . Erbs et al. (1983) developed a model that needs as input only the average $\bar{t}_o$ for each month of the year. The standard deviations σ_m for each month are then estimated from the correlation

$$\sigma_m = 3.54 - 0.0290\bar{t}_o + 0.0644\sigma_{yr} \quad (49)$$

This is a dimensional equation with t and σ in $^{\circ}\text{C}$; σ_{yr} is the standard deviation of the monthly average temperatures about the annual average $\bar{t}_{o, yr}$:

$$\sigma_{yr} = \sqrt{\frac{1}{12} \sum_{i=1}^{12} (\bar{t}_o - \bar{t}_{o, yr})^2} \quad (50)$$

To obtain a simple expression for the degree-days, a normalized temperature variable ϕ is defined as

$$\phi = \frac{\bar{t}_{bal} - \bar{t}_o}{\sigma_m \sqrt{N}} \quad (51)$$

where N = number of days in the month (N has units of day/month and ϕ has units of $\sqrt{\text{month/day}}$). While temperature distributions can be different from month to month and location to location, most of this variability can be accounted for by the average and the standard deviation of $\bar{t}_o$. Being centered around $\bar{t}_o$ and scaled by σ_m , the quantity ϕ eliminates these effects. In terms of ϕ , the monthly heating degree-days for any location are well approximated by

$$DD_h(t_{bal}) = \sigma_m N^{1.5} \left[\frac{\phi}{2} + \frac{\ln(e^{-a\phi} + e^{a\phi})}{2a} \right] \quad (52)$$

where $a = 1.698 \sqrt{\text{day/month}}$.

For nine locations spanning most climatic zones of the United States, Erbs et al. (1983) verified that the annual heating degree days can be estimated with a maximum error of 175 K·days if Equation (52) is used for each month. For cooling degree-days, the largest error is 150 K·days. Such errors are quite acceptable, representing less than 5% of the total.

Table 5 lists monthly heating degree-days for New York City, using the model of Erbs et al. (1983), given monthly averages of t_o as reproduced in column 2 of Table 5. The degree-days are based on a balance temperature of 15.6 $^{\circ}\text{C}$. Column 2 lists the given values of monthly average outdoor temperature, and N is the number of days in the month. Intermediate quantities are shown in columns 4 and 5, and $t_{o, yr}$ and σ_{yr} are shown at the bottom. Column 6 shows the monthly and annual results.

Table 6 contains degree-day data for several sites and monthly averaged outdoor temperatures needed for the algorithm. More complete tabulations of the latter are contained in Cinquemani et al. (1978) and in local climatological data summaries available from the National Climatic Data Center, Asheville, NC (NOAA 1973 and www.ncdc.noaa.gov). Monthly degree-day data at various bases, as well as other climatic information for 209 U.S. and 14 Canadian cities, may be found in Appendix 3 to Balcomb et al. (1982).

Bin Method

For many applications, the degree-day method should not be used, even with the variable-base method, because the heat loss coefficient K_{lor} , the efficiency η_h of the HVAC system, or the balance point temperature t_{bal} may not be sufficiently constant. The efficiency of a heat pump, for example, varies strongly with outdoor temperature; or the efficiency of the HVAC equipment may be affected indirectly by t_o when the efficiency varies with the load, a common situation for boilers and chillers. Furthermore, in most commercial buildings, the occupancy has a pronounced pattern, which affects heat gain, indoor temperature, and ventilation rate.

In such cases, a steady-state calculation can yield good results for the annual energy consumption if different temperature intervals and time periods are evaluated separately. This approach is known as the bin method because the consumption is calculated for several values of the outdoor temperature t_o and multiplied by the number of hours N_{bin} in the temperature interval (bin) centered around that temperature:

Table 5 Degree-Day Calculation from Monthly Averaged Data

Month	$\bar{t}_o$, $^{\circ}\text{C}$	N , day/mo.	σ_m , $^{\circ}\text{C}$	ϕ , $\sqrt{\text{mo./day}}$	$DD_h(t_{bal})$, K·days
January	0.1	31	2.03	1.32	463
February	0.8	28	2.01	1.34	399
March	5.1	31	1.89	0.95	312
April	11.2	30	1.71	0.41	133
May	16.8	31	1.55	-0.21	31
June	22.0	30	1.40	-0.92	3
July	24.8	31	1.32	-1.33	1
August	23.8	31	1.34	-1.18	1
September	20.2	30	1.45	-0.66	7
October	14.8	31	1.60	0.02	59
November	8.6	30	1.79	0.66	202
December	1.9	31	1.98	1.19	406
$t_{o, yr}$	12.51			Sum	2018
σ_{yr}	8.80				

Note: Use Equation (52) to calculate $DD_h(t_{bal})$.

Table 6 Degree-Day and Monthly Average Temperatures for Various Locations

Site	Variable-Base Heating Degree-Day, K·days ^a					Monthly Average Outdoor Temperature $\bar{t}_o$, $^{\circ}\text{C}$ ^b											
	18.3	15.6	12.8	10.0	7.2	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Los Angeles, CA	692	290	88	14	0	12.5	13.1	13.6	14.9	16.6	18.1	20.3	20.8	20.4	18.4	15.8	13.8
Denver, CO	3342	2624	2001	1474	1029	-1.2	0.4	2.8	8.6	13.9	18.9	22.8	22.0	17.1	11.1	4.1	0.3
Miami, FL	114	30	4	0	0	19.6	19.9	21.8	23.9	25.6	27.2	27.9	28.3	27.6	25.4	22.3	20.2
Chicago, IL	3404	2751	2173	1666	1233	-4.3	-2.6	2.7	9.9	15.6	21.4	23.7	23.2	18.8	13.0	4.7	-1.9
Albuquerque, NM	2384	1797	1294	865	535	1.8	4.4	7.7	13.2	18.5	23.7	25.9	24.8	21.2	14.6	6.9	2.3
New York, NY	2727	2104	1559	1100	728	0.1	0.8	5.1	11.2	16.8	22.0	24.8	23.8	20.2	14.8	8.6	1.9
Bismarck, ND	5024	4253	3569	2959	2430	-13.2	-10.3	-3.8	6.1	12.4	17.7	21.6	20.7	14.2	8.2	-1.7	-9.1
Nashville, TN	2053	1532	1091	743	473	3.5	5.0	9.3	15.6	20.3	24.8	26.4	25.8	22.2	16.1	9.1	4.7
Dallas/Ft. Worth, TX	1272	858	527	292	139	7.4	9.7	13.2	19.1	23.2	27.6	29.8	29.9	25.7	20.0	13.3	9.0
Seattle, WA	2626	1816	1162	663	334	3.4	5.7	6.7	9.3	12.7	15.4	18.1	17.7	15.3	11.2	7.0	4.7

^aSource: NOAA (1973).

^bSource: Cinquemani et al. (1978).

Table 7 Sample Annual Bin Data

Site	Bin																				
	39/ 41	36/ 38	33/ 35	30/ 32	27/ 29	24/ 26	21/ 23	18/ 20	15/ 17	12/ 14	9/ 11	6/ 8	3/ 5	0/ 2	-3/ -1	-6/ -4	-9/ -7	-12/ -10	-15/ -13	-18/ -16	-21/ -19
Chicago, IL			74	176	431	512	960	660	591	780	510	770	686	1671	380	304	125	66	49	11	4
Dallas/Ft. Worth, TX	4	170	322	511	922	1100	1077	750	803	870	581	728	418	464	37	3					
Denver, CO			81	217	406	390	570	726	712	902	809	783	750	1467	446	216	106	85	52	44	8
Los Angeles, CA	4	10	9	16	56	194	1016	1874	2280	2208	843	227	23								
Miami, FL			14	648	2147	2581	1852	734	390	202	100	76	14	2							
Nashville, TN		4	82	366	717	756	1291	831	693	801	670	858	639	793	141	89	29				
Seattle, WA			10	88	139	330	497	898	1653	1392	1844	1127	715	40	26	1					

Table 8 Calculation of Annual Heating Energy Consumption for Example 4

Climate			House	Heat Pump							Supplemental			
A	B	C	D	E	F	G	H	I	J	K	L	M	N	
Temp. Bin, °C	Temp. Diff., $t_{bal} - t_{bin}$	Weather Data Bin, h	Heat Loss Rate, kW	Heat Pump Integrated Heating Capacity, kW	Cycling Capacity Adjustment Factor ^a	Adjusted Heat Pump Capacity, kW ^b	Rated Electric Input, kW	Operating Time Fraction ^c	Heat Pump Supplied Heating, kWh ^d	Seasonal Heat Pump Electric Consumption, kWh ^e	Space Load, kWh ^f	Supplemental Heating Required, kWh ^g	Total Electric Energy Consumption, kWh ^h	
	16	1.8	693	0.70	12.80	0.764	9.78	3.74	0.072	488	187	485	187	
	13	4.8	801	1.87	12.01	0.789	9.48	3.63	0.197	1496	573	1497	573	
	10	7.8	670	3.04	11.22	0.818	9.18	3.52	0.331	2036	781	2037	781	
	7	10.8	858	4.21	9.80	0.857	8.40	3.40	0.501	3611	1462	3612	1462	
	4	13.8	639	5.38	8.49	0.908	7.71	3.18	0.698	3439	1418	3438	1418	
	1	16.8	793	6.55	7.98	0.955	7.62	3.10	0.860	5196	2114	5195	2114	
	-2	19.8	141	7.72	7.47	1.000	7.47	3.02	1.000	1053	426	1089	36	462
	-5	22.8	89	8.89	6.95	1.000	6.95	2.93	1.000	618	261	791	173	434
	-8	25.8	29	10.06	6.48	1.000	6.48	2.85	1.000	188	83	292	104	187
-11	28.8	0	11.23	5.69	1.000	—	—	—	—	—	—	—	—	
Totals:									18125	7305	18436	313	7618	

^aCycling Capacity Adjustment Factor = $1 - C_d(1 - x)$, where C_d = degradation coefficient (default = 0.25 unless part load factor is known) and x = building heat loss per unit capacity at temperature bin. Cycling capacity = 1 at the balance point and below. The cycling capacity adjustment factor should be 1.0 at all temperature bins if the manufacturer includes cycling effects in the heat pump capacity (Column E) and associated electrical input (Column H).

^bColumn G = Column E × Column F

^cOperating Time Factor equals smaller of 1 or Column D/Column G

^dColumn J = Column I × Column G × Column C

^eColumn K = Column I × Column H × Column C

^fColumn L = Column C × Column D

^gColumn M = Column L - Column J

^hColumn N = Column K + Column M

$$Q_{bin} = N_{bin} \frac{K_{tot}}{\eta_h} [t_{bal} - t_o]^+ \quad (53)$$

The superscript plus sign indicates that only positive values are counted; no heating is needed when t_o is above t_{bal} . Equation (53) is evaluated for each bin, and the total consumption is the sum of the Q_{bin} over all bins.

In the United States, the necessary weather data are available in ASHRAE (1995) and USAF (1978). The bins are usually in 2.8 K increments (when derived from 5°F bins) and are often collected in three daily 8 h shifts. Mean coincident wet-bulb temperature data (for each dry-bulb bin) are used to calculate latent cooling loads from infiltration and ventilation. The bin method considers both occupied and unoccupied building conditions and gives credit for internal loads by adjusting the balance point. For example, a calculation could be performed for 5°C outdoors (representing all occurrences from 3.6 to 6.4°C) and with building operation during the midnight to 0800 shift (5°C outdoors, representing all occurrences from 4°C). Because there are 23 2.8 K bins between -23 and 40.4°C and 3 8 h shifts, 69 separate operating points are calculated. For many applications, the number of calculations can be reduced. A residential heat pump (heating mode), for example, could be calculated for just the bins below 18.3°C without the three-shift

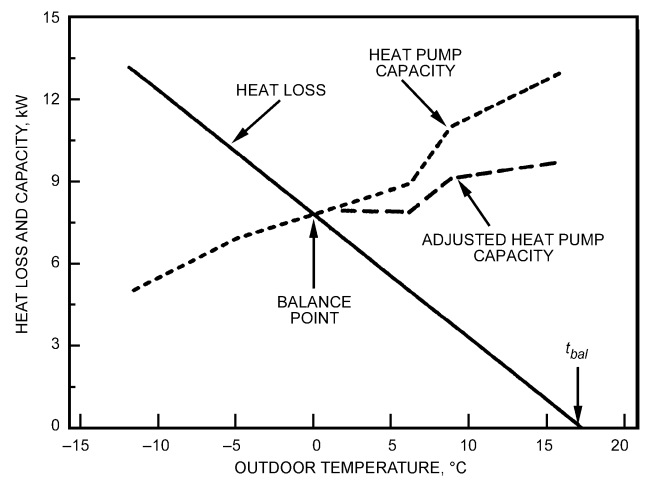


Fig. 15 Heat Pump Capacity and Building Load

breakdown. The data included in Table 7 are samples of annual totals for a few sites, but ASHRAE (1995) and USAF (1978) include monthly data and data further separated into time intervals during the day.

Equipment performance may vary with load. For heat pumps, the U.S. Department of Energy has adopted test procedures to determine the effect of dynamic operations. The bin method uses these results for a specific heat pump to adjust the integrated capacity for the effect of part-load operation. [Figure 15](#) compares the adjusted heat pump capacity to the building heat loss in Example 4 below. This type of curve must be developed for each model heat pump as applied to an individual profile. The heat pump cycles on and off above the balance point temperature to meet the house load, while supplemental heat is required at lower temperatures. This cycling can reduce performance, depending on the part-load factor at a given temperature. The cycling capacity adjustment factors used in this example to account for cycling degradation can be calculated from the equation in footnote a of [Table 8](#).

Frosting and the necessary defrost cycle can reduce performance over steady-state conditions that do not include frosting. The effects of frosting and defrosting are already integrated into many (but not all) manufacturers' published performance data. Example 4 assumes that the manufacturer's data already accounts for the frosting/defrosting losses (as indicated by the characteristic notch of the capacity curve in [Figure 15](#)) and shows how to adjust an integrated performance curve for cycling losses.

Example 4. Estimate the energy requirements for a residence in Nashville, Tenn., with a design heat loss of 11 700 W at 30°C design temperature difference. The inside design temperature is 21°C. It is estimated that internal heat gains average 1250 W. Weather data in terms of hours for each bin are shown in [Table 7](#). Assume the selection of a 10.5 kW heat pump having the characteristics given in Columns E and H of [Table 8](#) and in [Figure 15](#).

Solution: The design heat loss is based on no internal heat generation. The heat pump system energy input is the net heat requirement of the space (i.e., the envelope loss minus the internal heat generation). The net heat loss per degree and the heating/cooling balance temperature may be computed:

$$K_{tot} = HL/\Delta t = 11\,700/30 = 390 \text{ W/K}$$

From Equation (38),

$$t_{bal} = 21 - (1250/390) = 17.8^\circ\text{C}$$

[Table 8](#) is then computed, resulting in 7618 kWh.

The **modified bin method** (Knebel 1983) extends the basic bin method to account for weekday/weekend and partial-day occupancy effects, to calculate net building loads (conduction, infiltration, internal loads, and solar loads) at four temperatures, rather than interpolate from design values, and to better describe secondary and primary equipment performance.

CORRELATION METHODS

One way to simplify energy analyses is to correlate energy requirements to various inputs. Typically, the result of a correlation is a simple equation that may be used in a calculator or small computer program or to develop a graph that provides a quick insight into the energy requirements. Examples of correlation methods are in ASHRAE *Standard* 90.1, which includes several empirical equations that may be used to predict energy consumption by many types of buildings.

The accuracy of correlation methods depends on the size and accuracy of the database and the statistical means used to develop the correlation. A database generated from measured data can lead to accurate correlations (Lachal et al. 1992). The key to the proper use of a correlation is that the case being studied matches the cases used in developing the database. Inputs to the correlation (the independent variables) indicate the factors that are considered to have significant impact on energy consumption. A correlation is invalid either when an input parameter is used beyond its valid range (corresponding to extrapolation rather than interpolation) or when some

important feature of the building/system is not included in the available inputs to the correlation.

SIMULATING SECONDARY AND PRIMARY SYSTEMS

Traditionally, most energy analysis programs include a set of preprogrammed models that represent various systems, such as variable air volume, terminal reheat, multizone, etc. In this scheme, the equations for each system are arranged so they can be solved sequentially. If this is not possible, then the smallest number of equations that must be solved simultaneously is solved using an appropriate technique. Furthermore, individual equations may vary from hour to hour in the simulation, depending on controls and operating conditions. For example, a dry coil uses different equations than a wet coil.

The primary disadvantage of this scheme is that it is relatively inflexible—in order to modify a system, the program source code may have to be modified and recompiled. Alternative strategies (Klein et al. 1994, Park et al. 1985) have viewed the system as a series of components (e.g. fan, coil, pump, duct, pipe, damper, thermostat) that may be organized in a component library. Users of the program specify the connections between the components. The program then resolves the specification of components and connections into a set of simultaneous equations.

A refinement of component-based modeling is known as equation-based modeling (Sowell and Moshier 1995, Buhl et al. 1993). In this scheme, the models do not follow well-defined rules for a solution, and input and output variables are not predetermined.

MODELING OF SYSTEM CONTROLS

From a mathematical viewpoint, controls represent equations that must be satisfied at each point during the simulation. For example, the room thermostat can be represented as a function relating heating and cooling delivery to space temperature. Similarly, cooling coil reset controls can be modeled as a relationship between outside or zone temperature and coil discharge temperature. An accurate secondary system model must ensure that all controls are properly represented and that the governing equations are satisfied at each simulation time step. This often creates a need for iteration or, alternately, for use of values from an earlier solution point.

The controls on space temperature affect the interaction between loads calculations and the secondary system simulation. A realistic model might require a dead band in space temperature in which no heating or cooling is called for; within this range, the true space sensible load is zero, and the true space temperature must be adjusted accordingly. If the thermostat has proportional control between zero and full capacity, the space temperature will rise in proportion to the load during cooling and fall similarly during heating. Capacity to heat or cool also varies with space temperature after the control device has reached its maximum because capacity is proportional to the **difference** between supply and space temperatures. Failure to properly model these phenomena results in overestimating required energy.

INTEGRATION OF SYSTEM MODELS

Energy calculations for secondary systems involve construction of the complete system from the set of HVAC components. For example, a VAV system is a single-path system that controls zone temperature by modulating the airflow while maintaining a constant supply air temperature. VAV terminal units, located at each zone, adjust the quantity of air reaching each zone depending on its load requirements. Reheat coils may be included to provide required heating for perimeter zones.

This VAV system simulation consists of a central air-handling unit and a VAV terminal unit with reheat coil located at each zone,

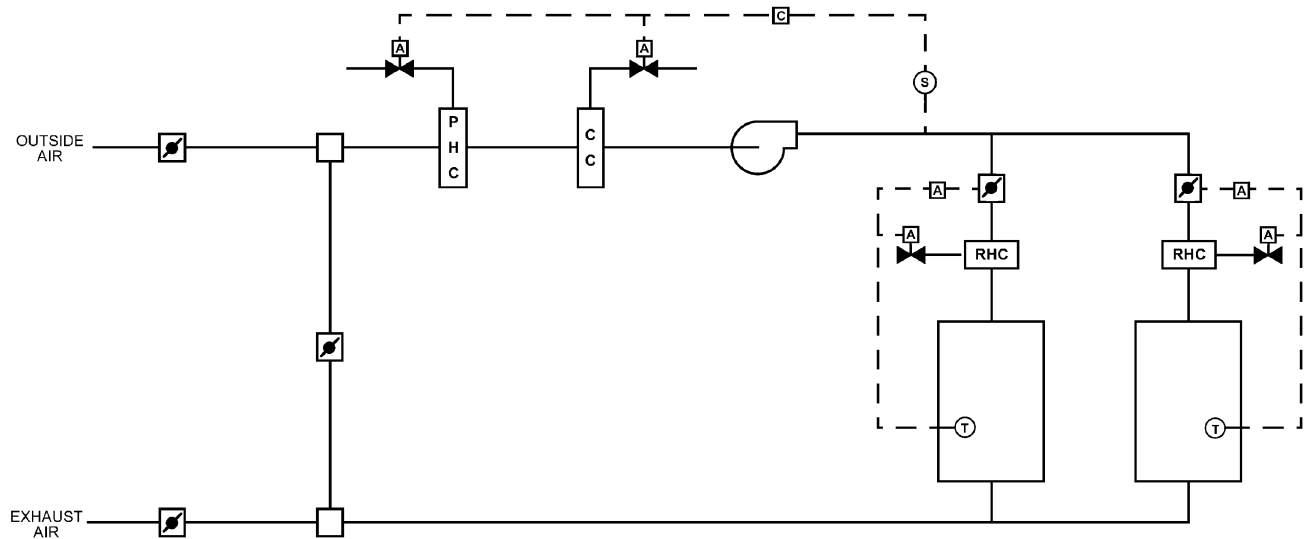


Fig. 16 Schematic of Variable Air Volume System with Reheat

as shown in Figure 16. The central air-handling unit includes a fan, a cooling coil, a preheat coil, and an outside air economizer. The supply air leaving the air-handling unit is controlled to a fixed set point. The VAV terminal unit at each zone varies the airflow to meet the cooling load. As the zone cooling load decreases, the VAV terminal unit decreases the zone airflow until the unit reaches its minimum position. If the cooling load continues to decrease, the reheat coil will be activated to meet the zone load. As the supply air volume leaving the unit decreases, the fan power consumption will also be reduced. A variable-speed drive is used to control the supply fan.

The simulation is based on system characteristics and zone design requirements. For each zone, the inputs include the sensible and latent loads, the zone set point temperature, and the minimum zone supply air mass flow. System characteristics include the supply air temperature set point, the entering water temperature of the reheat, preheat and cooling coils, the minimum mass flow of outside air, and the economizer temperature/enthalpy set point for minimum airflow.

The algorithm for performing the calculations for this VAV system is shown in Figure 17. The algorithm directs sequential calculations of system performance. Calculations proceed from the zones forward along the return air path to the cooling coil inlet and back through the supply air path to the cooling coil discharge.

Moving back along the supply air path, the fan entering air temperature is calculated by setting fan outlet air temperature to the system design supply air temperature. The known fan inlet air temperature is then used as both the cooling coil and preheat coil discharge air temperature set point. Moving forward along the return air path, the cooling coil entering air temperature can be determined by sequentially moving through the economizer cycle and the preheat coil.

Unlike temperature, the humidity ratio at any point in a system cannot be explicitly determined due to the dependence of the cooling coil performance on the mixed air humidity ratio. The latent load defines the difference between zone humidity and supply air humidity. However, the humidity ratio of the supply air depends on the humidity ratio entering the coil, which in turn depends on that of the return air. This calculation must be performed either by solving simultaneous equations or, as in this case, by an iterative process.

Assuming a trial value for the humidity ratio at the cooling coil discharge (e.g., 13°C, 90% rh), the humidity ratio at all other points throughout the system can be calculated. With known cooling coil inlet air conditions and a design discharge air temperature, the inverted cooling coil subroutine iterates on the coil fluid mass flow

BEGIN LOOP Calculate zone related design requirements

- Calculate required supply airflow to meet zone load
- Sum actual zone mass airflow rate
- Sum zone latent loads

IF zone equals last zone **THEN Exit Loop**

END LOOP

- Calculate system return air temperature from zone temps
- Assume an initial cooling coil leaving air humidity ratio

BEGIN LOOP Iterate on cooling coil leaving air humidity ratio

- Calculate return air humidity ratio from latent loads
- Calculate supply fan power consumption and entering fan air temperature
- Calculate mixed air temperature and humidity ratio using an economizer cycle

IF mixed air temperature is less than design supply air temperature **THEN**

- Calculate preheat coil load

ELSE

- Calculate cooling coil load and leaving air humidity ratio

ENDIF

IF cooling coil leaving air humidity ratio converged

THEN Exit Loop

END LOOP

BEGIN LOOP Calculate the zone reheat coil loads

IF zone supply air temperature is greater than system design supply air temperature **THEN**

- Calculate reheat coil load
(Subroutine: COILINV/HCDDET)

ENDIF

- Sum reheat coil loads for all zones

IF zone equals last zone **THEN Exit Loop**

END LOOP

Fig. 17 Algorithm for Calculating Performance of VAV with System Reheat

to converge on the discharge air temperature with the discharge air humidity ratio as an output. The cooling coil discharge air humidity ratio is then compared to the previous discharge humidity ratio. This iterative process continues calculating through the loop several

times until the values of the cooling coil discharge air humidity ratio stabilize within a specified tolerance.

This basic algorithm for simulation of a VAV system might be used in conjunction with a heat balance type of load calculation. For a weighting factor approach, it would have to be modified to allow zone temperatures to vary and consequently zone loads to be readjusted. It should also be enhanced to allow for possible limits on reheat temperature and/or cooling coil limits, zone humidity limits, outside air control (economizers), and/or heat-recovery devices, zone exhaust, return air fan, heat gain in the return air path because of lights, the presence of baseboard-type heaters, and more realistic control profiles. Most current building energy programs incorporate these and other features as user options, as well as algorithms for other types of systems.

INVERSE MODELING

CATEGORIES OF INVERSE METHODS

Inverse methods for energy-use estimation in buildings and related HVAC&R equipment can be classified into three broad categories. These approaches are widely disparate in data requirements, in time and effort needed to develop the associated models, in user skill, and in the sophistication and reliability that they provide.

Empirical or “Black-Box” Approach

With this approach, a simple or multi-variate regression model is identified between measured energy use and the various influential parameters (climatic variables, building occupancy). The form of the regression models can be either purely statistical or loosely based on some basic engineering formulation of energy use in the building. In any case, the identified model coefficients are such that no (or very little) physical meaning can be assigned to them. This approach can be used with any time scale—monthly, daily, hourly or subhourly—provided appropriate data are available. Single-variate, multivariate, change point, Fourier series, and artificial neural network (ANN) models fall under this category, as noted in [Table 1](#).

Model identification is relatively straightforward, usually requires little effort, and can be used in several diverse types of circumstances. The empirical approach is thus the most widely used inverse approach. Although more sophisticated regression techniques such as maximum likelihood and two-stage regression schemes can be used for model identification, least-squares regression is most common. The purely statistical approach is usually adequate for evaluating demand-side management (DSM) programs to identify simple and conventional energy conservation measures in an actual building (lighting retrofits, air handler retrofits such as CV to VAV retrofits) and for baseline model development in energy conservation measurement and verification (M&V) projects (Fels 1986; MacDonald and Wasserman 1989; Ruch and Claridge 1991; Reddy et al. 1997; Claridge 1998b; Kissock et al. 1998; Katipamula et al. 1998; Dhar 1995; Dhar et al. 1998, 1999a, 1999b; Miller and Seem 1991; Kreider and Wang 1991; Krarti et al. 1998). It is also appropriate for modeling equipment such as pumps and fans, and even more elaborate equipment such as chillers and boilers, provided the necessary performance data are available (Phelan et al. 1996, Braun 1992, Englander and Norford 1992, Lorenzetti and Norford 1993). Although this approach allows detection or flagging of equipment or system faults, it is usually of limited value for diagnosis and on-line control (with ANN as a possible exception).

Calibrated Simulation Approach

With this approach, one uses an existing building simulation computer program and “tunes” or calibrates the various physical inputs to the program so that observed energy use matches closely

with that predicted by the simulation program. Once that is achieved, more reliable predictions can be made than with the statistical approaches. The calibrated simulation approach is advocated in cases where only whole-building metering is available and M&V calls for estimating the energy savings of individual retrofits. Practitioners of this approach have largely tended to adopt existing and widely used forward simulation programs such as DOE-2 to subsequently perform the calibration with performance data. Hourly subaggregated monitored energy data (most compatible with the time step adopted by most building energy simulation programs) allow the development of the most accurate calibrated model, but analysts are usually forced to work with less data. Tuning can be done with monthly data or data that span only a few weeks or months over the year, but the resulting model is very likely to be increasingly less accurate with decrease in performance data.

The main reservations with the widespread use of calibrated simulation are that it is labor-intensive, requires a high level of user skill and knowledge in both simulation and practical building operation, is time-consuming, and is often dependent on the person doing the calibration. Several practical difficulties prevent achieving a calibrated simulation or a simulation that nearly reflects the actual building performance, including (1) the measurement and adaptation of weather data for use by the simulation programs (e.g., converting global horizontal solar into beam and diffuse solar radiation), (2) the choice of methods used to calibrate the model, and (3) the choice of methods used to measure the required input parameters for the simulation (i.e., the weight of the building, infiltration coefficients, and shading coefficients). Truly “calibrated” models have been achieved in only a few applications because they require a very large number of input parameters, a high degree of expertise, and enormous amounts of computing time, patience, and financial resources. Bronson et al. (1992), Haberl and Bou-Saada (1998), Kaplan et al. (1990), Corson (1992), Bou-Saada and Haberl (1995a, 1995b), Manke et al. (1996), and Norford et al. (1994) provide examples of different methods used to calibrate simulation models.

In recent years, Katipamula and Claridge (1993) and Liu and Claridge (1998) have suggested that models simpler than those used in the detailed simulation programs such as DOE-2 could also serve the intended purpose while allowing model calibration to be done much faster. Typically, the building is divided into two zones: an exterior or perimeter zone and an interior or a core zone. The core zone is assumed to be insulated from the envelope heat losses/gains, while the solar heat gains, infiltration heat loss/gain, and conduction gains/losses from the roof are taken to appear as loads on the external zone only. Given the internal load schedule, the building description, the type of HVAC system, and the climatic parameters, the HVAC system loads can be estimated for each hour of the day and for as many days of the year as needed by the simplified systems model. Since there are fewer parameters to vary, the calibration process is much faster. Therefore, these models have a significant advantage over general-purpose models in buildings where the HVAC systems can be adequately modeled. These studies, based on the ASHRAE Simplified Energy Analysis Procedure (Knebel 1983), illustrate the applicability of this method both to baseline model development for M&V purposes and as a diagnostic tool for identifying potential operational problems and for estimating potential savings from optimized operating parameters.

Gray-Box Approach

With this approach, a physical model is first formulated to represent the structure or physical configuration of the building or HVAC&R equipment or system, and then important parameters representative of certain key and aggregated physical parameters and characteristics are identified by a statistical analysis

(Rabl and Riahle 1992). This approach requires a high level of user expertise both in setting up the appropriate modeling equations and in the estimation of these parameters. Often an intrusive experimental protocol is necessary for proper parameter estimation that also requires a certain amount of user expertise. This approach has great potential, especially for fault detection and diagnosis (FDD) and on-line control, but its applicability to whole-building energy use is limited. Examples of parameter estimation studies as applied to building energy use are Sonderegger (1977), Hammersten (1984), Subbarao (1988), Rabl (1988), Reddy (1989), Andersen and Brandemuehl (1992), Braun (1990), Reddy et al. (1999), Gordon and Ng (1995), and Guyon and Palomo (1999).

TYPES OF INVERSE MODELS

We distinguish between two types of models: steady-state and dynamic. **Steady-state models** are those that do not consider such effects such as thermal mass or capacitance that cause short-term temperature transients. Generally these models are appropriate for monthly, weekly, or daily data and are often used for baseline model development. **Dynamic models** capture effects such as building warm-up or cool-down periods and peak loads and are appropriate for building load control, FDD, and equipment control. A simple criterion to determine whether a model is steady-state or dynamic is to look for the presence of time-lagged variables, either in the response or regressor variables. Steady-state models do not contain time-lagged variables.

Steady-State Models

There are several types of steady-state models used for both building and equipment energy use. They are single-variate, multivariate, polynomial, and physical models.

Single-Variate Models. Single-variate models (i.e., models with one regressor variable only) are perhaps the most widely used. They formulate energy use in a building as a function of one driving force that impacts building energy use. An important aspect in identifying statistical models of baseline energy use is the choice of the functional form and the independent (or regressor) variables. Extensive studies (Fels 1986, Kissock et al. 1993, Katipamula et al. 1994, Reddy et al. 1997) have clearly indicated that the outdoor dry-bulb temperature is the most important regressor variable, especially at monthly time scales but also at daily time scales.

The simplest steady-state inverse model is one developed by regressing monthly utility consumption data against average billing-period temperatures. The model must identify the balance point temperatures (or change points) at which energy use switches from weather-dependent to weather-independent behavior. In its simplest form, the 18.3°C degree-day model is a change-point model that has a fixed change point at 18.3°C. Other examples include three- and five-parameter Princeton Scorekeeping Methods (PRISM) based on the variable-base degree-day concept (Fels 1986). An allied modeling approach for

commercial buildings is the four-parameter (4-P) model developed by Ruch and Claridge (1991), which is based on the monthly mean temperature (and not degree-days). Table 9 shows the appropriate model functional forms. The three parameters are a weather-independent base-level use, a change point, and a temperature-dependent energy use, characterized as a slope of a line that is determined by regression. The four parameters include a change point, a slope above the change point, a slope below the change point, and the energy use associated with the change point. An inverse bin method has also been proposed to handle more than four change points (Thamilseran and Haberl 1995).

Figure 18 shows several types of steady-state, single-variate inverse models. Figure 18A shows a simple one-parameter, or constant, model, and Table 9 gives the equivalent notation for calculating the constant energy use using this model. Figure 18B shows a steady-state two-parameter (2-P) model where b_0 is the y-axis intercept and b_1 is the slope of the regression line for positive values of x , where x represents the ambient air temperature. The 2-P model represents cases when either heating or cooling is always required.

Figure 18C shows a three-parameter, change-point model. This model is typical of natural gas energy use in a single-family residence that uses gas for space heating and domestic water heating. In the notation of Table 9 for the three-parameter model, b_0 represents the baseline energy use and b_1 is the slope of the regression line for values of ambient temperature less than the change point b_2 . In this type of notation, the superscript plus sign indicates that only positive values of the parenthetical expression are considered. Figure 18D shows a three-parameter model for cooling energy use, and Table 9 provides the appropriate analytic expression.

Figure 18E and Figure 18F illustrate four-parameter models for heating and cooling, respectively. The appropriate expressions for calculating the heating and cooling energy consumption using a four-parameter model are found in Table 9: b_0 represents the baseline energy exactly at the change point b_3 , and b_1 and b_2 are the lower and upper region regression slopes for ambient air temperature below and above the change point b_3 . Figure 18G illustrates a 5-P model (Fels 1986). Such a model is useful for modeling buildings that are electrically heated and cooled. The 5-P model has two change points and a base level consumption value.

The advantage of these steady-state inverse models is that their use can be easily automated and applied to large numbers of buildings where monthly utility billing data and average daily temperatures for the billing period are available. Steady-state single-variate inverse models have also been applied with success to daily data (Kissock et al. 1998). In such a case, the variable-base degree-day method and the monthly mean temperature models described earlier for utility billing data analysis become identical in their functional form. Single-variate models can also be applied to daily data to compensate for differences such as weekday and weekend use by separating the data accordingly and identifying models for each period separately.

Table 9 Single-Variate Models Applied to Utility Billing Data

Model Type	Independent Variable(s)	Form	Examples
One-parameter or constant (1-P)	None	$E = b_0$	Non-weather-sensitive demand
Two-parameter (2-P)	Temperature	$E = b_0 + b_1(T)$	
Three-parameter (3-P)	Degree-days/ Temperature	$E = b_0 + b_1(DD_{BT})$ $E = b_0 + b_1(b_2 - T)^+$ $E = b_0 + b_1(T - b_2)^+$	Seasonal weather-sensitive use (fuel in winter, electricity in summer for cooling)
Four-parameter change point (4-P)	Temperature	$E = b_0 + b_1(b_3 - T)^+ - b_2(T - b_3)^+$ $E = b_0 - b_1(b_3 - T)^+ + b_2(T - b_3)^+$	Energy use in commercial buildings
Five-parameter (5-P)	Degree-days/ Monthly mean temperature	$E = b_0 - b_1(DD_{TH}) + b_2(DD_{TC})$ $E = b_0 + b_1(b_3 - T)^+ + b_2(T - b_4)^+$	Heating and cooling supplied by same meter

Note: DD denotes degree days and T is the monthly mean daily outdoor dry-bulb temperature.

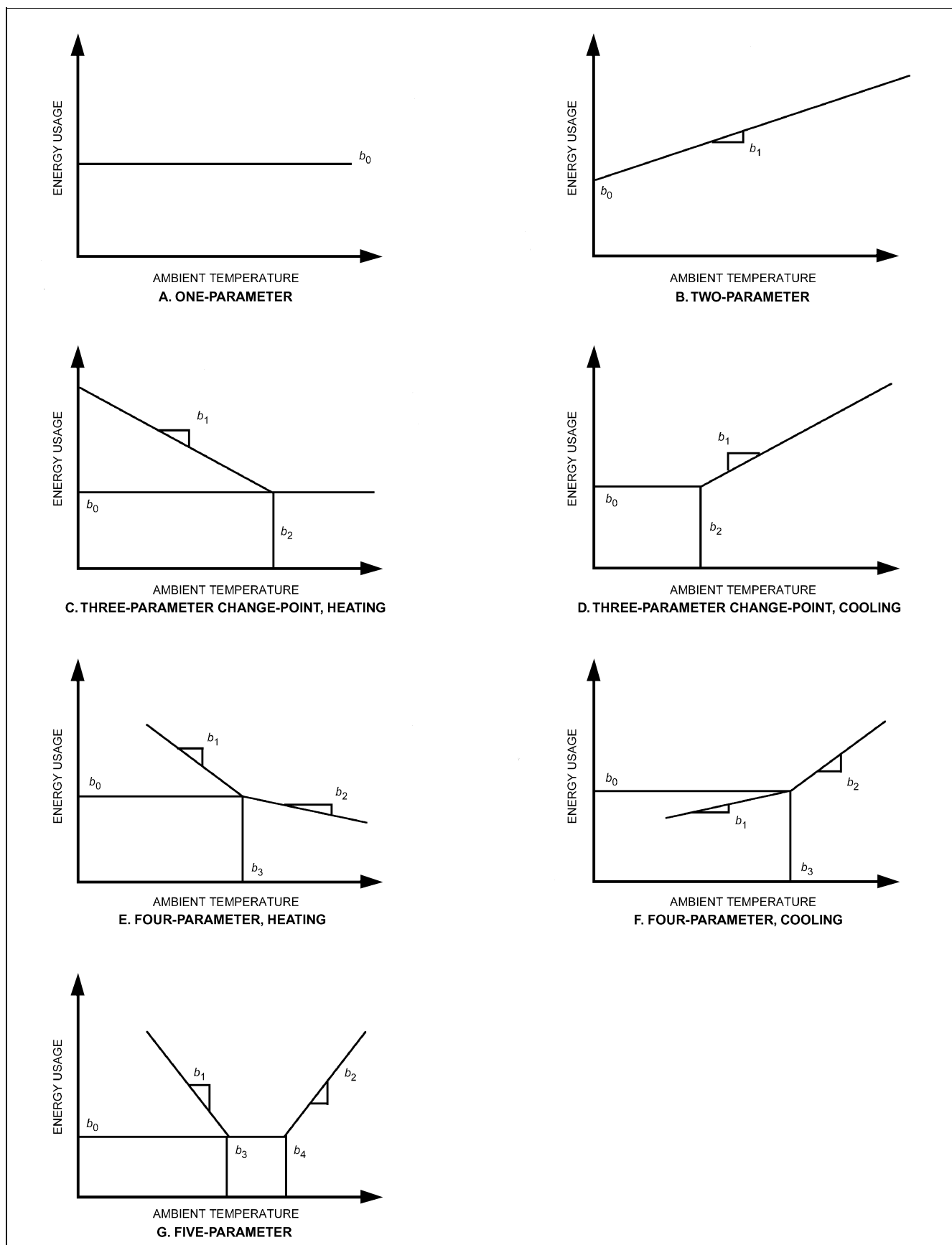


Fig. 18 Steady-State, Single-Variate Models Appropriate for Modeling Energy Use in Residential and Commercial Buildings

Disadvantages of steady-state single-variate inverse models include insensitivity to dynamic effects (e.g., thermal mass), insensitivity to variables other than temperature (e.g., humidity and solar gain), and inappropriateness for some buildings (e.g., buildings with strong on/off schedule-dependent loads or buildings with multiple change points). Moreover, the use of a single-variable, 3-P model such as the PRISM model (Fels 1986) has a physical basis only when energy use above a base level is linearly proportional to degree-days. This is a good approximation in the case of heating energy use in residential buildings where the heating load never exceeds the capacity of the heating system. However, commercial buildings, in general, have higher internal heat generation with simultaneous heating and cooling energy use and are strongly influenced by HVAC system type and control strategy. This makes energy use in commercial buildings less strongly influenced by outdoor air temperature alone. Therefore, it is not surprising that blind use of single-variate models has had mixed success at modeling energy use in commercial buildings (MacDonald and Wasserman 1989).

Change-point regression models work best with heating data from buildings with systems that have little or no part-load nonlinearities (i.e., systems that become less efficient as they begin to cycle on-off with part loads). In general, change-point regression models do not predict cooling loads as well because outdoor humidity has a large influence on latent loads on the cooling coil. Other factors that decrease the accuracy of change-point models include solar effects, thermal lags, and on-off HVAC schedules. Four-parameter models exhibit a better statistical fit than three-parameter models in buildings with continuous, year-round cooling or heating (e.g., grocery stores and office buildings with high internal loads). However, every model should be checked to ensure that the regression is not falsely indicating an unreasonable relationship.

A major advantage of using a steady-state inverse model to evaluate the effectiveness of energy conservation retrofits lies in its ability to factor out year-to-year weather variations by using a normalized annual consumption (NAC) (Fels 1986). Basically, the annual energy conservation savings can be calculated by comparing the difference obtained by multiplying the preretrofit and postretrofit parameters by the weather conditions for the average year. Typically, 10 to 20 years of average daily weather data from a nearby weather service site are used to calculate 365 days of average weather conditions, which are then used to calculate the average preretrofit and postretrofit conditions.

Utilities and government agencies have found it advantageous to prescreen many buildings against test regression models. Such inverse models can be used to develop comparative figures of merit for buildings in a similar standard industrial code (SIC) classification. In such applications, a minimum goodness of fit is usually established that determines whether the monthly utility billing data are well fitted by the one-, two-, three-, four- or five-parameter model being tested. Comparative figures of merit can then be determined by dividing the parameters by the conditioned floor area to yield average daily energy use per unit area of conditioned space. For example, an area-normalized comparison of base-level parameters across residential buildings would be used to analyze weather-independent energy use. Such information can be used by energy auditors to focus their efforts on those systems needing assistance (Haberl and Komor 1990a, 1990b).

Multivariate Models. Two types of steady-state, multivariate models have been reported:

1. **Standard multiple-linear or change-point regression models**, where the set of data observations is treated without retaining the time series nature of the data (Katipamula et al. 1998).
2. **Fourier series models** that retain the time-series nature of the building energy use data and capture the diurnal and seasonal cycles according to which buildings are operated (Seem and Braun 1991; Dhar 1995; Dhar et al. 1998, 1999a, 1999b).

These models are a logical extension to single-variate models, provided that the choice of the variables to be included and their functional forms are based on the engineering principles on which HVAC systems and other systems in commercial buildings operate. The goal of modeling energy use by the multivariate approach is to characterize building energy use with a few readily available and reliable input variables. These input variables should be selected with care. The model should contain variables not affected by the retrofit and likely to change (for example, climatic variables) from preretrofit to postretrofit periods. Other less obvious variables, such as changes in operating hours, in base load, and in occupancy levels, should be included in the model if these are not energy conservation measures (ECMs) but variables that may change during the postretrofit period.

Environmental variables that meet the above criteria for modeling heating and cooling energy use include outdoor air dry-bulb temperature, solar radiation, and outdoor specific humidity. Some of these parameters are difficult to estimate or measure in an actual building and hence are not good candidates for regressor variables. Further, some of the variables vary little. Although their effect on energy use may be important, an inverse model will implicitly lump their effect into the parameter that represents constant load. In commercial buildings, internally generated loads, such as the heat given off by people, lights, and electrical equipment, also impact heating and cooling energy use. Such internal loads are difficult to measure in their entirety given the ambiguous nature of occupant loads and latent loads. However, monitored electricity used by internal lights and equipment is a good surrogate for total internal sensible loads (Reddy et al. 1999). For example, when the building is fully occupied, it is also likely to be experiencing high internal electric loads, and vice versa.

The effect of environmental variables is important for such buildings as offices but may be less so for mixed-use buildings (e.g., hotels and hospitals) and buildings such as retail buildings, schools, and assembly buildings. Differences in HVAC system behavior during occupied and unoccupied periods can be modeled by a dummy or indicator variable (Draper and Smith 1981). For some office buildings, there seems to be little need to include such a dummy variable, but its inclusion in the general functional form will provide added flexibility.

Several standard statistical tests exist for evaluating the goodness-of-fit of the model and the degree of influence that each of the independent variables exerts on the response variable (Draper and Smith 1981, Neter et al. 1989). Although energy use is in fact dependent on several variables, there are strong practical incentives for identifying the simplest model that results in acceptable accuracy. Multivariate models require more metering and are unusable if even one of the variables becomes unavailable. In addition, some of the regressor variables may be linearly correlated. This condition, called **multicollinearity**, can result in large uncertainty in the estimates of the regression coefficients (i.e., unintended error) and can also lead to poorer model prediction accuracy compared to a model where the regressors are not linearly correlated.

Several authors recommend using **principal component analysis** (PCA) to overcome multicollinearity effects. PCA was one of the strongest analysis methods in the ASHRAE Predictor Shoot-out I and II contests (Kreider and Haberl 1994, Haberl and Thamilsaran 1996). Analysis of multiyear monitored daily energy use in a grocery store found a clear superiority of PCA over multivariate regression models (Ruch et al. 1993), but this conclusion is unproven for commercial building energy use in general. A more general evaluation by Reddy and Claridge (1994) of both analysis techniques using synthetic data from four different geographic locations in the U.S. found that injudicious use of PCA may exacerbate rather than overcome problems associated with multicollinearity. Draper and Smith (1981) also caution against indiscriminate use of PCA.

The functional basis of air-side heating and cooling use in various HVAC system types has been addressed by Reddy et al. (1995) and subsequently applied to monitored data in commercial buildings (Katipamula et al. 1994, 1998). Because the quadratic and cross-product terms of the engineering equations are not usually picked up by the multivariate models, one is often left with models for energy use that are strictly **linear**.

In addition to T_o , internal electric equipment and lighting load E_{int} , solar loads q_{sol} , and latent effects via the outdoor dew-point temperature T_{dp} are candidate regressor variables. In commercial buildings, a major portion of the latent load is due to fresh air ventilation. However, this load appears only when the outdoor air dew-point temperature exceeds the cooling coil temperature. Hence, the term $(T_{dp} - T_s)^+$ (where the + sign indicates that the term is to be set to zero if negative, and T_s is the mean surface temperature of the cooling coil, typically about 11 to 13°C) is a more realistic descriptor of the latent loads than is T_{dp} alone. The use of $(T_{dp} - T_s)^+$ as a regressor in the model is a simplification that seems to yield good accuracy.

Therefore, a multivariate linear regression model with an engineering basis has the following structure:

$$Q_{bldg} = \beta_0 + \beta_1(T_o - \beta_3)^- + \beta_2(T_o - \beta_3)^+ + \beta_4(T_{dp} - \beta_6)^- + \beta_5(T_{dp} - \beta_6)^+ + \beta_7q_{sol} + \beta_8E_{int} \quad (54)$$

Based on the above discussion, $\beta_4 = 0$. Introducing indicator variable terminology (Draper and Smith 1981), Equation (54) becomes identical to

$$Q_{bldg} = a + bT_o + cI + dIT_o + eT_{dp}^+ + fq_{sol} + gE_{int} \quad (55)$$

where the indicator variable I is introduced to handle the change in slope of the energy use due to T_o . The variable I is set equal to 1 for T_o values to the right of the change point (i.e., for high T_o range) and set equal to 0 for low T_o values. As with the single-variate segmented models (i.e., 3-P and 4-P models), a search method is used in order to determine the change point that minimizes the total sum of squares of residuals (Fels 1986, Kissock et al. 1993).

Another finding from the Katipamula et al. (1994) study was that the model given by Equation (55), appropriate for VAV systems, could be simplified for constant volume HVAC systems:

$$Q_{bldg} = a + bT_o + eT_{dp}^+ + fq_{sol} + gE_{int} \quad (56)$$

Note that instead of using $(T_{dp} - T_s)^+$, one could equally use the absolute humidity potential $(W_o - W_s)^+$, where W_o is the outdoor absolute humidity, and W_s , the absolute humidity level at the dew point of the cooling coil, is typically about 0.009 kg/kg. A final aspect to be kept in mind is that the term T_{dp}^+ should be omitted from the regressor variable set when regressing heating energy use because there are no latent loads on a heating coil.

The above multivariate models have been found to be very accurate for daily time scales and slightly less so for hourly time scales. This is because changes in the way the building is operated during the day and the night lead to different relative effects of the various regressors on energy use, which cannot be accurately modeled by one single hourly model. Breaking up the energy use data into hourly bins corresponding to each hour of the day and then identifying 24 individual hourly models leads to appreciably greater accuracy (Katipamula et al. 1994).

Polynomial Models. Historically, polynomial models have been widely used as pure statistical models to model the behavior of such equipment as pumps, fans, and chillers (Stoecker and Jones 1982). The theoretical aspects of calculating pump performance are well understood and documented. Pump capacity and efficiency are calculated from measurements of pump pressure, flow rate, and pump

electrical power input. Phelan et al. (1996) have studied the predictive ability of linear and quadratic models for electricity consumed by pumps and water mass flow rate and concluded that quadratic models are superior to linear models. For fans, Phelan et al. (1996) have studied the predictive ability of linear and quadratic polynomial single-variate models of fan electricity consumption as a function of the supply air mass flow rate and concluded that, although quadratic models are superior in terms of predicting energy use, the linear model seems to be the better overall predictor of both energy and demand (i.e., maximum monthly power consumed by the fan). This is a noteworthy conclusion given that a third-order polynomial is warranted analytically as well as from monitored field data presented by previous authors (e.g., Englander and Norford 1992, Lorenzetti and Norford 1993).

Polynomial models have been used to correlate chiller (or evaporator) thermal cooling capacity or load Q_{evap} and the electrical power consumed by the chiller (or compressor) E_{comp} with the relevant number of influential physical parameters. For example, based on the functional form of the DOE-2 building simulation software (York and Cappiello 1982), models for part-load performance of energy equipment and plant, E_{comp} can be modeled as the following triquadratic polynomial:

$$E_{comp} = a + bQ_{evap} + cT_{cond}^{in} + dT_{evap}^{out} + eQ_{evap}^2 + fT_{cond}^{in2} + gT_{evap}^{out2} + hQ_{evap}T_{cond}^{in} + iT_{evap}^{out}Q_{evap} + jT_{cond}^{in}T_{evap}^{out} + kQ_{evap}T_{cond}^{in}T_{evap}^{out} \quad (57)$$

In this model, there are 11 model parameters to identify. However, since all of them are unlikely to be statistically significant, a step-wise regression to the sample data set yields the optimal set of parameters to retain in a given model. Other authors, such as Braun (1992), have used slightly different polynomial forms.

Physical Models. In contrast to polynomial models, which have no physical basis (merely a convenient statistical one), physical models are based on fundamental thermodynamic or heat transfer considerations. These types of models are usually associated with the parameter estimation approach. Often such models are preferred because they generally have fewer parameters. Furthermore, their mathematical formulation can be traced to actual physical principles that govern the performance of the building or equipment. Hence the model coefficients tend to be more robust, leading to sounder model predictions. Only a few studies have used steady-state physical models for parameter estimation relating to commercial building energy use (for example, Reddy et al. 1999). Unlike in single-family residences, it is difficult to perform elaborately planned experiments in large buildings and obtain representative values of indoor fluctuations.

A physical model of a chiller has been proposed by Gordon and Ng (1994, 1995) and Gordon et al. (1995). It is a simple, analytical, universal model for chiller performance based on thermodynamic considerations and linearization of heat losses. The model predicts the dependence of chiller COP [defined as the ratio of chiller (or evaporator) thermal cooling capacity Q_{evap} divided by the electrical power consumed by the chiller (or compressor) E_{comp}] with certain key (and easily measurable) parameters such as the fluid (water or refrigerant) return temperature from the condenser T_{cond}^{in} , the fluid temperature leaving the evaporator (or the chilled water supply temperature to the building) T_{evap}^{out} , and the thermal cooling capacity of the evaporator. The complete Gordon-Ng model is a three-parameter model that takes the following form:

$$\left(\frac{1}{COP} + 1 - \frac{T_{cond}^{in}}{T_{evap}^{out}} \right) Q_{evap} = -A_0 + A_1 T_{cond}^{in} - A_2 \frac{T_{cond}^{in}}{T_{evap}^{out}} \quad (58)$$

The three parameters are identified by multiple linear regression. Results of applying such models to field monitored data are fully described by the Gordon et al. papers as well as by Phelan et al. (1996) and Haberl et al. (1997).

Dynamic Models

In general, steady-state inverse models are used with monthly and daily data containing one or more independent variables. Dynamic inverse models are usually used with hourly or subhourly data in cases where the thermal mass of a building is sufficiently significant to delay the heat gains or losses. Dynamic models traditionally required the solution of a set of differential equations. The disadvantages of dynamic inverse models include their complexity and the need for more detailed measurements to tune the model. Unlike steady-state inverse models, dynamic inverse models usually require a high degree of user interaction and knowledge of the building or system being modeled.

Several residential energy studies using dynamic inverse models based on parameter estimation approaches have been reported, most of them involving intrusive data gathering. Rabl (1988) has classified the various types of dynamic inverse models used for whole-building energy use and drawn attention to the common underlying features of these models. There are essentially four different types of model formulations: thermal network models, time series models, differential equation models, and modal models. They all qualify as parameter-estimation approaches. Table 1 lists several pertinent studies in each category. A few studies (Hammersten 1984, Rabl 1988, Reddy 1989) have evaluated these different approaches with the same data set. A number of papers have reported results of applying such different techniques such as thermal network models and ARMA models to residential and commercial building energy use (see Table 1). Examples of dynamic inverse models for commercial building are found in Rabl (1988), Andersen and Brandemuehl (1992), and Braun (1990).

Dynamic inverse models based on pure statistical approaches have also been reported. Two examples are machine learning (Miller and Seem 1991) and artificial neural networks (Miller and Seem 1991, Kreider and Wang 1991, Kreider and Haberl 1994).

Neural networks are considered to be intuitive because they learn by example rather than by following programmed rules. The ability to “learn” is one of the key aspects of neural networks. A neural network consists of one input layer (which can contain one or more inputs), one or more hidden layers, and an output or target layer. One challenge of this technology is to construct a net with sufficient complexity to learn accurately without imposing excessive computational time.

The weights of a net are initiated with small random numbers. Then, the weights are adjusted iteratively or “trained” so that the application of a set of inputs produces the desired set of outputs. Usually a network is trained with a training data set that consists of many input-output pairs. Artificial neural networks have been trained by a wide variety of methods (McClelland and Rumelhart 1988, Wasserman 1989). One such training method is called **back propagation**.

Neural networks have been useful in predicting energy use in commercial buildings for such reasons as

- Prediction of what a properly operating building should be doing compared to actual operation. If there is a difference, it can be used in an expert system to produce early diagnoses of building operation problems.
- Prediction of what a building, prior to an energy retrofit, would have consumed under present conditions. When compared to the measured consumption of the retrofitted building, the difference represents a good estimate of the energy savings due to the retrofit. This represents one of the few ways that actual energy savings

can be determined after the preretrofit building configuration has ceased to exist.

EXAMPLES OF INVERSE METHODS

Modeling of Utility Bill Data

The following example (taken from Sonderegger 1998) illustrates a utility bill analysis. Assume that values of the utility bills over an entire year have been measured. To obtain the equation coefficients through regression, the utility bills must be normalized by the length of the time interval between utility bills. This is equivalent to expressing all utility bills, degree-days, and other independent variables by their daily averages.

An appropriate software program is used in which one assumes values for heating and cooling balance points; from these, the corresponding heating and cooling degree-days for each utility bill period are determined. Repeated regression is done till the regression equation represents the best fit to the meter data. The model coefficients are then assumed to be tuned. Some computer programs allow direct determination of these optimal model parameters without the user’s manual tuning of the parameters.

A widely used statistic to gage the goodness-of-fit of the model is the **coefficient of determination** R^2 . A value of $R^2 = 1$ indicates a perfect correlation between actual data and the regression equation; a value of $R^2 = 0$ indicates no correlation. For purposes of tuning for a performance contract, as a rule of thumb the value of R^2 should never be less than 0.75.

When more than one independent variable is included in the regression, the value of R^2 is no longer sufficient to determine the goodness-of-fit. The standard error of the estimate of the coefficients becomes the more important determinant. The smaller the standard error compared to the coefficient’s magnitude, the more reliable the coefficient estimate. To facilitate the significance of individual coefficients, the so-called **t-statistics**, or simply **t-values**, are used. These are simply the ratio of the coefficient estimate divided by the standard error of the estimate.

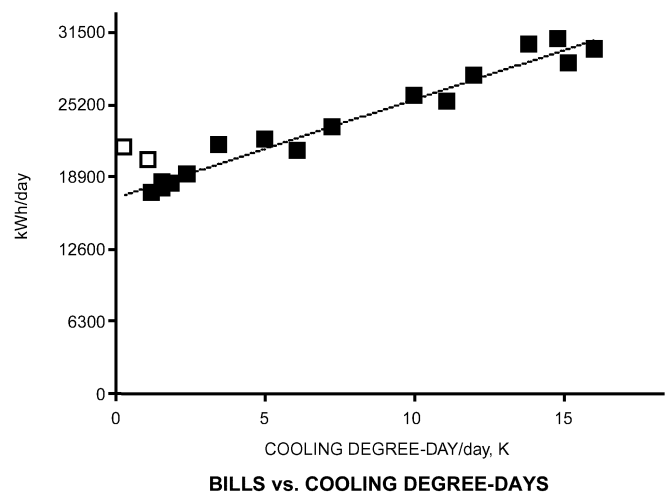
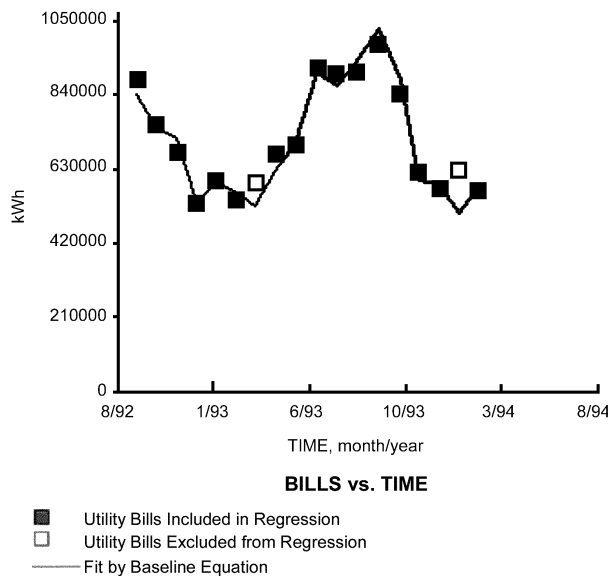
The coefficient of each variable included in the regression has a *t*-statistic. For a coefficient to be statistically meaningful, the absolute value of its *t*-statistic must be at least 2.0. Another way of stating this is that under no circumstances should a variable be included in a regression if the standard error of its coefficient estimate is greater than half the magnitude of the coefficient. The latter is true even when including a variable that increases the R^2 . Generally speaking, including more variables in a regression results in a higher R^2 , but the significance of most individual coefficients will likely decrease.

Figure 19 illustrates how well a regression fit captures measured baseline energy use in a hospital building. Cooling degree-days are found to be a significant variable, with the best fit for a base temperature of 12.2°C.

There are good reasons why individual utility bills may be unsuitable to develop a baseline and should be excluded from the regression. For example, a bill may be atypically high because of a one-time equipment malfunction that was subsequently repaired. However, it is often tempting to look for reasons to exclude bills that fall far from “the line” and not question those that are close to it. For example, bills for periods containing vacations or production shutdowns may look anomalously low, but excluding them from the regression would result in a chronic overestimate of the future baseline during the same period.

Neural Network Models

Figure 20 shows results for a single neural network typical of several hundred networks constructed for an academic engineering center located in central Texas. The cooling load is created by solar gains, internal gains, outdoor air sensible heat, and outdoor



Note: Utility bills excluded from the regression due to a degree-day threshold.

Fig. 19 Variable-Base Degree-Day Model Identification Using Electricity Utility Bills at a Hospital
(Sonderegger 1998)

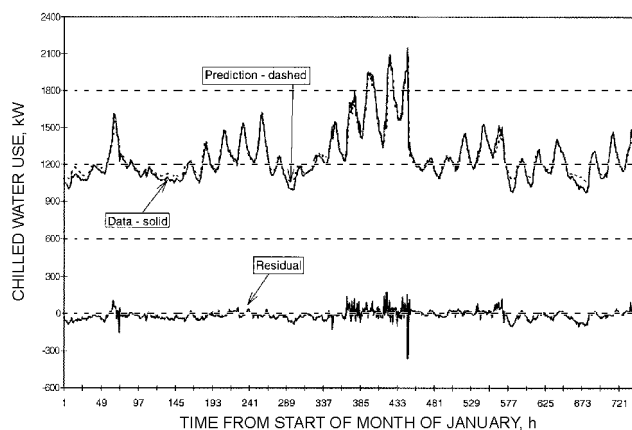


Fig. 20 Neural Network Prediction of Whole Building, Hourly Chilled Water Consumption for a Commercial Building

air humidity loads. The neural network is used to predict the pre-retrofit energy consumption for comparison with measured consumption of the retrofitted building. Six months of preretrofit data were available with which to train a network. The solid lines show the known building consumption data while the dashed lines show the neural network predictions. This figure shows that a neural network trained for one period (September 1989) can predict energy consumption well into the future (here, January 1990).

The network used for this prediction had two hidden layers. The input layer contained eight neurons that receive eight different types of input data as listed below. The output layer consisted of one neuron that gave the output datum (chilled water consumption). Each training fact (i.e., training data set), therefore, contained eight input data (independent variables) and one pattern datum (dependent variable). The eight hourly input data used in each hour's data vector were selected on physical bases (Kreider and Rabl 1994) and were as follows:

- Hour number (0 to 2300)
- Ambient dry-bulb temperature

- Horizontal insolation
- Humidity ratio
- Wind speed
- Weekday/weekend binary flag (0, 1)
- Past hour's chilled water consumption
- Second past hour's chilled water consumption

These measured independent variables were able to predict the chilled water use to an RMS error of less than 4% (JCEM 1992).

The choice of an optimal network's configuration for a given problem remains an art. The number of hidden neurons and layers must be sufficient to meet the requirement of the given application. However, if too many neurons and layers are used, the network tends to memorize data rather than learning, that is, finding the underlying patterns in the data. Further, choosing an excessively large number of hidden layers significantly increases the required training time for certain learning algorithms. Anstett and Kreider (1993), Kreider and Wang (1991), Wang and Kreider (1992), and Krarti et al. (1998) report additional case studies for commercial buildings.

Closing Remarks

Steady-state and dynamic inverse models can be used with energy management and control systems to predict energy use (Kreider and Haberl 1994). Hourly or daily comparisons of measured energy use against predicted energy use can be used to determine whether systems are being left on unnecessarily or are in need of maintenance. Combinations of predicted energy use and a knowledge-based system can indicate above-normal energy use and diagnose the possible cause of the malfunction if sufficient historical information has been previously gathered (Haberl and Claridge 1987). Hourly systems that use artificial neural networks have also been constructed (Kreider and Wang 1991).

Table 10 presents a decision diagram for selecting a forward or inverse model where use of the model, degree of difficulty in understanding and applying the model, time scale for the data used by the model, calculation time, and input variables used by the models are the criteria used to choose a particular model.

Table 10 Capabilities of Different Forward and Inverse Modeling Methods

Methods	Usage ^a	Difficulty	Time Scale ^b	Calc. Time	Variables ^c	Accuracy
Simple linear regression	ES	Simple	D, M	Very fast	T	Low
Multiple linear regression	D, ES	Simple	D, M	Fast	T, H, S, W, t	Medium
ASHRAE bin method and inverse bin method	ES	Moderate	H	Fast	T	Medium
Change point models	D, ES	Simple	H, D, M	Fast	T	Medium
ASHRAE TC 4.7 modified bin method	ES, DE	Moderate	H	Medium	T, S, tm	Medium
Artificial Neural Networks	D, ES, C	Complex	S, H	Fast	T, H, S, W, t, tm	High
Thermal network	D, ES, C	Complex	S, H	Fast	T, S, tm	High
Fourier series analysis	D, ES, C	Moderate	S, H	Medium	T, H, S, W, t, tm	High
ARMA model	D, ES, C	Moderate	S, H	Medium	T, H, S, W, t, tm	High
Modal analysis	D, ES, C	Complex	S, H	Medium	T, H, S, W, t, tm	High
Differential equation	D, ES, C	Complex	S, H	Fast	T, H, S, W, t, tm	High
Computer simulation (component-based)	D, ES, C, DE	Very complex	S, H	Slow	T, H, S, W, t, tm	Medium
Computer simulation (fixed schematic)	D, ES, DE	Very complex	H	Slow	T, H, S, W, t, tm	Medium
Computer emulation	D, C	Very complex	S, H	Very slow	T, H, S, W, t, tm	High

Notes:

^aUsage shown includes diagnostics (D), energy savings calculations (ES), design (DE), and control (C).^bTime scales shown are hourly (H), daily (D), monthly (M), and subhourly (S).^cVariables include temperature (T), humidity (H), solar (S), wind (W), time (t), and thermal mass (tm).

REFERENCES

- Alamdari, F. and G.P. Hammond. 1982. Time-dependent convective heat transfer in warm-air heated rooms. Energy Conservation in the Built Environment: *Proceedings CIB W67 Third International Symposium*. pp. 209-20. Dublin, Ireland.
- Alamdari, F. and G.P. Hammond. 1983. Improved data correlations for buoyancy-driven convection in rooms. *Building Services Engineering Research and Technology* 4(3):106-12.
- Alereza, T. and T. Kusuda. 1982. Development of equipment seasonal performance models for simplified energy analysis methods. *ASHRAE Transactions* 88(2):249-62.
- Altmayer, E.F., A.J. Gadgil, F.S. Bauman, and R.C. Kammerud. 1983. Correlations for convective heat transfer from room surfaces. *ASHRAE Transactions* 89(2A):61-77.
- Andersen, I. and M.J. Brandemuehl. 1992. Heat storage in building thermal mass: A parametric study. *ASHRAE Transactions* 98(1):910-18.
- Anstett, M. and J.F. Kreider. 1993. Application of artificial neural networks to commercial building energy use prediction. *ASHRAE Transactions* 99(1):505-17.
- ASHRAE. 1995. *Bin and degree hour weather data for simplified energy calculations*.
- ASHRAE. 1999. Energy standard for buildings except low-rise residential buildings. ANSI/ASHRAE/IESNA *Standard* 90.1-1999.
- Ayres, M.J. and E. Stamper. 1995. Historical development of building energy calculations. *ASHRAE Transactions* 101(1):47-55.
- Bacot, P., A. Neveu, and J. Sicard. 1984. Analyse modale des phenomenes thermiques en regime variable dans le batiment. *Revue Generale de Thermique* 267:189.
- Balcomb, J.D., R.W. Jones, R.D. McFarland, and W.O. Wray. 1982. Expanding the SLR method. *Passive Solar Journal* 1(2).
- Bauman, F., A. Gadgil, R. Kammerud, E. Altmayer, and M. Nansteel. 1983. Convective heat transfer in buildings: Recent research results. *ASHRAE Transactions* 89(1A):215-32.
- Beck, J.V. and K.J. Arnold. 1977. *Parametric estimation in engineering and science*. John Wiley and Sons, New York.
- Bohn, M.S., A.T. Kirkpatrick, and D.A. Olson. 1984. Experimental study of three-dimensional natural convection high-Rayleigh number. *Journal of Heat Transfer* 106:339-45.
- Bou-Saada, T. and J. Haberl. 1995a. A weather-day typing procedure for disaggregating hourly end-use loads in an electrically heated and cooled building from whole-building hourly data. *Proceedings 30th IECEC*, pp. 349-56.
- Bou-Saada, T. and J. Haberl. 1995b. An improved procedure for developing calibrated hourly simulation models. *Proceedings Building Simulation '95*. IBPSA. Madison, Wisc.
- Bourdouxhe, J.P., M. Grodent, J. Lebrun, and C. Saavedra. 1994a. A toolkit for primary HVAC system energy calculation—Part 1: Boiler model. *ASHRAE Transactions* 100(2):759-73.
- Bourdouxhe, J.P., M. Grodent, J. Lebrun, C. Saavedra, and K. Silva. 1994b. A toolkit for primary HVAC system energy calculation—Part 2: Reciprocating chiller models. *ASHRAE Transactions* 100(2):774-86.
- Bourdouxhe, J.P., M. Grodent, and C. Silva. 1994c. Cooling tower model developed in a toolkit for primary HVAC system energy calculation—Part 1: Model description and validation using catalog data. *Proceedings Fourth International Conference on System Simulation in Buildings*.
- Brandemuehl, M.J. 1993. *HVAC 2 toolkit: Algorithms and subroutines for secondary HVAC system energy calculations*. ASHRAE.
- Brandemuehl, M.J. and S. Gabel. 1994. Development of a toolkit for secondary HVAC system energy calculations. *ASHRAE Transactions* 100(1):21-32.
- Brandemuehl, M.J. and J.D. Bradford. 1999. Optimal supervisory control of cooling plants without storage. *Final Report* RP-823. ASHRAE.
- Braun, J.E. 1988. Methodologies for the design and control of chilled water systems. *Ph.D. thesis*, University of Wisconsin-Madison.
- Braun, J.E. 1990. Reducing energy costs and peak electrical demand through optimal control of building thermal mass. *ASHRAE Transactions* 96(2): 876-88.
- Braun, J.E. 1992. A comparison of chiller-priority, storage-priority, and optimal control of an ice-storage system. *ASHRAE Transactions* 98(1): 893-902.
- Bronson, D., S. Hinchey, J. Haberl, and D. O'Neal. 1992. A procedure for calibrating the DOE-2 simulation program to non-weather dependent loads. *ASHRAE Transactions* 98(1):636-52.
- Buhl, W.F., A.E. Erdem, J.M. Nataf, F.C. Winkelmann, M.A. Moshier, and E.F. Sowell. 1990. The US EKS: Advances in the SPANK-based energy kernel system. *Proceedings Third International Conference on System Simulation in Buildings*, pp. 107-50.
- Buhl, W.F., A.E. Erdem, F.C. Winkelmann, and E.F. Sowell. 1993. Recent improvements in SPARK: Strong component decomposition, multi-valued objects and graphical interface. *Proceedings of Building Simulation '93*. IBPSA, pp. 283-390.
- Carroll, J.A. 1980. An "MRT method" of computing radiant energy exchange in rooms. *Systems Simulation and Economic Analysis*, pp. 343-48. San Diego.
- Chandra, S. and A.A. Kerestecioglu. 1984. Heat transfer in naturally ventilated rooms: Data from full-scale measurements. *ASHRAE Transactions* 90(1B):211-24.
- Chi, J. and G.E. Kelly. 1978. A method for estimating the seasonal performance of residential gas and oil-fired heating systems. *ASHRAE Transactions* 84(1):405.
- Cinquemani, V., J.R. Owenby, and R.G. Baldwin. 1978. Input data for solar systems. U.S. Department of Energy *Report* No. E(49-26)1041.
- Clark, D.R. 1985. *HVACSIM+ building systems and equipment simulation program: Reference manual*. NBSIR 84-2996, U.S. Department of Commerce, Washington, D.C.
- Clarke, J.A. 1985. *Energy simulation in building design*. Adam Hilger Ltd., Boston.
- Claridge, D. 1988a. Design methods for earth-contact heat transfer. *Progress in Solar Energy*, K. Boer, ed. American Solar Energy Society, Boulder, CO.
- Claridge, D. 1988b. A perspective on methods for analysis of measured energy data from commercial buildings, *ASME Journal of Solar Energy Engineering* 120:150.

- Claridge, D.E., M. Krarti, and M. Bida. 1987. A validation study of variable-base degree-day cooling calculations. *ASHRAE Transactions* 93(2):90-104.
- Cole, R.J. 1976. The longwave radiation incident upon the external surface of buildings. *The Building Services Engineer* 44:195-206.
- Cooper, K.W. and D.R. Tree. 1973. A re-evaluation of the average convection coefficient for flow past a wall. *ASHRAE Transactions* 79:48-51.
- Corson, G.C. 1992. Input-output sensitivity of building energy simulations. *ASHRAE Transactions* 98(1):618.
- Cumali, Z., A.O. Sezgen, et al. 1979. Extensions of methods used in analyzing building thermal loads. *Proceedings Thermal Performance of the Exterior Envelopes of Buildings*, pp. 411-20.
- Davies, M.G. 1988. Design models to handle radiative and convective exchange in a room. *ASHRAE Transactions* 94(2):173-95.
- Dhar, A. 1995. Development of Fourier series and artificial neural network approaches to model hourly energy use in commercial buildings. *Ph.D. thesis*, ME Dept., Texas A&M University.
- Dhar, A., T.A. Reddy, and D.E. Claridge. 1998. Modeling hourly energy use in commercial buildings with Fourier series functional forms. *Journal of Solar Energy Engineering* 120:217.
- Dhar, A., T.A. Reddy, and D.E. Claridge. 1999a. A Fourier series model to predict hourly heating and cooling energy use in commercial buildings with outdoor temperature as the only weather variable. *Journal of Solar Energy Engineering* 121:47-53.
- Dhar, A., T.A. Reddy, and D.E. Claridge. 1999b. Generalization of the Fourier series approach to model hourly energy use in commercial buildings. *Journal of Solar Energy Engineering* 121:54-62.
- Draper, N. and H. Smith. 1981. *Applied regression analysis*, 2nd ed. John Wiley and Sons, New York.
- Elmahdy, A.H. and G.P. Mitalas. 1977. A simple model for cooling and dehumidifying coils for use in calculating energy requirements for buildings. *ASHRAE Transactions* 83(2):103-17.
- Englander, S.L. and L.K. Norford. 1992. Saving fan energy in VAV systems—Part 1: Analysis of a variable-speed-drive retrofit. *ASHRAE Transactions* 98(1):3-18.
- Erbs, D.G., S.A. Klein, and W.A. Beckman. 1983. Estimation of degree-days and ambient temperature bin data from monthly-average temperatures. *ASHRAE Journal* 25(6):60.
- Fels, M., ed. 1986. Measuring energy savings: The scorekeeping approach. *Energy and Buildings* 9.
- Fels, M. and M. Goldberg. 1986. Refraction of PRISM results in components of saved energy. *Energy and Buildings* 9:169.
- Fracastoro, G., M. Masoero, and M. Cali. 1982. Surface heat transfer in building components. *Proceedings Thermal Performance of the Exterior Envelopes of Buildings II*, pp. 180-203.
- Gordon, J.M. and K.C. Ng. 1994. Thermodynamic modeling of reciprocating chillers. *Journal of Applied Physics* 75(6):2769-74.
- Gordon, J.M. and K.C. Ng. 1995. Predictive and diagnostic aspects of a universal thermodynamic model for chillers. *International Journal of Heat and Mass Transfer* 38(5):807-18.
- Gordon, J.M., K.C. Ng, and H.T. Chua. 1995. Centrifugal chillers: Thermodynamic modeling and a case study. *International Journal of Refrigeration* 18(4):253-57.
- Guyon, G. and E. Palomo. 1999. Validation of two French building energy programs—Part 2: Parameter estimation method applied to empirical validation. *ASHRAE Transactions* 105(2):709-20.
- Haberl, J.S. and T.E. Bou-Saada. 1998. Procedures for calibrating hourly simulation models to measured building energy and environmental data. *ASME Journal of Solar Energy Engineering* 120(August):193.
- Haberl, J.S. and D.E. Claridge. 1987. An expert system for building energy consumption analysis: Prototype results. *ASHRAE Transactions* 93(1):979-98.
- Haberl, J. and P. Komor. 1990a. Improving commercial building energy audits: How annual and monthly consumption data can help. *ASHRAE Journal* 32(8):26-33.
- Haberl, J. and P. Komor. 1990b. Improving commercial building energy audits: How daily and hourly data can help. *ASHRAE Journal* 32(9):26-36.
- Haberl, J.S. and S. Thamilsaran. 1996. The great energy predictor shootout II: Measuring retrofit savings and overview and discussion of results. *ASHRAE Transactions* 102(2):419-35.
- Haberl, J.S., T.A. Reddy, I.E. Figuero, and M. Medina. 1997. Overview of LoanSTAR chiller monitoring—Analysis of in-situ chiller diagnostics using ASHRAE RP-827 test method. Paper presented at Cool Sense National Integrated Chiller Retrofit Forum, Presidio, San Francisco, September.
- Hammersten, S. 1984. Estimation of energy balances for houses. National Swedish Institute for Building Research, M84.18, December.
- Howell, R.H. and S. Suryanarayana. 1990. Sizing of radiant heating systems: Part I and Part II. *ASHRAE Transactions* 96(1):652-65.
- JCEM. 1992. Final report: Artificial neural networks applied to LoanSTAR data. Joint Center for Energy Management Report TR/92/15.
- Kamal, S. and P. Novak. 1991. Dynamic analysis of heat transfer in buildings with special emphasis on radiation. *Energy and Buildings* 17(3): 231-41.
- Kaplan, M., J. McFerran, J. Jansen, and R. Pratt. 1990. Reconciliation of a DOE2.1C model with monitored end-use data from a small office building. *ASHRAE Transactions* 96(1):981.
- Katipamula, S. and D.E. Claridge. 1993. Use of simplified systems model to measure retrofit energy savings. *Transactions of the ASME Journal of Solar Energy Engineering* 115(May):57-68.
- Katipamula, S., T.A. Reddy, and D.E. Claridge. 1994. Development and application of regression models to predict cooling energy consumption in large commercial buildings. *Proceedings of the 1994 ASME/JSME/JSES International Solar Energy Conference*, San Francisco, March 27-30, p. 307.
- Katipamula, S., T.A. Reddy, and D.E. Claridge. 1998. Multivariate regression modeling. *ASME Journal of Solar Energy Engineering* 120 (August):176.
- Kays, W.M. and A.L. London. 1984. *Compact heat exchangers*, 3rd ed. McGraw-Hill, New York.
- Kerrisk, J.F., N.M. Schnurr, et al. 1981. The custom weighting-factor method for thermal load calculation in the DOE-2 computer program. *ASHRAE Transactions* 87(2):569-84.
- Khalifa, A.J.N. and R.H. Marshall. 1990. Validation of heat transfer coefficients on interior building surfaces using a real-sized indoor test cell. *International Journal of Heat and Mass Transfer* 33(10):2219-36.
- Kisssock, J.K., T.A. Reddy, J.S. Haberl, and D.E. Claridge. 1993. E-model: A new tool for analyzing building energy use data. *Proceedings Intl. Indust. Energy Tech. Conf.*, Texas A&M University.
- Kisssock, J.K., T.A. Reddy, and D.E. Claridge. 1998. Ambient temperature regression analysis for estimating retrofit savings in commercial buildings. *ASME Journal of Solar Energy Engineering* 120:168.
- Klein, S.A., W.A. Beckman, et al. 1994. *TRNSYS: A transient simulation program*. Engineering Experiment Station Report 38-14, University of Wisconsin-Madison.
- Knebel, D.E. 1983. *Simplified energy analysis using the modified bin method*. ASHRAE.
- Krarti, M. 1994a. Time varying heat transfer from slab-on-grade floors with vertical insulation. *Building and Environment* 29(1):55-61.
- Krarti, M. 1994b. Time varying heat transfer from horizontally insulated slab-on-grade floors. *Building and Environment* 29(1):63-71.
- Krarti, M. and P. Chuangchid. 1999. Cooler floor heat gain for refrigerated structures, *Final Report*, ASHRAE Project 953-TRP.
- Krarti, M., D.E. Claridge, and J. Kreider. 1988a. The ITPE technique applied to steady-state ground-coupling problems. *International Journal of Heat and Mass Transfer* 31:1885-98.
- Krarti, M., D.E. Claridge, and J. Kreider. 1988b. ITPE method applications to time-varying two-dimensional ground-coupling problems. *International Journal of Heat and Mass Transfer* 31:1899-1911.
- Krarti, M., J.F. Kreider, D. Cohen, and P. Curtiss. 1998. Estimation of energy savings for building retrofits using neural networks. *ASME Journal of Solar Energy Engineering* 120:211.
- Kreider, J.F. and J. Haberl. 1994. Predicting hourly building energy usage: The great predictor shootout—Overview and discussion of results. *ASHRAE Transactions* 100(2):1104-18.
- Kreider, J.F. and A. Rabl. 1994. *Heating and cooling of buildings*. McGraw-Hill, New York.
- Kreider, J.F. and X.A. Wang. 1991. Artificial neural networks demonstration for automated generation of energy use predictors for commercial buildings. *ASHRAE Transactions* 97(1):775-79.
- Kusuda, T. 1969. Thermal response factors for multi-layer structures of various heat conduction systems. *ASHRAE Transactions* 75(1):246-71.
- Labs, K., J. Carmody, R. Sterling, L. Shen, Y. Huang, and D. Parker. 1988. Building foundation design handbook, ORNL Report Sub/86-72143/1. Oak Ridge National Laboratory, Oak Ridge, TN.

- Lachal, B., W.U. Weber, and O. Guisan. 1992. Simplified methods for the thermal analysis of multifamily and administrative buildings. *ASHRAE Transactions* 98.
- Lebrun, J., J.-P. Bourdouxhe, and M. Grodent. 1999. *HVAC 1 toolkit: A toolkit for primary HVAC system energy calculation*. ASHRAE.
- Lewis, P.T. and D.K. Alexander. 1990. HTB2: A flexible model for dynamic building simulation. *Building and Environment*. pp. 7-16.
- Liu, M. and D.E. Claridge. 1998. Use of calibrated HVAC system models to optimize system operation. *ASME Journal of Solar Energy Engineering* 120:131.
- Lorenzetti, D.M. and L.K. Norford. 1993. Pressure reset control of variable air volume ventilation systems. *Proceedings ASME International Solar Energy Conference*, p. 445, April, Washington, D.C.
- MacDonald, J.M. and D.M. Wasserman. 1989. Investigation of metered data analysis methods for commercial and related buildings. Oak Ridge National Laboratory Report ORNL/CON-279.
- Manke, J.M., D.C. Hittle, and C.E. Hancock. 1996. Calibrating building energy analysis models using short-term data. *Proceedings ASME International Solar Energy Conference*, p.369, San Antonio, TX.
- McClelland, J.L. and D.E. Rumelhart. 1988. *Exploration in parallel distributed processing*. MIT Press, Cambridge, MA.
- McQuiston, F.C. and J. D. Spitler. 1992. *Cooling and Heating Load Calculation Manual*. ASHRAE
- Melo, C. and G.P. Hammond. 1991. Modeling and assessing the sensitivity of external convection from building facades in heat and mass transfer in building materials and structures. pp. 683-95. Hemisphere Publishing, New York.
- Metcalf, R.R., R.D. Taylor, C.O. Pederson, R.J. Liesen, and D.E. Fisher. 1995. Incorporating a modular system simulation program into a large energy analysis program: The linking of IBLAST and HVACSIM+. *Proceedings of Building Simulation '95*.
- Miller, D.E. 1980. The impact of HVAC process dynamics on energy use. *ASHRAE Transactions* 86(2):535-56.
- Miller, R. and J. Seem. 1991. Comparison of artificial neural networks with traditional methods of predicting return from night setback. *ASHRAE Transactions* 97(2):500-08.
- Mitalas, G.P. and D.G. Stephenson. 1967. Room thermal response factors. *ASHRAE Transactions* 73(1):III.2.1-III.2.10.
- Mitalas, G.P. 1968. Calculations of transient heat flow through walls and roofs. *ASHRAE Transactions* 74(2):182-88.
- Mitchell, J.W. 1983. *Energy engineering*. John Wiley and Sons, New York.
- NOAA. 1973. Degree-days to selected bases. U.S. National Climatic Data Center, Asheville, NC.
- Neter, J., W. Wasserman, and M. Kutner. 1989. *Applied linear regression models*, 2nd ed. Richard C. Irwin, Homewood, IL.
- Nisson, J.D.N. and G. Dutt. 1985. *The superinsulated home book*. John Wiley and Sons, New York.
- Norford, L.K., R.H. Socolow, E.S. Hsieh, and G.V. Spadaro. 1994. Two-to-one discrepancy between measured and predicted performance of a low-energy office building: Insights from a reconciliation based on the DOE-2 model. *Energy and Buildings* 21:121.
- Park, C., D.R. Clark, and G.E. Kelly. 1985. An overview of HVACSIM+, a dynamic building/HVAC control systems simulation program. *Proceedings First Building Energy Simulation Conference*.
- Parker, W.H., G.E. Kelly, and D. Didion. 1980. A method for testing, rating, and estimating the heating seasonal performance of heat pumps. National Bureau of Standards, NBSIR 80-2002, April.
- Phelan, J., M.J. Brandemuehl, and M. Krarti. 1996. *Final Report ASHRAE Project RP-827: Methodology development to measure in-situ chiller, fan, and pump performance*. JCEM Report No. JCEM/TR/96-3, University of Colorado at Boulder.
- Rabl, A. 1988. Parameter estimation in buildings: Methods for dynamic analysis of measured energy use. *Journal of Solar Energy Engineering* 110:52-66.
- Rabl, A. and A. Riahle. 1992. Energy signature model for commercial buildings: Test with measured data and interpretation. *Energy and Buildings* 19:143-54.
- Reddy, T. 1989. Application of dynamic building inverse models to three occupied residences monitored non-intrusively. *Proceedings Thermal Performance of Exterior Envelopes of Buildings IV*, ASHRAE/DOE/BTECC/CIBSE.
- Reddy, T. and D. Claridge. 1994. Using synthetic data to evaluate multiple regression and principle component analyses for statistical modeling of daily building energy consumption. *Energy and Buildings* 24:35-44.
- Reddy, T.A., S. Katipamula, J.K. Kisoock, and D.E. Claridge. 1995. The functional basis of steady-state thermal energy use in air-side HVAC equipment. *Journal of Solar Energy Engineering* 117:31-39.
- Reddy, T.A., N.F. Saman, D.E. Claridge, J.S. Haberl, W.D. Turner, and A. Chalifoux. 1997. Baseline methodology for facility level monthly energy use—Part 1: Theoretical aspects. *ASHRAE Transactions* 103(2): 336-47.
- Reddy, T.A., S. Deng, and D.E. Claridge. 1999. Development of an inverse method to estimate overall building and ventilation parameters of large commercial buildings. *Journal of Solar Energy Engineering* 121:47.
- Ruch, D. and D. Claridge. 1991. A four parameter change-point model for predicting energy consumption in commercial buildings. *Proceedings ASME International Solar Energy Conference*, 433-40.
- Ruch, D., L. Chen, J. Haberl, and D. Claridge. 1993. A change-point principle component analysis (CP/CAP) method for predicting energy use in commercial buildings: The PCA model. *Journal of Solar Energy Engineering* 115:77-84.
- Seem, J.E. and J.E. Braun. 1991. Adaptive methods for real-time forecasting of building electricity demand. *ASHRAE Transactions* 97(1):710.
- Shipp, P.H. and T.B. Broderick. 1983. Analysis and comparison of annual heating loads for various basement wall insulation strategies using transient and steady-state models. *Thermal Insulation, Materials, and Systems for Energy Conservation in the 80's*. ASTM STP 789, F.A. Govan, D.M. Greason, and J.D. McAllister, eds. American Society for Testing and Materials, West Conshohocken, PA.
- Shurcliff, W.A. 1984. *Frequency method of analyzing a building's dynamic thermal performance*. Cambridge, MA.
- Sonderregger, R.C. 1977. Dynamic models of house heating based on equivalent thermal parameters. *Ph.D. thesis*, Center for Energy and Environmental Studies Report No. 57. Princeton University, Princeton, NJ.
- Sonderregger, R.C. 1985. Thermal modeling of buildings as a design tool. *Proceedings of CHMA 2000*, Vol. 1.
- Sonderregger, R.C. 1998. Baseline equation for utility bill analysis using both weather and non-weather related variables. *ASHRAE Transactions* 104(2):859-70.
- Sowell, E.F. 1988. Classification of 200,640 parametric zones for cooling load calculations. *ASHRAE Transactions* 94(2):716-36.
- Sowell, E.F. 1990. Lights: A numerical lighting/HVAC test cell. *ASHRAE Transactions* 96(2):780-86.
- Sowell, E.F. and M.A. Moshier. 1995. HVAC component model libraries for equation-based solvers. *Proceedings of Building Simulation '95*. IBPSA, Madison, WI.
- Spitler, J.D., C.O. Pedersen, and D.E. Fisher. 1991. Interior convective heat transfer in buildings with large ventilative flow rates. *ASHRAE Transactions* 97(1):505-15.
- Steinman, M., L.N. Kalisperis, and L.H. Summers. 1989. The MRT-correction method: A new method of radiant heat exchange. *ASHRAE Transactions* 95(1):1015-27.
- Stephenson, D.G. and G.P. Mitalas. 1967. Cooling load calculations by thermal response factor method. *ASHRAE Transactions* 73(1):III.1.1-III.1.7.
- Stoecker, W.F. and J.W. Jones. 1982. *Refrigeration and air conditioning*, 2nd ed. McGraw-Hill, New York.
- Strand, R.K. and C.O. Pedersen. 1997. Implementation of a radiant heating and cooling model into an integrated building energy analysis program. *ASHRAE Transactions* 103(1):949-58.
- Subbarao, K. 1986. Thermal parameters for single and multi-zone buildings and their determination from performance data. SERI Report SERI/TR-253-2617. Solar Energy Research Institute, Golden, CO.
- Subbarao, K. 1988. PSTAR—Primary and secondary terms analysis and re-normalization: A unified approach to building energy simulations and short-term monitoring. SERI/TR-253-3175.
- Taylor, R.D., C.O. Pedersen, and L. Lawrie. 1990. Simultaneous simulation of buildings and mechanical systems in heat balance based energy analysis programs. *Proceedings Third International Conference on System Simulation in Buildings*. Liege, Belgium.
- Taylor, R.D. et al. 1991. Impact of simultaneous simulation of buildings and mechanical systems in heat balance based energy analysis programs on system response and control. *Proceedings Building Simulation '91*. Sophia Antipolis, Nice France: IBPSA.
- Thamilseran, S. and J. Haberl. 1995. A bin method for calculating energy conservation retrofit savings in commercial buildings. *Proceedings 1995 ASME/JSME/ISES Intl. Solar Energy Conference*, pp. 111-24.
- Threlkeld, J.L. 1970. *Thermal environmental engineering*, 2nd ed. Prentice-Hall, Englewood Cliffs, NJ.

- USAF. 1978. *Engineering weather data*. Department of the Air Force Manual AFM 88-29. U.S. Government Printing Office, Washington, D.C.
- Walton, G.N. 1980. A new algorithm for radiant interchange in room loads calculations. *ASHRAE Transactions* 86(2):190-208.
- Walton, G.N. 1983. Thermal analysis research program reference manual. NBSIR 83-2655. National Institute of Standards and Technology, Gaithersburg, MD.
- Walton, G.N. 1993. Computer programs for simulation of lighting/HVAC interactions. NISTIR 5322. NIST.
- Waltz, J.P. 1992. Practical experience in achieving high levels of accuracy in energy simulations of existing buildings. *ASHRAE Transactions* 98(1): 606-17.
- Wang, X.A. and J.F. Kreider. 1992. Improved artificial neural networks for commercial building energy use prediction. *Journal of Solar Energy Engineering*.
- Wasserman, P.D. 1989. *Neural computing, theory and practice*. Van Nostrand Reinhold, New York.
- Yazdanian, M. and J. Klems. 1993. Measurement of the exterior convective film coefficient for windows in low-rise buildings. *ASHRAE Transactions* 100(1):1087-96.
- York, D.A. and C.C. Cappiello, eds. 1982. *DOE-2 engineers manual*. Lawrence Berkeley Laboratory Report LBL-11353 (LA-8520-M, DE83004575). National Technical Information Services, Springfield, VA.

BIBLIOGRAPHY

- NEMVP. 1996. *U.S. DOE North-America energy monitoring and verification protocol*. U.S. Department of Energy, Washington, D.C.
- Shavit, G. 1995. Short-time-step analysis and simulation of homes and buildings during the last 100 years. *ASHRAE Transactions* 101(1):856-68.
- Sowell, E.F. and G.N. Walton. 1980. Efficient computation of zone loads. *ASHRAE Transactions* 86(1):49-72.
- Sowell, E.F. and D.C. Hittle. 1995. Evolution of building energy simulation methodology. *ASHRAE Transactions* 101(1):850-55.
- Spitler, J.D. 1996. *Annotated guide to load calculation models and algorithms*. ASHRAE.
- Subbarao, K., J. Burch, and C.E. Hancock. 1990. How to accurately measure the load coefficient of a residential building. *Journal of Solar Energy Engineering*.
- U.S. Army. 1979. *BLAST, The building loads analysis and system thermodynamics program—Users manual*. U.S. Army Construction Engineering Research Laboratory Report E-153.
- Yuill, G.K. 1990. *An annotated guide to models and algorithms for energy calculations relating to HVAC equipment*. ASHRAE.