Related Commercial Resources

CHAPTER 19

ENERGY ESTIMATING AND MODELING METHODS

ENERGY requirements and fuel consumption of HVAC systems directly affect a building's operating cost and indirectly affect the environment. This chapter discusses methods for estimating energy use for two purposes: modeling for building and HVAC system design and associated design optimization (**forward modeling**), and modeling energy use of existing buildings for establishing baselines and calculating retrofit savings (**data-driven modeling**).

GENERAL CONSIDERATIONS

MODELS AND APPROACHES

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*, whereas physicists call them *forcing variables*), which act on the system. There are two types: controllable by the experimenter, and uncontrollable (e.g., climate).
2. **System structure and parameters/properties**, which provide the necessary physical description of the system (e.g., thermal mass or mechanical properties of the elements).
3. **Output** (*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. There are two broad but distinct approaches to modeling; which to use is dictated by the objective or purpose of the investigation (Rabl 1988).

Forward (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. To ensure accuracy, 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 to predict its behavior. Thus, this approach is ideal in the preliminary design and analysis stage and is most often used then.

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Forward modeling of building energy use begins with a physical description of the building system or component of interest. For example, building geometry, geographical location, physical characteristics (e.g., wall material and thickness), type of equipment and operating schedules, type of HVAC system, building operating schedules, plant equipment, etc., are specified. 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 illustrates the ordering of the analysis typically performed by a building energy simulation program.

Data-Driven (Inverse) Approach. In this case, input and output variables are known and measured, and the objective is to determine a mathematical description of the system and to estimate system parameters. In contrast to the forward approach, the data-driven approach is relevant 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 predetermined or planned experiments on the system to elicit system response under a wider range of system performance than would have occurred under normal system operation. These performance data allow 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.

Data-driven modeling often allows identification of system models that are not only simpler to use but also are more accurate predictors of future system performance than forward models. The data-driven 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 yet been widely adopted in energy-related curricula and by the building professional community.

CHARACTERISTICS OF MODELS

Forward Models

Although procedures for estimating energy requirements vary considerably in their degree of complexity, they all have three common elements: calculation of (1) space load, (2) secondary

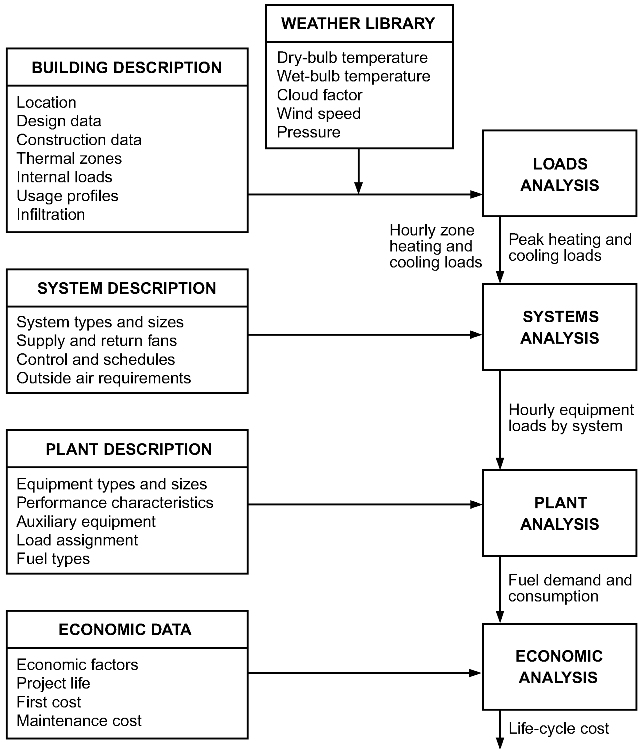

Fig. 1 Flow Chart for Building Energy Simulation Program
(Ayres and Stamper 1995)

equipment load, and (3) primary equipment energy requirements. Here, *secondary* refers to equipment that distributes the heating, cooling, or ventilating medium to conditioned spaces, whereas *primary* refers to central plant equipment that converts fuel or electric energy to heating or cooling effect.

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 17 and 18 discuss load calculation in detail.

Although 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 calculation of all forms of energy required by the secondary system (e.g., 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 ensure 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.

Complex and often unexpected interactions can occur between systems or between various modes of heat transfer. For example, radiant heating panels affect space loads by raising the mean radiant temperature in the space (Howell and Suryanarayana 1990). As a result, 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 caused by infiltration or ventilation decreases because of the reduced indoor-to-outdoor-air temperature difference. The infiltration rate may also decrease because the reduced air temperature difference reduces the stack effect.

Data-Driven Models

The data-driven model has to meet requirements very different from the forward model. The data-driven 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.) It 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). Because model parameters are deduced from actual building performance, it is much more likely to accurately capture 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 user skill and expertise. In general, data-driven models are less flexible than forward models in evaluating energy implications of different design and operational alternatives, and so are not a substitute in this regard.

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

- How does consumption compare with design predictions (and, in case of discrepancies, are they caused by anomalous weather, unintended building operation, improper operation, or other causes)?
- How would consumption change if 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 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 these questions are better addressed by the data-driven 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 using actual building schedules and operating modes, but this is tedious and labor-intensive, and materials and equipment often perform differently in reality 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 data-driven approach).

CHOOSING AN ANALYSIS METHOD

The most important step in selecting an energy analysis method is matching 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). ANSI/ASHRAE *Standard* 140, Method of Test for the Evaluation of Building Energy Analysis Computer Programs, was developed to identify and diagnose differences in predictions that may be caused by algorithmic differences, modeling limitations, coding errors, or input errors. More information on model validation and testing can be found in the Model Validation and Testing section of this chapter and in ANSI/ASHRAE *Standard* 140.
- **Sensitivity.** The method should be sensitive to the design options being considered. The difference in energy use between two choices should be adequately reflected.
- **Versatility.** The method should allow 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 affects both the economics of analysis (speed) and the reproducibility of results.

Selecting Energy Analysis Computer Programs

Selecting a building energy analysis program depends on its application, number of times it will be used, experience of the user, and 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 is also shaded by other buildings part of the time, the ability to analyze detached shading is an absolute requirement, regardless of any other factors.

Because almost all manual methods are now implemented on a computer, selection of an energy analysis method is the selection of a computer program. 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 of learning to use the program and of using it. Major issues that influence the cost of learning a program include (1) complexity of 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 continues to consume the time of even an experienced user until data are readily available in electronic form compatible with simulation programs.

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 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.

Quality of output is another factor to consider. Reports should be easy to read and uncluttered. Titles and headings should be unambiguous. Units should be stated explicitly. The user's manual should explain the meanings of 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 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, and support from the software supplier should be tested. The availability of training should be considered when choosing a more complex program.

Availability of weather data and 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 are 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. More information on weather data can be found in Chapter 14.

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 have been entered already for other purposes.

The results of computer calculations should be accepted with caution, because the software vendor does not accept responsibility for the correctness of calculations or use of the program. Manual calculation should be done to develop a good understanding of 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 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 expertise needed by 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.

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, such as degree-day and bin, may be used.

Table 1 classifies methods for analyzing building energy use as either forward or data-driven, and either 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 at http://www.energytoolsdirectory.gov.

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** and **weighting-factor methods** are used for these calculations. A third method, the **thermal-network method**, is not widely used but shows promise.

The **instantaneous space sensible load** is the rate of heat flow into the space air mass. This quantity, sometimes called the *cooling load*, differs from heat gain, which usually contains a radiative

Table 1 Classification of Analysis Methods For Building Energy Use

Method	Forward	Data-Driven: Empirical or Black-Box	Data-Driven: Calibrated Simulation	Data-Driven: Physical or Gray-Box	Comments
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, 1999b; 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 data-driven 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 (Rabl 1988; Reddy 1989; Sonderegger 1977)	X	—	—	X	Uses equivalent thermal parameters (data-driven mode).
Response factors (Kusuda 1969; Mitalas 1968; Mitalas and Stephenson 1967; Stephenson and Mitalas 1967)	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 (Rabl 1988; Reddy 1989; Subbarao 1986)	—	—	—	X	Autoregressive moving average (ARMA) 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, EnergyPlus (Crawley et al. 2001; Haberl and Bou-Saada 1998; Manke et al. 1996; Norford et al. 1994)	X	—	X	—	Hourly and subhourly simulation programs with system models.
Computer emulation (HVACSIM+, TRNSYS) (Clark 1985; Klein et al. 1994)	X	—	—	—	Subhourly simulation programs.
Artificial neural networks (Kreider and Haberl 1994; Kreider and Wang 1991)	—	X	—	—	Connectionist models.

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 analysis, so the air is always assumed to be in thermal equilibrium. Under these assumptions, the instantaneous space sensible load and rate of heat removal are equal in magnitude and opposite in sign.

The weighting-factor and heat balance methods use conduction transfer functions (or their equivalents) to calculate transmission heat gain or loss. The main 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, as described in the *ASHRAE Toolkit for Building Load Calculations* (Pedersen et al. 2001, 2003), 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 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 18 for use in design cooling load calculations, so a fuller description is omitted here.

However, the heat balance procedure described in Chapter 18 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 (27) of Chapter 18 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

$$q_{sys_j} = a + bt_{a_j} \tag{1}$$

where

q_{sys_j} = system heat transfer at time step j, W
a, b = coefficients that apply over a certain range of zone air temperatures
t_{a_j} = zone air temperature at time step j, °C

System heat transfer q_{sys_j} 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 18, when zone air temperature is fixed.

Substituting Equation (1) into Equation (27) of Chapter 18 and solving for zone air temperature,

$$t_{a_j} = \frac{a + \sum_{i=1}^{N} A_i h_{ci} t_{si_{i,j}} + \rho c V_{infil_j} t_{o_j} + \rho c V_{vent_j} t_{v_j} + q_{c,int_j}}{-b + \sum_{i=1}^{N} A_i h_{ci} + \rho c V_{infil_j} + \rho c V_{vent_j}} \tag{2}$$

where

N = number of zone surfaces
A_i = area of ith surface, m²
h_{ci} = convection coefficient for ith surface, W/(m²·K)
$t_{si_{i,j}}$ = surface temperature for ith 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_{o_j} = outdoor air temperature at time step j, °C
t_{v_j} = ventilation air temperature at time step j, °C
q_{c,int_j} = sum of 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 (26) and (25) in Chapter 18]. Also, the correct temperature range must be found 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 treatment of system heat transfer, other considerations that may be important in building energy analysis programs include simulations over periods as long as a year, treatment of radiant cooling and heating systems, treatment of interzone heat transfer, modeling convection heat transfer, and modeling radiation heat transfer.

The heat balance method in Chapter 18 assumes the use of a single design day. 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 used.

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) describe implementation of heat source conduction transfer functions, which may be used for modeling radiant panels, into a heat balance-based building simulation program.

In principle, this method extends directly to multiple spaces, with heat transfer between zones. In this case, some surface temperatures 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 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, more sophisticated exterior convection models (Cooper and Tree 1973; Fracastoro et al. 1982; Melo and Hammond 1991; Walton 1983; Yazdanian and Klems 1994) that incorporate the effects of wind speed, wind direction, surface orientation, etc., may be preferable. More detailed interior convection correlations for use in buildings are also available (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 [e.g., Cole (1976); Walton (1983)] and interior [e.g., Carroll (1980); Davies (1988); Kamal and Novak (1991); Steinman et al. (1989); Walton (1980)] long-wave radiation transfer have been implemented in detailed building simulation programs.

Weighting-Factor Method

The weighting-factor method of calculating instantaneous space sensible load is a compromise between simpler methods (e.g., steady-state calculation) that ignore the ability of building mass to store energy, and more complex methods (e.g., 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 (Kerrisk et al. 1981; York and Cappiello 1982). 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 the (1) relative amounts of energy appearing as convection to the air versus radiation, and (2) 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. 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 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, usually 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 heat gain is absorbed by walls or furniture and stored for later release to the air. At time θ, the calculation uses present and past values of the instantaneous heat gain (q_θ, $q_{\theta-1}$), past values of the cooling load ($Q_{\theta-1}$, $Q_{\theta-2}$, ...), and the **heat gain weighting factors** (v_0, v_1, v_2, ..., w_1, w_2, ...) for the type of heat gain under consideration. Thus, for each type of heat gain q_θ, cooling load Q_θ is calculated as

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

The heat gain weighting factors are a set of parameters that determine how much of the energy entering a room is stored and how rapidly stored energy is released later. 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. Heat gain weighting factors also differ for different rooms because room construction affects 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, 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 (with information on the room's HVAC system 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, air temperature can vary from the reference value used to calculate the cooling load, or (2) because of HVAC system characteristics. Deviation of air temperature t_θ from the reference value at hour θ is calculated as

$$\begin{aligned} t_\theta = 1/g_0 + [(Q_\theta - \mathrm{ER}_\theta) + P_1(Q_{\theta-1} - \mathrm{ER}_{\theta-1}) \\ + P_2(Q_{\theta-2} - \mathrm{ER}_{\theta-2}) + \cdots - g_1 t_{\theta-1} - g_2 t_{\theta-2} - \cdots] \end{aligned} \quad (4)$$

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

Values of weighting factors for typical building rooms are presented in the following table. 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/(m²·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 is not 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 (e.g., 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) radiant heat transferred from a surface depends on the temperature of other room surfaces (not on 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) 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 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 node temperature and energy flow between all connected nodes. Energy flows may include conduction, convection, and short- or 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 network discretization, the models become what are commonly thought of as finite-difference or finite-volume models (Clarke 2001; 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 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. However, they also require the most computation time, and, in current implementations, 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 25 of this volume and Chapter 43 of the 2007 *ASHRAE Handbook—HVAC Applications*. Chapter 18 provides information for calculating 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.

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 heat transfer from its foundation (Labs et al. 1988). Since then, 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 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 effect 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 Basements

The design tool for slab-on-grade floors developed by Krarti and Chuangchid (1999) can be modified to a simplified design tool for calculating heat loss for slabs and basements. The 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 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:

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

where

q_{mean} = annual-mean heat loss/gain, W
q_{amp} = heat loss/gain amplitude, W
θ = time, s
ω = annual angular frequency ($\omega = 1.992 \times 10^{-7}$ rad/s)
ϕ = phase lag between total slab heat loss/gain and soil surface temperature, radians

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:

$$q_{des} = q_{mean} + q_{amp} \tag{6}$$

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

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

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

where

k_s = soil thermal conductivity, W/(m·K)
P = slab perimeter, m
A = slab area, m^2

For mean calculations,

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

For annual calculations,

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

where

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

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

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

$$G = k_s R_{eq}\sqrt{\frac{\omega}{\alpha_s}} \tag{12}$$

where

R_{eq} = equivalent thermal resistance for entire slab, (m^2·K)/W
α_s = soil thermal diffusivity, m^2/s

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

$$R_{eq} = R_f + R_i \tag{13}$$

where

R_f = thermal resistance of floor, (m^2·K)/W
R_i = thermal resistance of insulation, (m^2·K)/W

For partial insulation configurations (both horizontal and vertical),

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

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

where c = insulation length of slab, m.

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

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

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

$$U_{eff,\,mean} = mU_oD \tag{17}$$

$$U_{eff,\,amp} = aU_oD^{0.16}G^{-0.6} \tag{18}$$

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

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

where

t_a = annual average ambient dry-bulb temperature, °C
t_r = annual average indoor dry-bulb temperature, °C

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

$$q_{amp} = U_{eff,\,amp}At_{amp} \tag{20}$$

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 metre. 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

102mm thick reinforced concrete slab, thermal resistance R_f = 0.5 (m^2·K)/W

Soil Thermal Properties

Soil thermal conductivity	k_s	= 1.21 W/(m·K)
Soil density	ρ	= 700 kg/m^3
Soil thermal diffusivity	α_s	= 5.975 × 10^{-7} m^2/s

Insulation
Uniform insulation R-value R_i = 3.52 (m^2·K)/W

Temperatures
Indoor temperature t_r = 20°C
Annual average ambient temperature t_a = 6.3°C
Annual amplitude ambient temperature t_{amp} = 20 K
Annual angular frequency ω = 1.992 × 10^{-7} rad/s

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

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

$$U_o = \frac{k_sP}{A} = \frac{1.21}{3.0} = 0.4033$$

$$H = \frac{A}{Pk_sR_{eq}} = \frac{3.0}{1.21(0.5+3.52)} = 0.6168$$

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

$$G = k_sR_{eq}\sqrt{\frac{\omega}{\alpha_s}} = 1.21(0.5+3.52)\sqrt{\frac{1.992\times10^{-7}}{5.975\times10^{-7}}} = 2.8086$$

Therefore,

$$\begin{aligned} Q_m &= U_{eff,\,m}A(T_r - T_a) \\ &= 0.4 \times 0.4033 \times 1.0748 \times 150 \times (20 - 6.3) \\ &= 357.00\ \text{W} \end{aligned}$$

and

$$\begin{aligned} Q_A &= U_{eff,\,a}AT_a \\ &= 0.25 \times 0.4033 \times 1.0748^{0.16} \times 2.8086^{-0.6} \times 150 \times 20 \\ &= 165.00\ \text{W} \end{aligned}$$

Example 2. Calculation for Basements. Determine the annual mean and 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 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 m
102 mm thick reinforced concrete slab, thermal resistance R_f = 0.5 (m^2·K)/W

Soil Thermal Properties

Soil thermal conductivity	k_s	= 1.21 W/(m·K)
Soil thermal diffusivity	α_s	= 4.47 × 10^{-7} m^2/s

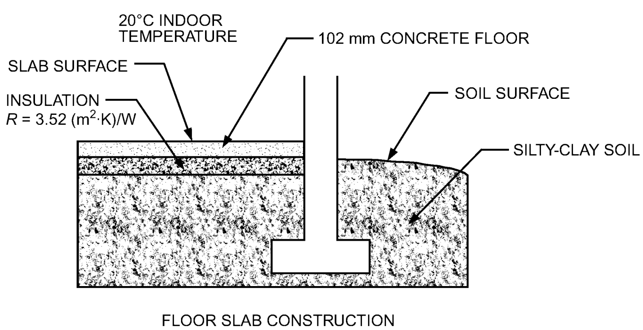

Fig. 2 Slab Foundation for Example 1

Insulation
Uniform insulation R-value $R_i = 1.152\ (\mathrm{m^2 \cdot K})/\mathrm{W}$

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

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

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

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

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

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

$$(A/P)_{eff,\,b,\,amp} = (1 + 0.4131 e^{-1.8139}) \times 11.91 = 12.7120$$

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

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

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

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

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

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

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

Therefore,

$$\begin{aligned} Q_m &= U_{eff,\,m} A (T_a - T_r) \\ &= 0.4 \times 0.3697 \times 1.7503 \times 225 \times (22.0 - 10.0) = 698.85\ \mathrm{W} \end{aligned}$$

and

$$\begin{aligned} Q_a = U_{eff,\,a} A T_a &= 0.25 \times 0.3124 \times 1.8839^{0.16} \\ &\times 1.3344^{-0.6} \times 225 \times 12.7 = 207.72\ \mathrm{W} \end{aligned}$$

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

Although 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 *HVAC2 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 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 by (1) heat transfer through pipes and ducts and (2) electrical input to fans and pumps. 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 20 and 43 of the 2008 *ASHRAE Handbook—HVAC Systems and Equipment*. In addition, Chapter 21 of this volume covers pressure loss calculations for airflow in ducts and duct fittings. Chapter 22 presents a similar discussion for fluid flow in pipes. Although 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 a building's fan and air distribution systems require a detailed pressure balance on the entire network. For example, in an air distribution system, airflow through the fan depends on its physical characteristics, operating speed, and pressure differential across the fan. Pressure drop through the duct system depends on duct design, position of all dampers, and airflow through the fan. 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 *HVAC2 Toolkit* (Brandemuehl 1993).

Detailed analysis of a distribution system requires flow and pressure balancing among the components, but nearly all commercially available energy analysis methods approximate the effect of the interactions with part-load performance curves. This eliminates the need to calculate pressure drop through the distribution system at off-design conditions. 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:

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

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, cfm
Q_{full} = fan airflow rate at full load or design, cfm
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). In the simulation program, the curves are represented by polynomial regression equations. Models and subroutines for performing these calculations are also available in the ASHRAE *HVAC2 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 because of fan operation increases air temperature. Although fan shaft power directly affects 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:

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

where

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

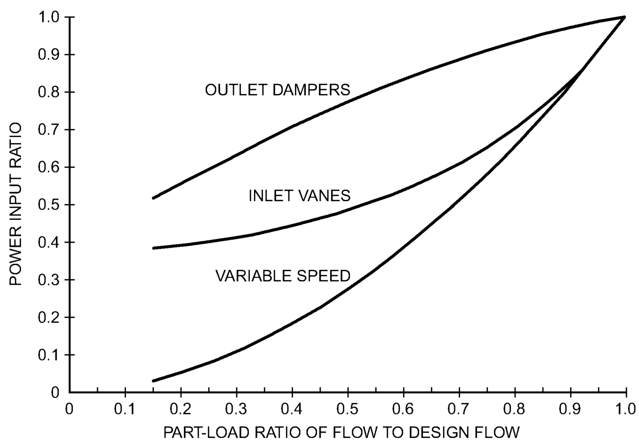

Fig. 3 Part-Load Curves for Typical Fan Operating Strategies
(York and Cappiello 1982)

Heat and Mass Transfer Components

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

For example, 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 chiller's energy consumption 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 cooling coil performance and 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 water flow through the coil. In such a scenario, the cooling coil model must be able to calculate the leaving air humidity, water temperature, and water flow rate given the cooling coil design characteristics and entering air temperature and humidity, airflow, and water temperature.

Virtually all building energy simulation programs include, and require, models of heat and mass transfer components. These models are generally relatively simple. Whereas 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 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 (number of transfer units) model is described in most heat transfer textbooks and briefly discussed in Chapter 4.

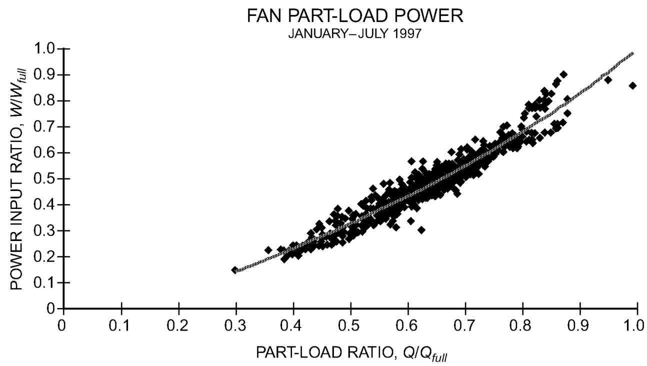

Fig. 4 Fan Part-Load Curve Obtained from Measured Field Data under ASHRAE RP-823
(Brandemuehl and Bradford 1999)

It is particularly appropriate for describing leaving fluid conditions when entering fluid conditions and equipment design characteristics are known. Also, 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; 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 manufacturers' data. Given detailed information about the materials, geometry, and construction of the heat exchanger, fundamental heat transfer principles can be applied to calculate the overall heat transfer coefficient. However, the method most appropriate for energy estimation is using manufacturers' performance data or direct measurements of installed performance. In reporting the design performance of a heat exchanger, a manufacturer typically gives the heat transfer rate under various operating conditions, with 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 evaluate 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. Although detailed information on the coil geometry and heat transfer surfaces is not available, the manufacturer states that the one-row hot-water heating coil delivers 240 kW of heat under the following design conditions:

Design Performance

Entering water temperature t_{hi} = 80°C
Water mass flow rate $\dot{m}_h$ = 5.0 kg/s
Entering air temperature t_{ci} = 20°C
Air mass flow rate $\dot{m}_c$ = 8.0 kg/s
Design heat transfer q = 240 kW

Solution: First determine the heat exchanger *UA* from design data, then use *UA* to predict performance at off-design conditions. Effectiveness-NTU relationships are used for both steps. The key assumption is that the *UA* is constant for both operating conditions.

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

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

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

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

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

where c_p is specific heat and c_{max} and c_{min} are the larger and smaller of the capacity rates, respectively,

b) Effectiveness can be directly calculated from the heat transfer definition.

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

where t_{co} is the leaving air temperature.

c) The effectiveness-NTU relationships for a crossflow heat exchanger with both fluids unmixed allow 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, in Kays and London (1984)]. Given the effectiveness and capacity rate ratio, NTU = 0.804.

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

$$UA = C_{min}\text{NTU} = (8.05)(0.804) = 6.472 \text{ kW/K}$$

Application to Cooling and Dehumidifying Coils

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. Although the complex heat and mass transfer theory 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.

The effectiveness-NTU method is typically developed and applied in analysis of sensible heat exchangers, but 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, capacity rates, and 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 is the basis for models by Brandemuehl (1993), Braun (1988), Elmahdy and Mitalas (1977), and Threlkeld (1970). The same principles also underlie the coil model described in Chapter 22 of the 2008 *ASHRAE Handbook—HVAC 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 performance of a cooling coil requires evaluating 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.

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:

$$c_{p,sat} = \frac{\Delta h_{l,sat}}{\Delta t_l} \tag{23}$$

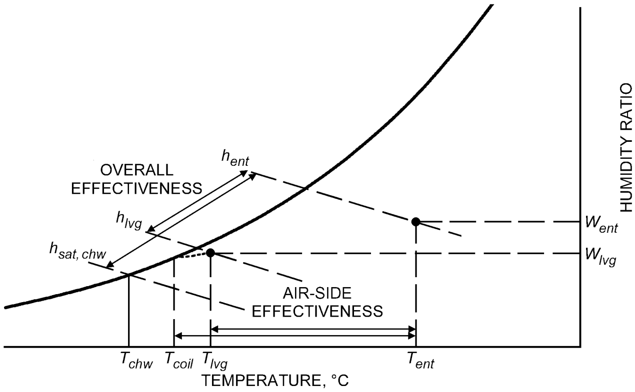

Fig. 5 Psychrometric Schematic of Cooling Coil Processes

Using the definition of Equation (23), the basic effectiveness relationships discussed in Chapter 4 can be written as

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

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

$$C_a = \dot{m}_a \tag{26}$$

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

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

where

q = heat transfer from air to water, W
C = fluid capacity, kg/h
$\dot{m}_a$ = 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 with sensible heat exchangers, effectiveness is also a function of the physical coil characteristics and can be obtained by modeling the coil as a counterflow heat exchanger. However, because 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:

$$\begin{aligned} q &= UA\Delta t = UA_h\Delta h \\ UA_h &= \frac{UA\Delta t}{\Delta h} = \frac{UA}{c_p} \end{aligned} \tag{29}$$

A similar analysis can be performed to evaluate the air-side effectiveness, which identifies the leaving air temperature. Whereas the overall enthalpy-based effectiveness is based on an overall heat transfer coefficient between the chilled water and air, air-side effectiveness is based on a heat transfer coefficient between the coil surface and 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. A sensible heat exchanger is modeled with a single effectiveness and can be described by a single parameter UA, but a wet cooling and dehumidifying coil requires two parameters to describe the two effectivenesses shown in Figure 5. These parameters are the internal and external UAs: one describes 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. UA values 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

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), temperatures and flow through the condenser and evaporator, and 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 vary constantly and require calculations on an hourly basis.

Regression Models. Although 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, 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. 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, but this 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:

$$\begin{aligned} P &= \mathrm{PIR} \times \mathrm{Load} \\ \mathrm{PIR} &= \mathrm{PIR}_{nom} f_1(t_a, t_b, \ldots) f_2(\mathrm{PLR}) \end{aligned} \tag{30}$$

$$\begin{aligned} C_{avail} &= C_{nom} f_3(t_a, t_b, \ldots) \\ \mathrm{PLR} &= \frac{\mathrm{Load}}{C_{avail}} \end{aligned} \tag{31}$$

where

P = equipment power, kW
PIR = energy input ratio
PIR_{nom} = energy input ratio under nominal full-load conditions

Load = power delivered to 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, ...) 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, ...) to nominal capacity
t_a, t_b = various operating temperatures that affect power
PLR = part-load ratio

The part-load ratio is 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 is a function of operating conditions.

The particular forms of 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 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 condenser and evaporator temperatures, which are often characterized in terms of their secondary fluids. For direct-expansion air-cooled chillers, operating temperatures are typically the wet-bulb temperature of air entering the evaporator and the dry-bulb temperature of 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 db and 19.4°C wb. However, performance changes as 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.

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

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

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.

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

The energy analyst often must choose the appropriate model for the job. For example, a complex boiler model is not appropriate if the boiler operates at virtually constant efficiency. Similarly, a regression-based model might be appropriate when the user has a

Table 4 Correlation Coefficients for Off-Design Relationships

Corr.	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

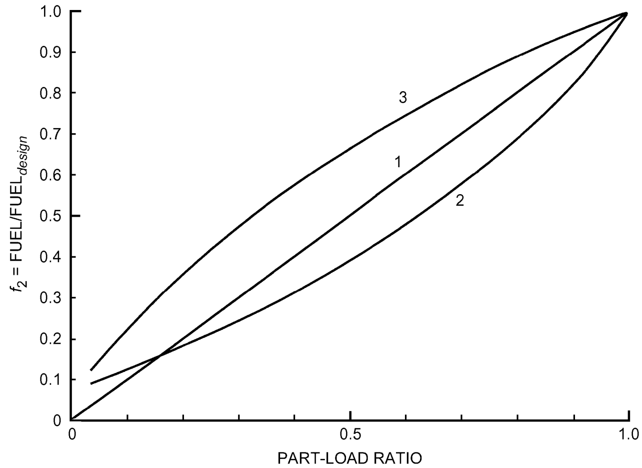

Fig. 6 Possible Part-Load Power Curves

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, which can be used 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 each for regressions of capacity, power, and refrigerant flow. By comparison, a physical compressor model may have as few as four or five unknown parameters. Thus, 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.

Physical models of primary HVAC equipment are generally based on fundamental engineering analysis and found in many HVAC textbooks, but the models described here are specifically based on the work of Bourdouxhe et al. (1994a, 1994b, 1994c) in developing the ASHRAE *HVAC 1 Toolkit* (Lebrun et al. 1999). Each elementary component's behavior 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.

Although physical models are based on physical characteristics, values obtained through a regression analysis of manufacturers'

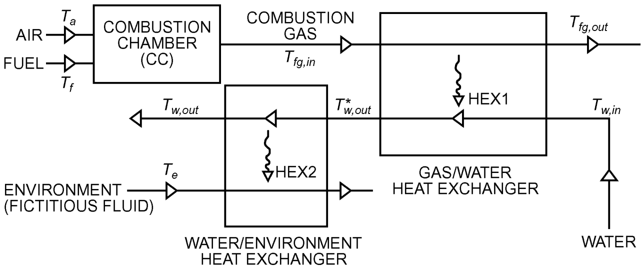

Fig. 7 Boiler Steady-State Modeling

data are not necessarily representative of the actual measured values. Strictly speaking, the parameter values are regression coefficients with estimated values, identified to minimize the error in overall system performance. In other words, errors in the fundamental models of equipment are offset by over- or under-estimation of the parameter values.

Boiler Model

The literature on boiler models is extensive, ranging from steady-state performance models (DeCicco 1990; Lebrun 1993) to detailed dynamic simulation models (Bonne and Jansen 1985; Lebrun et al. 1985), to a combination of these two schemes (Laret 1991; Malmström et al. 1985).

Dynamic models are meant to describe transient behavior of the equipment. Consequently, these models need to accurately capture the combustion process and the complex energy exchange that occurs inside the combustion chamber. Usually, this kind of model is very detailed and demanding to formulate and use. Hence, a dynamic boiler model should be considered only in more complex situations (e.g., large boilers in large buildings, district heating systems, cogeneration systems), where a complete, detailed representation of heat distribution, emission, and operation and control under varying external conditions is warranted.

Although all major variables of a boiler may vary with load and environmental conditions, assuming steady-state conditions during burner-on and burner-off times results in a relationship between input and output variables that is much simpler than those in dynamic models. Model evaluation against actual measurements shows that the steady-state model can be sufficiently accurate for energy calculations over relatively long time periods (e.g., weeks or months) with regard to the measuring accuracy.

In steady-state modeling, it is assumed that, during continuous operation, the boiler can be disaggregated into one adiabatic combustion chamber and two heat exchangers (Figure 7). The following fluid streams flow across the

- Combustion chamber (CC): air (subscript *a*) and fuel (subscript *f*) streams at the inlet, and combustion gas (subscript *fg*) at the outlet
- First heat exchanger (HEX1): combustion gas outlet and supply water streams (subscript *in*)
- Second heat exchanger (HEX2): heated water stream (subscript *out*) and a fluid representing the environment

The boiler model is characterized by three parameters, which represent the following heat transfer coefficients:

- UA_{ge}: between the flue gas and the environment in CC
- UA_{gw}: between the flue gas and the water in HEX1
- UA_{we}: between the water and the environment in HEX2

Primary model inputs to the model are the leaving water set-point temperature ($T_{w,out}$) and control model and the load characteristics (i.e., entering water temperature $T_{w,in}$ and water flow rate $\dot{m}_w$). Secondary model inputs include the air, fuel, and ambient temperatures (T_a, T_f, and T_e) as well as the fuel/air ratio f.

Modern boilers are airtight, so there is almost no air circulation across the combustion chamber when the burner is off. In this case, the boiler behaves as a simple water/environment heat exchanger (i.e., HEX1 and HEX2 are combined) and the thermal model is reduced to that of a simple heat exchanger.

Combustion Chamber Model. Mathematical description of this model allows the flue gas mass flow rate and enthalpy $h_{fg,in1}$ (in J/kg$_{fg}$) at the flue gas/water heat exchanger (HEX1) inlet to be calculated. The calculated flue gas mass flow rate is not necessarily the one associated with the specified value of the flue gas/water heat transfer coefficient/area product. Therefore, the following empirical relationship is used to adjust the value of this coefficient to the calculated value of the flue gas mass flow rate.

$$\dot{m}_{fg} = 1 + \frac{1}{f}\dot{m}_f \qquad (34)$$

$$h_{fg,in} = \frac{h_{fg,in1}}{1 + \frac{1}{f}} \qquad (35)$$

$$(UA_{gw})_{calc} = UA_{gw}\left[\frac{\dot{m}_{fg}}{(\dot{m}_{fg})_{rated}}\right]^{0.65} \qquad (36)$$

where

$h_{fg,in1}$ = known function of composition of combustion products and flue gas temperature at inlet of gas/water heat exchanger, J/kg$_{fg}$
$h_{fg,in}$ = gas enthalpy at outlet of gas/water heat exchanger, J/kg$_f$
$(\dot{m}_{fg})_{rated}$=flue gas mass flow rate associated with specified value of gas/water heat transfer coefficient/area product, kg/s

Flue Gas-Water Heat Exchanger Model. The first step is to calculate the heat transfer rate q_{gw} across HEX1:

$$q_{gw} = \varepsilon_{gw} C_{fg}(T_{fg,in} - T_{w,in}) \qquad (37)$$

where

$C_{fg} = c_{p,fg}\dot{m}_{fg}$ = heat capacity flow rate of flue gas
$\varepsilon_{gw} = \dfrac{1 - \exp[-\text{NTU}(1 - C)]}{1 - C\exp[-\text{NTU}(1 - C)]}$ = effectiveness for HEX1

For a counterflow heat exchanger,

$$\text{NTU} = \frac{UA_{gw}}{C_{fg}} \quad \text{and} \quad C = \frac{C_{fg}}{C_w} \qquad (38)$$

where $C_{fg} \le C_w$ and $C_w = c_{p,w}\dot{m}_w$.

The temperature of flue gas leaving HEX1 ($T_{fg,out}$) can be calculated from

$$\varepsilon_{gw}(T_{fg,in} - T_{w,in}) = (T_{fg,in} - T_{fg,out}) \qquad (39)$$

Other unknowns need also to be calculated. In HEX1, heat is transferred from hot flue gas to the water

$$q_{gw} = C_w(T^*_{w,out} - T_{w,in}) \qquad (40)$$

from which the temperature of water leaving HEX1 and entering HEX2 is

$$T^*_{w,out} = \frac{q_{gw}}{C_w} + T_{w,in} \qquad (41)$$

Water-Environment Heat Exchanger Model. In HEX2,

$$\varepsilon_{we}(T^*_{w,out} - T_e) = (T^*_{w,out} - T_{w,out}) \tag{42}$$

where $\varepsilon_{we} = 1 - \exp(-UA_{we}/C_w)$. Then water temperature at the outlet of HEX2 is

$$T_{w,out} = T_e + \frac{T^*_{w,out} - T_e}{\exp\left(\dfrac{UA_{we}}{C_w}\right)} \tag{43}$$

Consequently, heat loss from hot water in HEX2 is

$$q_{we} = C_w(T^*_{w,out} - T_{w,out}) \tag{44}$$

Useful heat given to the water stream is

$$q_b = q_{gw} - q_{we} \tag{45}$$

Finally, boiler efficiency is given by

$$\eta = \frac{q_b}{\dot{m}_f \times \text{FLHV}} \tag{46}$$

where FLHV is fuel lower heating value.

The main outputs of this model are

- The "useful" boiler output: its leaving water temperature (to be compared with its set point), or its corresponding "useful" power (i.e., net rate of heat transfer q_b by the heated water)
- Its energy consumption: burner fuel flow rate $\dot{m}_f$ or corresponding efficiency η

Secondary model outputs include

- Flue gas temperature, specific heat, and corresponding enthalpy flow in the chimney
- Environmental loss q_{we} in boiler room

The three-parameter model allows simulation of boilers using most conventional fuels under a wide range of operating conditions with less than 1% error. A two-exchanger model appears to be flexible enough to describe boiler behavior at different load conditions and water temperatures. This simple model is stated to accurately predict the sensitivity of a boiler to variations of burner fuel rate and airflow rates as well as water/environment losses.

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. Chiller components 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

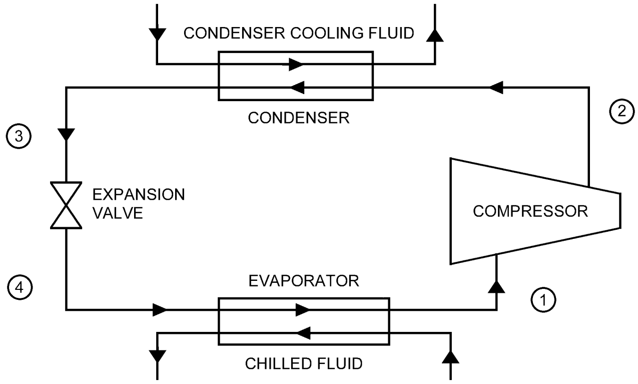

Fig. 8 Chiller Model Using Elementary Components
(See Figure 10 for description of points 1 to 4)

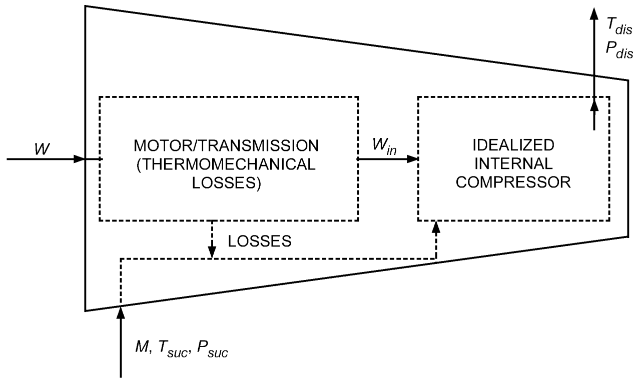

Fig. 9 General Schematic of Compressor

temperatures from the compressor discharge; thus, the mean temperature difference between refrigerant and water in the heat exchanger is significantly underestimated. Fortunately, this systematic error is offset by a significant overestimate of the corresponding heat transfer coefficient.

General Compressor Modeling. Modeling real compressors requires description of many thermomechanical losses (e.g., heat loss, fluid friction, throttling losses in valves, motor and transmission inefficiencies) within the compressor. Some of these losses can be modeled within the compressor, but 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 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. Losses from these inefficiencies are assumed to heat the fluid before compression. Mathematically, it can be modeled by the following linear relationship:

$$W = W_{lo} + (1 + \alpha)W_{int} \tag{47}$$

where

W = electrical power for a hermetic or semihermetic compressor, or shaft power for an open compressor
W_{lo} = constant electromechanical loss
W_{int} = idealized internal compressor power (depends on type of compressor)
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_{int}, depending on the type of compressor.

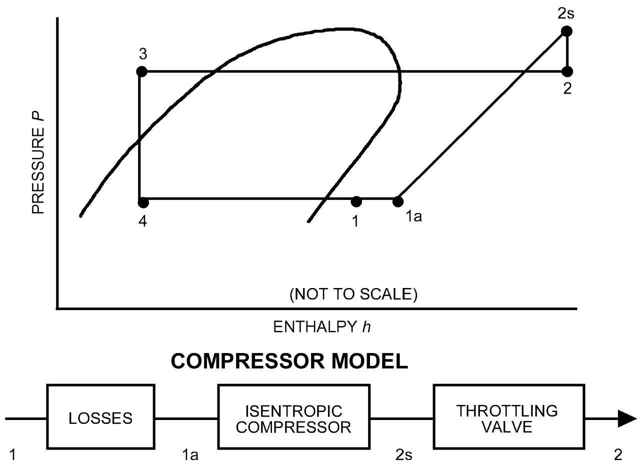

Fig. 10 Schematic of Reciprocating Compressor Model

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 schematic for a reciprocating compressor, for use with the general model, is shown in Figure 10. Refrigerant enters the compressor at state 1 and is heated to state 1a by thermomechanical losses of the motor-transmission model in Figure 9. The refrigerant undergoes isentropic compression to state 2s, followed by throttling to the compressor discharge at state 2. The throttling valve is a simplified approach to model known losses within the compressor caused by pressure drops across the suction and discharge valves. A more accurate model might include pressure losses at both the compressor inlet and outlet, but analysis of compressor data reveals that the simpler model is adequate 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 because of vapor re-expansion in the clearance volume. With refrigerant vapor modeled as an ideal gas, the volumetric flow rate is given by

$$V = V_s\left[1 + C_f - C_f\left(\frac{p_{ex}}{p_{suc}}\right)^{1/\gamma}\right] \qquad (48)$$

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.

Although the models discussed apply to full-load operation, Equation (48) 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 but often involve additional parameters. For example, the effect of cylinder unloading can be modeled by the following relationship:

$$W_{int} = W_s + \left(1 - \frac{N_c}{N_{c,FL}}\right)W_{pump} \qquad (49)$$

where

W_{int} = idealized internal compressor power
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_s = isentropic power

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

In summary, a realistic physical model of a reciprocating compressor, covering both full- 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 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- and part-load operations, can be developed based on five parameters: the (1) constant and (2) proportional loss terms of the motor-transmission model of Equation (47), (3) swept volumetric flow rate of the compressor screw, (4) internal leakage area, and (5) 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 (47) 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 (47), only three additional parameters are required: the (1) peripheral speed of the impeller, (2) vane inclination at the impeller exhaust, and (3) 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 (see Chapter 2 for more information). The absorption-generation subsystem includes an absorber, steam-fired generator, recovery heat exchanger, pump, and 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. Controls typically manage tower fans and pumps to maintain a desired water temperature entering the condenser. Like cooling and dehumidifying coils in secondary systems, cooling tower performance has a strong influence on the chiller's energy consumption. In addition, tower fans consume electrical energy directly.

Fundamentally, a cooling tower is a direct contact heat and mass exchanger. Equations describing the basic processes are given in

Chapter 6 and in many HVAC textbooks. Chapter 39 of the 2008 *ASHRAE Handbook—HVAC Systems and Equipment* describes the specific performance of cooling towers. Performance subroutines are also available in Klein et al. (1994) and Lebrun et al. (1999).

For energy calculations, cooling tower performance is typically described in terms of the outdoor wet-bulb temperature, temperature drop of water flowing through the tower (range), and difference between leaving water and air wet-bulb temperatures (approach). Simple models assume constant range and approach, but 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 components or subsystems and (2) overall modeling strategy. Modeling components, 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, 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. Solid lines represent data passed from one model to the next; 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 equipment capacity, but this cannot be modeled because 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 technique is based on linear mathematics, and wide departures of room temperatures from those used during execution of the load program can introduce errors.

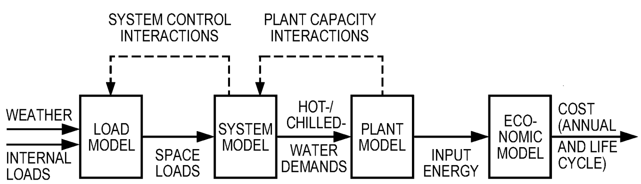

Fig. 11 Overall Modeling Strategy

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 secondary system equipment. In an actual building, when the central plant becomes overloaded, space temperatures should rise to reduce 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 possible. 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, although the magnitude and importance of the improvement are uncertain.

The principal disadvantage of this approach, and the reason that it was not widely used in the past, is that it demands more computing resources. However, most current desktop computers can now run programs using the alternative approach in a reasonable amount of time. Programs that, to one degree or another, implement simultaneous solution of the loads, system, and plant models have been developed by Clarke (2001), Crawley et al. (2001), Klein et al. (1994), Park et al. (1985), and Taylor et al. (1990, 1991). Some of these programs simulate the loads, systems, and plants using subhourly time steps.

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 use 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 Bibliography lists several models, which are also described in Walton (1983) and York and Cappiello (1982). Generally, load models tend to be the most complex and time-consuming, whereas the central plant model is the least complex.

Because detailed models are computationally intensive, several simplified methods have been developed, including the degree-day, bin, and correlation methods.

DEGREE-DAY AND BIN METHODS

Degree-day methods are the simplest methods for energy analysis and are appropriate if building use and HVAC equipment efficiency are constant. Where efficiency or conditions of use vary with outdoor temperature, 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, simple steady-state models must not be used.

Although computers can easily calculate the energy consumption of a building, the concepts of degree-days and balance point temperature remain valuable tools. A climate's severity 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.

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.

$$q_{gain} = K_{tot}(t_i - t_{bal}) \tag{50}$$

where K_{tot} is the total heat loss coefficient of the building in W/K. For any steady-state method 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

$$t_{bal} = t_i - \frac{q_{gain}}{K_{tot}} \tag{51}$$

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

$$q_h = \frac{K_{tot}}{\eta_h}[t_{bal} - t_o(\theta)]^+ \tag{52}$$

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 counted. If t_{bal}, K_{tot}, and η_h are constant, the annual heating consumption can be written as an integral:

$$Q_{h,yr} = \frac{K_{tot}}{\eta_h}\int[t_{bal} - t_o(\theta)]^+ d\theta \tag{53}$$

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 results are called **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 $\mathrm{DD}_h(t_{bal})$ are obtained as

$$\mathrm{DD}_h(t_{bal}) = (1\text{ day})\sum_{\text{days}}(t_{bal} - t_o)^+ \tag{54}$$

with dimensions of kelvin·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

$$Q_{h,yr} = \frac{K_{tot}}{\eta_h}\mathrm{DD}_h(t_{bal}) \tag{55}$$

Heating degree-days or degree-hours for a balance point temperature of 18.3°C have been widely tabulated (this temperature represents 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 (54) for heating degree-days as

$$\mathrm{DD}_c(t_{bal}) = (1\text{ day})\sum_{\text{days}}(t_o - t_{bal})^+ \tag{56}$$

Although 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 (55) is

$$Q_{c,yr} = \frac{K_{tot}}{\eta_h}\mathrm{DD}_c(t_{bal}) \tag{57}$$

for a building with static K_{tot}. 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 exceeds the threshold t_{max}. This threshold is given by an equation analogous to Equation (51), replacing the closed-window heat transmission coefficient K_{tot} with K_{max} for open windows:

$$t_{max} = t_i - \frac{q_{gain}}{K_{max}} \tag{58}$$

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_{max} 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

$$Q_c = K_{tot}[\mathrm{DD}_c(t_{max}) + (t_{max} - t_{bal})N_{max}] \tag{59}$$

where $\mathrm{DD}_c(t_{max})$ 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}. This is merely a schematic model of air conditioning. In practice, heat gains and ventilation rates vary, as does occupant behavior in using the windows and air conditioner. Also, in commercial buildings with economizers, the extra fan energy for increased ventilation must be added to the calculations. Finally, air-conditioning

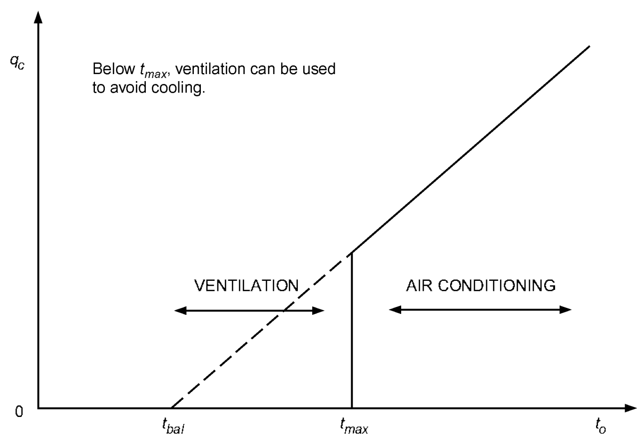

Fig. 12 Cooling Load as Function of Outdoor Temperature t_o

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 (59):

$$q_{latent} = \dot{m} h_{fg}(W_o - W_i) \tag{60}$$

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}, variations average out without changing consumption. But for the situation in Figure 13, t_o rises above t_{bal} from shortly after 1000 h to 2200 h; the consequences for energy consumption depend on thermal inertia and HVAC system control. If this building had low inertia and 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 occupants keep windows closed during mild weather, t_i will rise above the set point. If they open 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 consumption during mild weather. In fact, 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 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, energy consumption in mild weather is small; hence, a relatively large error here has only a small effect on the total for the season.

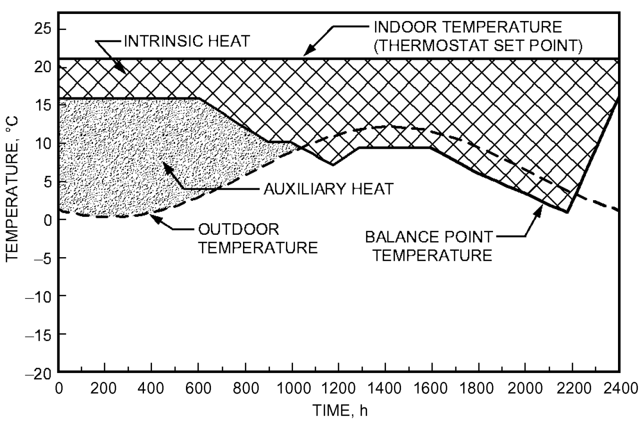

Fig. 13 Variation of Balance Point Temperature and Internal Gains for a Typical House
(Nisson and Dutt 1985)

Variable-Base Annual Degree-Days. Calculating 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, 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 heating degree-days vary with t_{bal} for a particular site (New York). The plot is obtained by evaluating Equation (54) 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. 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 Houston, Washington, D.C., and Denver. If the annual average of t_o is known, the cooling degree-days to any base below 22°C ± 1.4 K can also be found.

Seasonal Efficiency. The seasonal efficiency η_h of heating equipment depends on factors such as steady-state efficiency, sizing, cycling effects, and energy conservation devices. It can be much lower than or comparable to steady-state efficiency. Alereza and Kusuda (1982) developed expressions to estimate 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):

$$\eta = \frac{\eta_{ss} CF_{pl}}{1 + \alpha_D} \tag{61}$$

where

η_{ss} = steady-state efficiency (rated output/input)
CF_{pl} = part-load correction factor
α_D = fraction of heat loss from ducts

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:

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

where

BLC = building loss coefficient, W/K
t_{od} = outside design temperature, °C
CHT = capacity (rated output) of heating equipment, W

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 using the factor (1 + α_D). RLC assumes values in the range 0 to 1.0, appropriate for typical cases when heating equipment is oversized. Seasonal efficiency is also discussed by Chi and Kelly (1978), Mitchell (1983), and Parker et al. (1980).

Monthly Degree-Days

Many formulas have been proposed for estimating 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

$$\sigma_m = 1.45 - 0.0290\,\bar{t}_o + 0.0664\,\sigma_{yr} \tag{62}$$

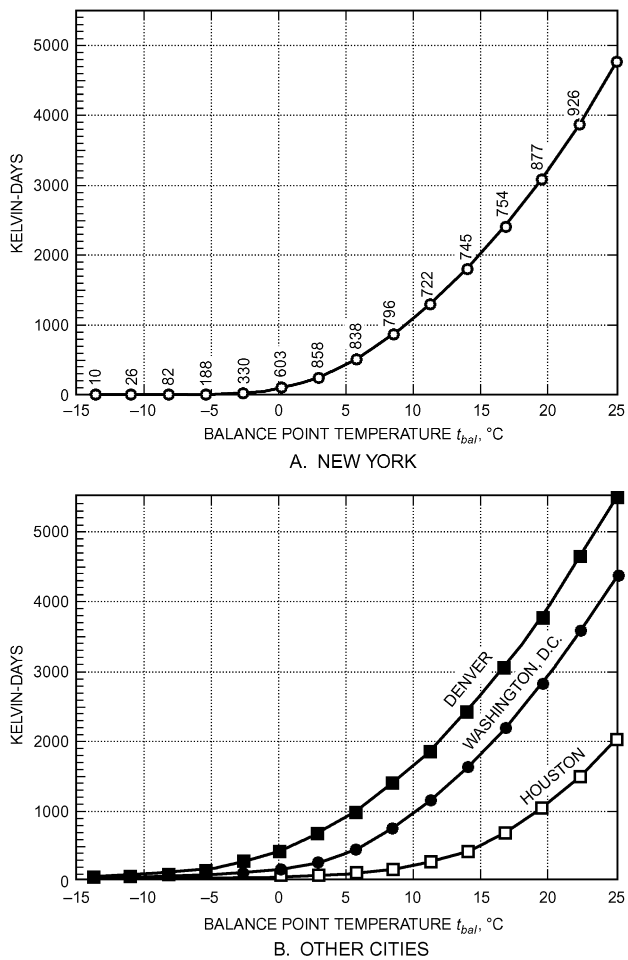

Fig. 14 Annual Heating Days $DD_h(t_{bal})$ as Function of Balance Temperature t_{bal}

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

$$\sigma_{yr} = \sqrt{\frac{1}{12}\sum_{1}^{12}(\bar{t}_o - \bar{t}_{o,yr})^2} \tag{63}$$

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

$$\phi = \frac{\bar{t}_{bal} - \bar{t}_o}{\sigma_m\sqrt{N}} \tag{64}$$

where *N* = number of days in the month (*N* has units of day/month and ϕ has units of $\sqrt{\text{month/day}}$). Although 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 standard deviation of $\bar{t}_o$. Being centered around $\bar{t}_o$ and scaled by σ_m, ϕ eliminates these effects. In terms of ϕ, the monthly heating degree-days for any location are well approximated by

$$DD_h(t_{bal}) = \sigma_m N^{1.5}\left[\frac{\phi}{2} + \frac{\ln(e^{-a\phi} + e^{a\phi})}{2a}\right] \tag{65}$$

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 kelvin-days if Equation (65) is used for each month. For cooling degree-days, the largest error is 150 kelvin-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°C.

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; 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).

Table 5 Degree-Day Calculation for New York City from Monthly Averaged Data

Month	$\bar{t}_o$, °C	*N*, day/mo.	σ_m, °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 (65) to calculate DD_h (t_{bal})

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

	Variable-Base Heating Degree-Day, K·days[a]					Monthly Average Outdoor Temperature $\bar{t}_o$, °C[b]											
Site	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

[a]*Source*: NOAA (1973). [b]*Source*: Cinquemani et al. (1978).

Table 7 Sample Annual Bin Data

	Bin																				
Site	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				

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_{tot}, the efficiency η_h of the HVAC system, or the balance point temperature t_{bal} may not be sufficiently constant. Heat pump efficiency, for example, varies strongly with outdoor temperature; efficiency of HVAC equipment may be affected indirectly by t_o when efficiency varies with load (common for boilers and chillers). Furthermore, in most commercial buildings, occupancy has a pronounced pattern, which affects heat gain, indoor temperature, and ventilation rate.

In such cases, steady-state calculation can yield good results for annual energy consumption if different temperature intervals and time periods are evaluated separately. This approach is known as the *bin method* because 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:

$$Q_{bin} = N_{bin}\frac{K_{tot}}{\eta_h}[t_{bal} - t_o]^+ \qquad (66)$$

The superscript plus sign indicates that only positive values are counted; no heating is needed when t_o is above t_{bal}. Equation (66) 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). 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 breakdown. The data 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 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 adjusted heat pump capacity to building heat loss in Example 4. 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; 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) manufacturer's published performance data. Example 4 assumes that the manufacturer's data already account for 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 with a design heat loss of 11 700 W at 30°C design temperature difference. The inside design temperature is 21°C. Average internal heat gains are estimated to be 1250 W. Assume a 10.5 kW heat pump with the characteristics given in Columns E and H of Table 8 and in Figure 15.

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 Adjust-ment Factor[a]	Adjusted Heat Pump Capacity, kW[b]	Rated Electric Input, kW	Opera-ting Time Fraction[c]	Heat Pump Supplied Heating, kWh[d]	Seasonal Heat Pump Electric Consump-tion, KWh[e]	Space Load, kWh[f]	Supple-mental Heating Required, kWh[g]	Total Electric Energy Consump-tion, 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	1 496	573	1 497	—	573
10	7.8	670	3.04	11.22	0.818	9.18	3.52	0.331	2 036	781	2 037	—	781
7	10.8	858	4.21	9.80	0.857	8.40	3.40	0.501	3 611	1 462	3 612	—	1 462
4	13.8	639	5.38	8.49	0.908	7.71	3.18	0.698	3 439	1 418	3 438	—	1 418
1	16.8	793	6.55	7.98	0.955	7.62	3.10	0.860	5 196	2 114	5 195	—	2 114
–2	19.8	141	7.72	7.47	1.000	7.47	3.02	1.000	1 053	426	1 089	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:	18 125	7 305	18 436	313	7 618

[a]Cycling 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).
[b]Column G = Column E × Column F
[c]Operating Time Factor equals smaller of 1 or Column D/Column G
[d]Column J = Column I × Column G × Column C
[e]Column K = Column I × Column H × Column C
[f]Column L = Column C × Column D
[g]Column M = Column L – Column J
[h]Column N = Column K + Column M

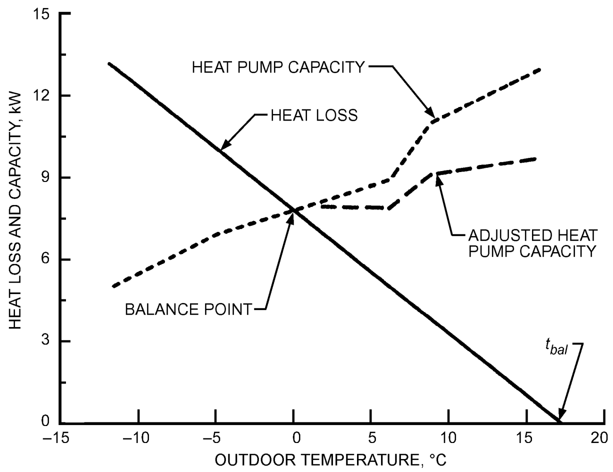

Fig. 15 Heat Pump Capacity and Building Load

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., envelope loss minus internal heat generation). The net heat loss per degree and the heating/cooling balance temperature may be computed:

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

From Equation (51),

$$t_{bal} = 21 - (1250/390) = 17.8°C$$

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 quick insight into the energy requirements. Examples 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 proper use of a correlation is ensuring that the case being studied matches the cases used in developing the database. Inputs to the correlation (independent variables) indicate factors that are considered to significantly affect 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 (e.g., variable-air-volume, terminal reheat, multizone). 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: 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) view 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** (Buhl et al. 1993; Sowell and Moshier

1995). These models do not follow predetermined rules for a solution, and the user can specify which variables are inputs and which are outputs.

MODELING OF SYSTEM CONTROLS

Building control systems are typically hierarchical: higher-level, supervisory controls generate set points for lower-level, local loop controls. Supervisory-level controls, which include reset and optimal control, directly influence energy consumption. Local loop controllers may also affect energy performance; for example, proportional-only room temperature control results in a tradeoff between energy use and comfort. Faults in control systems and devices can also affect energy consumption (e.g., leaking valves and dampers can significantly increase energy use). It is particularly important to account for these departures from ideal behavior when simulating performance of real buildings using calibrated models. Modeling and simulation of supervisory control are increasingly handled by whole-building simulation programs. Simulation of local loop controls requires more specialized, component- or equation-based modeling environments.

Modern control systems, particularly direct digital controls (DDC), typically use integral action to drive the controlled variable to its set point. For energy modeling purposes, the controlled variable (e.g., supply air temperature) can be treated as being at the set point unless system capacity is insufficient. The simulation must determine whether the capacity required to meet set point exceeds available capacity. If it does, the available capacity is used to determine the actual value of the controlled variable. Where there is only proportional action, the resulting relationship between the controlled variable and the output of the system can be used to determine both values. For example, the action of a conventional pneumatic room temperature controller can be represented by a function relating heating and cooling delivery to space temperature. Similarly, supply air temperature reset control can be modeled as a relationship between outside or zone temperature and coil or fan 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 for use of values from an earlier solution point.

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 rises in proportion to the load during cooling and falls 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 variable-air-volume (VAV) system is a single-path system that controls zone temperature by modulating airflow while maintaining 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, as shown in Figure 16. The central air-handling unit includes a fan, cooling coil, preheat coil, and outside air economizer. Supply air leaving the air-handling unit is controlled to a fixed set point. The VAV terminal unit at each zone varies airflow to meet the cooling load. As zone cooling load decreases, the VAV terminal unit decreases zone airflow until the unit reaches its minimum position. If the cooling load continues to decrease, the reheat coil is activated to meet the zone load. As supply air volume leaving the unit decreases, fan power consumption also reduces. 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 sensible and latent loads, zone set-point temperature, and minimum zone supply-air mass flow. System characteristics include supply air temperature set point; entering water temperature of reheat, preheat, and cooling coils; minimum mass flow of outside air; and economizer temperature/enthalpy set point for minimum airflow.

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

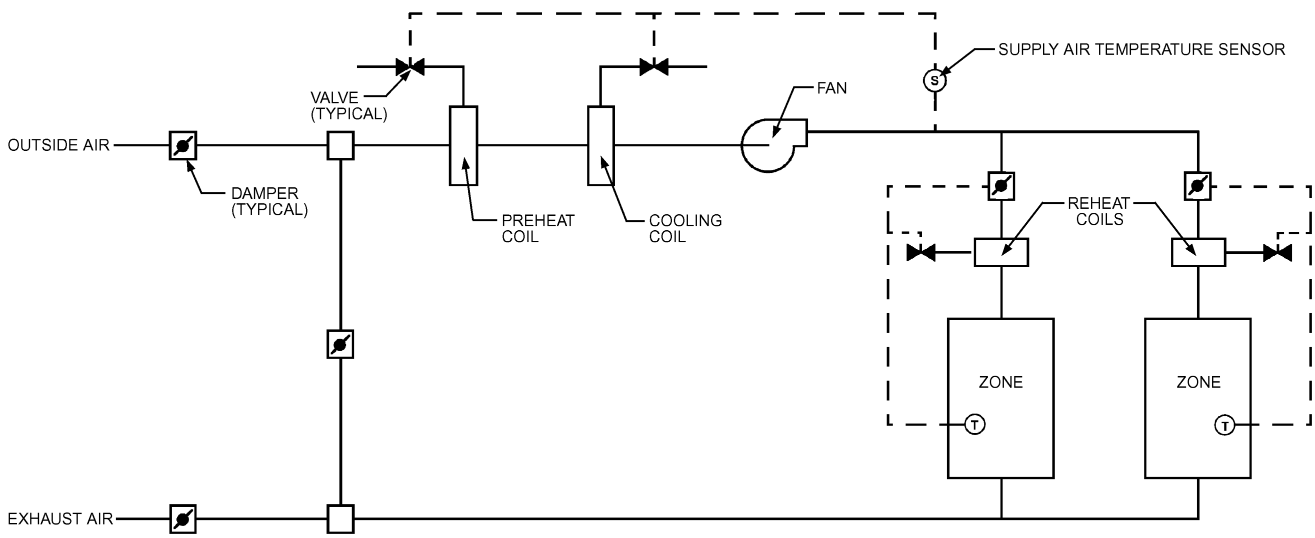

Fig. 16 Schematic of Variable-Air-Volume System with Reheat

```
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/HCDET)
  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

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 along the return air path, the cooling coil entering air temperature can be determined by sequentially moving through the economizer cycle and preheat coil.

Unlike temperature, the humidity ratio at any point in a system cannot be explicitly determined because of the dependence of 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 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, iteration.

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 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. Iteration continues 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 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 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.

DATA-DRIVEN MODELING

CATEGORIES OF DATA-DRIVEN METHODS

Data-driven methods for energy-use estimation in buildings and related HVAC&R equipment can be classified into three broad categories. These approaches differ widely in data requirements, time and effort needed to develop the associated models, user skill demands, and sophistication and reliability provided.

Empirical or "Black-Box" Approach

With this approach, a simple or multivariate regression model is identified between measured energy use and the various influential parameters (e.g., 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) if 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 circumstances. The empirical approach is thus the most widely used data-driven 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 (Claridge 1998b; Dhar 1995; Dhar et al. 1998, 1999a, 1999b; Fels 1986; Katipamula et al. 1998; Kissock et al. 1998; Krarti et al. 1998; Kreider and Wang 1991; MacDonald and Wasserman 1989; Miller and Seem 1991; Reddy et al. 1997; Ruch and Claridge 1991). It is also appropriate for modeling equipment such as pumps and fans, and even more elaborate equipment such as chillers and boilers, if the necessary performance data are available (Braun 1992; Englander and Norford 1992; Lorenzetti and Norford 1993; Phelan et al. 1996). 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

This approach 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 statistical approaches. Calibrated simulation is advocated where only whole-building metering is available and M&V calls for estimating energy savings of individual retrofits. Practitioners tend to use common forward-simulation programs such as DOE-2 to calibrate with performance data. Hourly subaggregated monitored energy data (most compatible with the time step adopted by most building energy simulation programs) allow development of the most accurate calibrated model, but analysts usually must 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 challenges 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 often depends on the person doing the calibration. Several practical difficulties prevent achieving a calibrated simulation or a simulation that closely reflects actual building performance, including (1) measurement and adaptation of weather data for use by simulation programs (e.g., converting global horizontal solar into beam and diffuse solar radiation), (2) choice of methods used to calibrate the model, and (3) choice of methods used to measure required input parameters for the simulation (i.e., building mass, 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. Bou-Saada and Haberl (1995a, 1995b), Bronson et al. (1992), Corson (1992), Haberl and Bou-Saada (1998), Kaplan et al. (1990) Manke et al. (1996), and Norford et al. (1994) provide examples of different methods used to calibrate simulation models.

Katipamula and Claridge (1993) and Liu and Claridge (1998) suggested that simpler models could also work, and allow 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 envelope heat losses/gains, and solar heat gains, infiltration heat loss/gain, and conduction gains/losses from the roof are taken as loads on the external zone only. Given the internal load schedule, building description, type of HVAC system, and climatic parameters, 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. Because there are fewer parameters to vary, calibration 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

This approach first formulates a physical model to represent the structure or physical configuration of the building or HVAC&R equipment or system, and then identifies important parameters representative of certain key and aggregated physical parameters and characteristics by statistical analysis (Rabl and Riahle 1992). This requires a high level of user expertise both in setting up the appropriate modeling equations and in estimating these parameters. Often an intrusive experimental protocol is necessary for proper parameter estimation, which also requires skill. This approach has great potential, especially for fault detection and diagnosis (FDD) and online control, but its applicability to whole-building energy use is limited. Examples of parameter estimation studies applied to building energy use are Andersen and Brandemuehl (1992), Braun (1990), Gordon and Ng (1995), Guyon and Palomo (1999a), Hammersten (1984), Rabl (1988), Reddy (1989), Reddy et al. (1999), Sonderegger (1977), and Subbarao (1988).

TYPES OF DATA-DRIVEN MODELS

Steady-state models do not consider 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 cooldown 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

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

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 affects 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; Katipamula et al. 1994; Kissock et al. 1993; 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 data-driven 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 data-driven 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 data-driven 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, 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 superscripted 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.

Figures 18E and 18F illustrate four-parameter models for heating and cooling, respectively. The appropriate expressions for

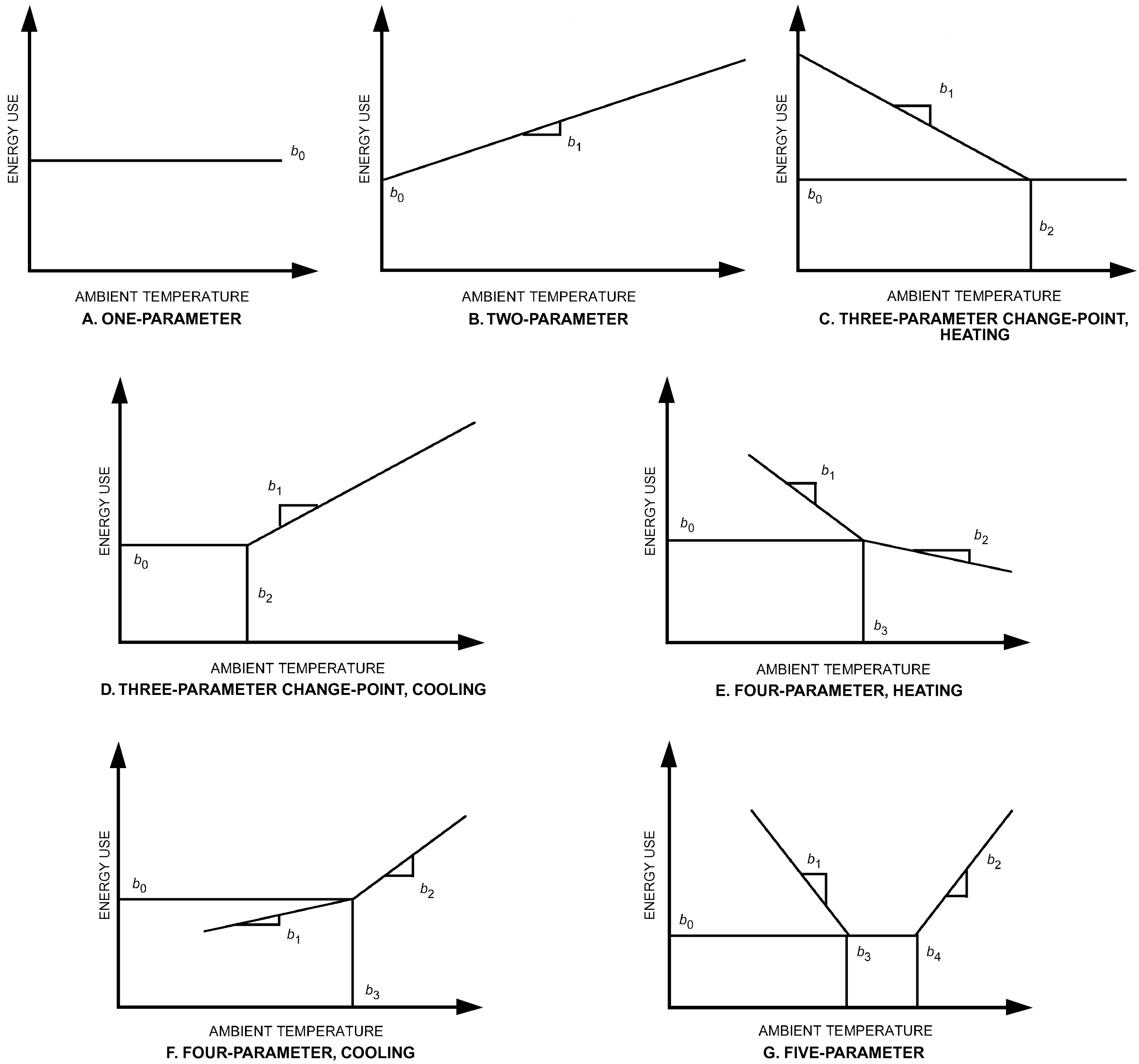

Fig. 18 Steady-State, Single-Variate Models for Modeling Energy Use in Residential and Commercial Buildings

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	$E = b_0 + b_1(\mathrm{DD}_{BT})$ $E = b_0 + b_1(b_2 - T)^+$ $E = b_0 + b_1(T - b_2)^+$	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	$E = b_0 - b_1(\mathrm{DD}_{TH}) + b_2(\mathrm{DD}_{TC})$ $E = b_0 + b_1(b_3 - T)^+ + b_2(T - b_4)^+$	Heating and cooling supplied by same meter

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

calculating the heating and cooling energy consumption 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), which 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 data-driven 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 data-driven 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 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.

Disadvantages of steady-state single-variate data-driven models include insensitivity to dynamic effects (e.g., thermal mass) and 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, 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 heating load never exceeds the heating system's capacity. However, commercial buildings generally 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 few 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 are 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 does not falsely indicate an unreasonable relationship.

A major advantage of using a steady-state data-driven model to evaluate the effectiveness of energy conservation retrofits is its ability to factor out year-to-year weather variations by using a normalized annual consumption (NAC) (Fels 1986). Basically, annual energy conservation savings can be calculated by comparing the difference obtained by multiplying the pre- 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 pre- and postretrofit conditions.

Utilities and government agencies have found it advantageous to prescreen many buildings against test regression models. These data-driven models can be used to develop comparative figures of merit for buildings in a similar standard industrial code (SIC) classification. 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. This 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:

- **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).
- **Fourier series models** that retain the time-series nature of building energy use data and capture the diurnal and seasonal cycles according to which buildings are operated (Dhar 1995; Dhar et al. 1998, 1999a, 1999b; Seem and Braun 1991).

These models are a logical extension of single-variate models, provided that the choice of 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, base load, and 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 these criteria for modeling heating and cooling energy use include outdoor air dry-bulb temperature, solar radiation, and outdoor specific humidity. Some of these 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, a data-driven 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 affect heating and cooling energy use. These internal loads are difficult to measure in their entirety given the ambiguous nature of occupant 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 buildings such 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 a dummy variable, but its inclusion in the general functional form adds flexibility.

Several standard statistical tests evaluate the goodness-of-fit of the model and the degree of influence that each independent variable exerts on the response variable (Draper and Smith 1981; Neter et al. 1989). Although energy use in fact depends 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 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 Shootout I and II contests (Haberl and Thamilseran 1996; Kreider and Haberl 1994). 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 U.S. locations 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 quadratic and cross-product terms of engineering equations are not usually picked up by multivariate models, strictly linear energy use models are often the only option.

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 derives from 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. Using $(T_{dp} - T_s)^+$ 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:

$$Q_{bldg} = \beta_0 + \beta_1(T_o - \beta_3)^- + \beta_2(T_o - \beta_3)^+ + \beta_4(T_{dp} - \beta_6)^- + \beta_5(T_{dp} - \beta_6)^+ + \beta_7 q_{sol} + \beta_8 E_{int} \quad (67)$$

Based on the preceding discussion, $\beta_4 = 0$. Introducing indicator variable terminology (Draper and Smith 1981), Equation (67) becomes

$$Q_{bldg} = a + bT_o + cI + dIT_o + eT_{dp}^+ + fq_{sol} + gE_{int} \quad (68)$$

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 to determine the change point that minimizes the total sum of squares of residuals (Fels 1986; Kissock et al. 1993).

Katipamula et al. (1994) found that Equation (68), appropriate for VAV systems, could be simplified for constant-volume HVAC systems:

$$Q_{bldg} = a + bT_o + eT_{dp}^+ + fq_{sol} + gE_{int} \quad (69)$$

Note that instead of using $(T_{dp} - T_s)^+$, the absolute humidity potential $(W_0 - W_s)^+$ could also be used, where W_0 is the outdoor absolute humidity, and W_s is the absolute humidity level at the dew point of the cooling coil (typically about 0.009 kg/kg). A final aspect to keep 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.

These multivariate models are 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 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 equipment such 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) 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) studied the predictive ability of linear and quadratic polynomial single-variate models of fan electricity consumption as a function of 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 use 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:

$$E_{comp} = a + bQ_{evap} + cT_{cond}^{in} + dT_{evap}^{out} + eQ_{evap}^2 + fT_{cond}^{in\,2} + gT_{evap}^{out\,2} + hQ_{evap}T_{cond}^{in} + iT_{evap}^{out}Q_{evap} + jT_{cond}^{in}T_{evap}^{out} + kQ_{evap}T_{cond}^{in}T_{evap}^{out} \quad (70)$$

In this model, there are 11 model parameters to identify. However, because 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, physical models are preferred because they generally have fewer parameters, and their mathematical formulation can be traced to actual physical principles that govern the performance of the building or equipment. Hence, 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 [e.g., 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.

The generalized Gordon and Ng (GN) model (Gordon and Ng 2000) is a simple, analytical, universal model for chiller performance based on first principles of thermodynamics and linearized heat losses. The model predicts the dependent chiller coefficient of performance (COP) [the ratio of chiller (or evaporator) thermal cooling capacity Q_{ch} to electrical power E consumed by the chiller] with specially chosen independent, easily measurable parameters such as the fluid (water or air) temperature entering the condenser T_{cdi}, fluid temperature entering the evaporator T_{cdi}, and the thermal cooling capacity of the evaporator. The GN model is a three-parameter model in the following form:

$$\left(\frac{1}{\text{COP}}+1\right)\frac{T_{chi}}{T_{cdi}}-1 = a_1\frac{T_{chi}}{Q_{ch}}+a_2\frac{(T_{cdi}-T_{chi})}{T_{cdi}Q_{ch}} + a_3\frac{(1/\text{COP}+1)Q_{ch}}{T_{cdi}} \tag{71a}$$

where temperatures are in absolute units.

Substituting the following,

$$x_1=\frac{T_{chi}}{Q_{ch}},\qquad x_2=\frac{(T_{cdi}-T_{chi})}{T_{cdi}Q_{ch}},\qquad x_3=\frac{(1/\text{COP}+1)Q_{ch}}{T_{cdi}}$$

and

$$y=\left(\frac{1}{\text{COP}}+1\right)\frac{T_{chi}}{T_{cdi}}-1 \tag{71b}$$

the model given by Equation (71a) becomes

$$y = a_1x_1 + a_2x_2 + a_3x_3 \tag{71c}$$

which is a three-parameter linear model with no intercept term. The parameters of the model in Equation (71c) have the following physical meaning:

$a_1 = \Delta S$ = total internal entropy production in chiller

$a_2 = Q_{leak}$ = heat losses (or gains) from (or into) chiller

$a_3 = R$ = total heat exchanger thermal resistance = $1/C_{cd} + 1/C_{ch}$, where C is effective thermal conductance

Gordon and Ng (2000) point out that Q_{leak} is typically an order of magnitude smaller than the other terms, but it is not negligible for accurate modeling, and should be retained in the model if the other two parameters identified are to be used for chiller diagnostics. The same linear model structure as Equation (71c) can be used if the fluid temperature leaving the evaporator T_{cho} is used instead of T_{chi}. However, the physical interpretation of the term a_3 is modified accordingly.

Reddy and Anderson (2002) and Sreedharan and Haves (2001) found that the GN and multivariate polynomial (MP) models were comparable in their predictive abilities. The GN model requires much less data if selected judiciously [even four well-chosen data points can yield accurate models, as demonstrated by Corcoran and Reddy (2003)]. Jiang and Reddy (2003) tested the GN model against more than 50 data sets covering various generic types and sizes of water-cooled chillers (single- and double-stage centrifugal chillers with inlet guide vanes and variable-speed drives, screw, scroll), and found excellent predictive ability (coefficient of variation of RMSE in the range of 2 to 5%).

Dynamic Models

In general, steady-state data-driven models are used with monthly and daily data containing one or more independent variables. Dynamic data-driven models are usually used with hourly or subhourly data in cases where the building's thermal mass is significant enough to delay heat gains or losses. Dynamic models traditionally required solving a set of differential equations. Disadvantages of dynamic data-driven models include their complexity and the need for more detailed measurements to tune the model. More information on measurements, including whole-building metering, retrofit isolation metering, and whole-building calibrated simulation, can be found in ASHRAE *Guideline* 14, Measurement of Energy and Demand Savings, and the International Performance Measurement and Verification Protocol (IPMVP) (U.S. Department of Energy 2001a, 2001b, 2003). Unlike steady-state data-driven models, dynamic data-driven models usually require a high degree of user interaction and knowledge of the building or system being modeled.

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

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

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 their key aspects. 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 applying 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), including back propagation.

Neural networks have been useful in modeling energy use in commercial buildings for

- Predicting 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.
- Predicting what a building, before 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 USING DATA-DRIVEN METHODS

Modeling Utility Bill Data

The following example (taken from Sonderegger 1998) illustrates a utility bill analysis. Assume that values of 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.

Appropriate modeling software is used in which values are assumed 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 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 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, 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 identify the significance of individual coefficients, ***t*-statistics** (or ***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. In other words, 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 (even when including a variable that increases the R^2). Generally, including more variables in a regression results in a higher R^2, but the significance of most individual coefficients is likely to 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.

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 air humidity loads. The neural network is used to predict the preretrofit energy consumption for comparison with measured consumption of the retrofitted building. Six months of preretrofit data were available to train the network. Solid lines show the known building consumption data, and 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 (in this case, 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)

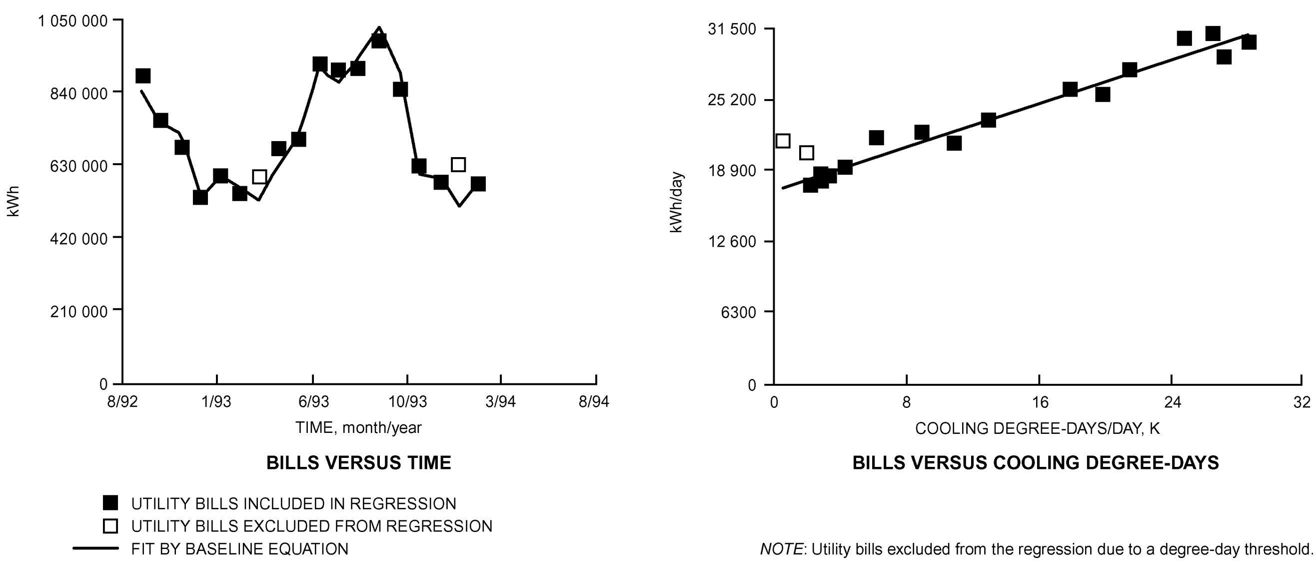

Fig. 19 Variable-Base Degree-Day Model Identification Using Electricity Utility Bills at Hospital
(Sonderegger 1998)

- Past hour's chilled-water consumption
- Second past hour's chilled-water consumption

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

Choosing 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 (i.e., 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), Krarti et al. (1998), Kreider and Wang (1991), and Wang and Kreider (1992) report additional case studies for commercial buildings.

MODEL SELECTION

Steady-state and dynamic data-driven models can be used with energy management and control systems to predict energy use (Kreider and Haberl 1994). Hourly or daily comparisons of measured versus 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).

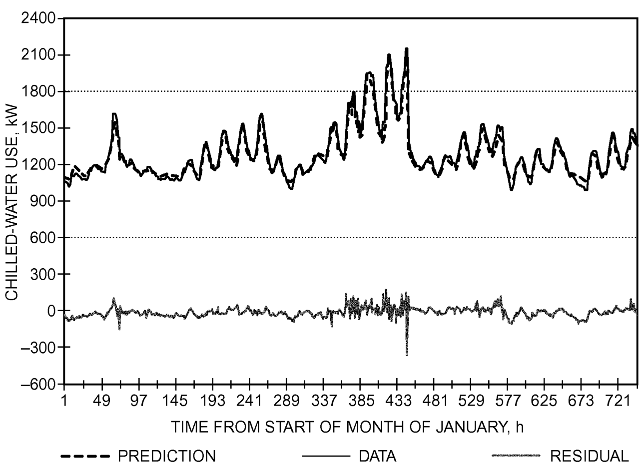

Fig. 20 Neural Network Prediction of Whole-Building, Hourly Chilled-Water Consumption for Commercial Building

More information on data-driven models can be found in the ASHRAE *Inverse Modeling Toolkit* (Haberl et al. 2003; Kissock et al. 2003). This toolkit contains FORTRAN 90 and executable code for performing linear and change-point linear regressions, variable-based degree-days, multilinear regression, and combined regressions. It also includes a complete test suite of data sets for testing all models.

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

MODEL VALIDATION AND TESTING

ANSI/ASHRAE *Standard* 140, Method of Test for the Evaluation of Building Energy Analysis Computer Programs, was developed to identify and diagnose differences in predictions that may be caused by algorithmic differences, modeling limitations, or coding or input errors. *Standard* 140 allows all elements of a complete validation approach to be added as they become available. This structure corresponds to the following validation methodology, with subdivisions creating a matrix of six areas for testing:

1. Comparative tests—building envelope
2. Comparative tests—mechanical equipment
3. Analytical verification—building envelope
4. Analytical verification—mechanical equipment
5. Empirical validation—building envelope
6. Empirical validation—mechanical equipment

The current set of tests focus on categories 1 and 4. These tests are based on procedures developed by the National Renewable Energy Laboratory and field-tested by the International Energy Agency (IEA) over three IEA research tasks (Judkoff and Neymark 1995a; Neymark and Judkoff 2002). Additional tests are being developed under ASHRAE research projects (Spitler et al. 2001; Yuill and Haberl 2002) and under joint IEA Solar Heating and Cooling Programme/Energy Conservation in Buildings and Community Systems Task 34/Annex 43 (Judkoff and Neymark 2004) that are intended to fill in other categories of the validation matrix.

Table 10 Capabilities of Different Forward and Data-Driven Modeling Methods

Methods	Use[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 data-driven 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
(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:
[a]Use shown includes diagnostics (D), energy savings calculations (ES), design (DE), and control (C).
[b]Time scales shown are hourly (H), daily (D), monthly (M), and subhourly (S).
[c]Variables include temperature (*T*), humidity (*H*), solar (*S*), wind (*W*), time (*t*), and thermal mass (*tm*).

METHODOLOGICAL BASIS

There are three ways to evaluate a whole-building energy simulation program's accuracy (Judkoff et al. 1983; Neymark and Judkoff 2002):

- *Empirical validation*, which compares calculated results from a program, subroutine, algorithm, or software object to monitored data from a real building, test cell, or laboratory experiment
- *Analytical verification*, which compares outputs from a program, subroutine, algorithm, or software object to results from a known analytical solution or a generally accepted numerical method calculation for isolated heat transfer under very simple, highly constrained boundary conditions
- *Comparative testing*, which compares a program to itself or to other programs

Table 11 compares these techniques (Judkoff 1988). In this table, the term "model" is the representation of reality for a given physical behavior. For example, heat transfer may be simulated with one-, two-, or three-dimensional thermal conduction models. The term "solution process" encompasses the mathematics and computer coding to solve a given model. The solution process for a model can be perfect, while the model remains inappropriate for a given physical situation, such as using a one-dimensional conduction model where two-dimensional conduction dominates. The term "truth standard" represents the standard of accuracy for predicting real behavior. An analytical solution is a "mathematical truth standard," but only tests the solution process for a model, not the appropriateness of the model. An approximate truth standard from an experiment tests both the solution process and appropriateness of the model within experimental uncertainty. The ultimate (or "absolute") validation truth standard would be comparison of simulation results with a perfectly performed empirical experiment, with all simulation inputs perfectly defined.

Establishing an absolute truth standard for evaluating a program's ability to analyze physical behavior requires empirical validation, but this is only possible within the range of measurement uncertainty, including that related to instruments, spatial and temporal discretization, and the overall experimental design. Test cells and buildings are large, relatively complex experimental objects. The exact design details, material properties, and construction in the field may not be known, so there is some uncertainty about the simulation model inputs that accurately represent the experimental object. Meticulous care is required to describe the experimental apparatus as clearly as possible to modelers to minimize this uncertainty. This includes experimental determination of as many material properties as possible, including overall building parameters such as overall steady-state heat transmission coefficient, infiltration rate, and thermal capacitance. Also required are detailed meteorological measurements. For example, many experiments measure global horizontal solar radiation, but very few experiments measure the splits between direct, diffuse, and ground reflected radiation, all of which are inputs to many whole-building energy simulation programs.

The National Renewable Energy Laboratory (NREL) divides empirical validation into different levels, because many validation studies produced inconclusive results. The levels of validation depend on the degree of control over possible sources of error in a simulation. These error sources consist of seven types, divided into two groups:

External Error Types

- Differences between actual building microclimate versus weather input used by the program
- Differences between actual schedules, control strategies, effects of occupant behavior, and other effects from the real building versus those assumed by the program user
- User error deriving building input files
- Differences between actual physical properties of the building (including HVAC systems) versus those input by the user

Internal Error Types

- Differences between actual thermal transfer mechanisms in the real building and its HVAC systems versus the simplified model of those processes in the simulation (all models, no matter how detailed, are simplifications of reality)
- Errors or inaccuracies in the mathematical solution of the models
- Coding errors

The simplest level of empirical validation compares a building's actual long-term energy use to that calculated by a computer program, with no attempt to eliminate sources of discrepancy. Because this is similar to how a simulation tool is used in practice, it is favored by many in the building industry. However, it is difficult to interpret the results because all possible error sources are acting simultaneously. Even if there is good agreement between measured and calculated performance, possible offsetting errors prevent a definitive conclusion about the model's accuracy. More informative levels of validation involve controlling or eliminating various combinations of error types and increasing the density of output-to-data comparisons (e.g., comparing temperature and energy results at time scales ranging from subhourly to annual). At the most detailed level, all known sources of error are controlled to identify and quantify unknown error sources and to reveal causal relationships associated with error sources.

This principle also applies to intermodel comparative testing and analytical verification. The more realistic the test case, the more difficult it is to establish causality and diagnose problems; the simpler

Table 11 Validation Techniques

Technique	Advantages	Disadvantages

Empirical (test of model and solution process)	• Approximate truth standard within experimental accuracy
	• Any level of complexity
		• Experimental uncertainties:
		  • Instrument calibration, spatial/temporal discretization
		  • Imperfect knowledge/specification of experimental object (building) being simulated
		• High-quality, detailed measurements are expensive and time-consuming
		• Only a limited number of test conditions are practical

Analytical (test of solution process)	• No input uncertainty • Exact mathematical truth standard for given model • Inexpensive	• No test of model validity • Limited to highly constrained cases for which analytical solutions can be derived
Comparative (relative test of model and solution process)	• No input uncertainty • Any level of complexity • Many diagnostic comparisons possible • Inexpensive and quick	• No absolute truth standard (only statistically based acceptance ranges are possible)

Source: Neymark and Judkoff (2002).

Table 12 Types of Extrapolation

Obtainable Data Points	Extrapolation
A few climates	Many climates
Short-term total energy use	Long-term total energy use, or vice versa
Short-term (hourly) temperatures and/or fluxes	Long-term total energy use, or vice versa
A few equipment performance points	Many equipment performance points
A few buildings representing a few sets of variable and parameter combinations	Many buildings representing many sets of variable and parameter combinations, or vice versa
Small-scale: simple test cells, buildings, and mechanical systems; laboratory experiments	Large-scale complex buildings with complex HVAC systems, or vice versa

Source: Neymark and Judkoff (2002).

and more controlled the test case, the easier it is to pinpoint sources of error or inaccuracy. Methodically building up to realistic cases is useful for testing interactions between algorithms modeling linked mechanisms.

A comparison between measured and calculated performance represents a small region in an immense *N*-dimensional parameter space. Investigators are constrained to exploring relatively few regions in this space, yet would like to be assured that the results are not coincidental (e.g., not a result of offsetting errors) and do represent the validity of the simulation elsewhere in the parameter space. Analytical and comparative techniques minimize the uncertainty of extrapolations around the limited number of sampled empirical domains. Table 12 classifies these extrapolations. Use of the term "vice versa" in Table 12 is intended to mean that the extrapolation can go both ways (e.g., from short-term to long-term data and from long-term to short-term data). This does not mean that such extrapolations are correct, but only that researchers and practitioners have either explicitly or implicitly made such inferences in the past.

Figure 21 shows one process to combine analytical, empirical, and comparative techniques. These three techniques may also be used together in other ways; for example, intermodel comparisons may be done before an empirical validation exercise, to better define the experiment and to help estimate experimental uncertainty by propagating all known error sources through one or more whole-building energy simulation programs (Hunn et al. 1982; Lomas et al. 1994).

For the path shown in Figure 21, the first step is running the code against analytical verification test cases to check its mathematical solution. Discrepancies must be corrected before proceeding further.

Second, the code is run against high-quality empirical validation data, and errors are corrected. Diagnosing error sources can be quite difficult and is an area of research in itself. Comparative techniques can be used to create diagnostics procedures (Judkoff 1988; Judkoff and Neymark 1995a, 1995b; Judkoff et al. 1980, 1983; Morck 1986; Neymark and Judkoff 2002; Spitler et al. 2001) and better define the experiments.

The third step is to check agreement of several different thermal solution and modeling approaches (that have passed through steps 1 and 2) in a variety of representative cases. This uses the comparative technique as an extrapolation tool. Deviations in the program predictions indicate areas for further investigation.

When programs successfully complete these three stages, they are considered validated for cases where acceptable agreement was achieved (i.e., for the range of building, climate, and mechanical system types represented by the test cases). Once several detailed simulation programs have satisfactorily completed the procedure, other programs and simplified design tools can be tested against them. A validation code does not necessarily represent truth. It does represent a set of algorithms that have been shown, through a repeatable procedure, to perform according to the current state of the art.

NREL methodology for validating building energy simulation

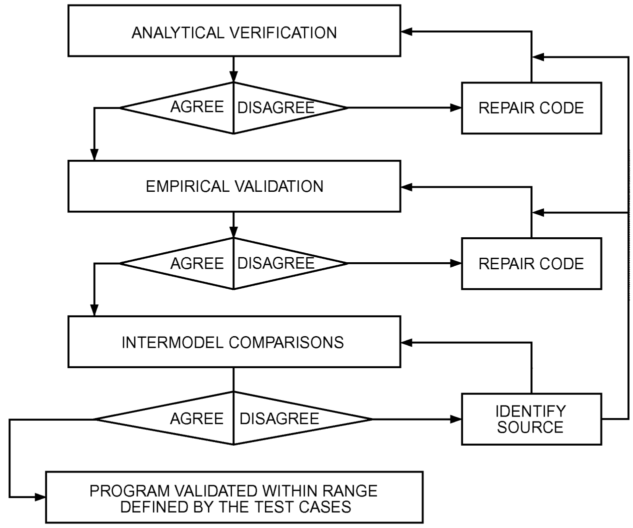

Fig. 21 Validation Method
(Neymark and Judkoff 2002)

Agency (Irving 1988), ASHRAE *Standard* 140 and Addendum p to ASHRAE *Standard* 90.1, and elsewhere, with refinements suggested by other researchers (Bland 1992; Bloomfield 1988, 1999; Guyon and Palomo 1999b; Irving 1988; Lomas 1991; Lomas and Bowman 1987; Lomas and Eppel 1992). Additionally, the Commission of European Communities has conducted considerable work under the PASSYS program (Jensen 1989; Jensen and van de Perre 1991).

SUMMARY OF PREVIOUS TESTING AND VALIDATION WORK

Neymark and Judkoff (2002) summarize approximately 100 articles and research papers on analytical, empirical, and comparative testing, from 1980 to 2004. Some of these works are listed by subject in the Bibliography.

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