First Principles Model for Integrated Cooling Systems

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ABSTRACT

A component-based modeling algorithm has been developed and tested for HVAC systems consisting of chillers, cooling towers or air-cooled condensers, constant or variable flow water systems, and constant or variable flow air-handling units. The model has been shown to predict actual power consumption and operating states with reasonable accuracy.

The component-based model uses a blend of empirical and physical models to predict operation of individual HVAC system components and then couples the individual models, accounting for the component's interaction to predict the performance of the central plant and the entire system. The model is general and can be configured and calibrated to simulate any chiller-based HVAC system using information and data that can be collected over a short period of time. It has been developed so that it can run either off-line using historical data or can be operated on-line in parallel with an actual system, using only a small number of inputs.

Efforts have been taken to identify the minimum amount of historical data necessary to calibrate the model to provide accurate prediction of system performance. The calibrated component-based model is a tool for activities such as scenario testing, fault detection and diagnostics (FDD), and optimal supervisory control. This paper discusses the models used, model performance observed during use on actual buildings, the data requirements for calibration, and the uses and benefits of such a tool.

Introduction

Mathematical models of processes or systems are commonly used in applications such as economics and industrial process for testing scenarios, system optimization, and fault detection and diagnostics (FDD). In the area of heating, ventilating and air conditioning (HVAC), there have been several research efforts and publications on system modeling and their use. A subset of the published work in this area is included in the References section of this paper.

One such model is a *component-based model* developed by Bradford and Brandemuehl (1998). This component-based model can be set up to operate either on-line in parallel with an actual HVAC system (to perform optimization or FDD), or off-line in a batch processing mode (to perform scenario analysis or FDD on historical data).

A useful characteristic of the component-based model is that it can be calibrated to provide accurate estimates of system states using only a small data set. The necessary data can be derived from a combination of rating data, short-term monitoring, and spot measurement. The ability to calibrate the model quickly for specific HVAC systems simplifies the use and application of this model compared to other modeling techniques that require a large amount of historical training data.

This paper outlines some of the important features and characteristics of the model and demonstrates, through laboratory testing, that it can be calibrated with a small data set.

Model Description

The component-based system model is a collection of algorithms that together model the performance of systems comprised of chillers, pumping, air handling units (AHUs) and heat rejection devices. The system model combines two types of component models: empirical power models and thermodynamic/heat transfer models. The thermodynamic/heat transfer models predict fluid states, component operating speeds, loads, and sub-system interaction using the fundamental laws of thermodynamics and established heat transfer principles. Using the results from the thermodynamic/heat transfer models, the empirical power models predict individual component power consumption using regressions generated from measured (historical) data.

Using a small number of inputs, the model can estimate a number of other useful variables.

Thermodynamic and Heat Transfer Models

The thermodynamic/heat transfer portion of the component-based model includes load estimators, coil performance models, and heat rejection-device performance models. These models are used to estimate the loads from measured data and predict the system air and water flow rates necessary to meet the load given the system parameters and operational states. The flow rates, temperatures, and loads can then be used in the power models. Table 1 shows the inputs and outputs for each of these sub-models. The cooling tower capabilities of the component-based model are not discussed or used here since the focus of this paper is on a system with an air cooled chiller. Bradford and Brandemuehl (1998) describe tower models that can be used in the component-based model.

Loads are calculated using basic first-law analysis. For wet or partially wet cooling coils, it is necessary either to know or to assume the supply air humidity to calculate the latent loads. It has been found (Brandemuehl, Bradford 1998) that, for wet or partially wet coils, assuming a leaving humidity of 90% to 95% provides relatively accurate results.

Chiller plants often serve small loads not associated with the main VAV air handlers in a system. In these cases, it is necessary to measure or assume constant loads from "other" sources. These constant loads can be added onto the calculated AHU loads to arrive at the chiller plant total load.

Energy exchanged at the cooling coil is modeled either using a standard NTU-effectiveness model in the case of dry-coil operation or an enthalpy-based NTU–effectiveness method (Threlkeld, 1970) when the coil is wet. When the coil is partially wet, the coil performance is predicted assuming that it is either fully wet or fully dry, whichever predicts the maximum heat transfer. Braun (1988) showed that this assumption predicts heat transfer to within 5% of more rigorous methods.

In the NTU methods, effectiveness of a cooling coil is a function of the airflow rate, chilled water flow rate through the coil, and heat transfer coefficients of the cooling coil (UA values). UA values are used to describe the energy exchanged between the water and the air. The energy exchange is a function of two UA values: UA internal and UA external. UA internal describes energy exchanged between the water and the coil. UA external describes the energy being exchanged between the coil and the air. These UA values can be obtained from rating or field data.

Table 1. Thermodynamic and heat transfer models inputs and outputs (air cooled systems)

Models	Inputs	Outputs
Load Estimator	Supply air temperature (F) Mixed air temperature (F) Mixed air relative humidity (%) Supply air flow rate (CFM) Temperature rise across fan (F)	Sensible (and latent*) AHU load (tons)
Coil Performance	Chilled water supply temperature (F) Supply air temperature (F) Mixed air temperature (F) Mixed air relative humidity (%) Sensible AHU load (tons) Rated internal and external UA values	Internal and external coil UA value Chiller load (tons) Chilled water flow rate (GPM) Chilled water return temperature (F) Supply air flow rate (CFM) Latent AHU load (tons)
Heat Rejection	Outside air dry-bulb temperature (F) Outside air relative humidity (%) Saturated refrigerant temperature (F) Chiller load and power	Air-cooled condenser air flow rate

*Latent load can be calculated knowing the entering and leaving coil conditions, but is also calculated in the coil models from the enthalpy-based NTU method.

Equations 1 and 2 are used to model the change in UA values of the cooling coils as a function of air or water flow rate:

$$UA_{external} = UA_{external,rated} \cdot \left(\frac{m_{air}}{m_{air,rated}} \right)^{n_{external}} \tag{1}$$

$$UA_{internal} = UA_{internal,rated} \cdot \left(\frac{m_{water}}{m_{water,rated}} \right)^{n_{internal}} \tag{2}$$

Equations 1 and 2 are appropriate since UA values are primarily functions of the forced convection coefficients. For both the internal and external flow, the forced convection coefficient is primarily a function of the Reynolds Number to the *n* power. The Reynolds Number, in turn, varies linearly with mass flow.

Using a regression analysis on a small data set, the rated UA values and flows, and exponents, *n,* can be determined. Once the coefficients for Equations 1 and 2 are known, the relationships can be used in the coupling of the water and air-sides of the system. The coupled performance is estimated by iteratively solving for the water flow rate that forces the coil effectiveness to be equal to the required coil effectiveness given the current sensible load, entering air conditions and setpoint temperatures.

If there is more than one AHU in a building, the cooling coils can be treated as a single virtual coil. The inputs for the single virtual coil then include the sum of all the airflow rates in the AHUs, and the average supply and mixed air temperatures and humidities.

The load on the heat rejection devices is equal to the cooling load plus the work of the chiller compressors. The mass flow rate of an air-cooled condenser (ACC) can be modeled using the NTU-effectiveness on a heat exchanger assuming infinite flow (condensation) on the refrigerant side. Inputs for the ACC model include a rated UA value, outside air temperature, airflow rate, and the saturated condensing refrigerant temperature. Coupling between the chiller and the ACC is accomplished by iteratively varying the air flow rate until the resulting coil effectiveness is equal to the effectiveness required to transfer the heat at the particular outside air conditions, load, and saturated refrigerant temperature.

Power Models

Using the results of the thermodynamic and heat transfer models, power models calculate the power consumption for the energized components of a particular system, including fans for air distribution and heat rejection, chilled and condenser water pumps, and chillers. The power for each component is calculated from empirical regressions based on the independent variables that effect electrical demand for each component. Independent variables may include temperatures, loads, and flow rates.

To develop rigorous fan or pump power models, the equipment characteristics, installation characteristics, pressure differential, and speed must all be considered. For fans and pumps that are already installed in a building, however, use of flow rate alone often results in sufficiently accurate power models provided the system, setpoints (or reset strategy) and control sequences remain unchanged (Phelan, et al. 1997).

Power models of fan systems and pump systems were generated using short-term data and the formulation shown in Equation (3):

$$P = A_2 \cdot F^2 + A_1 \cdot F + A_0 \qquad (3)$$

where
P = Power (kW)
A_2, A_1, A_0 = Regression Coefficients
F = Flow Rate (GPM or CFM)

The choice of the formulation depends on the particular system performance. The different special cases include linear (A_2= 0), linear forced through zero (A_2= 0 and A_0= 0), quadratic, quadratic forced through zero (A_0= 0), and constant power (A_2= 0 and A_1= 0).

Rigorous modeling of chiller power is difficult. However, simplified empirical formulations generated from short term measured data or manufacturer's data can be used to predict chiller power. Chiller power consumption can be modeled as a quadratic function of the chilled water supply temperature (T_{chw}), refrigerant saturated condensing temperature (T_{rsat}), and the part load ratio (PLR) for an air-cooled condenser. Such a formulation is commonly used in simulations such as DOE2 (LBL 1980) and others. The equation used in the component-based model is shown below

$$P = A_1 + A_2 \cdot T_{chw} + A_3 \cdot T_{chw}^{\ 2} + A_4 \cdot T_{rsat} + A_5 \cdot T_{rsat}^{\ 2} + A_6 \cdot PLR + A_7 \cdot PLR^{\ 2} + A_8 \cdot T_{chw} \cdot T_{rsat} + A_9 \cdot T_{chw} \cdot PLR + A_{10} \cdot T_{rsat} \cdot PLR \quad (4)$$

For systems employing a cooling tower, chiller power consumption can be modeled as in Equation 4, except the saturated refrigerant temperature is replaced with the condenser water supply temperature (T_{cws}). Saturated refrigerant temperature or, equivalently, pressure, is often available in local chiller controls, but may not be available in building control systems unless specified in the design.

Chillers can be cooled with cooling towers, evaporative condensers, or air-cooled condensers. Because validation experiments described in this paper focus on air-cooled condensers, simplified modeling for other heat rejection devices (Brandemuehl, Bradford 1998) are not covered here.

Model Validation

The component-based model was tested in a laboratory to demonstrate that it can be used to estimate a cooling system's operation with short-term data. Testing was performed at the Larson Building Systems Laboratory at the University of Colorado at Boulder (Kreider et al. 1999), which includes a complete VAV HVAC system and air-cooled chiller plant. The laboratory allows imposition of realistic loads on the system in a controlled, repeatable environment.

For the tests, the laboratory was configured to impose daily load profiles on the system for both near-peak cooling days and mild swing-season days. The test also included variations in setpoint temperatures for chilled water and supply air. The objectives of the test were to evaluate the accuracy with which the model could track system performance and to assess the ability to calibrate the model with short-term data.

Three days of testing were performed. The model parameters were calibrated using the training data from two days and the models were evaluated by comparing predicted and measured performance from the third day.

Laboratory Description

The test system consists of an air-cooled chiller, a primary/secondary chilled water loop, two air handlers, four parallel fan powered mixing boxes, and a return fan.

The central AHU includes a mixing box, filter bank, chilled water coil, hot water coil, and a variable speed supply fan. This AHU supplies conditioned air to four terminal boxes. The zones served include two full-size rooms and two zone simulators in which zone loads are represented by programmable heating and cooling coils. A second air-handling unit located upstream of the central air handler provides control of the air supplied to the main air-handling unit to simulate various outside air conditions.

Chilled glycol is supplied to the system by a two-compressor screw chiller with a nominal capacity of 70 tons. Since the chiller is oversized for the laboratory as it is currently configured, only one of the unit's two circuits was energized during the experiments.

Heat is rejected from the chiller with a 50-ton nominal, air-cooled condenser (ACC). The ACC has two separate 25-ton refrigerant circuits, each of which is connected to one of the chiller's two compressors.

Operating Conditions and Load Profiles

During testing, the main AHU was controlled to deliver 55°F supply air and maintain a supply duct static pressure of 1.85 inches of water gage (in WG). The return fan was controlled to maintain a static pressure of -0.50 in WG in the return duct. Other system setpoints and operating conditions were varied to simulate operation at various loads and conditions. Programmed load profiles were used during testing to investigate the effectiveness of the component-based model over a wide range of operating conditions.

Table 2 is summary of the minimum and maximum loads and setpoint temperatures used in each of the fours days of testing.

Table 2. Summary of testing conditions

Day	T_{sa}	T_{zone}	T_{chws}	$T_{oa,min}$	$T_{oa,max}$	Min chiller tons	Max chiller tons
8/25/99	55	72	45	76	93	5.8	18.7
8/27/99	55	72	49	60	79	2.5	11.2
9/3/99	55	77	42	76	94	0	22.7

Diurnal load and outside air temperature profiles similar to what might be found in a real building were imposed to allow the system to operate at varying conditions during the test days.

Supply Air Fan Power Model

The supply air fan power consumption (kW) was best modeled as a linear function of the supply airflow rate (CFM). A graph of the measured power consumption versus the measured airflow rates for the supply air fan is shown in Figure 1. The linear relationship for the laboratory is typical and expected for VAV systems (Brandemuehl, Bradford 1998, Phelan, et al., 1997).

Secondary Chilled Water Pump Power Model

The secondary chilled water pump in the test HVAC system is a constant speed pump and the system water flow rate varies as a result of the modulating two-way cooling coil valve. Consequently, a relatively flat power curve is as expected. As has been seen in other primary/secondary pumping systems (Brandemuehl, Bradford 1998, Phelan, et al. 1997) the secondary chilled water pump power consumption (kW) was best modeled as a linear function of the secondary chilled water flow rate (GPM). A graph of the measured power consumption versus the measured water flow rates for the secondary chilled water pump is shown in Figure 2.

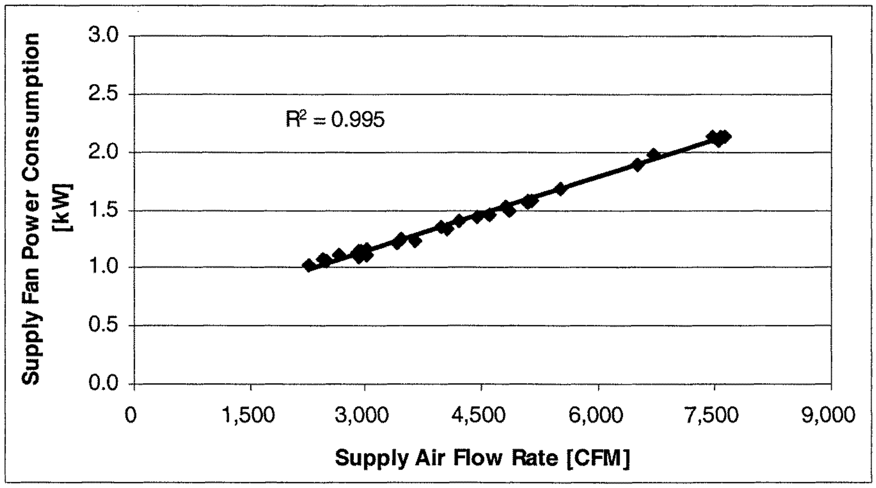

Figure 1. Measured supply air fan power consumption versus air flow rate

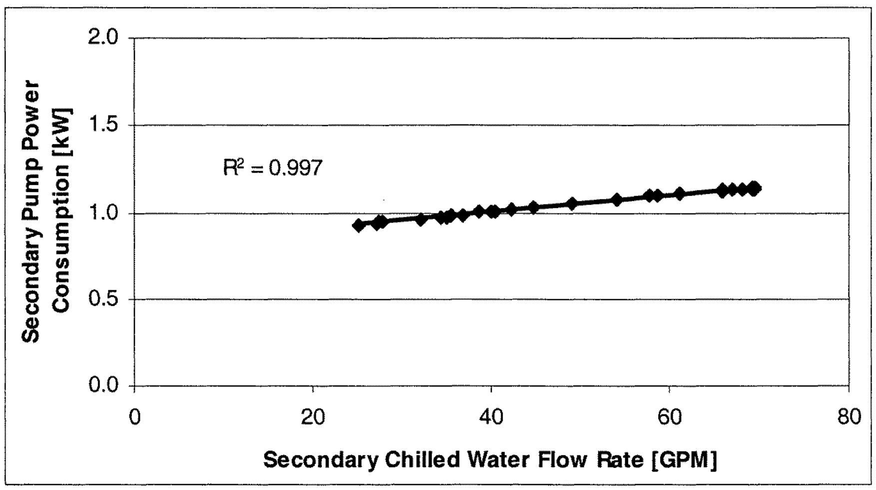

Figure 2. Measured secondary chilled water pump power consumption versus flow rate.

Chiller Power Model

To develop an accurate model of the chiller using a small data set, it is important to make sure that the chilled water temperature, saturated refrigerant temperature, and the PLR, data covers a reasonable range of the expected operating range of the system.

Examination of the ranges of the PLR, chilled water temperature and saturated condenser refrigeration temperature revealed that August 27 and September 3 together provided the broadest ranges of independent variables. Figure 3 shows that the multivariable quadratic representation predicts chiller power well.

Air-Cooled Condenser Thermodynamic and Power models

The ACC heat exchanger model requires calculation of an overall heat transfer coefficient, UA, at a nominal rated condition. Because there is no manufacturer's data describing the lab's particular chiller/ACC combination, a "rated" UA of the coil was calculated based on measured performance at a single point of operation.

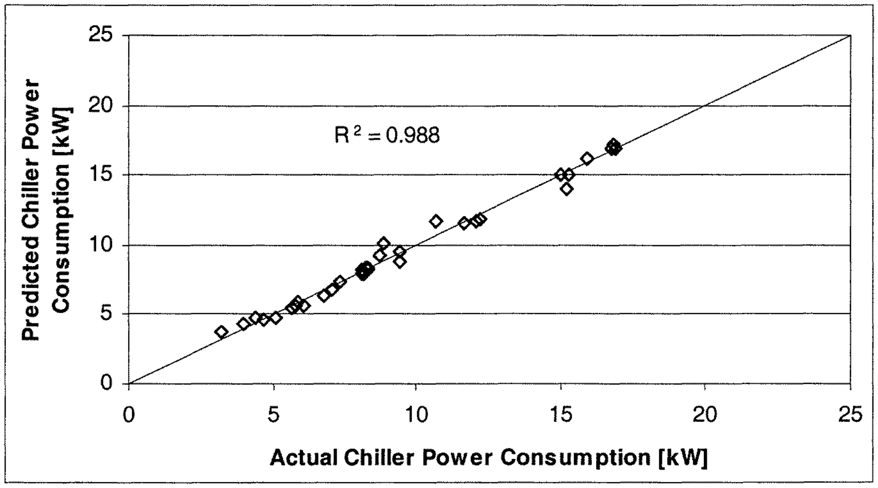

Figure 3. Quadratic chiller model performance.

During the test, the ACC fans were switched on when the chiller was operating and were not modulated. Therefore, the power consumption, effectiveness, and UA value of the air-cooled condenser were constant. If the fans were modulated to maintain a refrigerant temperature setpoint, the necessary airflow could be found by iterating until the condenser effectiveness was equal to the effectiveness required to reject the heat load and outside conditions.

Figure 4 shows the actual ($Q_{chiller} + W_{compressor}$) and predicted load on the ACC. Note that the model does a good job of predicting during most of the hours, but that there are times when the model does not accurately predict ACC load. The differences show that the model, which assumes steady-state operation, can not be expected to predict operation accurately when the loads are transient or when the chiller is cycling on and off because the load is serving a load that is lower than its maximum turn-down ratio.

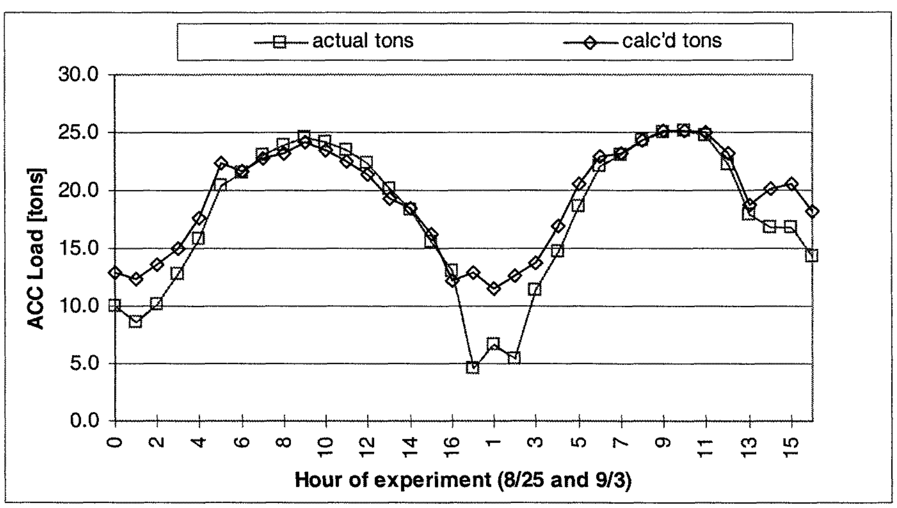

Figure 4. ACC actual and predicted load

Cooling Coil Model

The cooling coil performance is a function of the airflow rate across the coil (CFM), the chilled water flow rate through the coil (GPM), the internal and external UA values of the cooling coil as well as the entering air conditions and setpoints. "Rated" UA internal and external values can be calculated from measured performance when the coil is wet, and a single overall UA value can be calculated when the coil is dry. The rated UA values can then be adjusted for varying flows using Equations 1 and 2. The resulting regressions as a function of the respective mass flow rates are illustrated in Figure 5 and Figure 6.

The internal and external UA values found during wet coil operation can, in theory, be combined to equal the total UA value found during dry coil operation. Because the total UA values found when the coil is wet and dry are not precisely the same, a step-change the coil performance between the wet and dry coil calculation occurs, causing non-convergence on coil effectiveness. Assure convergence problems, the algorithm assuming a wet coil was exclusively used. As shown in Figure 7, below, assuming a wet coil during all conditions results in accurate water flow rate, however, simple software changes are warranted to develop more robust methods for coil performance modeling.

The regressions provide a good fit except for the external UA at high airflow rates. The divergence from theory at the higher airflow rates may have resulted from the exclusive use of the wet coil algorithm, or may result from transient load conditions.

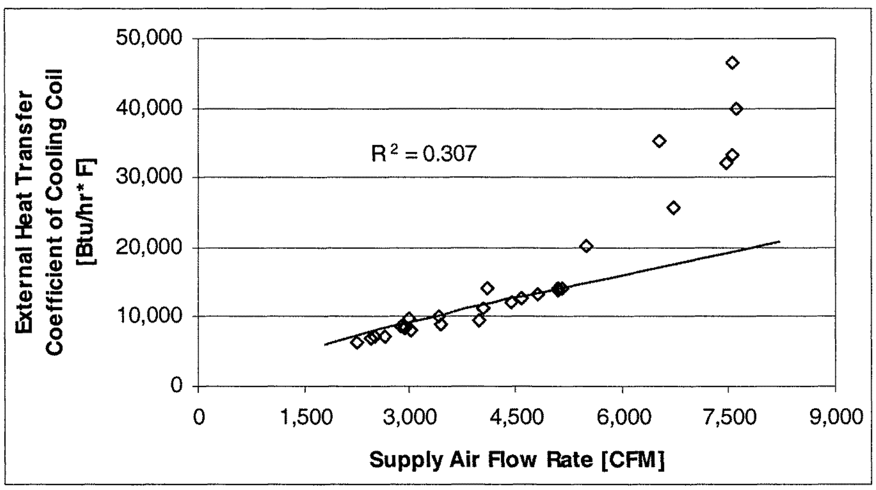

Figure 5. Regression of cooling coil external heat transfer coefficient

Model Performance

In the preceding sections, two days of data (August 27 and September 3) were used to calibrate the component models. Using the calibrated models, the component-based model was used to predict the performance of the integrated system for August 25.

Table 3 shows the R^2 and coefficient of variation (COV) resulting from the predictions during the test period. Figure 7 shows graphical representations of the performance of some of the model in estimating some of each of the system operational parameters, including overall power use, which is the sum of the power use of all components.

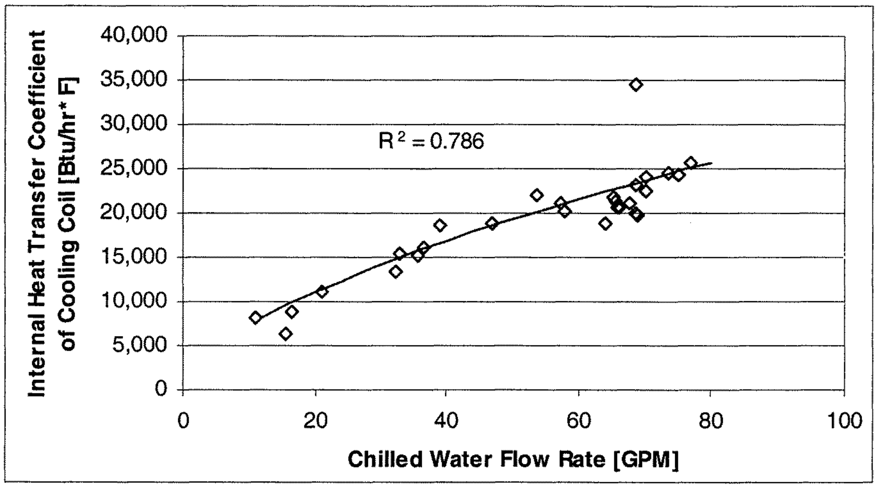

Figure 6. Regression of cooling coil internal heat transfer coefficient.

Table 3. Test data prediction results by building system component

Component	R^2	COV (%)
Supply Air Fan Power Consumption	0.992	4.02
Secondary Chilled Water Pump Power Consumption	0.979	1.16
Chiller Power Consumption	0.894	16.30
Air-Cooled Condenser Power Consumption	0.0835	18.32
Chilled Water Flow Rates	0.978	4.52
Overall System Power Consumption	0.889	12.13

Considering the restricted amount of data used for calibration, the results are good in the well-controlled conditions of the laboratory. The components that had rather high COV were the chiller and the ACC. The chiller COV was high because the two days of power data of the chiller were not representative of the higher operating range, which was obtained on the third day. The ACC was high because the power consumption was being predicted on a component that is a constant power device. Therefore, the graphical plot of predicted versus actual performance should be a tight cluster of points, which is observable with the majority of the data in Figure 7.

Training data

When calculating the coefficients, it was found that the quality of data was more important then the quantity of data. The data used to calculate the various coefficients needs to cover a representative subset of the expected operational range. Large data sets can be avoided, and gaps in the training set can be tolerated, however, since the shape of the various curves is generally known *a priori* and manufacturer's data can be used in many cases for coils, ACCs, and chillers.

Generally, the best time to collect the data would be when the cooling system's components are operating at a variety of ranges (i.e., during the summer or swing months). It is possible to calibrate the model successfully using as little as one day's worth of data if they cover a reasonably broad range of operation.

The potential of using manufacturer's data to calibrate the model was investigated. It was found that rating information could be used if the building components were properly commissioned and operating in a way consistent with the manufacturer's data. It was found, however, that in some cases, such as the case of the ACC/chiller combination, the manufacturer's data were not representative of the operation if these components due to age, configuration or sizing. In these situations, field data must be used.

The chiller model is the most difficult to develop with limited field-test data. Since the model has ten separate regression coefficients, a relatively large amount of data may be required. However, it is possible to obtain reliable quadratic regressions based on manufacturer's data. The regressions based on manufacturer's data can be corrected to match measured performance using linear base and gain adjustments (Brandemuehl, Bradford 1998).

Discussion of the Model Use

Since the component-based model is based on simple individual models that are coupled using proven techniques, it is possible to build-up and calibrate the representation for unique building systems with minimal data. The model has been shown to provide accurate estimations both in the Larson lab and in a 270,000 square foot commercial building (Brandemuehl, Bradford 1998).

Preliminary research has been completed on the development of methodologies and guidelines for the model use and calibration (Zarske 2000). In that work, it has been shown that as little as one day of data can be used in calibration of each of the sub-models, provided the data has certain characteristics. Zarske outlines the desirable data characteristics and how to produce, recognize and condition useful data sets.

Once a model has been calibrated, it maybe used in a number of ways: to test scenarios, to perform system optimization, and to perform FDD functions.

An example of scenario testing is the evaluation of different sub systems to assess the demand and energy impacts of various options or efficiency changes. To use the model to test scenarios, it would be necessary to generate load profiles for input into the model.

The model can be used (on or off-line) to identify the optimal setpoints to minimize power demand (Brandemuehl, Bradford 1998). To minimize demand, a cost function equal to the sum of the demand of each sub system is calculated and a solution space search method is used to find the set of setpoints that will minimize this cost function. Typically the setpoints to be adjusted to minimize demand include the supply air temperature, the chilled water temperature, and the condenser water temperature or saturated refrigerant temperature. Reductions of demand and energy use from optimization have been shown to be in the range of 5 to 10% over typically used design setpoint values (Brandemuehl, Bradford 1998).

FDD systems typically include two separate modules, in the first, the "pre-processor," the data from the system is processed to provide expected values that would indicate non-fault conditions. The processed data is then passed to the second module where actual values are compared to expected values and detection and diagnosis is performed. The component-based model provides several outputs (such as flow and power) that can be compared to actual values in an FDD system.

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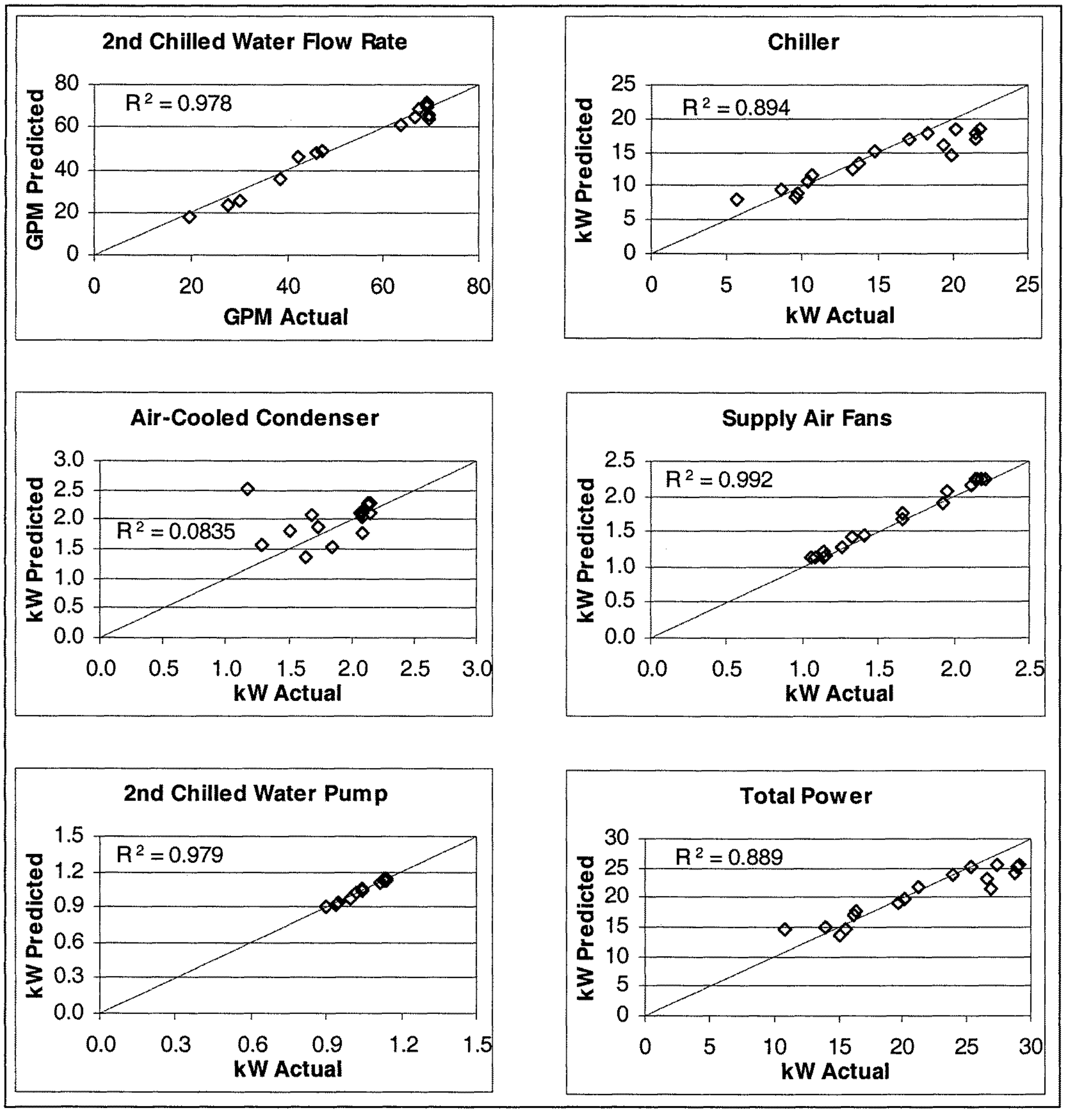

Figure 7. Predicted versus actual model performance

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