Model-based Performance Monitoring: Review of Diagnostic Methods and Chiller Case Study

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ABSTRACT

The paper commences by reviewing the variety of technical approaches to the problem of detecting and diagnosing faulty operation in order to improve the actual performance of buildings. The review covers manual and automated methods, active testing and passive monitoring, the different classes of models used in fault detection, and methods of diagnosis. The process of model-based fault detection is then illustrated by describing the use of relatively simple empirical models of chiller energy performance to monitor equipment degradation and control problems. The CoolTools™ chiller model identification package is used to fit the DOE-2 chiller model to on-site measurements from a building instrumented with high quality sensors. The need for simple algorithms to reject transient data, detect power surges and identify control problems is discussed, as is the use of energy balance checks to detect sensor problems. The accuracy with which the chiller model can be expected to predict performance is assessed from the goodness of fit obtained and the implications for fault detection sensitivity and sensor accuracy requirements are discussed. A case study is described in which the model was applied retroactively to high-quality data collected in a San Francisco office building as part of a related project (Piette et al. 1999).

Introduction

Over the last few years, a number of researchers in the US and elsewhere have developed automated methods for detecting and diagnosing faults in buildings, primarily in HVAC systems (Hyvarinen 1997) and are now starting to demonstrate their use in real buildings. What follows is an overview of the application of diagnostic methods in buildings. One aim of this overview is to provide a conceptual framework and a common set of terms for describing diagnostic methods. An extended version of this review appears in Haves (1999). Other reviews of fault detection and diagnosis methods and their application to HVAC&R systems have been performed in the context of ASHRAE research projects (e.g. 1139-RP, which is concerned with training methods for chiller models).

Review of Automated Fault Detection and Diagnosis Methods

Fault *detection* is the determination that the operation of the building is incorrect or unacceptable in some respect; whereas, fault *diagnosis* is the identification or localization of the cause of faulty operation.

Fault detection

Fault detection can be done either by:

- assessing the performance of all or part of the building over a period of time (e.g. from utility bills or complaint frequencies) and then comparing that performance to what is expected; or
- monitoring the temperatures, flow rates and power consumptions and continuously checking for incorrect operation or unsatisfactory performance.

Unacceptable behavior may occur over the whole operating range or be confined to a limited region and hence only occur at certain times.

Fault detection is easier than fault diagnosis in that, for fault detection, it is only necessary to determine whether the performance is incorrect or unsatisfactory; knowledge of the different ways in which particular faults affect performance is not required. Two methods of representing the baseline for performance are:

- knowledge bases;
- quantitative models.

One common form of knowledge base is a set of rules produced by experts, e.g.

IF the control valve is closed AND the supply fan is running AND the temperature rise across the heating coil is greater than the combined uncertainty of the sensor readings THEN the operation is faulty.

A knowledge base can be considered to be a qualitative model.

Quantitative models can take a number of forms, including:

- first principles ('textbook') models, e.g. effectiveness-NTU for coils;
- polynomial curve fits, e.g. fan curves or chiller performance maps;
- artificial neural networks.

Faults are detected with a quantitative model by using measured values of the control signals and some of the sensor signals as inputs to the model. The remaining sensor signals are then compared with the predictions of the model, as shown in Figure 1. Significant differences ('innovations') indicate the presence of a fault somewhere in the part of the system treated by the model.

Empirical or 'black box' models, such as polynomial curve fits or neural networks, are only as good as the data used to generate them. In particular, their accuracy usually falls off rapidly in regions of the operating space for which there are no training data. The main advantage of black box models is that they can be chosen to be linear in the parameters, making the process of estimating the parameters of the model both less demanding computationally and more robust. One advantage of physical models is that the prior knowledge that they embody improves their ability to extrapolate to regions of the operating space for which no training data are available. They also require fewer parameters for a given degree of model accuracy. A further feature of physical models is that the parameters correspond to physically meaningful quantities, which has two advantages:

1. Estimates of the values of the parameters can be obtained from design information and manufacturers' data;
2. Abnormal values of particular parameters can be associated with the presence of particular faults.

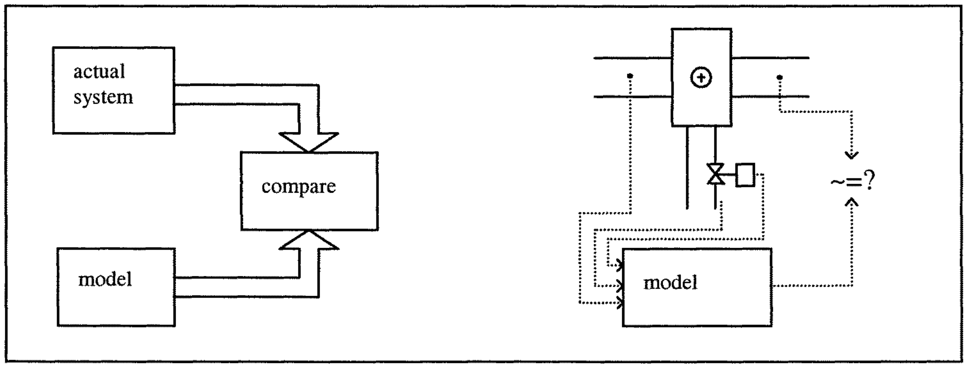

Figure 1. A model-based fault detection scheme. The left hand diagram shows the general principle and the right hand diagram shows the application to a heating coil, in which the inputs to the model are the inlet temperatures and the control signal and the output of the model is the outlet air temperature.

Fault diagnosis

Fault diagnosis involves determining which of the possible causes of faulty behavior are consistent with the observed behavior. Automated fault diagnosis relies entirely on sensors and so may not be able to identify the nature of the fault unambiguously, although it may be able to eliminate some of the possible causes.

In addition to establishing the physical cause of faulty operation (e.g. fouled coil, over-ridden control function), it is desirable to be able to estimate both the cost of fixing the fault and the cost of delaying fixing it. In order to know that the observed operation is incorrect or unsatisfactory, it is necessary to have some reference, or baseline, to which actual performance may be compared. This baseline may be obtained from published material such as from a designer or manufacturer, codes and standards, or it may be based on 'standard practice' and professional experience.

Fault *diagnosis* is more difficult than fault *detection* because it requires knowledge of how the system behaves when faults are present. There are three main approaches:

1. Analysis of how the innovations (the differences between the predicted and the observed performance) vary with operating point;
2. Comparison of the actual behavior with the predictions of different models, each of which embodies a particular type of fault;
3. Estimation of the parameters of an on-line model that has been extended to treat particular faults.

One method of implementing the first approach is to use a rule-based classifier (Benouarets et al. 1994). The rules, which may be Boolean or fuzzy, can either obtained from experts and then checked for consistency, completeness and correct implementation by testing using simulation. Alternatively, the rules can be generated using simulation. If black box models are used in the second approach, simulation may be the only way to generate training data, since it is not usually possible to obtain training data from real, faulty, systems. One exception is the case of factory-built standard products, such as chillers or VAV boxes, where the production of large numbers of identical units may justify the cost of generating training data for common faults. The third approach involves extending the model to represent both faulty and correct operation using physical principles and engineering knowledge; the estimated values for the parameters relating to the faulty behavior are then used for fault diagnosis (Buswell, Haves and Salsbury 1997).

Automation of FDD

Current commissioning procedures are almost all completely manual, in that they rely on a commissioning engineer or operator to perform the tests and analyze the results. There has been some research and development on automating performance verification procedures for use in commissioning (Haves et al. 1996) but few commercial products appear to have been produced as yet. An automated commissioning tool is more complicated than a performance monitoring tool because it needs to be able to override the control system, either by forcing actuators or changing set-points, in order to exercise the equipment being tested. It also needs to include test sequences for each type of equipment for which it will be used

Work on manual performance monitoring procedures for use during 'normal' operation has focused on graphical methods of displaying the measurements to the operator to allow efficient fault detection and then fault diagnosis. Displaying information to an operator is also important for automated tools, since such tools are unlikely to be accepted unless they can display the evidence and provide a justification for a fault detection and diagnosis. The main benefit of automated performance monitoring tools is that they can 'pre-filter' data from many points, avoiding the need for manual inspection of all the measurements from every point. By acting as 'smart alarms', automated performance monitoring tools have the potential to allow a building operator to spend less time keeping on top of performance and to allow remote operators and service companies to monitor multiple buildings efficiently. Ultimately, automated tools may be able to make reliable diagnoses and automatically contact service contractors and direct them to replace particular components.

Dynamic Behavior and Control Performance

In principle, reference models used in FDD should treat dynamic behavior as well as steady-state behavior. However, the variations in operating point encountered in HVAC systems are often slow enough that most items of equipment can be regarded as being in a quasi-steady state, such that the error produced by using a static reference model is acceptably small. Static reference models are simpler to develop and configure; the dynamic behavior of HVAC equipment is often non-linear and poorly understood. Static models can be used for FDD if it is possible to determine when their predictions are valid, and when measurements can safely be used to estimate their parameters. Several *steady state detectors* have been produced by Annex 25 participants (Hyvarinen 1997).

Even though the dynamic response of most HVAC equipment is fast compared to typical rates of change of operating point, there are still circumstances in which the dynamic aspect of a system's controlled performance is important. Unstable operation, due to excessive controller gain, has a number of undesirable effects. These include excessive component wear, leading to premature failure and increased maintenance costs, and may also include discomfort or increased energy consumption. An overly damped response, due to low controller gain, may also lead to unacceptably sluggish performance in some situations.

An Integrated Approach to Performance Verification and Performance Monitoring

An approach to diagnostics that links design, commissioning and operation is to use a baseline derived from a combination of design data and manufacturers' performance data for performance verification. The data obtained during the performance verification tests is then used to 'fine-tune' this baseline for use in performance monitoring, as in the following procedure:

Performance Verification:

1. Configure the reference models of correct operation using design information and manufacturers' performance data.
2. Perform a predefined series of tests to verify correct performance.
3. If any tests fail, perform specific additional tests to determine the cause of failure.
4. Remedy defects diagnosed by the tests (e.g. replace mechanical equipment or retune controllers).
5. Repeat appropriate tests to verify system now performs correctly.

Performance Monitoring:

1. Use data collected during successful performance verification tests to refine the values of the parameters of the models of correct operation.
2. Use routine operating data to detect and, if possible, diagnose faults.
3. If a fault is detected but not adequately diagnosed, perform a performance verification test, typically during the next unoccupied period, to improve the diagnosis of the fault.
4. Remedy the fault.
5. Confirm that the fault has been correctly remedied by repeating the performance verification test.

Evaluation of Diagnostic Systems

Diagnostic systems can be evaluated by assessing the extent to which they supply reliable, needed, information at low cost. In particular, a good diagnostic system should:

1. Have sufficient sensitivity to detect faults before they become problems (e.g. cause complaints or damage);
2. Provide a useful diagnosis by:
    a) Localizing the fault (which building, which floor, which AHU, which coil, is it in the valve or the actuator...?);

b) Recommending action (which trade to call: mechanical, electrical, controls?), is action required immediately (what is the expected cost of delay?);

3. Have a low false alarm rate;
4. Have a low first cost and low maintenance costs;
5. Be easy to learn and use.

What follows is a case study that addresses the first issue by assessing how accurately a particular semi-empirical chiller model can predict the performance of a chiller in a commercial office building

Case Study: Model-based Monitoring of Chiller Performance

Selection of the model

The model used in this study is the polynomial chiller model from the DOE-2 simulation program, as implemented in Pacific Gas and Electric's CoolTools™ package (PG&E 1999). The model takes the evaporator duty and the condenser water and chilled water supply temperatures as inputs and predicts the electrical power as its output. The CoolTools™ package facilitates the fitting of chiller models to performance data and allows these models to be used in a stand-alone version of the DOE-2 chilled water plant simulation. The chilled water plant simulation can be used to analyze system performance and address issues such as chiller replacement. CoolTools™ includes a library of curves derived from detailed measurements of the performance of a wide range of chillers. This library is used in cases in which a comprehensive set of measurements covering full load and part load operation is not available. In the case reported here, the rated capacity of the chiller is 228 tons whereas the highest duty observed is less than 170 tons. The use of such a library addresses one of the principal disadvantages of empirical models, i.e. the poor extrapolation accuracy obtained in cases where the training data cover a restricted part of the operating range.

The inputs to the DOE-2 chiller model are the evaporator duty and the entering water temperatures for the condenser and the evaporator. The output is the electric power consumed by the compressor. These quantities were measured at one-minute intervals of a period of approximately 18 months using high accuracy sensors (Piette et al. 1998). The water temperature sensors, which were located in the main flow, were calibrated to 0.01°F (although other factors are likely to prevent this level of accuracy being achieved in practice). The water flow rates through the evaporator and the condenser were measured using magnetic flow meters with a specified accuracy of 0.5 percent. The true electric power (i.e. including the effect of the power factor) was measured with a specified accuracy of 1.2 percent. Additional information may be found at http://poet.lbl.gov/tour/.

The condenser and evaporator duties were determined from water-side heat balances and are believed to be accurate to about 1 percent. The condenser duty was determined in order to be able to perform an energy balance on the chiller so as to provide a consistency check on the instrumentation (see below).

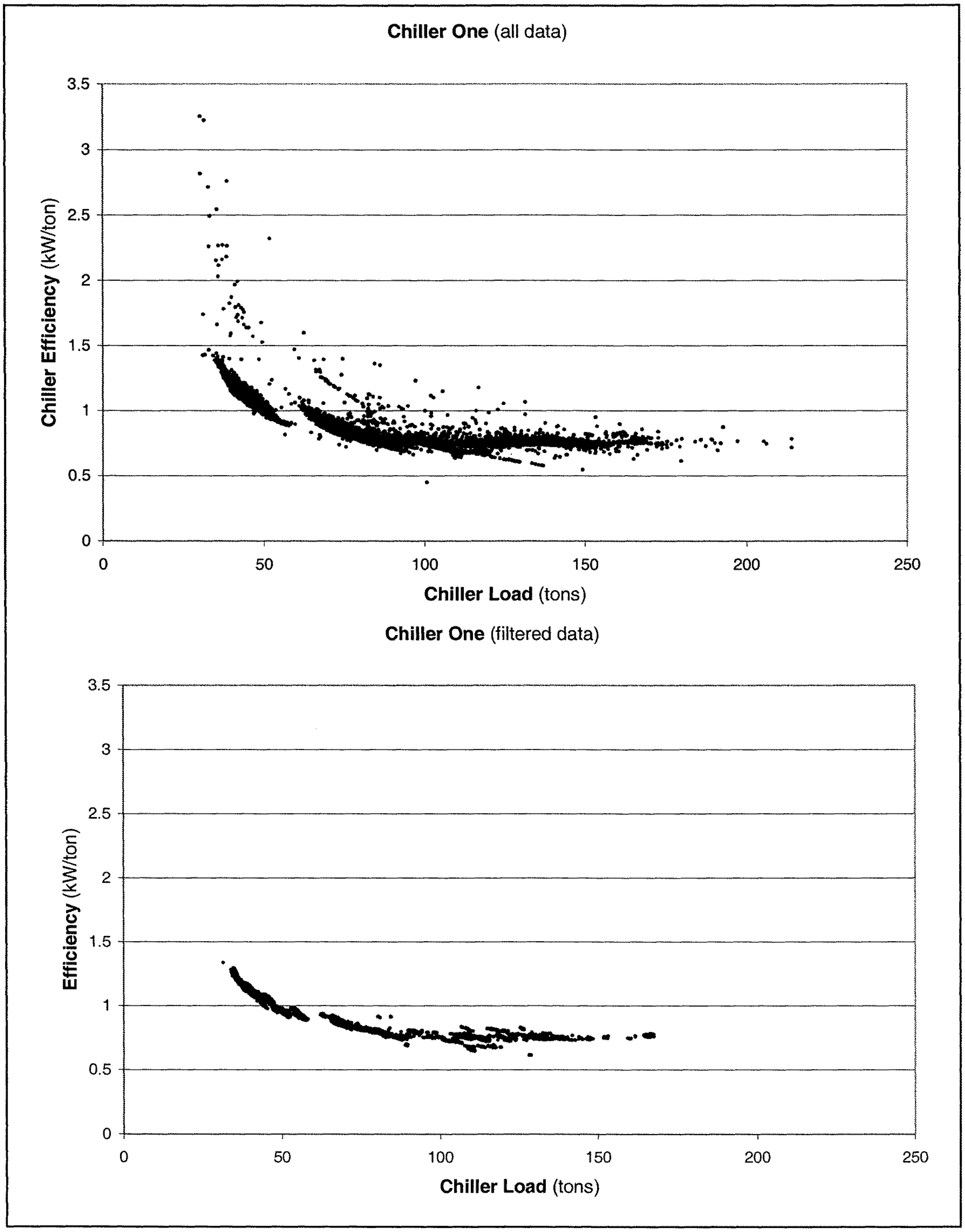

Figure 2. Power per unit load before and after filtering out transient data

Setting up the steady-state detector

Both the DOE-2 chiller model and the energy balance used to check the sensors are steady state models in that they ignore thermal capacity and other transient effects. The measured electric power and the condenser and evaporator duties calculated from the measured water temperatures and flow rates were filtered to remove transient data. An exponentially weighted moving average of the absolute value of the change in value from minute to minute was calculated for each duty and the power and the data record rejected if any of the moving averages exceeded an empirically determined threshold. Figure 2 shows plots of power per unit load (kW/ton) versus load (tons) before and after filtering.

Energy balance

The steady state data were used to check the energy balance of the chiller. If heat losses from the surface of the machine are ignored, the measured heat rejected by the condenser should equal the sum of the measured electric power and the heat absorbed by the evaporator. Figure 3 shows the residual of this energy balance for a selected period that included a sensor fault. The units of the residual are tons and the maximum and average evaporator duties during the selected period were 145 tons and 102 tons respectively. The average value of the residual in the absence of the known fault is about 4 tons, indicating that the combined effect of sensor offsets and case losses is approximately 3 percent of full load. More significant for the detection of sensor faults is that the typical longer-term variations in the residual are around 1 ton. The temperature sensor fault that occurred on July 6 and 7 is clearly detectable on July 6 when it produced a change in the residual of about 5 tons.

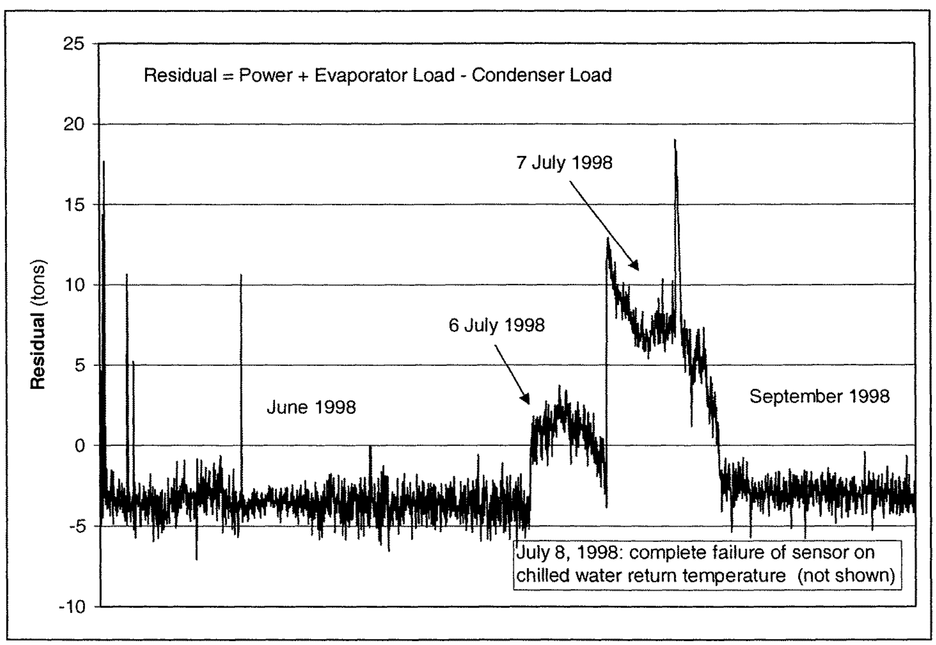

Figure 3. Energy balance residual for a period including power spikes and a sensor failure

The occasional spikes in the residual are worthy of note and require some explanation. The steady-state filter used to select the data plotted in Figure 2 only considered the evaporator duty. The spikes are due to short-term surges in the measured electric power and indicate either an equipment fault or an instrumentation fault. These spikes are filtered out when using a steady state filter that considers electric power, suggesting that a comprehensive fault detection scheme based on steady state models should classify transient data rejected by the steady state filter. The filter should discriminate between the effect of load changes, which are expected, and oscillations and other undesirable transients, which indicate faulty operation. (Significant periods of data were rejected during the period covered in Figure 2 because oscillations in the cooling tower controller caused significant fluctuations in the evaporator duty.)

Configuring and checking the model

Since the number of data points in the entire set of one-minute data is much too large for the CoolTools™ fitting procedure, the data were collected into bins, each bin representing a two-degree F range of condenser water supply temperature, a two-degree F range of chilled water supply temperature and a six-ton range of load. The values of each of the input variables and the output variable (electric power) were averaged for each bin and the resulting averaged values presented as training data for CoolTools™ .

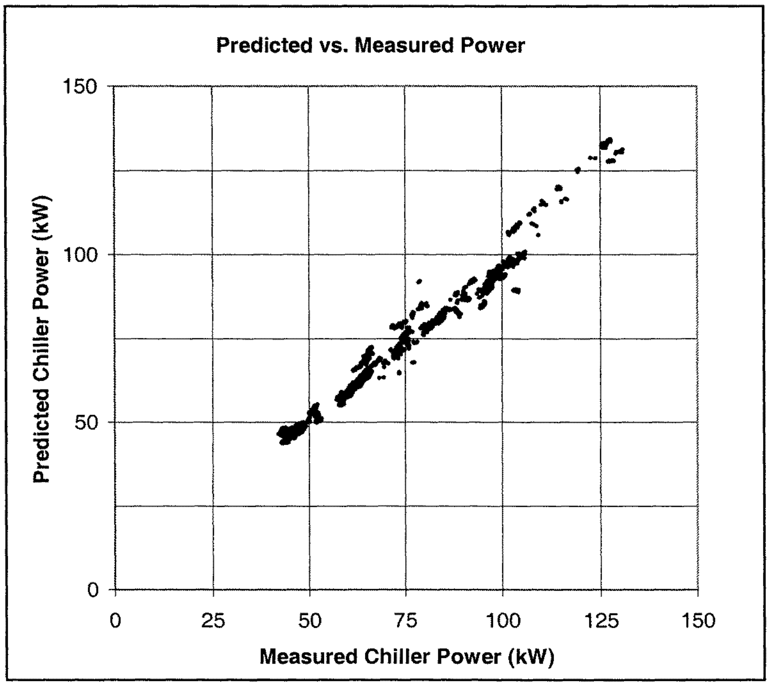

Figure 4. Predicted Power vs. Measured Power

To check the adequacy of the model structure, the model was applied to the entire set of data available (5/1/98 to 7/7/98 and 9/11/98 to 6/30/99). Figure 4 is a plot of predicted versus measured power. It shows a number of features, including two populations at high power (greater than 100 kilowatts). These two populations are much less evident in the binned data used to train the model, suggesting the influence of an additional independent variable. (Examination of the data indicates that this additional independent variable is not time.) In particular, the small set of points with a measured power of ~105 kW and a predicted power of ~90 kW is currently unexplained. The question of the accuracy with which the model can be expected to predict power depends on whether this set of points corresponds to correct or faulty operation. If that operation is deemed correct, or at least acceptable, then the threshold for fault detection cannot be set lower than about 15 percent. If they are found, or assumed, to correspond to faulty operation, then the threshold could be set to about seven percent. The relatively narrow width of the various features in Figure 4 suggests that, if these features can be understood through further investigation, it may be possible to set the threshold as low as three percent, providing a much more sensitive fault detector. Both further, detailed, analysis of this data set and a study involving a number of chillers are called for to clarify the degree of model accuracy that can be expected in practice.

Conclusions

On-line performance monitoring and diagnostics require some form of baseline to define correct operation. This baseline can take the form of a quantitative model that must be configured using either design data or measured performance data. A case study involving the use of high quality performance data suggests that models have the potential to act as accurate baselines for energy performance. However, measurements in addition to those required to drive the model would be very useful in differentiating between inadequacy of model structure and faulty operation, when configuring a baseline model.

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