Condition monitoring in HVAC subsystems using first principles models

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Condition Monitoring in HVAC Subsystems Using First Principles Models

Member ASHRAE

ABSTRACT

The paper describes a condition-monitoring scheme based on first principles models. The scheme involves estimating the values of model parameters that are expected to change in the event of a fault. The first principles models are, in general, not linear in the parameters, and recursive estimation of the parameters of these models is avoided by estimating the parameters of an intermediate model that is linear in the parameters. This intermediate model, which takes the form of a radial basis function network, is used periodically to generate data covering the complete operating range of the system. These data are then used in the estimation of the parameters of the first principles model. The paper describes the techniques used and presents results from applying the method to the task of detecting two faults in the cooling coil subsystem of an air-handling unit.

INTRODUCTION

The sensor and control signals in a heating, ventilating, and air-conditioning (HVAC) system contain potentially valuable information about the state of the system, and energy management and control systems (EMCS) have the ability to monitor and store these signals. In practice, the only checks that are carried out are to verify that setpoints are being maintained and that certain critical variables remain within predetermined limits. This may allow the detection of certain abrupt or catastrophic faults, but the task of identifying the underlying cause of the failure often requires a detailed manual analysis of trend data up to the point of failure or a test of the system so that a diagnosis may be made. The slow changes in performance caused by degradation faults may be even more difficult to observe manually, and these faults may remain undetected until their effects are quite severe. One reason for this is that feedback control tends to reduce the effect of such faults on the ability of the system to maintain comfort, even though other aspects of the performance of the system, such as energy consumption, may be significantly impaired.

An alternative approach is to use the sensor and control signal data collected by the EMCS to monitor the state of the system and infer the nature and extent of any faults using an automatic fault detection and diagnosis (FDD) system. Fault detection involves the determination that the observed behavior of the target system is unacceptably different from the expected behavior. The unacceptable behavior may occur over the whole operating range or may be confined to a limited region. Fault diagnosis involves determining which of the possible causes is consistent with the observed behavior. In some cases, it may be possible to identify the nature of the fault unambiguously, but often it is only possible to eliminate some of the possible causes. The process of diagnosis requires that the most important possible causes of faulty operation be identified in advance and that these different causes give rise to behaviors that can be distinguished with the available instrumentation.

Fault detection and diagnosis in HVAC systems has been explored as part of an International Energy Agency collaborative research project (Annex 25) and by a number of other researchers (e.g., Usoro et al. 1985; Pape et al. 1991). Significant research has been carried out by other industries, such as chemical processing. All of the approaches require the use of models of some sort. These models may be qualitative (Kaler 1990; Dexter and Benouarets 1995) or quantitative (Iserman 1984) or a combination of the two (Yu and Lee 1991). For fault detection, only a single model of correct operation is required; the system is deemed to be faulty if its behavior does not match that of the model of correct operation. Diagnosis of different faults requires either an analysis of how the difference between the observed and predicted behaviors varies with the operating point or the use of models of the different types of faulty operation (Benouarets et al. 1994).

The approach presented here involves identifying a model of the system on-line and analyzing its parameter values to ascen-
tain whether a fault has occurred. The paper describes an FDD method designed to diagnose multiple faults and presents results of tests performed on a simulated cooling coil subsystem with a fouled coil and a leaking valve.

OVERVIEW OF THE FDD METHOD

Figure 1 is a schematic of the condition-monitoring scheme that comprises a radial basis function (RBF) model and a first principles ("physical") model. The RBF models the local behavior of the HVAC system and is updated using a recursive gradient-based estimator when the system is (approximately) in steady state. To avoid estimator windup (or overtraining), the RBF is only updated when the difference between the predicted and measured outputs exceeds a certain threshold, indicating that the performance of the system has changed. The RBF is then exercised over the operating range of the system and the data generated are used in the estimation of the parameters of the physical model using a direct search technique (Box 1965). The parameters that are estimated for the physical model are physically meaningful and represent a tangible measure of system performance. Determination of detection thresholds is therefore greatly simplified, and they can be set to suit each particular system and its performance criteria.

![Figure 1](image)

**Figure 1** The condition monitoring scheme.

This indirect method of estimating the parameters of the physical model has been adopted because physical models generally are not linear in the parameters and are therefore unsuited to recursive parameter estimation. Because the RBF is a local model, it provides an estimate of the most recently observed behavior of the system in different parts of the operating space, responding relatively quickly to changes in the behavior of the system.

The rest of this paper describes the application of the method to the detection and diagnosis of coil fouling and valve leakage in a cooling coil.

**FIRST PRINCIPLES MODEL**

The model represents the principal static characteristics of cooling coil subsystems of the type found in air-handling units. The air-side approach of a coil is defined by:

\[ \alpha = \frac{T_{ai} - T_{ao}}{T_{ai} - T_{wi}} \]  

The NTU-effectiveness relationship for counterflow operation of a dry coil is used to estimate the approach from the overall conductance, \( U_A \), and the air- and water-side capacity rates, \( C_a \) and \( C_w \), respectively:

\[ \alpha = \frac{\min(C_a, C_w)}{C_a} \]  

where

\[ \epsilon = \frac{1 - \exp(-NTU(1 - \omega))}{1 - \exp(-NTU(1 - \omega))} \]

\[ NTU = \frac{UA}{\min(C_a, C_w)} \]

and

\[ \omega = \frac{\min(C_a, C_w)}{\max(C_a, C_w)} \]

The capacity rate of the air can be calculated directly since the air mass flow rate is usually available (or can be calculated from the velocity), but the water mass flow rate through the coil is not usually measured and needs to be inferred from the control signal to the actuator of the control valve. To achieve this, a model has been developed to approximate the behavior of a typical equal percentage three-port valve. The model consists of a modified exponential function characterized by the parameter \( c \). The relationship between the fractional water mass flow rate into the coil, \( \frac{m_w}{m_{w,max}} \), and the valve actuator control signal, \( u_c \), is given by:

\[ \frac{m_w}{m_{w,max}} = \frac{\exp(c u_c) - 1}{\exp(c) - 1} \]

The modification avoids the need to switch to a different function in the lower part of the range in order to avoid the significant opening at zero stem position that would occur with a pure exponential. The model also treats leakage resulting from restriction of the travel of the stem due to foreign matter on or near the valve seat. The leakage parameter, \( l \), specifies the fractional flow when the valve is nominally closed. The fractional water flow into the coil is then:

\[ \frac{m_w}{m_{w,max}} = \max\left(\frac{\exp(c u_c) - 1}{\exp(c) - 1}, l\right) \]

Four parameters \( (m_{w,max}, c, l, UA) \) are required for the combined valve and coil model. For simplicity, the coil model uses a constant value of \( UA \) and therefore does not treat the effect of varying fluid flow rate on the corresponding heat transfer coefficient. However, it is possible for the variation in the waterside heat transfer coefficient to be partly compensated for by a change in the value of the valve characteristic, \( c \). An extension to
the model would be needed to treat the corresponding effect of variations in the airflow rate, e.g., in variable-air-volume (VAV) systems.

The approach that is estimated by the model is compared with the approach calculated from the measured temperatures using Equation 1. There are different problems associated with the measurement of each of these temperatures. The temperature of the air entering the coil, $T_{ai}$, is equal to the temperature of the air leaving the mixing box. However, this temperature is difficult to measure accurately due to imperfect mixing of the outside and recirculation airstreams in many systems. The approach adopted here is to treat as invalid any measurements made when the mixing box dampers are not in either of their extreme positions. The temperature of the air leaving the coil, $T_{ao}$, is generally not measured in a draw-through system, so the supply (discharge) air temperature is used after correcting for the temperature rise across the supply fan, $\Delta T$. This temperature rise may vary with the flow rate through the fan, e.g., in a VAV system. The relationship between the temperature rise and the flow rate depends both on the characteristics of the fan and the way in which it is controlled. Since the rise is relatively small (~ 1 K [2°F]), an approximate correction has been assumed:

$$\Delta T = \frac{m_a}{m_{a,\text{max}}} \Delta T_{\text{max}}$$

The maximum temperature rise across the fan, $\Delta T_{\text{max}}$, can be measured as part of commissioning, and the maximum air mass flow rate, $m_{a,\text{max}}$, can be estimated from the system specifications.

Initialization of the First Principles Model

The parameters of the physical model are initialized in two stages. Design information and manufacturers' performance data are used to produce initial estimates of the parameter values and to define the regions of feasibility for each parameter. Training data collected when the plant is deemed to be operating correctly (e.g., at commissioning time) are then used to estimate the parameter values corresponding to the fault-free system. Significant differences between the initial values and the values identified from the training data indicate differences in performance between the system as designed and the system as built.

Since the physical model is not linear in the parameters, analytical techniques cannot be used to locate the optimum parameter values for a given data set. Problems were experienced with gradient-based methods as a result of discontinuous derivatives in the valve model. Box's (1965) complex direct-search method has therefore been adopted since it does not require derivative information. The search is also effective in handling parameter bounds. Each of the parameters of the physical model is normalized so that its feasible range maps onto a range of zero to one, in an effort to produce circular objective function surface contours that can help to increase robustness. The objective function used is the mean of the squares of the errors (MSE) of the physical model predictions at each of the training data samples. The search process is terminated when the objective function value fails to improve for a number of iterations.

Updating the Parameters of the First Principles Model

During operation of the condition-monitoring scheme, a subset of the parameters of the physical model (fault parameters) is updated so as to provide the best fit to data generated by the RBF model. The fault parameters that are included in the search are the $UA$ of the coil and the fractional flow leakage, $l$; all other parameters remain fixed at their initial values. The RBF model is used to generate outputs at points distributed uniformly within the input space and these are compared with the outputs of the physical model in order to calculate the MSE. The complex method is then employed to minimize the MSE by searching for the optimum fault parameters.

RADIAL BASIS FUNCTION MODEL

Radial basis function models are mathematical tools for approximating multidimensional surfaces using local nonlinear functions. The most common function used is the Gaussian function. A model is constructed by centering a number of Gaussian functions at selected positions within the input space and selecting widths so that the tails of neighboring functions overlap (see Figure 2, which shows two Gaussian functions in a single input dimension). The output of a particular function (its activation) decreases with the Euclidean distance between the input to the model and the center of the function, giving the model its local properties. The output of the network, $y_p$, at a particular point, $x$, is the sum of the activations, $\phi_i(x)$, multiplied by the corresponding weights, $w_i$:

$$y_p = \left[ \phi_1(x) \phi_2(x) \ldots \phi_c(x) \right] ^T$$

The weights are estimated initially from the training data and are then updated using approximately steady-state operating data from the system. An important property of RBF networks is that, if the number and shape of the basis functions are fixed

Figure 2 An RBF network and Gaussian functions.
prior to training, estimation of the weight vector is a linear optimization task that can be solved analytically using conventional least-squares methods.

For this application, the RBF network is used to model the static relationship between the system inputs (the fractional air mass flow rate through the coil, \( \dot{m}_a/\dot{m}_{a,max} \), and the control signal to the valve, \( u_c \)) and the system output (the air-side approach calculated from the temperature measurements, \( \alpha \)). The weight vector is updated using a simple linear gradient descent method. Usually, if an RBF model is trained to approximate a system off-line from a finite data set, then the positioning of the centers and the degree of overlap between the Gaussian functions can be optimized to suit the system characteristic by employing nonlinear optimization methods. However, since the system characteristics will change, these attributes cannot be fixed \textit{a priori} and on-line refinement would make the model nonlinear in the parameters. A general, fixed configuration of basic functions is therefore required that will allow the model to approximate arbitrary nonlinearities by optimizing the weights alone. To achieve this, it is ensured that the range of each input is normalized to be between 0 and 1; the centers are then positioned on a uniform grid in this normalized input space. The widths are selected to be equal to the distance between adjoining centers, thereby providing a parsimonious activation surface. It was determined that the nonlinearity of the cooling coil subsystem could be accurately modeled by having eight centers in each dimension (giving a total of 64 centers for the two-dimensional input space).

**Initialization of the RBF**

The RBF weights are initialized using a conventional least-squares estimation procedure. This procedure is sensitive to outlier points and any “holes” in the training data that may lead to an ill-conditioned solution. To avoid these problems and to produce consistency between the two models at the outset, the RBF model is initialized using training data generated from the calibrated physical model. The data are generated on a fine, regular grid of points that span the operating space. If a series of \( n \) data points is generated by the physical model, the multiple-input, single-output RBF model can be written as:

\[
y_p = \Phi w + \varepsilon
\]

where

\[
y_p = \begin{bmatrix}
y_p(1) \\
y_p(2) \\
\vdots \\
y_p(n)
\end{bmatrix}, \quad \Phi = \begin{bmatrix}
\phi_1(x(1)) & \phi_2(x(1)) & \cdots & \phi_c(x(1)) \\
\phi_1(x(2)) & \phi_2(x(2)) & \cdots & \phi_c(x(2)) \\
\vdots & \vdots & \ddots & \vdots \\
\phi_1(x(n)) & \phi_2(x(n)) & \cdots & \phi_c(x(n))
\end{bmatrix}, \quad w = \begin{bmatrix}
w_1 \\
w_2 \\
\vdots \\
w_c
\end{bmatrix}, \quad \varepsilon = \begin{bmatrix}
\varepsilon_1 \\
\varepsilon_2 \\
\vdots \\
\varepsilon_n
\end{bmatrix}
\]

\( y_p(i) \) is the \( i \)th prediction of the physical model, \( w \) is the vector of RBF weights, \( \Phi \) is the matrix of basis functions at each input point \( x \), and \( \varepsilon \) is the vector of prediction errors between the RBF and the physical model. The least-squares criterion can be applied to calculate the unbiased estimate of \( w \) that has minimum variance, which is:

\[
\hat{w} = (\Phi^T\Phi)^{-1}\Phi^Ty_p
\]

**Updating the RBF**

Once the RBF has been initialized by training it to represent the correct operational state of the system, it is updated using normal operating data from the system. A gradient-based recursive parameter estimation method known as normalized least mean squares (Åström and Wittenmark 1989) was chosen for its modest data storage and processing requirements. For the scalar output RBF described in the previous section, the prediction at sample \( i \), \( \hat{y}(i) \) in response to an input vector, \( x(i) \), is given by:

\[
\hat{y}(i) = \Phi^T\hat{w}
\]

where \( \Phi^T(i) = [\phi_1(x(i)) \ldots \phi_c(x(i))] \) is the vector of basis function activations and \( \hat{w} \) is the vector of weights. If the weight vector at sample \( i-1 \) is used to generate the model prediction, then a reasonable criterion of how well the model performs is:

\[
V_i(w) = \frac{1}{2}(y(i) - \Phi^T(i)w(i-1))^2
\]

where \( y(i) \) is the measured output of the system. Differentiation with respect to \( w(i-1) \) shows that the gradient of this criterion is:

\[
V_i'(w) = -\Phi(y(i) - \Phi^T(i)w(i-1))
\]

\[= -\Phi e(i)
\]
where \( e(i) \) denotes the prediction error. The projection algorithm involves moving the parameter estimate in the direction of the negative gradient by an amount \( \kappa \) such that:

\[
\mathbf{w}(i) = \mathbf{w}(i-1) + \kappa \phi(i) e(i).
\]  

(14)

If \( \mathbf{w}(i) \) is assumed to be the correct weight vector at sample \( i \), then:

\[
y(i) = \phi^T(i) \mathbf{w}(i-1) + \kappa \phi^T(i) \phi(i) e(i).
\]  

(15)

Rearranging for \( \kappa \):

\[
\kappa = \frac{1}{\phi^T(i) \phi(i)}
\]  

(16)

Hence, the updating formula is:

\[
\mathbf{w}(i) = \mathbf{w}(i-1) + \frac{\phi(i)}{\phi^T(i) \phi(i)} e(i).
\]  

(17)

In this form, the updating formula would converge on the optimum parameter values for a finite set of training data samples if the number of samples were equal to the number of parameters. In practice, where the number of presented samples is greater than the number of parameters, a learning rate, \( \lambda \), is introduced so that:

\[
\mathbf{w}(i) = \mathbf{w}(i-1) + \frac{\lambda \phi(i)}{\gamma + \phi^T(i) \phi(i)} e(i)
\]  

(18)

where \( \gamma \) is a small number that is introduced to protect against division by zero for the case when \( \phi(i) = 0 \). In situations where the system parameters are time invariant, then the learning rate affects the speed of convergence and the accuracy of the solution (Abu el Ata-Doss et al. 1985). For this application, in which the system has time-varying parameters, the learning rate determines the tracking speed of the estimator.

**Data Preprocessing**

Both the RBF and the physical model are static models. The dynamics of the system are ignored due to the difficulty of modeling them accurately using physical equations. A transient detector is used to prevent updating of the RBF when the measured system variables are varying significantly. A discrete-time, low-pass filter is used to reduce the effect of noise. The activity of each variable, defined as the absolute change from one time step to the next, is then averaged using another discrete-time, low-pass filter. Finally, the averaged activity is normalized and compared with a threshold value. When the activity is below the threshold, the system is deemed to be sufficiently close to steady state to update the RBF. A description of a similar detector is given by Dexter and Benouarets (1995b).

**RESULTS**

The results of tests on a simulated air-conditioning system are presented to demonstrate the ability of the scheme to detect both fouling and leakage faults in the cooling coil of an air-handling unit. The test data are generated from an HVACSIM+ simulation of a three-zone VAV air-conditioning system. The main component models used in the simulation are described by Haves (1994). The structure of the plant and the control scheme are similar to those described by Dexter and Haves (1990), but the sizing of the equipment is taken from the detailed design of a recently completed office building in London. The simulated building has three zones, each having time-varying occupancy, equipment, and lighting loads. In addition, each zone is subject to significant, highly variable solar gains. Figures 3 and 4 show the behavior of the correctly operating cooling coil on two different days.

Training data were generated by performing closed-loop tests on the simulated plant. Tests of this sort could be carried out as part of the commissioning process in a real building. Constant loads and inlet conditions were maintained during the tests. The supervisory control scheme was disabled and the setpoint for the supply air temperature varied in a series of steps. Three tests were performed—the first with the VAV boxes under closed-loop

![Figure 3 Test data on first day with no faults.](image1)

![Figure 4 Test data on second day with no faults.](image2)
control, the second with the VAV boxes demanding maximum airflow, and the third with the VAV boxes demanding minimum airflow. The training data are shown in Figure 5. Due to the problems associated with the measurement of mixed-air temperature discussed in a previous section, the training data are restricted to the part of the operating range of the plant in which the mixing box dampers are set to provide full outside air.

![Figure 5 The training data.](image)

Table 1 shows the values of the parameters estimated for the physical model by using the complex method to optimize the fit of the model to the training data.

The condition-monitoring scheme was configured to estimate the UA of the coil and the leakage through the coil valve. The scheme was then tested using three different fault cases: 3% flow rate leakage through the control valve, 1 mm of calcium carbonate fouling on the tubes, and both faults present at the same time. The results of applying the scheme to these three cases on each of the test days are presented in Figure 6. There are three graphs for each of the fault cases. The upper graph shows the difference between the predicted and the actual change in the estimated value of the UA parameter estimated from the data generated by the RBF, and the lower graph shows the estimated leakage. The breaks in the lines indicate times when data were rejected by the transient detector. The parameter estimates at the end of each run for each of the two days are given in Table 2. The value of the learning rate, λ, was 0.1. The UA value for the fault-free case is slightly different from that given in Table 1 because it was estimated from data generated by the RBF instead of directly from the measured training data.

![Table 1 The Values of the Parameters Estimated from the Training Data](image)

Figure 5 shows the difference between the prediction of the correct operational physical model and the measured output of the system gives a good indication of the presence of a fault. For the fouling faults, the residual is positive at high coil duty, whereas for the leakage faults, it is negative at low duty. The correlation between the nature of the residual and the type of fault can be exploited for fault diagnosis as described by Benouarets et al. (1994). However, this approach requires the model to be accurate for the complete range of operation, as modeling errors will lead to false alarms. The effect of modeling error can be observed in the graph showing the fouling fault on the second day. On this occasion, the residual has a negative value when the coil is at low duty. Reference to the raw data revealed that the control signal to the valve at this point is ~10%; at other times during the test when the control signal had a similar value but the air mass flow rate was different, there is no corroborating evidence of leakage. This suggests a modeling error within this operating region. Because of the lack of corroborative leakage evidence, the
Figure 6  Test results.
scheme is best able to fit the physical model to the evidence by decreasing the estimated value of the $UA$.

**CONCLUSIONS**

A condition-monitoring scheme based on physical models has been described and its ability to detect the presence of valve leakage and water-side coil fouling within the cooling coil subsystem of an air-handling unit demonstrated. The $UA$ of the coil and the fractional flow rate of water leaking through the coil were the quantities reported by the scheme. These quantities could be transformed into more tangible measures of performance, such as the reduction in coil capacity and the increase in energy use, thus simplifying the task of setting detection thresholds. No detection threshold values have been proposed in this paper; ideally, their magnitude should be tailored to each particular system based on the level of deterioration in performance that could be tolerated by the building owner and/or occupant.

Estimation of the parameter values of the physical model is a nonlinear optimization task, and there will always be a danger of converging to a local minimum, regardless of the technique used. If the data used for the optimization cover only a small region of the operating space, then the chance of the method failing to converge to the true (global) optimum is increased. Use of the RBF model enables data to be generated across the range of operation, and this helps to make the nonlinear optimization more robust. However, the method requires the use of two parameter estimation procedures, each having potential inaccuracies. It is difficult to quantify the estimation inaccuracies that are incurred with the present method. The algorithm that is used to estimate the parameters of the RBF does not allow confidence intervals to be calculated directly, but this could be achieved by using a more computationally intensive estimator, such as recursive least squares, that would make the covariance matrix directly available at each time step. However, since the system is assumed to have time-varying parameters, then forgetting would need to be employed, which would serve to keep the covariance matrix high, leading to overestimated levels of parameter uncertainty. Inaccuracies also occur when estimating the parameters of the physical model from the RBF. The nonlinear form of the physical model prevents analytical evaluation of confidence intervals for each of the parameters, but an assessment of the overall fit of the physical model to the RBF can be made from the MSE.

The accuracy of the estimated parameters will also depend on the structural adequacy of the physical model. The model that has been used in the paper is a simplified representation of a cooling coil subsystem that has been developed with the objective of capturing the principal static characteristics of the system while keeping the number of parameters to a minimum. One of the approximations made by the model is that of a fixed $UA$; in reality, the $UA$ will vary as a function of the air and water flow rates. The overall effect of the change in the $UA$ due to variations in the water flow rate can be compensated for to a certain extent by the valve model. The effective value of the valve characteristic parameter, $c$, is determined by the combined effects of the inherent characteristic of the valve, the valve authority, and the variation in $UA$ with water flow rate. The variation in $UA$ with airflow rate is not accounted for within the structure of the physical model. If the $UA$ value were estimated using data from different regions of the operating range at different times, the estimated value would vary due to the variations in the flow rates. However, because the RBF is used to generate data throughout the whole range of operation, the physical model optimization process yields an effective $UA$ that is a good indicator of coil performance.

The method that has been described is best suited to the tracking of degradation faults, where the system continues to be operated throughout its range of operation but with changed characteristics. Failure faults typically result in the system saturating at one operating point, which would make it impossible to build a global model of the new, faulty characteristic. Failure faults could be detected by observing changes in the weights of the RBF, but diagnosis of failure faults may require the use of test signals to acquire more information about the system.

**ACKNOWLEDGMENTS**

The authors thank A.L. Dexter and S.J. Hepworth for useful discussions. This work is supported by the U.K. Department of Environment EnREI Program and forms part of the U.K. contribution to IEA Annex 25.

**TABLE 2 The Values of the Parameters Estimated from the Updated RBF**

<table>
<thead>
<tr>
<th>System State</th>
<th>$UA \text{ K}^{-1}$</th>
<th>$l$</th>
<th>$UA \text{ K}^{-1}$</th>
<th>$l$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-free</td>
<td>5.19</td>
<td>0.03</td>
<td>5.19</td>
<td>0.03</td>
</tr>
<tr>
<td>3% leakage</td>
<td>5.13</td>
<td>0.11</td>
<td>5.19</td>
<td>1.09</td>
</tr>
<tr>
<td>1 mm fouling</td>
<td>5.04</td>
<td>0.03</td>
<td>4.90</td>
<td>0.27</td>
</tr>
<tr>
<td>3% leakage+</td>
<td>4.93</td>
<td>0.18</td>
<td>4.76</td>
<td>1.37</td>
</tr>
<tr>
<td>1 mm fouling</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$\text{kW K}^{-1}$ (kBtu h$^{-1}\text{F}^{-1}$) % $\text{kW K}^{-1}$ (kBtu h$^{-1}\text{F}^{-1}$) %
NOMENCLATURE

c  =  valve model curvature parameter
C_a  =  capacity rate of air
C_{pa}  =  specific heat of air
C_w  =  capacity rate of water
C_{pw}  =  specific heat of water
l  =  valve model leakage parameter
m_{aq}  =  mass flow rate of air onto coil
m_{aw}  =  mass flow rate of water into coil
NTU  =  number of transfer units for the coil
\dot{Q}  =  heat transfer rate of coil
\dot{Q}_{max}  =  maximum possible heat transfer rate of coil
T_{ai}  =  air temperature entering the coil
T_{ao}  =  air temperature leaving the coil
T_{wi}  =  chilled-water supply temperature
UA  =  overall heat transfer conductance
u_c  =  control signal to cooling coil valve actuator
w  =  RBF weight
x  =  RBF input vector
y_p  =  physical model prediction of approach
\alpha  =  actual air-side temperature approach
\alpha  =  predicted air-side temperature approach
\Delta T  =  temperature rise across fan
\Delta T_{max}  =  maximum temperature rise across fan
\varepsilon  =  effectiveness of the coil
\lambda  =  RBF learning rate
\gamma  =  a small number
\phi(.)  =  RBF activation
\phi  =  ratio of fluid capacities

REFERENCES


QUESTIONS AND COMMENTS

Jean Lebrun, Laboratoire de Thermodynamique, University of Liege, Liege, Belgium: Should we not better resolve the problem of accurately measuring the variables with which we are working? Would it not be necessary to work more on the initial commissioning of all detectors (as they are located in the installation)?

Philip Haves: Three problems relating to sensors are improper positioning, inadequate calibration at commissioning time, and drift during the course of operation.

One approach to detecting and diagnosing sensor drift is to include a model of each relevant sensor in the subsystem model and try to estimate the values of parameters representing offset errors. Sensor drift usually results in an offset that is approximately constant across the operating range and can be distinguished from faults that have different effects at different operating points, such as fouling and leakage. Distinguishing between faults in different sensors is more difficult, and it may only be possible to identify relative errors between sensors. More work is required on this aspect of fault diagnosis.

Improper positioning and inadequate initial calibration are more difficult to detect and diagnose. One way they could be detected is if it is impossible to obtain a good fit of the model to the initial training data with reasonable parameter values. This would then indicate a need for manual checking of calibration. Clearly an improvement in the thoroughness of commissioning would reduce subsequent problems. This topic was addressed in the first symposium of this meeting.