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Developing Component Models for Automated Functional Testing

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ABSTRACT

Reference models developed from first principles and empirical relationships are used to represent correct operation of air-handling units. The models are incorporated into software capable of comparing actual system output measurements with model outputs and detecting deviations from correct operation. Tests of the model-based system with data from a real system, operating with and without introduced faults, are reported.

ROLE OF COMPONENT MODELS IN AUTOMATED FUNCTIONAL TESTING

This paper presents the development of reference models for use in automated functional testing during commissioning of building HVAC systems. A companion paper (Kelso and Wright 2005) discusses the concepts of model-based automated testing.

Model-based fault detection and diagnosis uses reference models of the system or components to provide analytic redundancy. Values of output variables read from the system are compared with reference values predicted by the models. Differences between the two, or errors, are indicators for detection of faulty operation (Figure 1).

Neural network ("black box") models have been applied to this task, but they require training on correctly operating systems and are thus limited to continuous commissioning rather than initial functional testing. The models chosen for this investigation were based on first principles or empirical relationships. The variables represent values that can be chosen from design intent information and do not require that the system be operating correctly.

The model equations chosen are algebraic, nonlinear, deterministic, and discrete. The thermodynamic relationships from which the models are derived are valid for steady-state conditions, and the models are therefore constrained by this limitation. A quasi-dynamic first-order model is considered below. The model inputs are state variables measured by the digital HVAC control system. The parameters are variables related to physical characteristics of the components and are constant for a selected component. The parameter values form the links that convert the general component model to a specific model of a component in the system to be tested. The models must have parameters that (1) are specifically indicative of certain fault conditions and (2) have values that are readily available from construction documents, manufac-

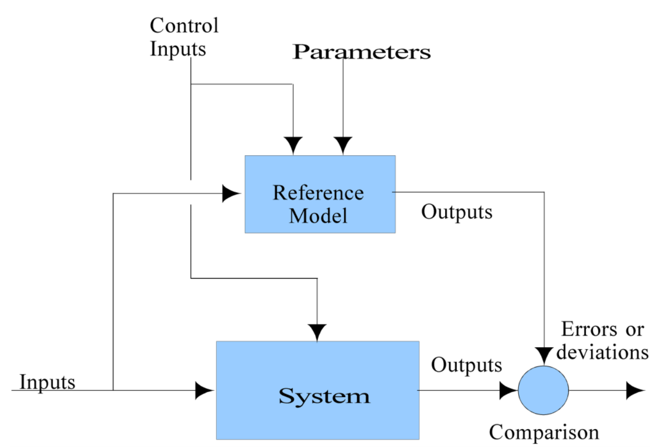

Figure 1 *Information flow diagram for reference models.*

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turer's literature, or other engineering design intent information. The output variables, or variables, are state variables that can be compared to measured quantities for fault detection.

It is essential that the models be able to represent the full range of operating conditions that may be encountered, since it is not feasible to wait for design conditions to test the systems. Part-load conditions are likely, and the models must be able to extrapolate to design conditions from the test conditions. The models should be as simple and easy to understand as possible. There must be parameters to represent control characteristics such as leakage, nonlinearity, and hysteresis.

Models intended to represent correct operation almost always have some degree of divergence from the performance of the real system. For these reasons, the automated commissioning process must include some information about the degree of confidence the user can have in the truth of an outcome. The tool must minimize false-positives (false alarms) yet not be so tolerant that only catastrophic failures are detected. The issue is to understand the degree of uncertainty due to the structure of the model as distinct from the uncertainty due to that in the input variables and the parameters.

Signals from digital control systems are not continuous, but discrete. The HVAC control system typically sends and receives signals between its various sensors, controllers, and actuators at a rate of fractions of a second. Because of the normally slow rate of change in an HVAC system, intervals between signals extracted from the control system and used in FDD work are on the order of one minute or more. An interval of one minute is used here. The signals can be considered deterministic, since instrument noise is of far higher frequency and random inputs are not present. Uncertainties must be accounted for, however.

The system can be represented by the vector of n components:

$$y(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \\ \vdots \\ y_n(t) \end{bmatrix} \tag{1}$$

Components in the system can be modeled by

$$y_n(t) = f(x_t, p, u_t) , \tag{2}$$

where y represents the state outputs, x the state inputs and u the control signals, both of which are functions of time, and p the parameters. For a fault to be detectable and distinguishable from the uncertainties, the component equations must be in a form that includes the uncertainty.

Diagnosis can follow detection of a fault condition. Two methods have been identified. One is to apply an optimization procedure so the model output variables match the faulty system outputs. Changes in the parameters required to make the outputs match indicate the faults. Faults can also be diagnosed by a set of expert rules. Each component can be excited by a series of control inputs, and a fault can be isolated to the selected component by testing each component in series while progressing downstream along the air path. Testing each component in turn simplifies the expert rules.

EXPRESSING DESIGN INTENT WITH MODELS

The model-based functional testing concept described in this paper was applied in a testing program utilizing real air-handling units at the Iowa Energy Center's Energy Resource Station (IEC ERS). Examples of two of the models used are described in some detail, and results of tests of correct and faulty operation are presented.

As an illustration of the role and derivation of the model parameters, the heating coil parameters will be examined in detail. The parameters are listed in Table 1.

Of these parameters, values for numbers 8, 10, and 15 were found in the construction drawings; 1, 2, 3, and 6 were obtained from manufacturer's submittal data; and 4 and 5 required direct inquiry to the manufacturer. Number 7 is a logical design intent, and number 9 is a realistic acceptance of typical commercial performance. Numbers 11-14 were taken

Table 1. Heating Coil Parameters

Parameter	Value		Parameter	Value
1. Coil width	0.9 m (36 in.)		2. Coil height	0.6 m (23 in.)
3. Number of rows	2		4. Number of circuits	18
5. Tube internal diameter	0.012 m(0.47 in.)		6. Valve curvature	2.95
7. Valve leakage	0.0		8. Valve authority	0.64
9. Valve hysteresis	0.14		10. Water maximum flow	1.3 kg/s (21gpm)
11. Air side resistance	1.1(6.24)		12. Metal resistance	0.38 (2.15)
13. Water side resistance	0.22 (1.25)		14. UA scale	1.0
15. Maximum duty	61KW (208MBH)		16. Convergence tolerance	0.0005

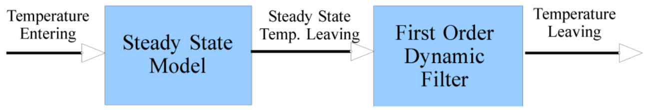

Figure 2 *Information flow diagram for dynamic filter model.*

from the Holmes coil model paper (Holmes 1982) and number 16 is based on experience with ASHRAE RP-1020.

DYNAMIC MODELS

To avoid the difficulties associated with partial differential equation dynamic models, workers in FDD research have utilized models based on steady-state relationships, as has been discussed above. Real systems are dynamic, and three options for enabling the use of steady-state models in a real system simulation are:

1. Incorporate a steady-state detector to filter out data points not meeting some criterion for "steadiness."
2. Increase the uncertainty of data points during periods of change (Buswell 2000).
3. Add a simple first-order dynamic term to the equation to enable it to track changes over the period of a few time constants until steady state is reached (Bourdouxhe et al. 1998).

To explain the concept of the dynamic "filter" as described by Bourdouxhe, Figure 2 shows the flow of information for the modeling of air temperature leaving a heating or cooling coil. Similar models would be required for enthalpy, moisture content, and wet-bulb temperatures for coils. Fans and damper actuators would also have similar flow diagrams.

The general form of the first-order dynamic filter is

$$T_L(t) = T_L - \Delta T \exp\left(-\frac{\Delta t}{\tau}\right), \quad (3)$$

where $T_L(t)$ is dynamic leaving air temperature at time t, T_L is steady-state leaving air temperature, ΔT is the difference between the steady-state leaving air temperature at the time of control input ($t = 0$) and the steady-state leaving air temperature after the control input, Δt is time since control input, and τ is time constant. The time constant may be a parameter, in the simplest case, or a variable.

This equation produces the curve shown in Figure 3. This is the classic thermal lag curve for an increasing step such as a valve opening to allow water flow through a heating coil. The changing variable reaches 63% of its final value in one time step and 95% in three time steps. Thus, a variable such as leaving air temperature is still changing significantly over this time period, and, if steady-state models are used, the commissioning process must wait for this period to elapse before evaluating for deviations.

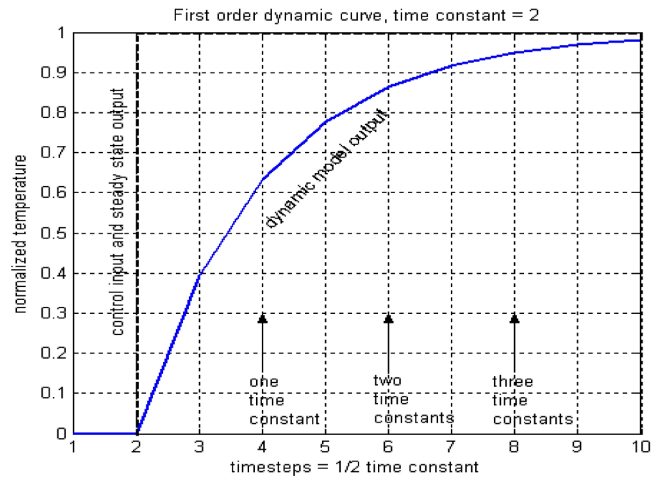

Figure 3 *Trajectory of temperatures produced by first-order filter.*

Figure 4 illustrates the effects of the steady-state or dynamic model options. A heating coil is operating with its control valve fully open and is in a reasonably steady state at time $t = 4$ minutes. Between $t = 4$ minutes and $t = 5$ minutes, an open-loop control signal to close the valve fully in a single step is injected. The time constant used here is 1.5 minutes. During the interval between $t = 4$ and 8 minutes, the steady-state model deviates significantly from the measured temperature. At $t = 9$ minutes, the models again are in agreement with the measured temperatures.

If the steady-state detector is used to filter the non-steady data, all that between $t = 4$ and 9 minutes is lost. The interval should actually be approximately three time constants long. This exacts a time penalty that is costly in commissioning. If uncertainty were to be increased during the t = 4-8 minute interval, the degree of uncertainty would be quite high. The difference is 13°C-14°C (23°F-25°F) at one point. If a dynamic term or filter is added to follow the first-order curve, the models become more complex and a new variable, the time constant, is introduced.

One question about the value of the dynamic model is whether the changing data can be used to detect faults. As an illustration of this issue, Figure 5 shows a test of a simulated leaking heating coil valve. Opening a bypass around the control valve simulated the leak. After the valve is signaled to close at $t = 11$ minutes, the steady-state detector screens out the data until $t = 16$ minutes, so the first deviation the steady-state model could detect is at $t = 16$ minutes. The values predicted by the steady-state model are unreliable, or have a large uncertainty, for this five-minute interval. The dynamic model can be used during the entire period, and the deviation due to the leak is observed at $t = 13$ minutes as the measured and modeled temperatures decrease but begin to diverge.

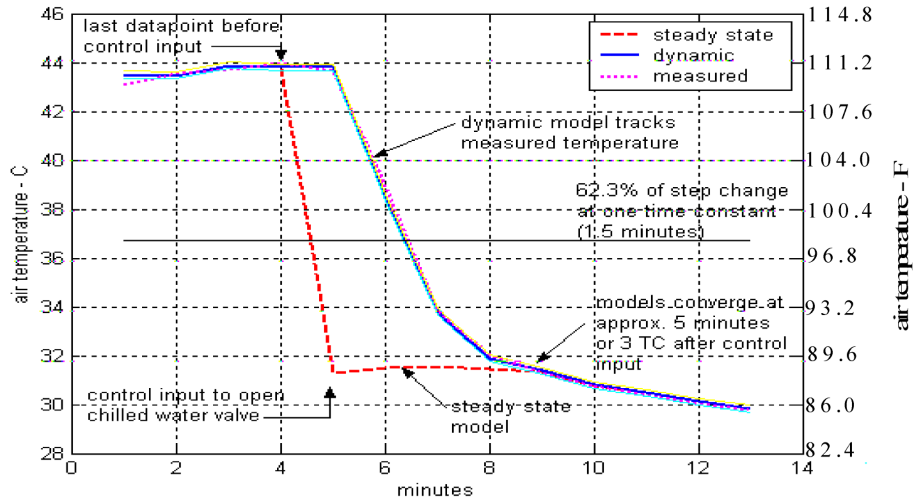

Figure 4 *Comparison of model outputs during changes.*

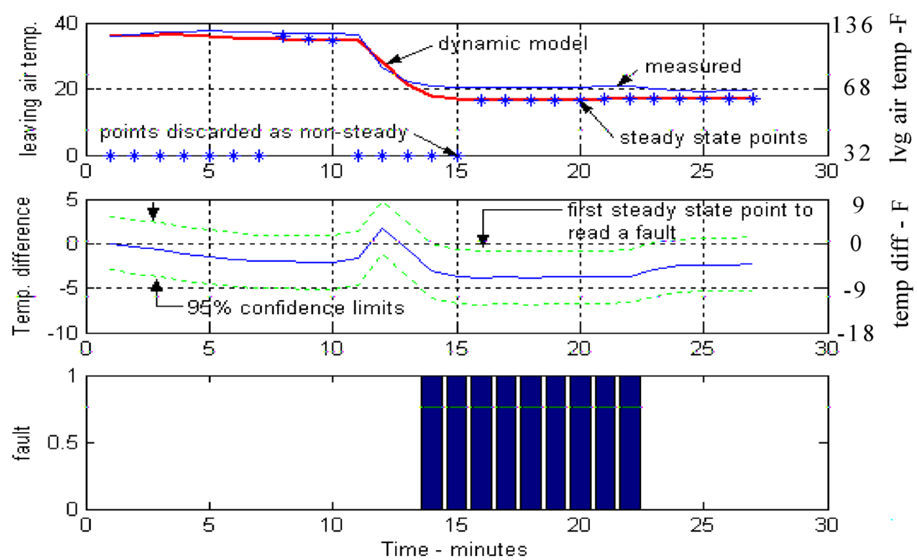

Figure 5 *Time delay until a heating coil control valve leak fault can be observed.*

In the test result of Figure 5 and Figures 8, 10, and 11, the second panel depicts the difference between measured and modeled outputs with the upper and lower bounds of the 95% confidence interval and the third panel depicts no fault (fault = 0) or the detection of a fault (fault = 1).

FAN AND DUCT MODELS

The duct model was developed from the D'Arcy equation, assuming standard air and a constant friction factor (Kelso 2003):

$$\Delta P_{total} = \left(\sum_1^n c_{friction_n} + \sum_1^m c_{fitting_m} \right) \frac{\rho v^2}{2} \qquad (4)$$

To apply this model to commissioning, it is necessary to determine coefficient values from construction documents. A study must be made of the duct drawings, and a manual estimate of the pressure losses due to each section and fitting must be compiled. The duct model parameters, cross-sectional area, and coefficient c for each duct section, can then be determined.

The technique developed by Wright (1991) forms the basis for the fan model used. An example of a performance curve produced by this model is shown in Figure 6. Fan parameters include wheel diameter, duct area, k (loss) factor, upper and lower bounds for speed and flow, and the coefficients for the nondimensional flow and pressure models. The wheel

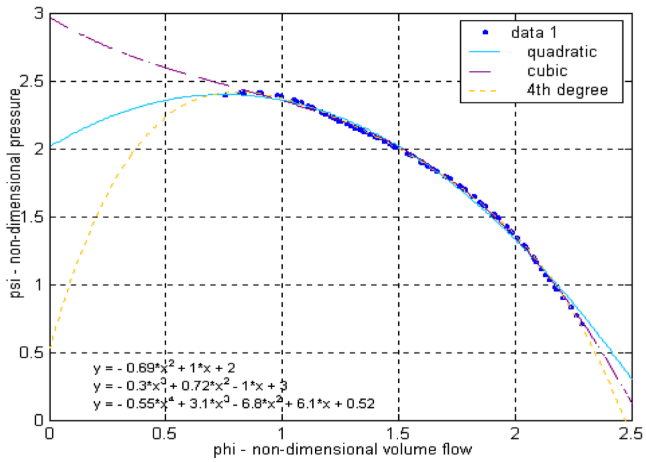

Figure 6 *Manufacturer's published performance data for a 0.254 m double-width forward-curved centrifugal fan nondimensionalized.*

diameter is part of the initial air-handling unit selection by the designer. The coefficients are determined by the curve fit and the speed and flow limits by the design conditions. The modeled pressures agree well with the manufacturer's published pressures at a fixed speed and various flows.

THERMAL MODELS

A closed-loop controller sensing supply air temperature and operating a chilled water control valve provides control of heat removal as shown in Figure 7. For testing and commissioning, these controls can be set in open-loop mode with manual or automatic inputs.

The cooling coil model is one developed by Holmes (1982), which uses the effectiveness-NTU method to calculate the heat transfer coefficient. He correlated performance data from a large number of manufacturer's coils to obtain a typical coil resistance. The overall conductance of the cooling coil is given by

$$UA = \frac{\gamma A_f N_r}{(shr \times r_a \times v_a^{-0.8} + r_m + r_w \times v_w^{-0.8})}, \tag{5}$$

where UA is the overall conductance; A_f is the coil face area; N_r is the number of rows; r_a, r_m, and r_w are the airside, metal, and water-side resistance coefficients, respectively; v_a is the air velocity based on the face area; and v_w is the water velocity per circuit. The sensible heat ratio method models the effect of the mass transfer on a wet coil by reducing the airside surface resistance in proportion to the sensible heat ratio, *shr*. An iterative solution gives the cooling duty and leaving dry- and wet-bulb temperatures (Kelso 2003). This model is similar to the heating coil model described in Kelso and Wright (2005).

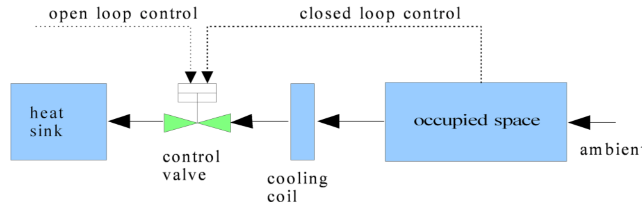

Figure 7 *Simplified heat removal and control diagram.*

The actuator model produces a stem position output that becomes an input to the control valve model (Equations 10 or 11) or the mixing box model. The actuator has a motor that rotates to a given position for each control input. The steady-state model is that used by Clark (1985) and by Salsbury (1996):

$$\text{If } (u_k - s_{k-1}) > v, \text{ then } s_k = u_k - v \tag{6}$$

$$\text{Else, } (u_k - s_{k-1}) < 0, \text{ then } s_k = u_k \tag{7}$$

$$\text{Else, } s_k = s_{k-1} \tag{8}$$

where u_k is control signal, s_k is stem position, and v is hysteresis or "slack." All are expressed as nondimensional (0-1.0) values. The subscripts k indicate time steps. This model results in a damper that cannot close if hysteresis is present, so the stem position is mapped onto the range $0 \le s \le 1$.

$$s = \frac{s_k}{1 - v} \tag{9}$$

Digital control systems for real valves include a software feature to accomplish this. Ideally, design intent for the actuator would be linear performance with no hysteresis, but by selecting real manufacturer's products, a designer, in effect, accepts some hysteresis. The acceptable level or the manufacturer's specifications are parameter values to be selected. The actuator motor is deliberately chosen to have a slow movement to avoid control dynamics problems. The manufacturer of a widely used damper actuator states it has a 150-second opening speed and a spring return speed of less than 20 seconds. A simple dynamic model using a filter similar to the speed controller model may have benefits in reducing the testing time required.

The water flow control valve model (Salsbury 1996) is:

$$\beta = 0 \qquad f(s) = \lambda + (1 - \lambda)s \tag{10}$$

$$\beta \ne 0 \qquad f(s) = \lambda + (1 - \lambda)\left[\frac{1 - e^{\beta s}}{1 - e^{\beta}}\right] \tag{11}$$

where s = the valve stem position, *f(s)* = the fraction of design water flow rate due to the inherent characteristic, and β is the curvature parameter. A curvature of 0 results in a linear characteristic. This function expresses the inherent characteristic of the valve, but the installed characteristic is often quite different. A parameter called the authority, A, can be utilized to account for the difference between inherent and installed performance.

$$f'(s) = \frac{1}{\left[1 + A\left(\frac{1}{s^2} - 1\right)\right]^{0.5}} \qquad (12)$$

where $f'(s)$ is the fractional flow under installed conditions.

RESULTS

The cooling coil can be tested using a step test. To demonstrate the proper direction of valve operation and full flow capacity, the valve is moved from closed to open in a single step. In the fully open position, the duty (capacity) of the coil is at its maximum for the airflow rate and air and water temperatures prevailing. If the model parameters are the design parameters for the system, the model duty represents the performance the designer expected at full water flow. After sufficient time to reach steady state at the open position, the control valve is signaled to return to the closed position. At this position, the test can reveal water leakage through the control valve if it exists.

Results of a single step test of this type, applied to the cooling coil in Ahu-A at the IEC ERS, are shown in Figure 8. In this test, the dynamic simulation is "on" and the design parameters are used. The upper panel shows the modeled temperature is about 2°C (3.6°F) lower than the measured temperature at the open position. While this was intended to be a correct operation test, it actually detected a water flow rate deficiency. The lower panel shows the modeled design flow was 1.7668 kg/s (28 gpm), but the actual maximum flow was about 1.23 kg/s (19.5 gpm). The explanation for the limited flow is that smaller three-way valves replaced the original two-way control valves, and the smaller orifice of the three-way valves limits the available flow. Thus, the automated commissioning succeeded as intended in detecting the reduced capacity resulting from the limited flow.

The fan model was tested on Ahu-B at the IEC ERS. The manufacturer's submittal documents for the air-handling unit specify that the supply fan deliver 1.8144 kg/s (3200 cfm) of standard air at a total static pressure of 792 Pa (3.2 in) and a fan speed of 1834 rpm. Figure 9 gives the results of a normal operation step test in the all-return air configuration. The difference between model predictions of pressure and the measured pressure is small and within the uncertainty limits, so no deviation would be detected.

Most of the faults used in testing the automated commissioning concepts are in the components. The software can also detect faults in the control system, such as a temperature controller with an offset error. Changing controller linearization parameter number 1 by 2.8°C (5°F) so the sensor output reads 2.8°C (5°F) lower than the true temperature simulated the error. The cooling coil was placed under closed-loop

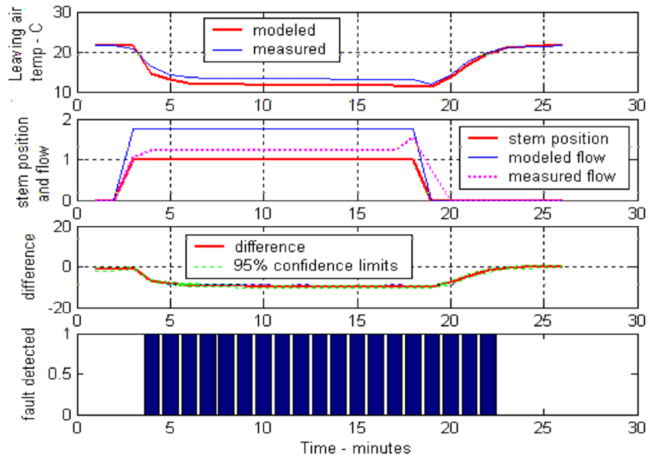

Figure 8 *Normal operation step test of cooling coil and control valve (note that the fault detected is a real reduced water flow due to undersized valves).*

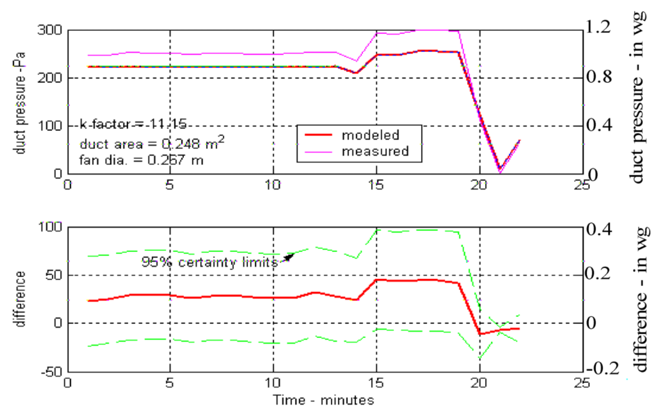

Figure 9 *Normal operation step test on Ahu-B supply fan in 100% return air configuration.*

control with a setting of 12.8°C (55°F) and the load was changed by stepping the mixing box dampers from full recirculation to full outside air in one step, then returning. The fan was set for design flow and the VAV terminals were fully open. The heating coil valve was closed.

Figure 10 shows that the supply air temperature controller is operating to maintain its setpoint of 12.8°C (55°F) but, due to the offset, it is actually maintaining a three to four degree higher temperature. As a closed-loop test, this fault can be distinguished from a fault that would produce a higher than expected supply temperature, such as insufficient coil duty during an open-loop step test.

A common fault encountered in system start-up is a fan rotating backward. This can be caused by reversed three-phase wiring connections. The fan is often not readily visible for

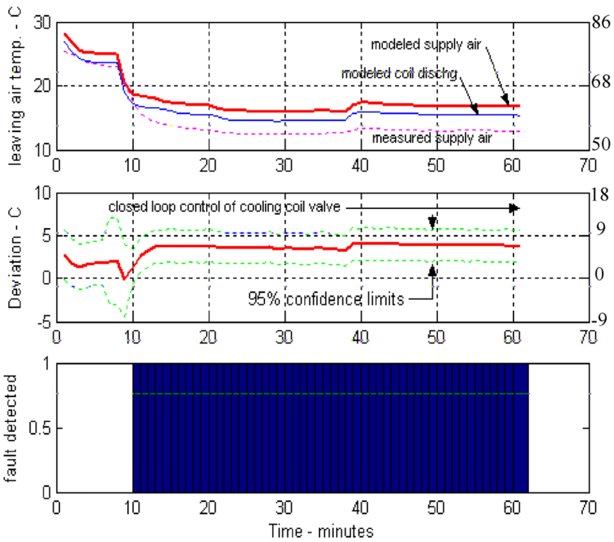

Figure 10 *Closed-loop control test of cooling coil with controller offset.*

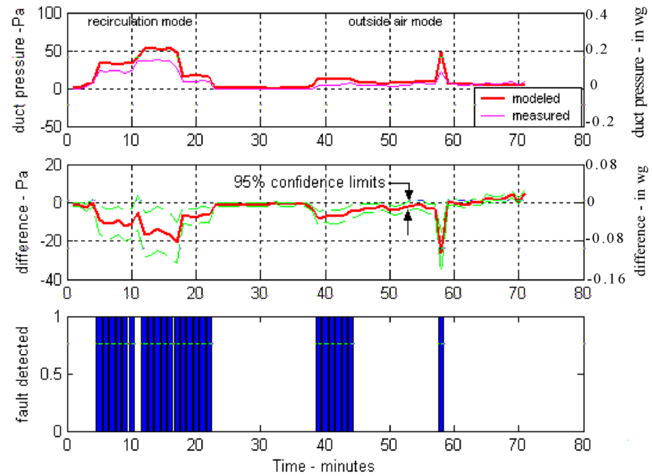

Figure 11 *Fan step test with reversed rotation.*

observation of direction of rotation, and the fan does create some flow, so the fault goes undetected. To simulate this fault using Ahu-B at the IEC ERS, two of the three supply fan motor power wires were reversed so that the fan rotation was reversed. The variable air volume terminals were fully open and the mixing box was set for full recirculation for one set of steps, then to full outside air. The coil valves were closed. The supply fan was stepped from 0 signal to full speed in 20% steps, then reversed in 40% steps.

Actually, the variable frequency drive settings were such that the supply fan reached full speed at about 50%-60% signal, so the opening steps were about 20%. The correlation between speed control signal and variable frequency drive output was at 35% signal the output was 49.9 Hz (83.2%). Expectations for this test were that the modeled fan static pressure, airflow rate, power, and speed would deviate from the measured values and, when parameters were estimated, the fan would appear to be undersized.

The pressure plotted in the upper panel of Figure 11 shows a deviation between the modeled and measured values, and the residual exceeds the uncertainty interval, so a fault is signaled. This occurs in both configurations.

CONCLUSIONS

Reference models of the components of an air-handling unit have been developed and applied to simulate the performance of a real air-handling unit. The models were developed from first principles or empirical relationships and have parameters that represent characteristics of the components. The values for these parameters were taken from engineering design intent information given by the construction drawings or manufacturers' submittals so the models represented design intent. Tests of the air-handling unit operating without intentional faults and again with introduced faults were conducted and compared with reference model performance off-line. The models were able to detect faults, both real and introduced, in the air-handling unit components and controls.

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