MODELING AND VALIDATION OF EXISTING VAV SYSTEM COMPONENTS

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ABSTRACT

Variable air volume (VAV) component models are required for different applications to improve the energy efficiency. Fan, damper as well as valve and cooling coil models are developed and presented in this paper. All model parameters are taken from the respective manufacturers or derived from the monitored data of an existing VAV system. Adaptive models are also presented, thus placing their parameters on-line and keeping them updated. The developed component models are validated against the monitoring data from the investigated existing VAV system.

INTRODUCTION

The performance of a heating, ventilating, and air-conditioning (HVAC) system can be improved through the optimization of supervisory control strategies (Nassif, Kajl, and Sabourin, 2003). In simulation and optimization calculations, the mathematical model of the HVAC system must include all the individual component models that influence energy use. For that reason, component models are developed and validated against measured monitored variables or the variables calculated through other validated models. The paper shows then the difficulties of the validation process when the monitored data of the existing VAV system are used. The model parameters for the optimization of the existing variable air volume (VAV) system are derived from the manufacturer's data. Adaptive models are also proposed for the optimization of the other VAV system.

SYSTEM DESCRIPTION AND MEASURED VARIABLES

The investigated existing VAV system is installed at the *École de technologie supérieure (ÉTS)* campus. Figure 1 shows the schematic of this investigated VAV system, with the measured variables. The component models of the investigated air handling unit (AHU) that are developed, and which serve the internal zones are validated against the monitored data. The following required variables are measured:

1. Outdoor and return air temperatures and relative humidity T_o, T_r, φ_o and φ_r, respectively)
2. Supply air and water temperatures (T_{sa} and T_{sw}, respectively)
3. Zone airflow rates ($\dot{Q}_{z,i}$)
4. Supply duct, outlet fan, mixing plenum static pressures ($P_{S,sd}$, $P_{S,out}$, and $P_{S,mix}$ respectively)
5. Fan speed (N)
6. Minimum and principal damper and cooling and heating coil valve positions ($O_{D,min}$, $O_{V,c}$, $O_{D,pr}$, and $O_{V,h}$, respectively)

The following are additional required variables, but they are not measured:

1. Fan and outdoor airflow rate ($\dot{Q}_{fan}$ and $\dot{Q}_o$, respectively)
2. Inlet and outlet cooling coil relative humidity ($\varphi_{in,c}$ and $\varphi_{ou,c}$, respectively)
3. Liquid flow rate through the heating or cooling coils ($\dot{Q}_l$)

These variables are determined using the component models.

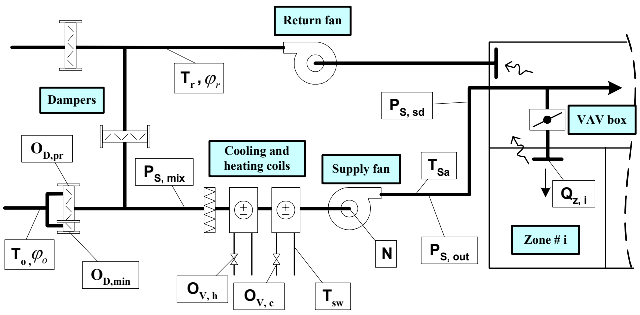

Figure 1. Schematic of VAV system with the measured variables

COMPONENTS MODELS

Developing the process for the optimization of the supervisory control strategy in an existing HVAC system (Nassif, Kajl, and Sabourin 2003) requires the use of component models. Figure 2 illustrates the process required in optimizing the supervisory control strategy. It includes (*i*) the VAV model, (*ii*) the two-objective genetic algorithm optimization program, and (*iii*) three main tools, namely, data acquisition, indoor load prediction, and selection tools. The VAV model consists of the fan, the damper, the cooling and heating coils, the chiller, etc. At each optimization period (i.e., 15 minutes), the genetic algorithm program (GAP) sends the trial controller set points to the VAV system model (component models), where the energy use and thermal comfort (objective function) are simulated and then returned to the GAP. The VAV model determines the energy use and thermal comfort levels resulting from the change in outdoor air conditions and indoor sensible loads (independent variables) and controller set points (dependent variables). This paper only presents the modeling and validation of these component models.

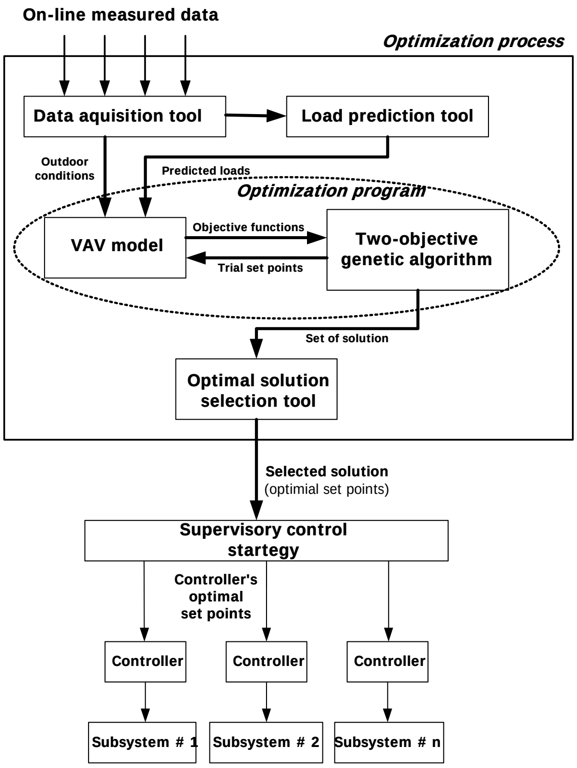

Figure 2. On-line optimization of supervisory control strategy

VALIDATION OF COMPONENT MODELS

The component models developed are validated against the monitored variables. Figure 3 shows the input and output variables of the component models for purposes of validation. However, certain component models used for optimization are inverted, i.e., the fan airflow rate for the fan model and the supply air temperature for the cooling coil are the inputs rather than the fan speed and water flow rate, respectively. Each component model, as well as its input and output variables are shown in Figure 3. The variable inputs of the cooling coil model are not measured, but are determined using the fan and damper models. The output variables (validation variables in Figure 3) could then be validated against reference variables which are available measured variables (i.e, Figure 4) or the variables calculated through other validated models (i.e., Figure 6). Consequently, the error of the validation models is determined as the absolute ratio of difference between the output and reference variables to the reference variable.

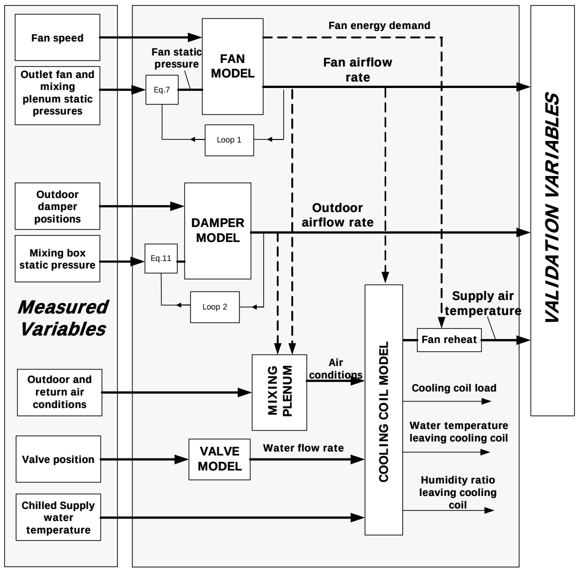

Figure 3. The input and output variables of component models for validation purpose

FAN MODEL

The fan model (FM) is used to calculate the power consumption over a wide range, using data acquired from the manufacturer. The fan model was introduced by Clark (Clark, 1985) to estimate airflow rates as a component of fluid flow networks. It uses the dimensionless coefficients of flow (Φ), pressure head (Ψ), and shaft power (η_f), as in the following.

$$\Phi = \frac{\dot{Q}_{fan}}{N \cdot d^3} \tag{1}$$

$$\Psi = \frac{P_{S,fan}}{\rho \cdot N^2 \cdot d^2} \tag{2}$$

$$\eta_f = \frac{\dot{Q}_{fan} \cdot P_{S,fan}}{\dot{W}_s} \tag{3}$$

where (d) is the fan diameter and (ρ) is the air density. The performance of a fan is represented by a polynomial regression of the manufacturer's data using these dimensionless coefficients.

$$\Psi = a_0 + a_1\Phi + a_2\Phi^2 + a_3\Phi^3 + a_4\Phi^4 \tag{4}$$

$$\eta_f = b_0 + b_1\Phi + b_2\Phi^2 + b_3\Phi^3 + b_4\Phi^4 \tag{5}$$

The coefficients, a_i and b_i are determined from the manufacturer's data, while the fan power ($\dot{W}_t$) is determined using the shaft power ($\dot{W}_s$) and the motor efficiency (η_m):

$$\dot{W}_t = \frac{\dot{W}_s}{\eta_m} \tag{6}$$

Since the fan is mounted in the air stream and motor losses directly affect the air temperature rise, the heat transferred to the air is equal to the fan power.

For validation purposes (see Figure 3), two variable inputs are used in the fan model: the fan static pressure ($P_{S,fan}$) and the fan speed (N). The fan speed is measured while the fan static pressure is determined through the following equation:

$$P_{S,fan} = P_{S,mix} + P_{S,out} + \Delta P_{comp} \tag{7}$$

It should be noted that the mixing plenum static pressure $P_{S,mix}$ and the static pressure at the fan outlet $P_{S,out}$ are measured. The static pressure drops ΔP_{comp} in the cooling and heating coils, in the filter, and in the humidifier are calculated:

$$\Delta P_{comp} = C_{comp} \cdot \dot{Q}_{fan}^{\,2} \tag{8}$$

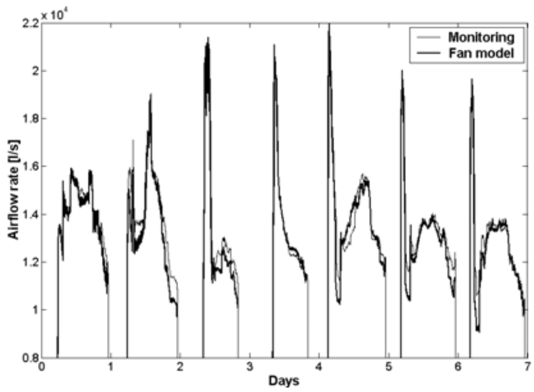

Figure 4. Comparison of the sum of measured zone airflow rates and fan airflow rate obtained by fan model for July 25 to 31

The coefficient, C_{comp}, is determined from the known components pressure drops at rating. In calculating the fan airflow rate through the fan model, the initial value of the fan airflow rate is assumed to be used in equation (8); the value calculated through the fan model is then reused in equation (8), and so on until the calculated and used values converge (loop 1 in Figure 3).

Since the fan airflow rate is not measured for the investigated existing system, the sum of the measured airflow rates of the VAV box in different zones are used for comparison with the airflow rate calculated through the investigated fan model. The error obtained for July 2003 is 2.9%. Figure 4 shows the comparison of the sum of the measured zone airflow rates and the fan airflow rate obtained through the fan model for July 25 to 31.

The fan performance curve, including the system curve (A) and operation curve (B) are illustrated in Figure 5. The formula representing the operation curve (B) can be expressed in terms of the known design point (D) and the measured duct static pressure ($P_{S,sd}$).

$$\dot{Q}_{fan} = \sqrt{\frac{P_{S,fan} - P_{S,sd}}{P_{S,fan,design} - P_{S,sd}}} * \dot{Q}_{fan,design} \tag{9}$$

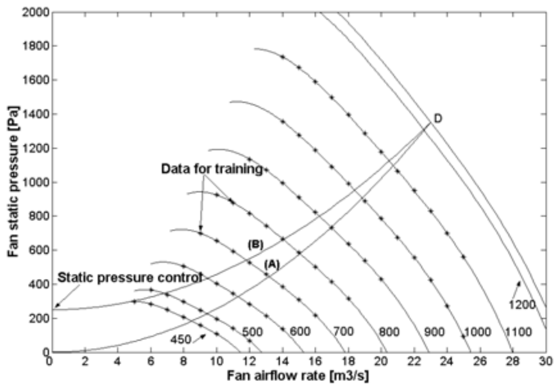

Figure 5. Fan performance curve

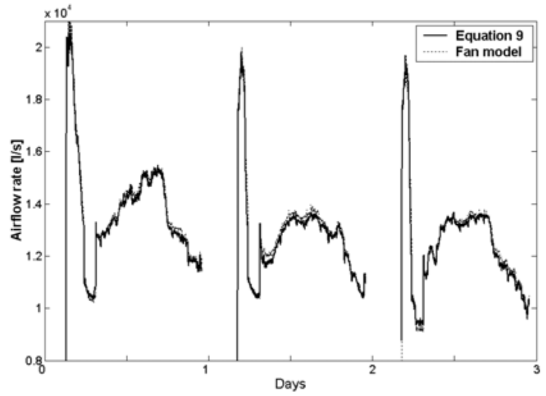

Figure 6 Comparison of airflow rates obtained through fan model and by equation 9 for July 29 to 31

The fan airflow rate calculated through the fan model is also validated against the airflow rate calculated by equation (9). In this case, the error obtained for summer 2002 does not exceed 1.3%. Figure 6 shows a comparison of the airflow rates obtained through the fan model and by equation 9 for July 29-31(2002).

In the optimization process calculations, the fan model should determine the energy use. The required fan airflow rate, based on the zone airflow rates required for meeting the loads, and the fan static pressure (calculated through the detailed system duct model or by rearranged equation (9)) are the input variables in the fan model.

The adaptive fan model using an artificial neural network can also be used in place of the detailed model described above for the existing system or for the other investigated VAV system. This network is initially trained using the results of the validated fan model. However, in the on-line optimization of the HVAC system, the calculated fan energy could be compared with the measured value in order to perform an on-line retraining of the network.

Seventy different operation points are used in training the artificial neural network, as illustrated in Figure 5. The fan airflow rate and static pressure representing the input layer (two neurons) are the inputs to the hidden layer based on nine neurons with a hyperbolic activation function (tanh). The output layer consists of one neuron with an activation function based on the sum of the weighted hidden layer neurons. Each neuron also has a bias. The weights and biases (37 variables) are determined using genetic algorithm methods in order to minimize the error between the calculated and the real values. The fan energy use is predicted by using this neural network for operation points, as illustrated in curve (B). A comparison of the values obtained by the neural and by the validated models indicates that the energy demand obtained by the neural network (NN data) is very close to that obtained by the validated fan model (FM data), as shown in Figure 7.

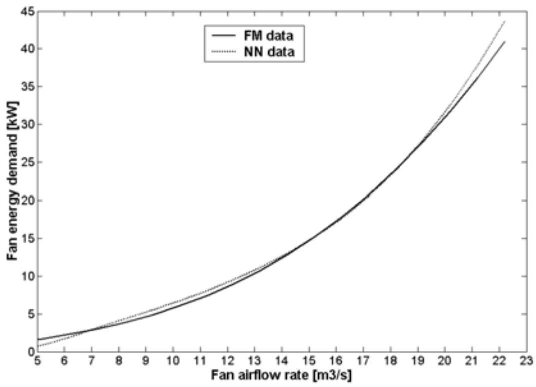

Figure 7. Energy demands obtained by artificial neural network and validated fan models

DAMPER MODEL

The damper model (DM) is based on an exponential relation, which leads to the outdoor airflow rate ($\dot{Q}_o$) being given as the following formula

$$\dot{Q}_o = C_{damper} * \Delta P_{damper}^{x} \tag{10}$$

The coefficients (C_{damper} and x), which are functions of the damper position (O_D), are determined from the manufacturer's data. In the optimization process, the damper model could be used to determine the damper position required to provide the optimal outdoor airflow set point (it depends on the outdoor air ventilation strategy).

In this paper, the damper is modeled for use solely for validation purposes. It should be noted that, for the existing system, the outdoor airflow rate and the relative humidity entering the coil are not measured, while the damper position and the air temperature entering the coil are. Thus, to validate the cooling coil model, the damper model is required for determining the air states entering the cooling coil. Since the damper pressure drop ΔP_{damper} is not measured, it is calculated using the measured mixing plenum static pressure as:

$$\Delta P_{damper} = P_{S,mix} - C \cdot \dot{Q}_o \tag{11}$$

The pressure drop coefficient C in the duct where the outdoor damper is installed is determined using the manufacture's data when the damper is wide open.

To determine the outdoor airflow rate using the damper model, the initial value of the outdoor air is assumed to be used in equation (11), and the value calculated through the damper model is reused in equation (11), and so on until the calculated and used values converge (loop 2 in Figure 3).

The damper model is validated against the monitored data for two operation modes: (*i*) when the damper is fully opened, and (*ii*) when the damper modulates. When the damper is fully opened, the outdoor airflow rate calculated through the damper model is compared with the fan airflow rate calculated through the fan model.

Figure 8 shows the comparison of the outdoor airflow rate obtained through the damper model (DM) with the fan airflow rate obtained through the fan model (FM) for May 3 to 5. When the damper modulates, the outdoor airflow rate calculated through the damper model (DM) is compared with the outdoor airflow rate calculated through the temperature balance method (TBM), taking into account only the data for when this method is applicable, such that the difference between the return and outdoor air temperature is sufficiently large (Schroeder, 2000). Figure 9 shows a comparison of the outdoor airflow rate obtained through the damper model and through the temperature balance method. The validation results indicate that the errors of these two operation modes are 4 and 5%, respectively.

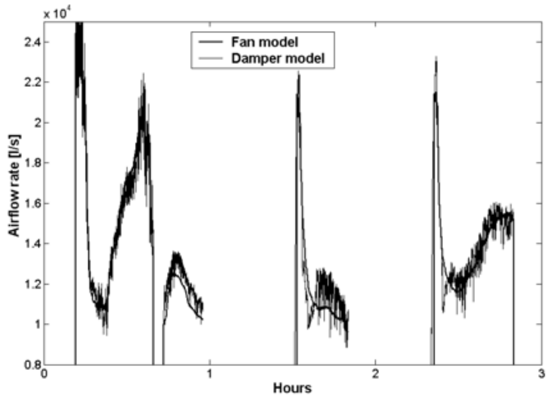

Figure 8. Comparison of airflow rate obtained through fan model and damper model (damper wide open) for May 3-5

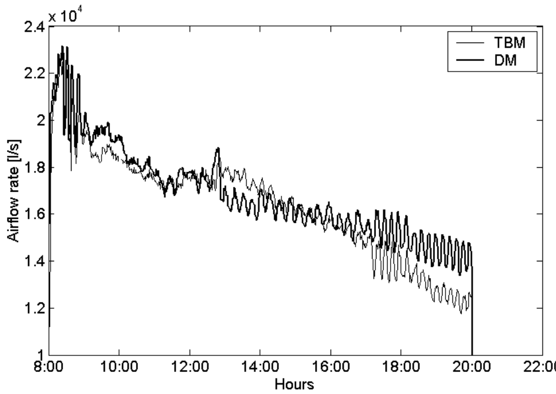

Figure 9. Comparison of outdoor airflow rate obtained through damper model (DM) and by temperature balance method (TBM)

COOLING COIL MODEL

Two cooling coil models are investigated here. They were developed based on the detailed and simple models presented in the ASHRAE HVAC 2 Toolkit (Brandemuel, Gabel, Andersen, 1993). Internal and external heat transfer coefficients for the detailed cooling coil model (CCDET) are determined from detailed information about the coil geometry. However, they are determined from the performance of the coil at a single rating point, and assumed to be constant for the simple cooling coil model (CCSIM). Since the opening of the cooling coil valve is measured rather than the water flow rate, the valve model (Valve and Actuator Manual, 1994) is also combined with the cooling coil model. The flow rate (inherent flow rate) through the valve is calculated for each valve position ($O_{V,c}$) through the following equation:

$$\dot{Q}_{l,inh} = \dot{Q}_{l,\max} R^{(O_{V,c}-1)} \qquad (12)$$

where $\dot{Q}_{l,\max}$ is the liquid maximum flow rate, and R is the valve rangeability defined as the ratio of the maximum to the minimum controllable flow through the valve.

This inherent flow rate is calculated by considering the pressure drop across the valve as being constant. This does not reflect the actual performance of the valve once it is installed within a system. The pressure drop varies with the flow and with other changes in the system. As the valve closes, the pressure drop shifts to the valve and away from the other system components. This has a significant impact on the actual flow rate of the installed valve, which is a function of the valve authority (A), defined as following

$$A = \frac{\Delta P_{valve}}{\Delta P_{system}} \qquad (13)$$

where ΔP_{valve} is the full flow valve pressure drop, and ΔP_{system} is the system pressure drop, including the valve.

The actual flow rate ($\dot{Q}_l$), when the valve is installed, is given by the following equation:

$$\dot{Q}_l = Q_{l,\max} * \sqrt{\frac{\frac{1}{A}}{\frac{1}{A} - 1 + \frac{1}{k^2}}} \qquad (14)$$

The inherent flow rate factor (K) is defined as the ratio of the inherent flow rate to the maximum flow rate.

The models are validated by comparing the supply air temperatures obtained through the model with the measured temperatures. In this case, the fan and duct air heat up, and are added to the leaving cooling coil air temperature simulated through the cooling coil model in order [illegible] calculate the supply air temperature. The er[illegible] obtained for July 2003 are 1.8% for the CCDET and 23% for the CCSIM. Figure 10 shows the supply air temperature measured and obtained through the cooling coil models for July 29.

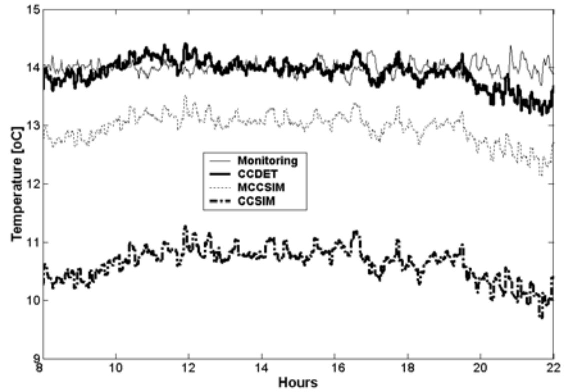

Figure 10. Comparison of measured supply air temperature and that obtained through CCDET, CCSIM, and MCCSIM models for July 29

Note that the fan airflow rate and humidity ratio (or relative humidity) and temperature entering the cooling coil used to validate the cooling coil model are determined using the fan and damper models, respectively. Since the CCSIM is not quite accurate for the existing system, the inverse form of the detailed cooling coil model presented in the HAVC 2 Toolkit, the INVCCDET, is used in the VAV system performance calculations required by the optimization process. In this inversed model, the input used is the supply air temperature set point, which is the optimization variable, rather than the water airflow rate.

The adaptive cooling coil model can also be used instead of the INVCCDET for the existing system or for other investigated systems. This model is based on the modification of the simple cooling coil model (CCSIM). Internal and external heat transfer coefficients are determined from the performance of the coil at a single rating point, and assumed to be functions of the liquid and airflow rates as follows:

$$UA_{\text{int}} = UA_{\text{int},rate}\left(\frac{\dot{Q}_l}{\dot{Q}_{l,rate}}\right)^{C_{\text{int}}} \tag{15}$$

$$UA_{ext} = UA_{ext,rate}\left(\frac{\dot{Q}_{fan}}{\dot{Q}_{fan,rate}}\right)^{C_{ext}} \tag{16}$$

This modified simple cooling coil model (MCCSIM) is investigated by Morisot, Marchio, Srabat (2002). The authors propose the values of the parameter model (C_{in}=0.8 and C_{ext}=0.77). Using these values, the MCCSIM model is also validated against the monitored value. The supply air temperature obtained by the modified simple cooling coil model is compared with the measured values as shown in Figure 10. The error obtained for this model is 6.5%.

During the optimization process, the model parameters could be updated on-line in order to improve the accuracy. Through previous on-line performance data of the cooling coil (outlet and inlet air states and air and liquid airflow rates), the internal and external heat transfer coefficients are determined using the method presented in the CCSIM, and the model parameters are calculated using equations (15) and (16). These parameters could be used in the next time step. When the fan air and water flow rates are not measured, as in the investigated system, the fan model and valve cooling coil models are used in determining them.

The adaptive cooling coil model based on the artificial neural network (NNCCM) is also investigated in this reaserch project. This NNCCM could be useful for HVAC system identification and control. It could be used in conjunction with the PID control in order to eliminate the steady state error (Ahmed, Mitchell, and Klein 1998). The inputs for the neural network are the air conditions entering the cooling coil, the valve cooling coil position, and the fan airflow rate. The controlled variable output is the supply air temperature. Figure 11 shows the supply air temperature calculated through the CCDET as a function of the valve position at different airflow rates and at design air states entering the cooling coil and chilled water supply temperature.

To train the neural network, the two hundred different operation points are selected, and two different neural network architectures are used. The first has only one hidden layer with eight neurons, and the second has two hidden layers with four neurons each. Figure 11 shows the supply air temperature determined through the NNCCM and CCDET models. The NNCCM with two hidden layers is able to trace the detailed cooling coil model curve except during the transition from laminar to turbulent flow in tubes.

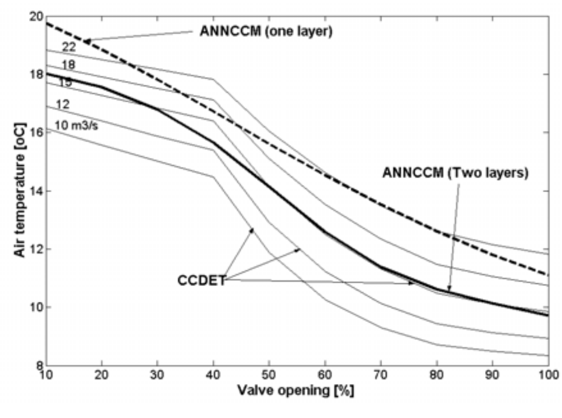

Figure 11. Comparison of supply air temperature obtained through detailed cooling coil models and neural network models

CONCLUSION

The performance of the HVAC system can be improved through better local-loop controllers and the optimization of supervisory control strategies. To develop the optimization process, the component models of the fan, the damper, and the cooling coil are developed and validated against monitored data of the existing VAV system. The models are validated against the measured variables or the variables calculated through other validated models. Only the models with high accuracy are selected to use in the optimization process. The paper shows also the difficulties of the validation process when the monitored data of the existing VAV system are used. The model parameters for the existing VAV system optimization are taken from the manufacturer's data. Adaptive models are also proposed for future VAV system optimization. The cooling coil model based on the neural network is investigated for use in system identification and control.

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