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Fault diagnosis for temperature, flow rate and pressure sensors in VAV systems using wavelet neural network

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ABSTRACT

Wavelet neural network, the integration of wavelet analysis and neural network, is presented to diagnose the faults of sensors including temperature, flow rate and pressure in variable air volume (VAV) systems to ensure well capacity of energy conservation. Wavelet analysis is used to process the original data collected from the building automation first. With three-level wavelet decomposition, the series of characteristic information representing various operation conditions of the system are obtained. In addition, neural network is developed to diagnose the source of the fault. To improve the diagnosis efficiency, three data groups based on several physical models or balances are classified and constructed. Using the data decomposed by three-level wavelet, the neural network can be well trained and series of convergent networks are obtained. Finally, the new measurements to diagnose are similarly processed by wavelet. And the well-trained convergent neural networks are used to identify the operation condition and isolate the source of the fault.

1. Introduction

Variable air volume (VAV) systems are widely used in actual buildings to save energy through employing some optimal control strategies. Obviously, energy conservation capacity of a real VAV system deeply depends on the executing efficiency of various control loops including outdoor air flow rate, supply air temperature, supply air static pressure and zone temperature controllers. These controllers modulate related components after comparing the measurements of the control variables with the optimal setpoints. With the effective control, energy conservation and better indoor air quality can be achieved. During the control process, however, one premise can never be ignored: the measurements are accurate. If the sensors are biased, the controller may be misled and give incorrect commands. The related components may be incorrectly modulated. Finally the energy consumption of the system may be unreasonably increased greatly. In summer conditions, for example, the positive biases (the measurements are larger than the true values) of supply air temperature mislead the controller to open the water valve at a larger position. The quantity of chilled water is increased incorrectly, which wastes more energy of the pumps. Similarly, the biases of outdoor air flow rate sensors may increase the chilled water flow rate or decrease the chilled water temperature that may increase energy consumption of the pumps or chillers. The faults of supply air static pressure sensor may require higher rotational speed of the supply fan, which means more energy consumption of the fan. Consequently, the waste of energy is always inevitable under those various faulty conditions although optimal control strategies are applied in the system. Finding a suitable method to detect and diagnose the faults occurred in the VAV system, to avoid the waste of energy, is a significant target.

Recently, the study of fault detection and diagnosis (FDD) for sensors in heating, ventilation and air conditioning field are more active than ever after the popularity of research on faults of facilities including chillers [1–4] and air-handling units [5–10]. Two typical diagnosis methods for sensor faults have been developed. One is the model-based, and the other is the data-driven.

The model-based method [11–14] is to obtain predicted values of the parameters calculated by the mathematical models first. Then the differences between the outputs of real process and those of predicted ones, so-called residuals, are calculated and used as the fault indexes to diagnose. Stylianou and Nikanour [1] used a first-order model to detect faults of temperature sensors by comparing the actual temperature decay with the model output using the hypothesis testing. Wang and Wang [15] developed model-based strategies to diagnose the faults of commonly used temperature and flow rate sensors in chilling plant. The premise of model-based method is that accurate mathematical models must be built. And this premise is also the difficult point for the application. The model-based method is efficient to discover the abrupt faults of sensors such as the complete failure through analyzing the great change of operation conditions caused by the abrupt faults. Limited by the precision of the prediction models, however, it is insensitive

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Nomenclature

S	original signal
S_{ij}	the jth wavelet decomposition coefficient on the ith level
E	energy of the wavelet node
I	input of neural network
O	output of neural network
X	variable
X'	decomposition variable using wavelet
X''	predicted variable using neural network
T	temperature (K)
M	flow rate (kg/s)
P	pressure (Pa)
n	rotational speed (r/min)
G	data group
Q	heat exchange quantity (kJ)
c_p	specific heat at constant pressure (kJ/kg/K)
$\bar{x}$	true value of variable x
f_x	measuring bias
υ_x	measuring noises
α	drifting speed of fault

Greek symbols

Π	eigenvectors matrix
σ	statistic variance for diagnosis

Subscripts and superscripts

SA	supply air
OA	outdoor air
RA	return air
EA	exhaust air
SW	supply water
RW	return water
SF	supply fan
RF	return fan
A	air
W	water

to detect the small fixed or drifting biases since not abrupt change but slow degradation of the operation or control efficiency happens.

The data-driven approaches [16–18], on the other hand, never construct physical models but just learn the intrinsic relations among variables or parameters through employing the process data including normal and faulty conditions. Recently, principal component analysis [19,20] and Fisher discriminant analysis [21] were presented to diagnose the sensor faults in heating, ventilation and air conditioning systems. Besides the statistic method, neural network and wavelet analysis also began to apply in this field. Lee [22] presented general regression neural network models to diagnose the abrupt and performance degradation faults in an air-handling unit. Wang and Chen [23] developed a neural network trained by lots of running data to diagnose the faults of outdoor, supply and return air flow rate sensors. Later, Chen et al. [18] employed wavelet analysis to diagnose the faults of flow rate sensors in central chilling systems. Obviously, the data-driven method highly relies on the quantity and quality of the data obtained. Fortunately, with the popularity of building automation and energy management and control systems, the various historical operation data including normality and fault can be collected and obtained easily.

A data-driven diagnosis method combining wavelet analysis with neural network is presented in this paper that can be used to diagnose the faults in the VAV systems. Wavelet decomposition is used to process the original data and then the characteristic data representing the main operation information of the system are obtained. Employing these data decomposed, the neural networks are well trained and then they can identify various faults of commonly used sensors including temperature, flow rate and pressure in the VAV systems.

2. Wavelet neural network

Neural network technique is a valuable pattern recognition method in theory and application. It is widely used in engineering application [24–26] especially to deal those issues concerned in non-linear or complicated systems. It is efficient to learn the certain status or operation condition of the objective systems. And then the well-trained network can recognize these various conditions. Actually, the process of fault diagnosis is essentially a kind of recognition classification or recognition. Therefore, the neural network can be used as a diagnosis method. In fact, it has been well applied to detect and diagnose faults in many fields [27–30].

2.1. Application opportunity in VAV systems

As a complicated non-linear system, the VAV system includes many control components and measuring sensors. According to the different control strategies, the variables have changeable control relations. Also, the variables have implicit physical relations because of the physical principles. For this complex system, it is difficult to construct not only general but also precise models for so many variables. As a data-driven method, however, neural network never construct detailed models but continually learn the operation data. Through lots of training, the neural network can capture the important physical and control relations among the different variables in the VAV system. Once the networks obtain the main information of different operation conditions, they can be used for fault diagnosis.

Though neural network is capable of learning and judging various operation conditions, its capacity of data processing or analyzing is not satisfied. Especially for the VAV system, there are large quantities of samples for many measuring and control points. Since the noises are always included in the measurements and some uncertainty factors usually disturb the control actions, the pure neural network method may be affected or disturbed. As a result, its diagnosis efficiency is limited. The mistaken-warnings or missing-warnings may happen inevitably. To solve this problem, the data selected for training must be preprocessed to remove those disturbing information.

Wavelet analysis, originally developed from the Fourier transform at the end of 1980s [31,32], is widely used in various engineering [33–35] systems. The wavelet analysis, also called wavelet transform, employs two opposite time intervals: shorter and longer. The shorter time interval can be used by wavelet analysis to analyze the high frequency characteristics of the signals. While the longer one is used to analyze the low frequency characteristics of the signals. Since it is capable of data processing, it can be used as the complement for neural network.

Through analyzing the time-varying signals of variables in the VAV system, the wavelet can capture the local time-frequency domain information. The main important information of the system can be seized. Simultaneously, the disturbing factors can be removed. Indeed, the data after processing are much better than those initial signals for related trainings of the networks. Wavelet analysis can improve the diagnosis process of neural network. Consequently, wavelet neural network, the integration of wavelet analysis and neural network that the former is to process data and the latter to diagnose, is a valuable approach.

2.2. Wavelet decomposition

According to wavelet analysis, the measurements signals from sensors in the VAV systems can be decomposed using three-level wavelet packets shown in Fig. 1. S is the original signal from various sensors. S_{ij} means the jth node or decomposition coefficient in the ith level. Consequently, the original signal S can be reconstructed using all of the nodes in the 3rd level and expressed as

$$S = S_{30} + S_{31} + S_{32} + S_{33} + S_{34} + S_{35} + S_{36} + S_{37} \quad (1)$$

With the decomposition of the wavelet packets, the signal energy of each frequency band can be calculated. Supposing E_{ij} represents the energy of jth ($i = 0,\ldots,7$) node in the ith ($i = 1,2$ and 3) level, then the energy of each node in the 3rd level can be given by

$$E_{3j} = \int_{-\infty}^{+\infty} |S_{3j}(t)|^2 dt \quad (2)$$

Therefore, an eigenvector matrix can be constructed using the series energy of the 3rd level

$$\Pi = [E_{30}, E_{31}, E_{32}, E_{33}, E_{34}, E_{35}, E_{36}, E_{37}] \quad (3)$$

Since the characteristic of frequency domain representing operation condition is captured using the wavelet packets, the original signal can be replaced by these decomposed wavelets. And the eigenvector matrix concluded by the wavelet decomposition can be used as the training data for neural network to diagnose.

2.3. Neural network

2.3.1. Structure of neural network

A typical neural network, generally composed of three layers: one input layer, one (or several) hidden layer(s) and one output layer, is shown in Fig. 2. There are two main steps to apply a neural network in the diagnosing process. Firstly, the neural network is trained using suitable quantities of characteristic information decomposed from the history data. The training data include normal conditions and faulty ones. Secondly, the fault diagnosis is carried out through comparing the outputs of new condition with those of known ones employing the well-trained neural network.

One input layer, one hidden layer and one output layer are selected to construct a neural network (Fig. 2) in this paper. I_1–I_m are the m input neurons and O_1–O_n are the n output neurons. Seventeen neurons are used in that hidden layer.

2.3.2. Training process

Supposing that there are m variables considered in the VAV system

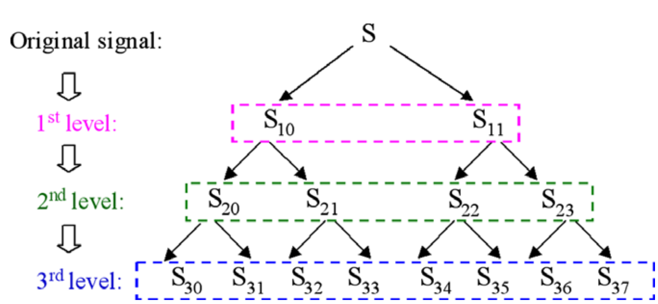

Fig. 1. Structure of the wavelet decomposition.

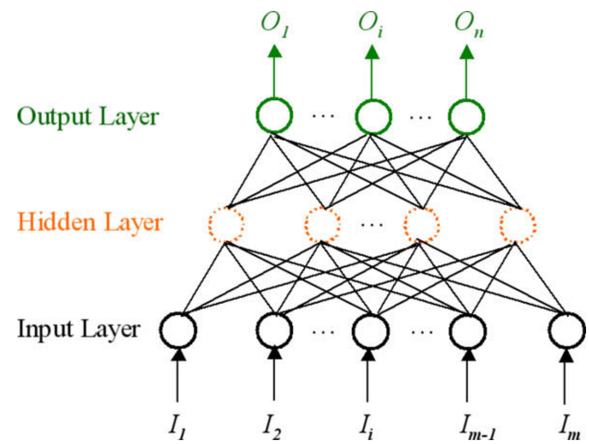

Fig. 2. Structure of neural network.

$$X = (X_1, X_2, \cdots, X_m) \quad (4)$$

Each variable X_i can be processed using three-level wavelet decomposition and expressed as

$$X_i = [E^i_{30}, E^i_{31}, E^i_{32}, E^i_{33}, E^i_{34}, E^i_{35}, E^i_{36}, E^i_{37}] \quad (5)$$

One variable X_k ($k = 1,\ldots,m$) is selected as the training objective vector (output neuron) and the other $(m-1)$ variables X_i ($i = 1,\ldots,m$ and $i \neq k$) are chosen as the input vectors (input neurons) shown in Fig. 3.

Then the neural network mentioned above is trained using lots of historical data including normal and faulty operation. The training is carried along two steps: feed forward and back propagation. The former is to calculate the errors according to the neuron weights at present calculation time. While the latter is to adjust the weights of neurons in the hidden layer according to the errors calculated.

When the mean errors are less than the setting convergent precision, the training is ended. And then the convergent network k for the variable of X_k is obtained. With similar training process, all of the m convergent networks are trained, respectively, and these convergent networks can identify the conditions of the variables from X_1 to X_m.

2.4. Diagnosis logic

The diagnosis logic based on wavelet neural network for the faults of sensors in VAV system is shown in Fig. 4.

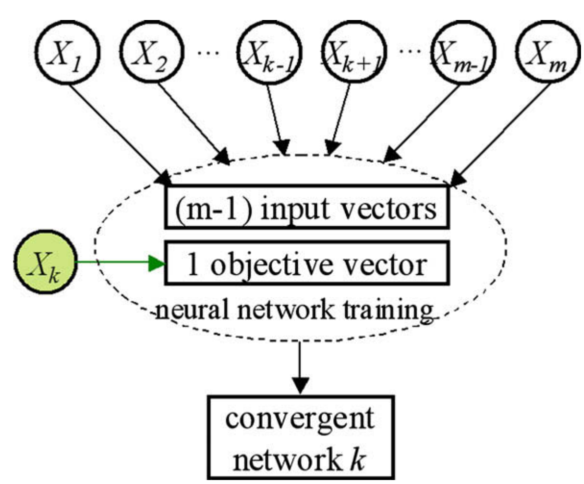

Fig. 3. Training process of neural networks.

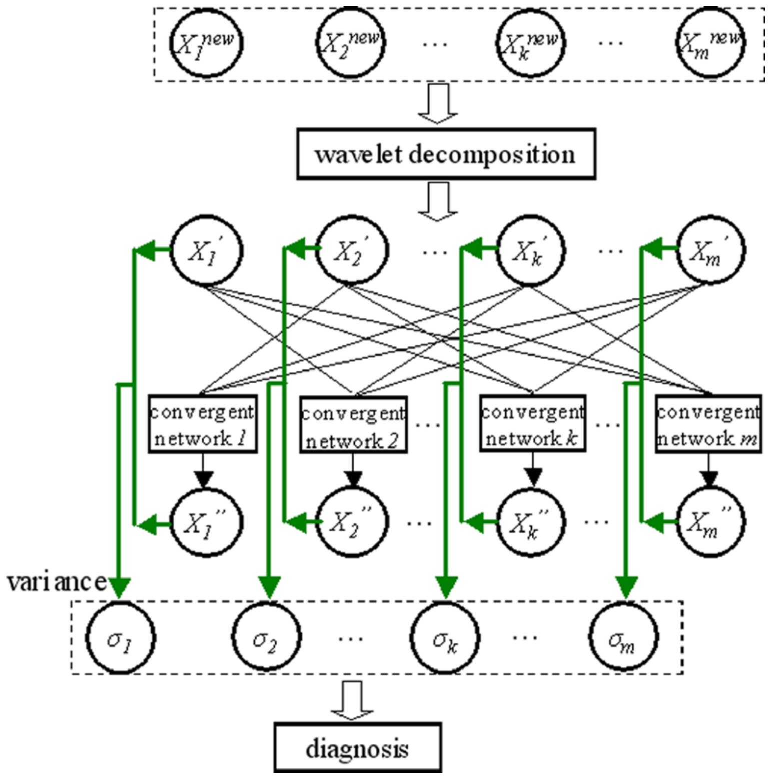

Fig. 4. Diagnosis logic using wavelet neural network.

Firstly, the new measurements $(X_1^{new}, X_2^{new}, \cdots, X_m^{new})$ are processed using three-level wavelet decomposition. The new data vectors after processing are represented as $(X'_1, X'_2, \cdots, X'_m)$, where X'_i can be expressed similarly using the 3rd level energy nodes (Eq. (5)) that includes the characteristic information of variables at present time.

Secondly, m convergent neural networks are, respectively, used to predict a series of output vectors. X'_i $(i = 1, \ldots, m$ and $i \neq k$ are selected as the $(m-1)$ inputs of the convergent network k and the output X''_k is obtained.

In addition, the statistic variances σ_i between X'_i and X''_i $(i = 1, \ldots, m)$ are calculated.

Finally, all of the diagnosis variances are compared to diagnose the source of the fault. The detailed diagnosis rules are the following Eqs. (6) and (7):

$$(\sigma_1 \approx \sigma_2 \approx \cdots \approx \sigma_m) < \varepsilon \tag{6}$$

where ε is a very small number. Two meanings are expressed in Eq. (6): all of the variances are very small; and each one is close to another. If Eq. (6) is met, it indicates normal operation of the system

$$\sigma_k < \varepsilon \ll \sigma_i \qquad (i = 1, \cdots, m \quad i \neq k) \tag{7}$$

Eq. (7) is the fault indicator and two meanings are expressed: only σ_k is very small; and the other $(m-1)$ variances are much larger. If Eq. (7) is satisfied, it indicates the faulty condition and the variable of X_k is source of the fault.

3. The system and related training groups

3.1. Description of the VAV system

A typical VAV system, including air-handling unit, supply fan, VAV terminals, return fan, controllers and various sensors, is shown in Fig. 5. The supply air, a mixture of outdoor air and recycle air, is cooled down (in summer condition) in the air-handling unit using the chilled water coming from the chillers. The supply air is circulated to the VAV terminals to meet the demand of zones. The return air from the zones, on the other hand, is divided into two branches: one is circulated as the recycle air to join the next circulation, and the other is exhausted out of the building.

In this VAV system, five kinds of controllers are included to improve the operation efficiency of the system so as to save more energy. Outdoor air flow rate (M_{OA}) controller adjusts the air dampers to ensure enough outdoor air for the users. The supply air temperature (T_{SA}) controller modulates the chilled water valve to maintain suitable supply air temperature through comparing the feedback information of T_{SA} sensor with its optimal setpoint. The P_{SA} controller adjusts the variable-speed supply fan to ensure the proper supply air static pressure. The variable-speed return fan is modulated to ensure the positive indoor air pressure. Moreover, many VAV terminal controllers located in multi-zones adjust the terminal dampers to ensure the heat comfort through monitoring the temperature and air flow rate in each zone.

The diagnosis capacity of wavelet neural network may be limited if only separated measuring data of the variables are selected and used for training. After all the pure data-driven method does not directly describe the physical relations among variables. Actually, some of the variables are correlated and they influence each other because of the physical models and control relations. The relevant variables can be defined as one data group. Through classifying various groups, the diagnosis process can be improved greatly. Therefore, some physical balances representing strong relevant relations among variables are employed to improve the diagnosis efficiency.

3.2. Group G_I based on the air flow-pressure balance

Flow-pressure balance, describes the mass flow balance and mass conservation equations, is a key relation for the air circulation in the VAV system (Fig. 6). In the whole air circulation, the

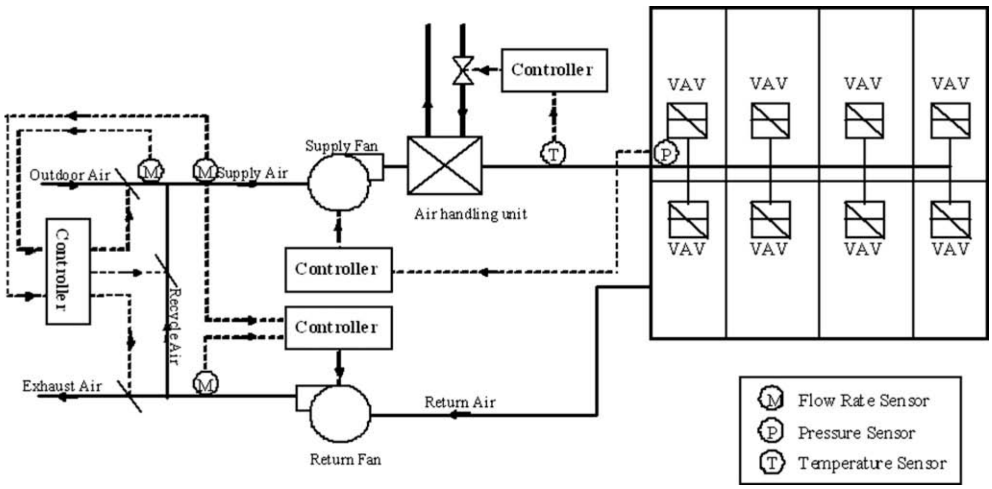

Fig. 5. Scheme of VAV systems.

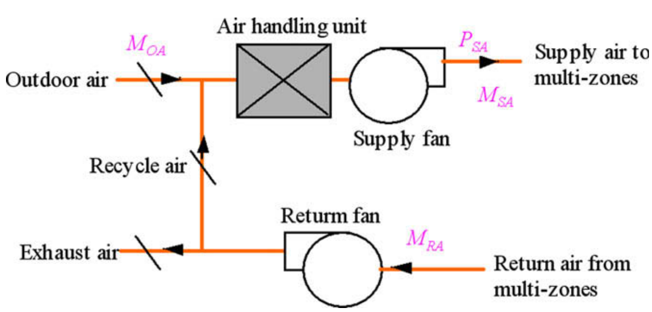

Fig. 6. Flow-pressure balance in the air circulation.

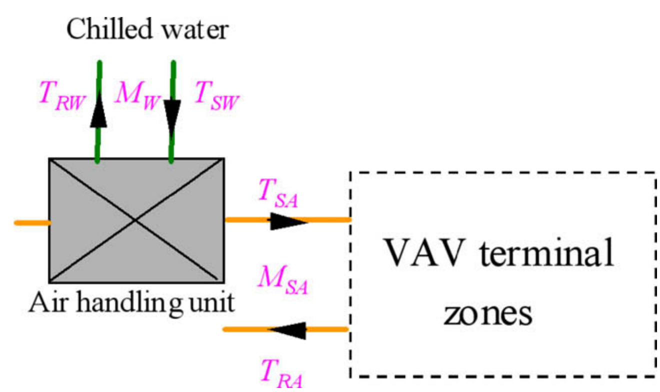

Fig. 7. Energy transfer from chilled water to zones.

mass conservation denoted as Eq. (8) is the essential flow relation among flow rate variables. Moreover, the variable-speed supply fan ensures enough pressure head. With the modulation of the supply fan, the values of P_{SA} and M_{SA} are changed accordingly. Consequently, P_{SA} has close relevant relation with M_{SA} and n_{SF} (speed of supply fan) expressed as Eq. (9). Obviously, M_{OA}, M_{SA}, M_{RA} and P_{SA} concerned in these equations have strong relevant relations and can be combined as the 1st training group G_I

$$M_{SA} - M_{OA} = M_{RA} - M_{EA} \tag{8}$$

$$P_{SA} \sim M_{SA}, n_{SF} \tag{9}$$

$$G_I = (M_{OA}, M_{SA}, M_{RA}, P_{SA}) \tag{10}$$

3.3. Group G_{II} based on energy transfer process

There are two energy transfer steps in the VAV system illustrated in Fig. 7, which representing two heat exchange processes. Firstly, the supply air is cooled down (in summer condition) by the chilled water coming from the chillers, which indicates the 1st energy transfer process from the chilled water to the supply air. If the heat loss of the water pipes is neglected, then the exchange heat can be given by

$$Q_{W-SA} = M_W c_{p,W}(T_{WR} - T_{SW}) \tag{11}$$

Furthermore, multiple zones are cooled down by the supply air, which indicates the 2nd energy transfer process from the supply air to the zones. If the heat loss of the air ducts is omitted, then the exchange heat can be expressed as

$$Q_{SA-Z} = M_{SA} c_{p,A}(T_{RA} - T_{SA}) \tag{12}$$

Actually, the heat of multiple zones is removed by chilled water indirectly. Anyway, the variables of M_W, T_{SW}, T_{RW}, M_{SA}, T_{SA} and T_{RA} have some relevant relations. Accordingly, the 2nd training group G_{II} can be given by

$$G_{II} = (M_{SA}, T_{SA}, T_{RA}, T_{SW}, T_{RW}, M_W) \tag{13}$$

3.4. Group G_{III} based on heat exchange between air and zones

As shown in Fig. 8, the supply air exchange heat with multiple zones to satisfy the demand of users. On the other hand, M_{OA}, M_{SA} and M_{RA} are affected by P_{SA} according to the flow-pressure balance. Since M_{OA}, M_{SA}, M_{RA}, T_{SA}, T_{RA} and P_{SA} are relevant through the heat

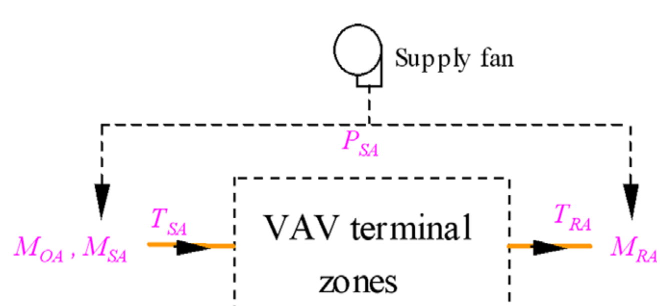

Fig. 8. Heat exchange between air and zones.

exchange process between supply air and multiple zones, they are used to construct the 3rd training group G_{III}

$$G_{III} = (M_{OA}, M_{SA}, M_{RA}, T_{SA}, T_{RA}, P_{SA}) \tag{14}$$

4. Validation

The diagnosis strategies based on wavelet neural network for sensor faults in the VAV system (Fig. 5) are validated in the simulator developed. A fault generator has been incorporated into the simulator that can generate different kinds of sensor faults. For any measuring variable x in the VAV system, it can be denoted as

$$x = \bar{x} + f_x + \upsilon_x \tag{15}$$

where $\bar{x}$ is the true value of the variable x, f_x is the measuring bias of x, υ_x denotes the disturbing factors such as the measuring noises. The fixed and drifting biases of sensors are tested in this paper. The fixed bias refers that the difference (f_x) between the measurement and its true value is a fixed one (Eq. (16))

$$f_x = C_0 \tag{16}$$

While the drifting bias means the differences (f_x) are time variable (e.g. linearly), shown as Eq. (17)

$$f_x = \alpha(t - t_0) \tag{17}$$

where α is the drifting speed of the faulty sensor, t is the present time, t_0 is the initial time that the sensor begins to drift.

Historical data including normal and faulty operation are used as the training samples of the neural network. The training samples are classified into three groups according to G_I, G_{II} and G_{III}. The training data are analyzed to get the characteristic information using wavelet decomposition firstly. And then the data decomposed are used as the inputs of neural network. With training, a series of convergent networks are obtained that can be used to identify the new measurements.

Different magnitudes of the fixed and drifting biases of the sensors are tested in this paper. As to the fixed biases, −10%, −8%, 8% and 10% of the true values are selected as the biases of the temperature sensors (T_{SA}, T_{RA}, T_{SW} and T_{RW}). −10% and 10% of the true values are selected as the biases of the flow rate sensors (M_{OA}, M_{SA}, M_{RA} and M_W). Twenty percentages of the true values are selected as that of the pressure sensor (P_{SA}). As to the drifting biases, on the other hand, the drifting magnitudes of temperature sensors are selected as 0.1 °C/h and −0.1 °C/h. The drifting slopes of −0.2 kg/s/h, 0.2 kg/s/h and 30 Pa/h are chosen for the flow rate and pressure sensors, respectively. It should be noted that the drifting speeds selected are larger than the real conditions. In the real systems, the magnitudes of drifting biases are usually very small and the drifting speed is always slow. If the similar small magnitudes are selected in the simulation, one validation case may cost several days or weeks. Therefore, the drifting speed is increased exaggeratedly to make the validation convenient.

4.1. Efficiency analysis for networks

First of all, the prediction capacity of the neural network is validated. A case about the normal operation of the system is discussed here. It can be seen in Fig. 9 that most of the prediction values calculated from the neural networks are close to the real ones. After training, the convergent networks possess the capacity of prediction and recognition for the operation of the VAV system. Therefore, the neural network can be used to identify the operation conditions of the system after it is well trained.

However, it is also illustrated in Fig. 9 that some prediction values are not accurate. The largest error compared with the real value is more than 5%. Obviously, if only neural network is used for diagnosis, more mistaken-warnings will be given. As mentioned above, the possible reason is that the neural network was disturbed by some uncertain factors. Therefore, wavelet analysis should be used to preprocess the initial data. Once the main information is seized while the disturbing information is removed, the diagnosis process using neural network will be improved.

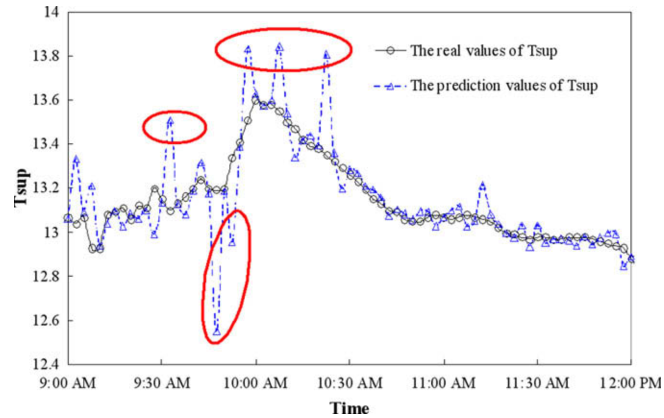

Fig. 9. Prediction values of neural networks.

In addition, the sensitivity of the neural network deeply relies on the quantity and quality of the training data. Insufficient training data may lead to the bad-learnt networks that possess poor diagnosis capacity. Different quantities of fault magnitudes are selected to train the neural network. Each fault magnitude includes enough samples. The diagnosis variances using samples with different quantities (4), (7), and (10) of magnitudes, respectively, are compared. Since the swings of diagnosis variances are the least illustrated in Figs. 10 and 11, the network using training samples with 10 kinds of fault magnitudes achieve the best efficiency for both T_{SA} and T_{SW}. The efficiency using 7 kinds is worse, that using 4 is the worst. On the other hand, there is no need to select much more kinds of magnitudes. After all too much data inevitably result in the difficulty of training convergence and inconvenience of its application.

4.2. Fault diagnosis for sensors in G_I

Training the historical data, the convergent networks can be used to identify whether there is any abnormity in the VAV system and isolate the source of the fault.

Various fault cases of sensors, including flow rate and pressure (M_{OA}, M_{SA}, M_{RA} and P_{SA}) sensors concerned in the data-group G_I, are

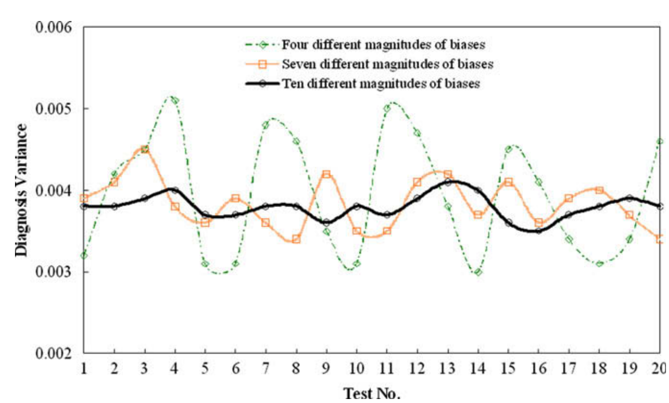

Fig. 10. Diagnosis sensitivity for T_{SA} with different quantities of magnitudes.

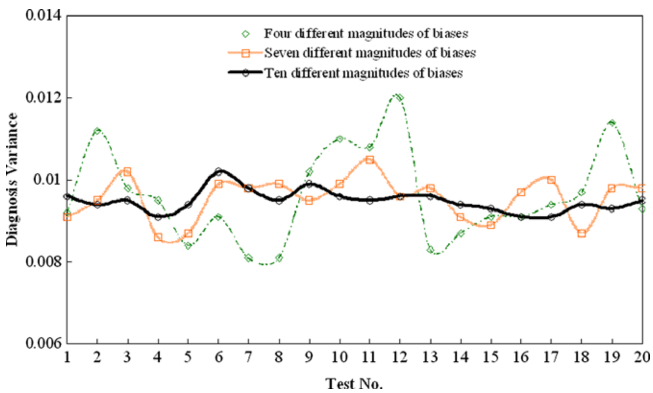

Fig. 11. Diagnosis sensitivity for T_{SW} with different quantities of magnitudes.

Table 1
Fault diagnosis for the sensors based on G_I.

Case	σ_{MOA}	σ_{MSA}	σ_{MRA}	σ_{PSA}	Diagnosis
1	0.0015	0.0024	0.0024	0.0011	Normal operation
2	**0.0068**	0.0099	0.0122	0.0072	M_{OA} biased
3	0.0042	**0.0028**	0.0078	0.0041	M_{SA} biased
4	0.0118	0.0082	**0.0012**	0.0046	M_{RA} biased
5	0.0116	0.0104	0.0099	**0.0063**	P_{SA} biased

tested. The diagnosis results are illustrated in Table 1. If there is no fault in the system (case 1), the diagnosis variances of the four sensors are all very small. Since Eq. (6) is satisfied, it indicates the normal operation of the system. As to the 2nd case, the variance of M_{OA} is very small while those of other sensors are larger. According to Eq. (7), it is the faulty condition and the source of the fault is the M_{OA} sensor. Similar analysis can be made for cases 3–5. Under these cases, the sources of the faults are M_{SA}, M_{RA} and P_{SA}, respectively.

4.3. Fault diagnosis for sensors in G_{II}

Besides two flow rate sensors, the data-group G_{II} also concerns four temperature sensors including T_{SA}, T_{RA}, T_{SW}, T_{RW} and the results are shown in Table 2. If all of the sensors in G_{II} are accurate (case 6), the diagnosis variances are close to one another. At the same time, all of them are very small. Obviously, it means the normal operation according to Eq. (6). As to the 8th case, on the other hand, only the diagnosis variance for T_{SA} is very small (0.0064), while those for others are much larger. Consequently, this case indicates the occurrence of fault and the source is isolated as T_{SA} according to Eq. (7). Similar analysis is made for cases 7, 9–12 and the sources of the faults are identified as M_{SA}, T_{RA}, T_{SW}, T_{RW} and M_W, respectively.

4.4. Fault diagnosis for sensors in G_{III}

Finally, the diagnosis strategies based on data-group G_{III} concerning temperature, flow rate and pressure sensors simultaneously are validated and the results are shown in Table 3. When M_{OA} sensor is biased (case 14), the diagnosis variance for M_{OA} is 0.0020 and those for others are at least 5 times larger. This indicates that the 14th case is the faulty condition and the source of the fault is M_{OA}. As to the 17th case, since the variance for T_{SA} is 0.0037 and those for others are at least 2 times larger, it indicates the biased measurements of T_{SA} sensor. As to the 19th case, the variance for P_{SA} is very small while those for others are much larger that shows the bias of P_{SA} sensor. Similar analysis can be made for other cases.

4.5. Diagnosis risk

In this paper, the fixed and drifting biases of the sensor faults are tested. Drifting biases of sensors widely exist in the real systems. The magnitude of the drifting fault may be very small at the beginning of the drifting process. Then the magnitude may increase gradually until it is as large as which can affect the control systems mistakenly. In fact, the drifting biases can be viewed as variable fixed biases via time.

If the new data to diagnose belong to the different operation conditions (such as switching condition) with the training ones, the wavelet neural network may give an incorrect conclusion. Some faults may be detected mistakenly, although the system is still running normally. To avoid the mistaken-warning, more conditions of the VAV system should be trained. At least, the conditions of main operation and basic control should be included.

Table 2
Fault diagnosis for the sensors based on G_{II}.

Case	σ_{MSA}	σ_{TSA}	σ_{TRA}	σ_{TSW}	σ_{TRW}	σ_{MW}	Diagnosis
6	0.0033	0.0025	0.0029	0.0036	0.0037	0.0029	Normal operation
7	**0.0042**	0.0427	0.0075	0.0070	0.0151	0.0899	M_{SA} biased
8	0.0269	**0.0064**	0.0302	0.0146	0.0179	0.0855	T_{SA} biased
9	0.0108	0.0757	**0.0052**	0.0090	0.0085	0.0377	T_{RA} biased
10	0.0122	0.0268	0.0150	**0.0052**	0.0165	0.0485	T_{SW} biased
11	0.0172	0.0344	0.0101	0.0120	**0.0042**	0.0555	T_{RW} biased
12	0.0939	0.0648	0.1156	0.3534	0.3074	**0.0230**	M_W biased

Table 3
Fault diagnosis for sensors based on G_{III}.

Case	σ_{MOA}	σ_{MSA}	σ_{MRA}	σ_{TSA}	σ_{TRA}	σ_{PSA}	Diagnosis
13	0.0014	0.0025	0.0031	0.0015	0.0026	0.0025	Normal operation
14	**0.0020**	0.0108	0.0109	0.0316	0.0120	0.0158	M_{OA} biased
15	0.0348	**0.0043**	0.0096	0.0330	0.0101	0.0099	M_{SA} biased
16	0.0120	0.0080	**0.0041**	0.0340	0.0078	0.0086	M_{RA} biased
17	0.0145	0.0071	0.0077	**0.0037**	0.0539	0.0314	T_{SA} biased
18	0.0137	0.0272	0.0093	0.0751	**0.0037**	0.0095	T_{RA} biased
19	0.0119	0.0097	0.0118	0.0282	0.0134	**0.0039**	P_{SA} biased

Besides the mistaken-warnings, missing-warnings always happen in the real systems. If the magnitudes of the faults are very small, the wavelet neural network cannot detect the faults because the slight faulty data are similar (still not different enough) with those of normal conditions. The successful diagnosis percentages for small magnitudes of different faults are only 25%, 23% and 21% for G_I, G_{II} and G_{III}, respectively. Obviously, the missing-warnings occurred more easily for the slight faults.

With the faults accumulated, however, the missing-warnings can be avoided gradually. Once the magnitudes of the faults are large enough, the wavelet neural network can identify the faulty conditions better. As to the drifting biases, for example, 52%, 85% and 90% faults have been successfully diagnosed for G_I, G_{II} and G_{III} when the magnitudes are accumulated to some extent during the drifting processes.

5. Conclusion

The faults in the VAV system may not only worsen the operation efficiency but also waste the energy of system. To ensure the capacity of energy conservation, wavelet neural network integrating wavelet analysis with neural network is presented to diagnose the faults of sensors in the VAV system.

Wavelet analysis is used to process the original data so as to seize the essential operation information of the VAV system. With three-level wavelet decomposition, the characteristic information of the system is obtained. Using these processed data, the neural networks are easily trained and recognize the system well. Once the convergent networks are obtained, the new data to diagnose are decomposed similarly using three-level wavelet. Finally, the new operation conditions, including normality and faults, can be diagnosed one by one using the well-trained networks.

Two main contributions have been made in this paper. Firstly, wavelet neural network is used to diagnose the faults in the VAV systems, which is the combination of wavelet analysis and neural network. The actual VAV and its control systems are very complex that include many measuring points and control components. The efficiency of pure neural network may be not satisfied because its prediction or recognition may be disturbed by some uncertain or subordinate factors such as the measuring noises. As a result, more mistaken-warnings or missing-warnings may happen during the diagnosis process. With the wavelet analysis, however, the main information can be seized and those disturbing factors can be well removed. After the wavelet-based data processing, the diagnosis efficiency of neural network can be improved.

As the universal mathematic methods, in addition, neither wavelet analysis nor neural network can well describe the physical relations between the variables in the VAV systems. If only separated data are used for training, its diagnosis efficiency may be inevitably limited. The second contribution in this paper is the construction of various data groups using the essential conservation relations and models in the VAV system. Once the data are classified according to those physical models, the recognition for the relevant relations among variables is strengthened. Consequently, the diagnosis capacity of wavelet neural network is improved.

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