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Online sensor fault diagnosis for robust chiller sequencing control

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ABSTRACT

Chiller chilled water flow rate, supply and return temperature are used in building cooling load direct measurement in central chilling systems. Healthy sensor measurements of them are essential for proper chiller sequencing control. Site experience indicates that these measurements are easily corrupted by systematic errors or measurement faults. Therefore, an online sensor fault detection and diagnosis (FDD) strategy based on data fusion technology is developed to detect faults in the building cooling load direct measurement. The confidence degree, generated by a data fusion algorithm, is used to indicate the existence of the faults. The faults in the chilled water flow rate and supply temperature measurements are diagnosed according to the redundant information provided in building automation system (BAS). The faults in the return water temperature measurements are diagnosed by reconstructing the confidence degree using the expected values of the chilled water flow rate and the supply temperature by taking account of the associated uncertainties. Cases studies are performed on a simulated central chilling plant equipped in a high-rising building in Hong Kong. The results demonstrate satisfactory effectiveness of the proposed method in diagnosing faults in the building cooling load direct measurement.

1. Introduction

Multiple chiller plants have been widely equipped nowadays in commercial buildings. Proper chiller sequencing control strategies play increasingly significant role in energy efficiency and indoor thermal comfort since chillers are the most energy consuming components and their individual cooling capacity is usually huge such that one in short supply may cause complaints from the building tenants [1,2]. The most commonly adopted sequencing control strategy is based on building total cooling load measurement, which in principle is the best [3]. In this strategy, the chilled water flow rate, supply and return temperature in the header pipe of chilling plants are measured by flow meters and temperature sensors and these measurements are used to calculate building total cooling load. This type of cooling load calculation is named "*direct measurement*' of building cooling load in this paper.

There are two significant issues which affect the reliability of the total cooling load based chiller sequencing control: building cooling load measurement uncertainties and chiller maximum cooling capacity variations. Measurement uncertainties exist because temperature and flow rate measurements are vulnerable to corruption by measurement noises, outliers and systematic errors (or measurement faults) due to sensor aging or improper calibration [4]. These measurement uncertainties, especially those associated with the temperature measurements, have a significant effect on the accuracy of the building total cooling load direct measurements. This is because the differential temperature of the chilled water loop is generally small and the design value is around 5 °C in most systems. If there are 0.5 °C deviations in both supply and return chilled water temperature measurements, the deviation of the cooling load measurement is about 20%. As a result, the inaccurate cooling load measurement will influence the reliability of chiller sequencing control seriously.

The chiller maximum cooling capacity is often used as a constant in chiller sequencing control, being equal to the chiller rated cooling capacity. However, the chiller maximum cooling capacity may vary with the chiller operating condition, such as the chiller evaporating temperature, condensing temperature, the suction temperature of the chiller compressor, etc. [5,6]. When an inaccurate chiller maximum cooling capacity is used, it is still possible that the chiller operating number given by chiller sequencing control is not appropriate even if the cooling load is measured exactly. As a consequence, the number will be either less than necessary (the cooling is deficient resulting in occupants' thermal discomfort) or more than necessary (the cooling is excessive resulting in energy waste).

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List of symbol

a	constant, coefficient
C	specific thermal capacity (kJ/kg K)
d	Moffat distance
e	measurement noise
$\underline{E}, \overline{E}$	constant, lower/upper bound
F	fault status
H	pump pressure drop (kPa)
k	current sampling time
L_p	number of operating pumps
M	water flow rate (kg/s)
$\widehat{M}$	reconstruct water flow rate (kg/s)
N_p	number of pumps
N_w	length of moving window
P_{com}	chiller power consumption (kW)
P_{ev}	chiller evaporating pressure (kPa)
P_{cd}	chiller condensing pressure (kPa)
Q	cooling load (kW)
$\widehat{Q}$	reconstructed cooling load (kW)
$\Delta\widehat{Q}$	increment in $\widehat{Q}$ (kw)
T	temperature (°C)
$\widehat{T}$	reconstructed temperature (°C)

Subscript

act	actual value
dm	direct measurement
f	fused measurement
hp	header pipe
im	indirect measurement
j	j^{th} pump
nom	nominal value
p	pump
rtn	return water
set	set point
sum	sum
sup	supply water
w	water

Superscript

i	ith item, $i = 1,\ldots,N_w$
*	calculated value

Greek symbols

α	positive constant
β	constant
δ	calculation uncertainty or disturbance
ε	constant
γ	confidence degree
$\widehat{\gamma}$	reconstructed confidence degree
σ	standard deviation
Δ	constant (uncertainty bound)
ρ	an index parameter used in diagnosis criterion 1 and 2

A robust chiller sequencing control strategy has been proposed to deal with these two issues [7]. In the robust strategy, a data fusion algorithm is developed to reconstruct the building cooling load measurements in order to reduce the influence of measurement uncertainties and an online computation algorithm to calculate the chiller maximum cooling capacity according to chiller operating conditions. The robust strategy can also detect the existence of systematic errors in the cooling load direct measurements through the data fusion algorithm [8]. However, it cannot specify which measurement suffers from faults. For further improving the performance of chiller sequencing control, it is necessary to diagnose the measurement faults promptly and correctly.

Sensor fault diagnosis at different levels (i.e., system, subsystem, component and sensor) have been widely practiced in Heating, Ventilation and Air-Conditioning (HVAC) systems for enhancing system performance and improving energy efficiency as well as indoor environmental comfort. Generally, sensor fault diagnosis methods can be grouped into two categories: model-based methods [9–14] and model-free methods [15–17]. The model-based diagnosis methods usually use an explicit model, such as physical models, data-driven models (black-box models) or semi-physical models (grey-box models), to describe the behaviors of the target systems or measurement tools. Model-free methods, on the other hand, do not utilize an explicit mathematical model of the target system. They detect faults depending mainly on redundant information as well as prior knowledge. Because most HVAC systems are complex and have a large number of sensors, actuators, control loops, etc., which require various types of sensor fault detection and diagnosis methods, whether model-based diagnosis methods or model-free methods can offer their benefits in HVAC systems.

This paper presents an online sensor fault diagnosis method for chiller sequencing control, which integrates model-based and model-free diagnosis techniques. The strategy cooperates with a data fusion algorithm [8] to diagnose the faults occurring in the building cooling load direct measurement. The data fusion algorithm is briefly introduced in Appendix A. In the data fusion algorithm, the complementary advantages of the direct cooling load measurement and the indirect cooling load measurement are fused to obtain a more accurate and reliable one. Meanwhile, a confidence degree ranging from 0 to 1 is generated to systematically evaluate the quality of fused cooling load. A low value of confidence degree indicates the faults existing in either of the chilled water flow rate, supply or return temperature measurements. Hence, the produced confidence degree can be firstly used to detect the sensor faults in the direct measurement.

When a fault is detected, the diagnosis algorithm will firstly diagnose the faults in the chilled water flow measurements in the header pipe by checking the consistency between the measurements with their expected values using Moffat distance [18,19]. The Moffat distance, defined in Appendix B, indicates the difference between two measurements concerning the associated uncertainties. If the two measurements are free of systematic errors, the Moffat distance is supposed to be less than one. It can, therefore, be used for checking whether two measurements are consistent or not by calculating the Moffat distance. The expected values of the chilled water flow measurements are constructed according to the sum of the water flow rates in the interlocked pumps of chillers. The consistency checking method is also applied to isolate faults in the chilled water supply temperature measurements since their expected values are the supply temperature set point if the supplied cooling load is sufficient. Because the chilled water return temperature varies according to the changing building cooling load, it is difficult to compute such expected values that can be used for consistency checking. A confidence degree reconstruction scheme is therefore developed to diagnose faults in the chilled water return temperature measurement, which reconstruct the confidence degree using the data in which the faults are removed (details are given in Section 3.3).

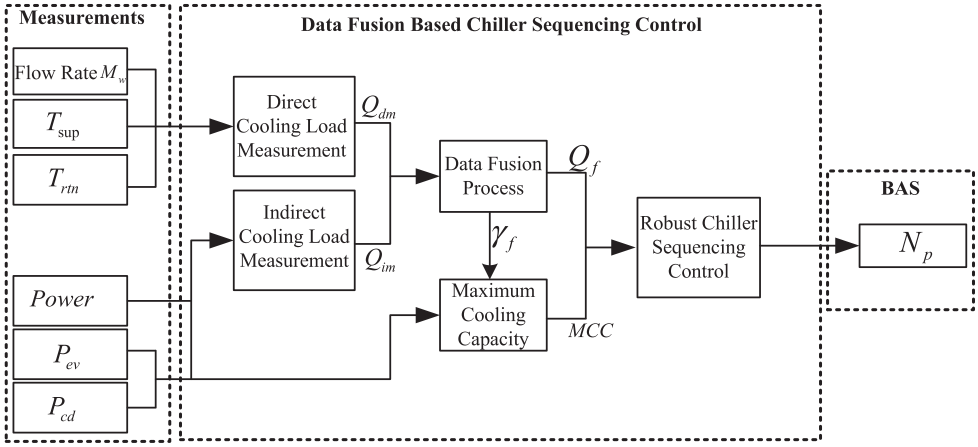

Fig. 1. Data fusion based chiller sequencing control.

The proposed fault diagnosis method is validated using a dynamic simulation package of a central chiller plant with six identical centrifugal chillers, which is used in the International Commerce Centre (ICC) in Hong Kong [20]. Different cases, including faults occurring in only 1 m or sensor and in more than one sensor simultaneously, are studied. Simulation results are presented and analyzed, which show that the proposed strategy can diagnose faults efficiently and therefore further improve the performance of chiller sequencing control.

2. Sensor fault diagnosis for enhanced chiller sequencing control

The basic idea of the robust sequencing control strategy is shown in Fig. 1, where there are two methods to measure building instantaneous cooling load. The first one is the building cooling load direct measurement, calculating the cooling load from the chilled water flow rate and the differential temperature between the chilled supply and return water in the header pipe of the chilling plant. The other one is the *building cooling load indirect measurement*, calculating cooling load using a simplified chiller inverse model based on the chiller power consumption, evaporating pressure and condensing pressure, see Eq. (A2) in Appendix A. The direct and indirect measurements are taken as the inputs of the data fusion process, which generates the cooling load fused measurements by combining the complementary advantage of the direct and indirect measurements. Generally, when the direct measurements are free of outliers and systematic errors and when the measurement noises are taken as a normal distribution with zero mean, the sum of a sequence of continuous direct measurements is more reliable than that of the indirect measurements. This is because the indirect measurements may suffer from model errors. The model error will be relatively constant when the building cooling load does not vary with a significant magnitude in a short interval (for example half an hour). In this case, the indirect measurements can provide more reliable cooling load variations than the direct measurements. Chiller maximum cooling capacity is calculated online using a simplified but reliable chiller model according, as well, to the chiller power consumption, the evaporating pressure and the condensing pressure [7]. The fused cooling load together with the calibrated maximum cooling capacity is sent to chiller sequencing control for determining the chillers operating number.

The fusion algorithm is also developed to detect systematic errors in the direct measurements by comparing the fused measurements with the indirect measurements. When the fused measurements fall outside of the acceptable region, defined as $[Q_{im} - \underline{E}, Q_{im} + \overline{E}]$ (see Fig. 2), a systematic error is believed to occur in the direct measurements. Note that the acceptable region is used to account for the model error in the chiller inverse model of computing the building cooling load and its parameters $\underline{E}, \overline{E}$ are setup experimentally during commissioning [8]. The existence of the systematic errors in the direct measurement is indicated by the confidence degree, which will decrease quickly to a threshold in this case.

When the confidence degree is below the threshold, the chiller maximum cooling capacity is calibrated in order to deal with the

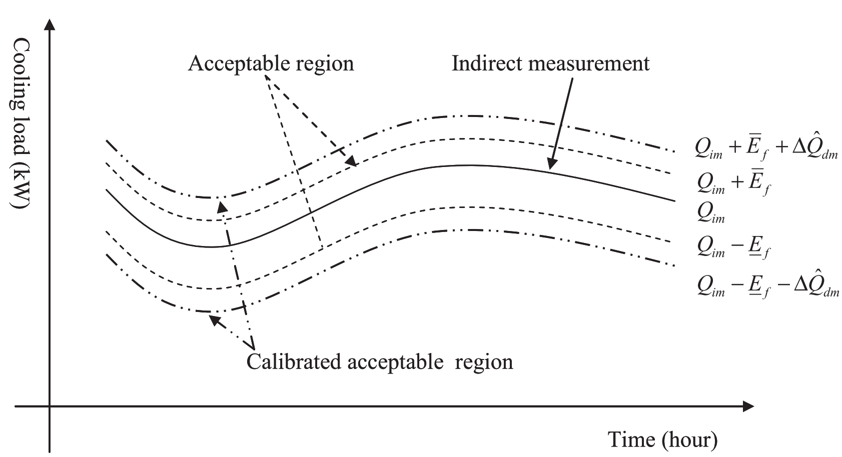

Fig. 2. Definition of the acceptable region for the fused measurement.

impact of sensor measurement faults (e.g. systematic errors) on chiller sequencing control. Although the robust chiller sequencing control can guarantee enough supplied cooling even when a systematic error in the direct measurements is detected, the sequencing control performance and the energy efficiency may deteriorate, especially when the actual building cooling load is much smaller than the measurements used for the sequencing control. Therefore, prompt diagnosis of sensor faults is essential to improve the performance of chiller sequencing control. The confidence degree is used as a trigger in the fault diagnosis strategy.

Sensor fault diagnosis aims at improving the performance of chiller sequencing control by helping building automation system (BAS) operators to remove sensor faults quickly. Since the confidence degree becomes low when there is a considerable discrepancy between the fused and indirect cooling load measurements, faults might occur in either the direct or indirect measurements. It is known that a number of sensor fault diagnosis methods has been developed for dealing with the sensor measurements concerning individual chiller (e.g. volts, currents, evaporating and condensing pressure), for example by Wang and Chen [21]. Therefore, this paper will focus on developing sensor fault diagnosis approach for isolating the faults occurring in the cooling load direct measurement, i.e., in the chilled water flow, supply and return temperature measurements.

3. Online sensor fault diagnosis algorithm

3.1. Overview of the fault diagnosis algorithm

The online sensor fault diagnosis algorithm is illustrated in Fig. 3. The fault diagnosis algorithm follows a procedure of two steps. The first step is to check whether there is any fault in the chiller water flow and supply temperature measurements, both of which have expected values. The expected value of the chiller water flow rate in the header pipe is calculated based on mass balance between the header pipe and the interlocked pumps of chillers. The expected value of the chilled water supply temperature is its set point, which can be tracked by the chiller control system when the operating chillers can provide sufficient cooling. The Moffat consistency test is conducted to diagnose fault by checking the Moffat distance between the measurements and their expected values [19]. The second step is to diagnose faults in the chilled water return temperature measurements. If no fault is found in the first step, a fault is believed to exist in the chilled water return temperature measurements and the diagnosis algorithm ends with a fault report to BAS. Otherwise, the diagnosis algorithm will continue to check whether there is any further fault. Since the chilled water return temperature varies with the building cooling load and the building cooling load is difficult to compute, the Moffat consistency test is not used in this case. The fault is diagnosed by reconstructing the confidence degree using the chilled water flow measurements (when a fault is detected) or its expected value (when no fault is detected) and the supply temperature measurements (when a fault is detected) of its expected value (when no fault is detected). Fault report is also sent to BAS.

3.2. Fault diagnosis of chiller water flow rate and supply temperature measurements

In the fault diagnosis for the header pipe chilled water flow measurements, the available redundant information in BAS include:

- Header pipe chilled water flow measurements M_{hp};
- Operating pump water flow direct measurements $M_{p,j}$, $j = 1,\ldots,N_p$;
- Operating pump water pressure drop (or pump head loss) measurements $H_{p,j}$.

The pump water pressure drop is related to the pump water flow rate by the pump performance curve, which can be described as

$$H_{p,j} = a_0 + a_1 \times M^*_{p,j} + a_2 \times \left(M^*_{p,j}\right)^2 \quad (1)$$

The pump water flow rate $M^*_{p,j}$, calculated from Eqn. (1), is titled as *pump water flow indirect measurement*. The diagnosis criterion for the header pipe water flow measurement is developed based on the mass balance between the header pipe water flow and the water flow in these operating pumps, i.e., the water mass flow through the header pipe is equivalent to the sum of the water mass flow through the operating pumps. The diagnosis criterion is descried as follows:

3.2.1. Diagnosis criterion 1

In a moving window with N_w continuous measurements of the chilled water flow rate in the header pipe, if ρ_1 (percentage) of the Moffat distances between *the header pipe chilled water flow measurements* and *the sum of the flow measurements in these operating pumps* are larger than unit, then there is a fault in the header pipe water flow measurement; otherwise, the header pipe water flow measurement is free of faults.

The Moffat distance in diagnosis criterion 1 is defined by Eqn. (2), where the sum of the flow measurements in the operating pumps M^i_{sum} is calculated by Eqn. (3) and the uncertainty Δ_{wm} associated with $M^i_{hp} - M^i_{sum}$ is computed by Eqn. (4). In Eqn. (3), M^i_{sum} consists of two parts: the direct measurements $M^i_{p,j}$ from the operating pump flow meters which work healthily and the indirect measurements $M^{*,i}_{p,j}$ from the operating pump flow meters which work unhealthily, i.e., with systematic errors. The index ρ_1 is a user-defined parameter and the choice of its value is discussed in Section 3.4.

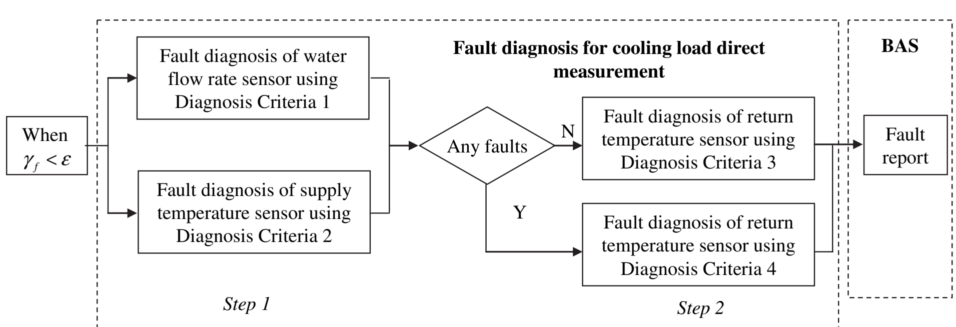

Fig. 3. Framework of the fault diagnosis algorithm.

$$d^i_{hs,k} = \frac{|M^i_{hp} - M^i_{sum}|}{\Delta_{wm}}, \quad i = 1,\dots,N_w \tag{2}$$

$$M^i_{sum} = \sum_{j=1}^{L_p} M^i_{p,j} + \sum_{j=L_p+1}^{N_p} M^{*,i}_{p,j} \tag{3}$$

$$\Delta_{wm} = \sqrt{(\Delta_{hp})^2 + \sum_{j=1}^{L_q} (\Delta_{p,j})^2} + \sum_{j=L_p+1}^{N_q} \Delta^*_{p\cdot j} \tag{4}$$

The uncertainty Δ_{wm} is derived as follows. When the header pipe water flow meter in primary loop is free of fault, the measurement M^i_{hp} can be written as

$$M^i_{hp} = M^i_{hp,act} + e^i_{hp}, \quad e^i_{hp} \sim N(0, \sigma^2_{hp}) \tag{5}$$

According to the study reported in [18], the uncertainty associated with M^i_{hp} can be defined as

$$\Delta_{hp} = 1.96\sigma_{hp} \tag{6}$$

Similarly, when the pump flow meters work healthily, the direct measurements $M^i_{p,j}$ have the form of

$$M^i_{p,j} = M^i_{p,act,j} + e^i_{p,j}, \quad e^i_{p,j} \sim N(0, \sigma^2_{p,j}) \tag{7}$$

and the associated uncertainty is

$$\Delta_{p,j} = 1.96\sigma_{p,j} \tag{8}$$

When the pump flow meters work unhealthily, the indirect measurement $M^{*,i}_{p,j}$ is used to replace the direct measurement $M^i_{p,j}$. Considering about model mismatches introduced in the pump performance curve (see Eqn. (1)), the indirect measurement $M^{*,i}_{p,j}$ can be expressed as

$$M^{*,i}_{p,j} = M^i_{p,act,j} + \delta^i_{p,j}, \quad \left|\delta^i_{p,j}\right| \le \Delta^*_{p,j} \tag{9}$$

Assume there are L_p pump flow meters work healthily and $N_p - L_p$ pump flow meters work unhealthily. The sum of the operating pump flow measurements M^i_{sum} in Eqn. (3) is rewritten as

$$M^i_{sum} = \sum_{j=1}^{N_p} M^i_{p,act,j} + e^i_{sum} + \delta^i_{sum}; \; e^i_{sum} = \sum_{j=1}^{L_p} e^i_{p,j}; \; \delta^i_{sum} = \sum_{j=L_p+1}^{N_p} \delta^i_{p,j} \tag{10}$$

The mass balance between the header pipe water flow and the operating pump water flow gives

$$M^i_{hp,act} = \sum_{j=1}^{N_p} M^i_{p,act,j} \tag{11}$$

which yields

$$M^i_{hp} - M^i_{sum} = e^i_{hp} - e^i_{sum} - \delta^i_{sum} \tag{12}$$

Since the operating pump flow meters works independently with each other and also with the header pipe flow meter, $(e^i_{hp} - e^i_{sum})$ follows a normal distribution

$$\left(e^i_{hp} - e^i_{sum}\right) \sim N\left(0, \sigma^2_{hp} + \sum_{j=1}^{L_p} \sigma^2_{p,j}\right) \tag{13}$$

The total calculation uncertainty δ^i_{sum} lies in the range

$$|\delta^i_{sum}| \le \sum_{j=L_p+1}^{N_p} \Delta^*_{p,j} \tag{14}$$

Hence, the uncertainty associated with $M^i_{hp} - M^i_{sum}$ is

$$\Delta_{wm} = 1.96\sqrt{(\sigma_{hp})^2 + \sum_{i=1}^{L_p} (\sigma_{p,j})^2} + \sum_{j=L_p+1}^{N_p} \Delta^*_{p,j} \tag{15}$$

Then, Eqn. (4) is obtained according to Eqn. (6), 8 and 15.

Diagnosis criterion 1 indicates that if the header pipe water flow measurements are not consistent with the sum of the pump flow measurements, then there is a fault in the header pipe flow measurements. It should be noted that when the measurement uncertainties Δ_{hp} and $\Delta_{p,j}$, $j = 1,\dots,L_p$, are appropriately set, a single Moffat consistency test still fails with 5% probability due to the normal distribution of the measurement noises [18]. Therefore, a moving window is adopted in diagnosis criterion 1, which is used to reduce the possibility of such misdiagnosis. It should also be noted that when the number of operating chillers is different, the measurement noises in the flow meter for the header pipe may be different. Therefore, σ_{hp} may be different, which will be discussed in Section 3.4.

The healthy operation of the pump flow meter is judged by examining the consistency between the pump water flow direct measurements and the corresponding indirect measurements. As in diagnosis criterion 1, Moffat distances are used and defined as

$$d^{*,i}_{p,j} = \frac{|M^i_{p,j} - M^{*,i}_{p,j}|}{\Delta_{p,j} + \Delta^*_{p,j}} \tag{16}$$

Once again, if $d^{*,i}_{p,j}$ is larger than unity, then a fault is found in the corresponding flow meter; otherwise, the flow meter works healthily. Note that this judgment is based on the fact that the pressure measurement is reliable.

3.2.2. Diagnosis criterion 2

In a moving window with N_w continuous measurements of the supply temperature, if ρ_2 (percentage) of the Moffat distances between *chilled water supply temperature measurements* and *the set point* are larger than unity, then there is a fault in the chilled water leaving temperature measurement.

The Moffat distances in diagnosis criterion 2 are defined by

$$d^i_{\sup,k} = \frac{|T^i_{\sup,mes} - T_{\sup,set}|}{\Delta_{\sup,mes} + \Delta_{\sup,set}}, \quad i = 1,\dots,N_w \tag{17}$$

The development of diagnosis criterion 2 is similar to diagnosis criterion 1. When the chiller sequencing control guarantees sufficient cooling supplied and the operating chillers are free of faults, the actual chilled water supply temperature can be manipulated to track its set point with small disturbances by the chiller closed-loop control. Hence, the chilled water actual supply temperature can be described by

$$T_{\sup,act} = T_{\sup,set} + \delta_{\sup,set} \tag{18}$$

The disturbance $\delta_{\sup,set}$ occurs due to chiller imperfect closed-loop control as well as its unstable operating environment. Again, the disturbance $\delta_{\sup,set}$ is assumed to lie in an uncertainty range, i.e., $|\delta_{\sup,set}| \le \Delta_{\sup,set}$. Without systematic errors, the temperature measurement $T_{\sup,mes}$ is described by

$$T_{\sup,mes} = T_{\sup,act} + e_{\sup,mes}, \quad e_{\sup,mes} \sim (0, \sigma^2_{\sup,mes}) \tag{19}$$

Similar to Eqn. (6), the measurement uncertainty $\Delta_{\sup,mes}$ is

$$\Delta_{\sup,mes} = 1.96\sigma_{\sup,mes} \quad (20)$$

The moving window is used in diagnosis criterion 2 for the same reason as it is used in diagnosis criterion 1. The index ρ_2 is also a user-defined parameter and the choice of its value is discussed in Section 3.4.

3.3. Fault diagnosis of the chilled water return temperature measurement

As illustrated in Fig. 3, two cases should be considered in the fault diagnosis of the chilled water return temperature measurements. The first case is that there are no faults found in both the chilled water flow and supply temperature measurements. In this case, the diagnosis criterion is described as follows.

3.3.1. Diagnosis criterion 3

When there is no fault found in the chilled water flow and supply temperature measurements, there is a fault in the chilled water return temperature measurements.

The second case is that a fault is detected in either the chilled water flow measurements or the supply temperature measurements. In this case, the fault diagnosis algorithm will check whether there is a further fault in the return water temperature measurements. Because the chilled water return temperature varies with the building cooling load and the building cooling load is difficult to calculate accurately, it is difficult to use the consistency test to diagnose fault. A confidence degree reconstruction scheme is developed to diagnose faults in the return water temperature measurements. In this scheme, the cooling load direct measurements are firstly reconstructed by

$$\widehat{Q}_{dm} = C_w \times \widehat{M} \times \left(T_{rtn,mes} - \widehat{T}_{\sup}\right) \quad (21)$$

where

$$\widehat{M} = \begin{cases} M_{hp}, & \text{if no fault is found} \\ M_{sum}, & \text{if a falut is found} \end{cases}$$

$$\widehat{T}_{\sup} = \begin{cases} T_{\sup,mes}, & \text{if no fault is found} \\ T_{\sup,set}, & \text{if a fault is found} \end{cases}$$

Then, the fusion algorithm introduced in Appendix A is used to reconstruct the fused measurements and the confidence degree. Compared with this fusion algorithm, the only difference is that the direct measurements (Q_{dm}) is replaced by the reconstructed fused measurements $(\widehat{Q}_{dm})$. The regenerated confidence degree $\widehat{\gamma}_f$ is used for fault isolation in the return chilled water temperature measurements.

3.3.2. Diagnosis criterion 4

If the reconstructed confidence degree $\widehat{\gamma}_f$ is still smaller than the threshold ε, then there is a fault in the chilled water return temperature measurements.

When M_{sum} and/or $T_{\sup,set}$ are used to replace the corresponding measurements M_{hp} and $T_{\sup,mes}$, the uncertainty $e_{sum} + \delta_{sum}$ and/or $\delta_{\sup,set}$ will be introduced in the computation of $\widehat{Q}_{dm}$. To see this, rewrite Eqn. (21) as Eqn. (22) when both M_{sum} and $T_{\sup,set}$ are used

$$\widehat{Q}_{dm} = C_w \times M_{sum} \times \left(T_{rtn,mes} - T_{\sup,set}\right) \quad (22)$$

The nominal value of the direct measurements $\widehat{Q}_{dm,nom}$ is the one without any faults in the water flow and chilled water supply temperature measurements

$$\widehat{Q}_{dm,nom} = C_w \times M_{hp} \times \left(T_{rtn,mes} - T_{\sup,mes}\right) \quad (23)$$

Assume Δ_{sum} and $\Delta_{\sup,set}$ are

$$\Delta_{sum} = \alpha_1 \times M_{sum} \quad \text{and} \quad \Delta_{\sup,set} = \alpha_2 \times \left(T_{rtn,mes} - T_{\sup,set}\right) \quad (24)$$

i.e., $|e_{sum} + \delta_{sum}| \le \alpha_1 \times M_{sum}$ and $|\delta_{\sup,set}| \le \alpha_2 \times (T_{rtn} - T_{\sup,set})$. According to Eqn. (12), (18) and (19), Eqn. (23) can be rewritten as

$$\widehat{Q}_{dm,nom} = C_{pw} \times (M_{sum} + \delta_{sum} + e_{sum}) \times \left[T_{rtn,mes} - T_{\sup,set} - \delta_{\sup,set} - e_{\sup,mes}\right] \quad (25)$$

Since the measurement noises e_{sum} and $e_{\sup,mes}$ are independent and with zero expectations, both of them will disappear in the fused measurement because the sum of a continuous sequence of $\widehat{Q}_{dm}$ is used to compute the fused measurement [8]. However, the uncertainties δ_{sum} and $\delta_{\sup,set}$ cannot be removed in this way. Therefore, the uncertainty δ_{sum} and $\delta_{\sup,set}$ will enter into the reconstructed fused measurement as well as $\widehat{\gamma}_f$.

The "worst" increment in the fused measurements is when $\delta_{sum} = \pm\alpha_1 \times M_{sum}$ and $\delta_{\sup,set} = \pm\alpha_2 \times (T_{rtn,mes} - T_{\sup,set})$

$$\Delta\widehat{Q}_{dm} = (\alpha_1 + \alpha_2 + \alpha_1 \times \alpha_2)\widehat{Q}_{dm} \quad (26)$$

This increment $\Delta\widehat{Q}_{dm}$ should be taken into account in reconstructing $\widehat{\gamma}_f$ in order to avoid the decrease of $\widehat{\gamma}_f$ due to the introduction of δ_{sum} and $\delta_{\sup,set}$. A simple way is to calibrate the acceptable region using $\Delta\widehat{Q}_{dm}$. The calibrated acceptable region is also shown in Fig. 2 by the solid-dotted lines, where the calibration value is $\pm\Delta\widehat{Q}_{dm}$, which is calculated according to Δ_{sum} and $\Delta_{\sup,set}$. For example, when both the chilled water flow rate and supply water temperature measurement are with faults, $\Delta\widehat{Q}_{dm}$ is be computed using Eqn. (26).

3.4. Parameters setup

The parameters of the online sensor fault diagnosis algorithm are summarized in Table 1. All these parameters are required to be set during on-site commissioning. For example, σ_{hp} and $\sigma_{\sup,mes}$ can be calculated by analyzing the stochastic distribution of a sequence of chilled water flow and supply temperature continuous measurements when the measurands are relatively constant and the measurements are free of faults. Then, Δ_{hp}, $\Delta_{p,j}$ and $\Delta_{\sup,mes}$ can be calculated using Eqn. (6), (8) and (20) separately. Generally, the pumps interlocked with chillers operate with constant speed, and $\Delta_{p,j}$ can be identified when the pumps operates normally. However, when different numbers of chillers are put into operation, Δ_{hp} should be identified for each number when these chillers operate normally.

The estimation of $\Delta_{\sup,set}$ requires a number of data when the chillers works at steady state. The commonly used 95% confidence

Table 1
Parameters of the online sensor fault diagnosis algorithm.

Parameter	Description
Δ_{hp}	Uncertainty associated with the water flow measurement in header pipe
$\Delta_{p,j}$	Uncertainty associated with the water flow measurement for jth operating pump
$\Delta^*_{p,j}$	Uncertainty associated with calculated water flow $M^*_{p,j}$ for jth operating pump based on pressure drop
$\Delta_{\sup,set}$	Uncertainty associated with the tracking control of $T_{\sup,set}$
$\Delta_{\sup,mes}$	Uncertainty associated with chilled water supply temp measurement
N_w	Length of the moving window used in the diagnosis criteria
ρ_1, ρ_2	Percentage index used in diagnosis criterion 1 and 2

rules can be used in this case, i.e., 95% of these measurements should fall inside the range specified by $\Delta_{\sup,set}$ [18]. As well, $\Delta^*_{p,j}$ can be also determined using the 95% confidence degree. Other confidence rule can also be used. However, it should be noted that when these uncertainty-related parameters, including $\Delta_{hp}, \Delta_{p,j}, \Delta^*_{p,j}, \Delta_{\sup,set}, \Delta_{\sup,mes}$, have a larger value, the diagnosis criterions become less sensitive to the faults. When the number of operating chillers are different, the uncertainty related to the sum of water flow of operating pumps Δ_{sum} might be different and therefore different values of Δ_{sum} should be used.

The user-defined parameters ρ_1 and ρ_2 in diagnosis criterion 1 and 2 can be set to 100%, i.e., all the measurements in the moving windows fail in the consistency checking. However, considering about measurement outliers which occur occasionally, ρ_1 and ρ_2 should have a value smaller than 100% and their values can be setup according to outliers frequency in the measurements. In the case studies shown in Section 4, 80% was used experimentally. Because the length of the moving window in both criteria were 8, one outliers in the data stored in the moving window will not affect the diagnosis results.

The fault report consists of three items $F_w, F_{\sup}, F_{rtn}$ denoting the fault status of the chilled water flow rate, supply and return temperature respectively. The value of these items is zero indicating there are no faults in the corresponding measurement; while the value is unity indicating a fault is found. The fault report will be sent to BAS to notify system operators to repair the faults promptly.

4. Case studies and validation

4.1. Simulation platform introduction

The central chiller plant equipped the ICC building in Hong Kong consists of six identical centrifugal chillers with the rated cooling capacity of 7230 kW. The schematic diagram of the central chiller plant is shown as Fig. 4. Each chiller is interlocked with a chilled water distribution pump with volumetric flow rate 345 L/s and a cooling water distribution pump with volumetric flow rate 410 L/s. The chilled supply water flows into a global air handling unit (AHU), providing cooling for the building by cooling down the supply air temperature to a predefined set point. The return chilled water is distributed evenly to the operating chillers. Eleven identical cross-flow cooling towers with designed heat rejection capacity of 5226 kW are used to cool down the condensers in the chillers. The supply cooling water, driven by the cooling water distribution pumps, is distributed evenly to the operating cooling towers. The central chiller plant was simulated using the commercial software, Transient Simulation Program TRNSYS 16 [22]. The sequencing control and sensor fault diagnosis strategies were programmed in MATLAB and embedded in TRNSYS 16 using the interface provided by TRNSYS 16. A typical 5 days cooling load profile of a high-rising building located in Hong Kong was used as the required cooling in the cases studies. The profile of the building cooling load is shown in Fig. 5.

For simulating the realistic sensor measurements, noises and outliers were deliberately added to the related measurements. The Gaussian noise with the distribution $N(0, 0.01)$ was added to the measurements of temperature sensors. The outliers were set to 1 °C or −1 °C randomly. Pseudo systematic errors were added to represent the faults occurred in the chilled water flow and temperature measurements. Four different cases were studied. In the first three cases, faults occurred solely in each of the three measurements; while in the last case, faults occurred in the three measurements simultaneously.

The threshold of the confidence degree for detecting systematic error was set to $\varepsilon = 0.001$. Least square fitting was used to identify the parameters of Eqn. (1), which yielded $a_0 = 972.7, a_1 = -3.0, a_2 = 0.0032$. Tests under different operating conditions showed that the relative error introduced by Eqn. (1) was less than

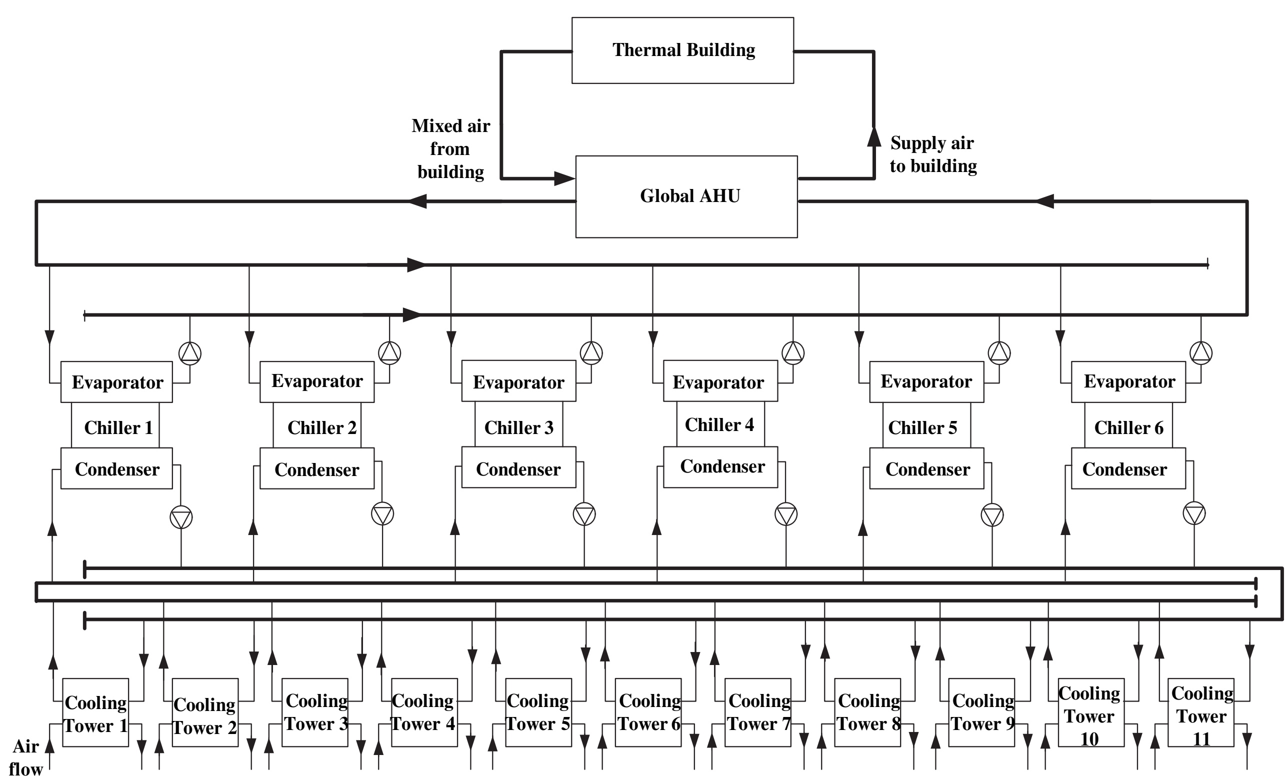

Fig. 4. Schematic diagram of the central chiller plant.

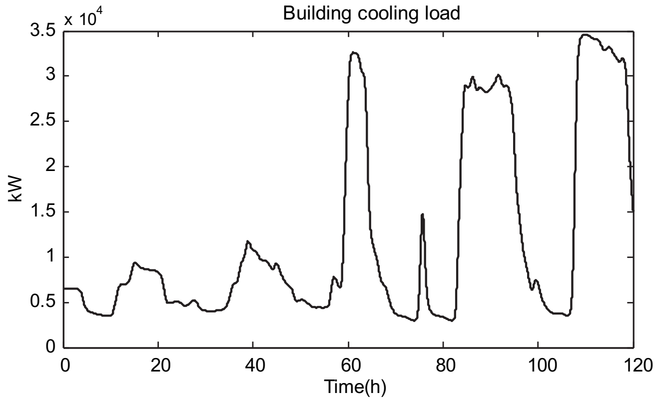

Fig. 5. Profile of building cooling load variation.

2%. Therefore, the uncertainty Δ_p^* was assigned the value $2\% \times M_p$. Δ_p due to measurement noises was set to 20.58 kg/s for operating pumps; while Δ_{hp} for the header pipe was set to 35.8 kg/s. The length of the moving window N_w was 8. The parameter $\Delta_{\text{sup},set}$, which is used to account for the imperfect close-loop temperature control of chillers as well as disturbances, was set to 0.18 °C because simulation study showed that when the set point for the chilled water was 5.5 °C, 95% of the temperature measurements were inside the range [5.5 ± 0.18] °C. The standard deviation of the noise in the chilled water supply temperature measurement was 0.1 °C, and hence $\Delta_{\text{sup},mes} = 0.196$ °C.

Two different types of errors were employed in the simulation. One was used to represent the slow drift fault of the sensor measurement and it was entitled *ramp error*. The ramp errors started with different changing rate and were kept at their maximum absolute value after reached them. The second one was used to represent abrupt faults in the sensor measurement and it was called *step error*. Its value was maintained constant in the duration.

4.2. Case with single fault occurring in the flow meter

Ramp and step errors were both added to the chilled water flow rate measurements. The durations of the ramp errors were 6 h. One of the ramp errors reached its maximum absolute value (i.e., 15% of its total water flow rate) at the end of the duration; others changed with a greater rate and achieved the peak absolute value earlier. The step errors also lasted for 6 h and their absolute values were assigned to 15% of the total water flow, shown in Fig. 6 (top). The systematic errors were detected by the confidence degree of the fused measurement. It can be seen from Fig. 6 (middle) that the confidence degree fell rapidly down to smaller than ε until the systematic error disappear. The bottom one is the chiller sequencing control performance. Fig. 7 illustrates the results of the sensor fault diagnosis algorithm, which shows that all systematic errors were successfully isolated. It should be noted that there is delay in the fault diagnosis for the ramp errors as well as in the step errors. This is because the data fusion algorithm needs time to detect the systematic errors and the time is smaller than the time span of the moving window [8]. Also, the moving window used in diagnosis criterion 1 will lead to the time delay. Since the fusion algorithm needs longer time to detect the ramp errors, the delay in diagnosing the ramp errors was larger than in diagnosing the step errors, see Fig. 7 the top plot.

The fusion algorithm stopped working during transients (i.e., a chiller was switched on or off and the chilling system has not reached its stable state), the fault diagnosis algorithm also stopped working. This was the reason why the duration of diagnosed faults was shorter than the duration of the actual fault, which can be observed in Fig. 7.

4.3. Case with single fault occurring in the supply temperature sensor

The systematic errors added to the supply water temperature measurement included both ramp and step errors. The maximum

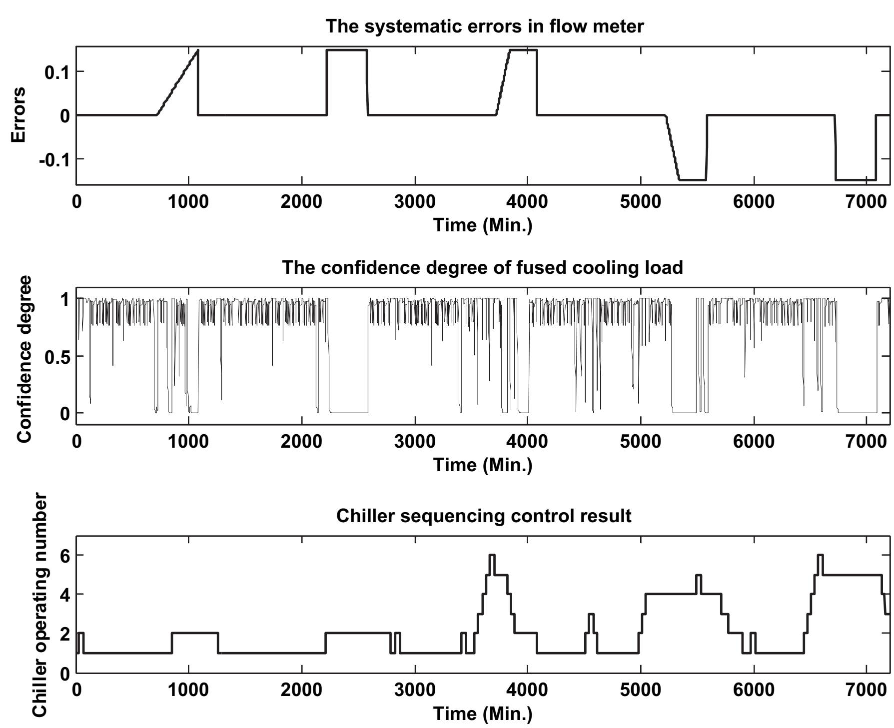

Fig. 6. Confidence degree and chiller sequencing control performance when faults only occurred in flow meter.

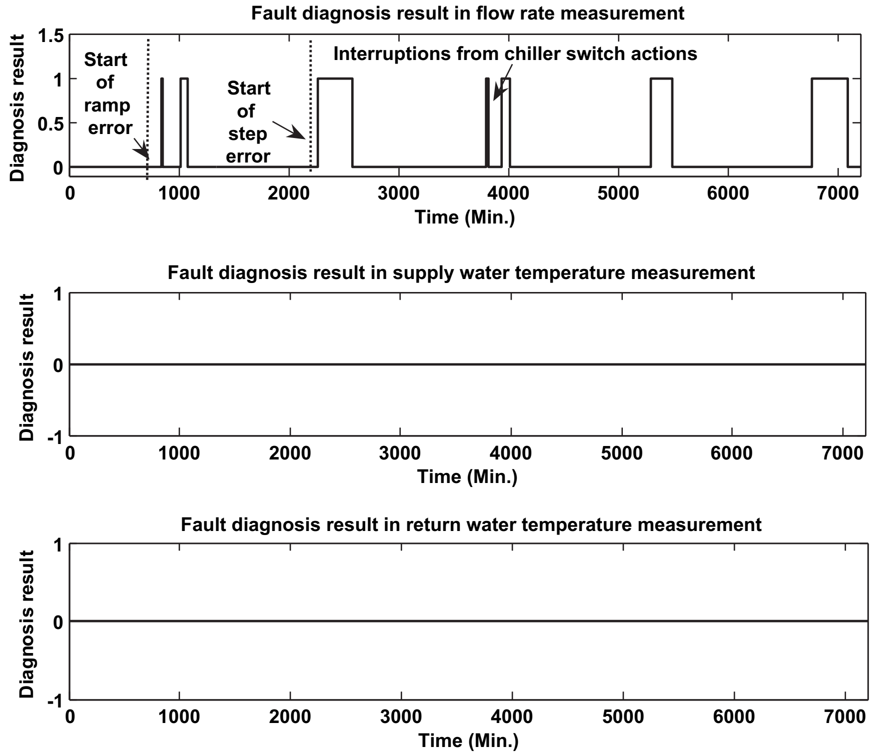

Fig. 7. Fault diagnosis results of the three measurements.

absolute value of the ramp errors was 0.9 °C and each of them lasted for 6 h. The varying rates of them were different from each other. The step errors kept their values at either 0.9 °C or −0.9 °C for 6 h, shown as Fig. 8 (top). Fig. 8 (middle) shows that all the faults in the supply temperature measurement were detected by the low confidence degree and they rose up when switch action of chiller occurred, shown in dotted box. Fig. 9 presents the diagnosis results. It can be seen that all the faults were successfully diagnosed although delay in the diagnosis and the influence of the transients on the diagnosis results were still observed. Note that the performance of chiller sequencing control in this case was slightly different from the one when faults occurred in the supply water flow measurements, which shows the necessity of fault diagnosis.

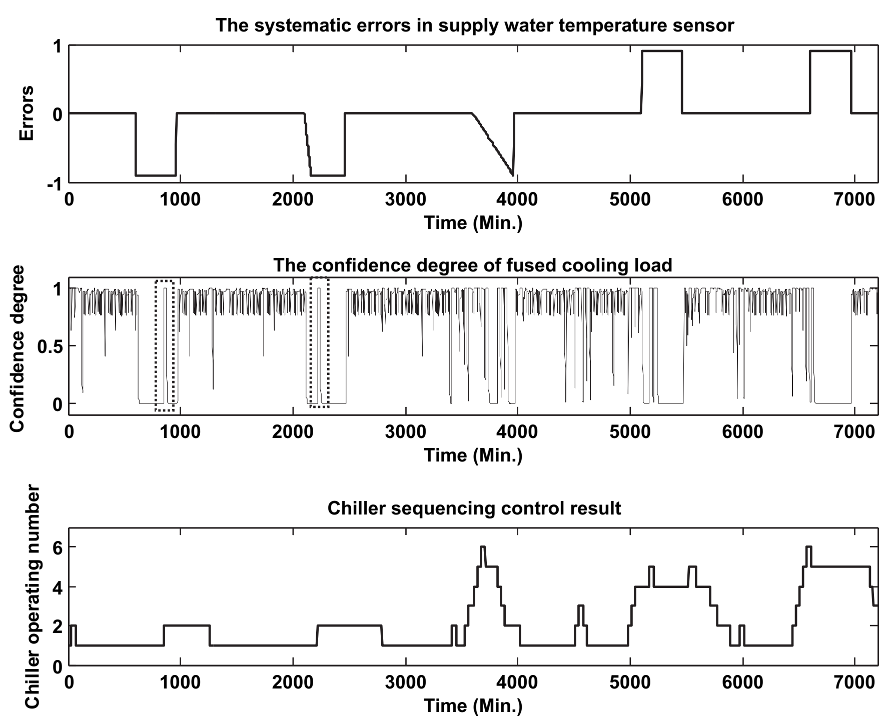

Fig. 8. Confidence degree and chiller sequencing control performance when faults only occurred in supply water temperature sensor.

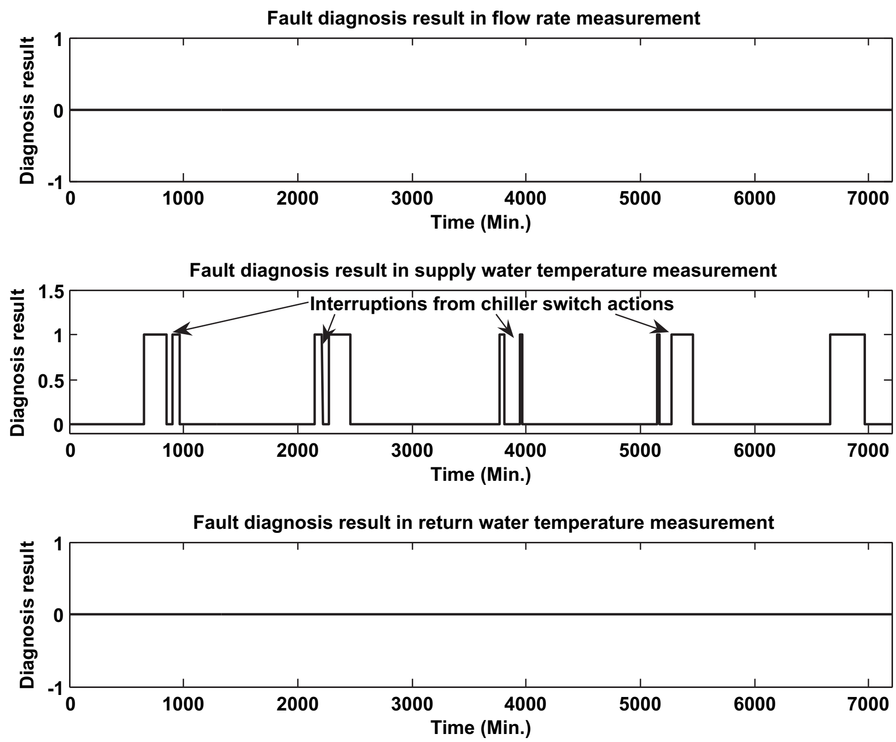

Fig. 9. The fault diagnosis results of the three measurements.

4.4. Case with single fault occurring in the return temperature sensor

The errors added to the return chilled water temperature measurement included two 6 h-lasting ramp errors with different increasing rates and the same maximum value 0.9 °C and three step errors with assigned value −0.9 °C lasting for 6 h, shown as Fig. 10. Fig. 10 (middle) described the confidence degree, which shows that the systematic errors were successfully detected. Fig. 10 (bottom) illustrates the operating chiller number given by chiller sequencing

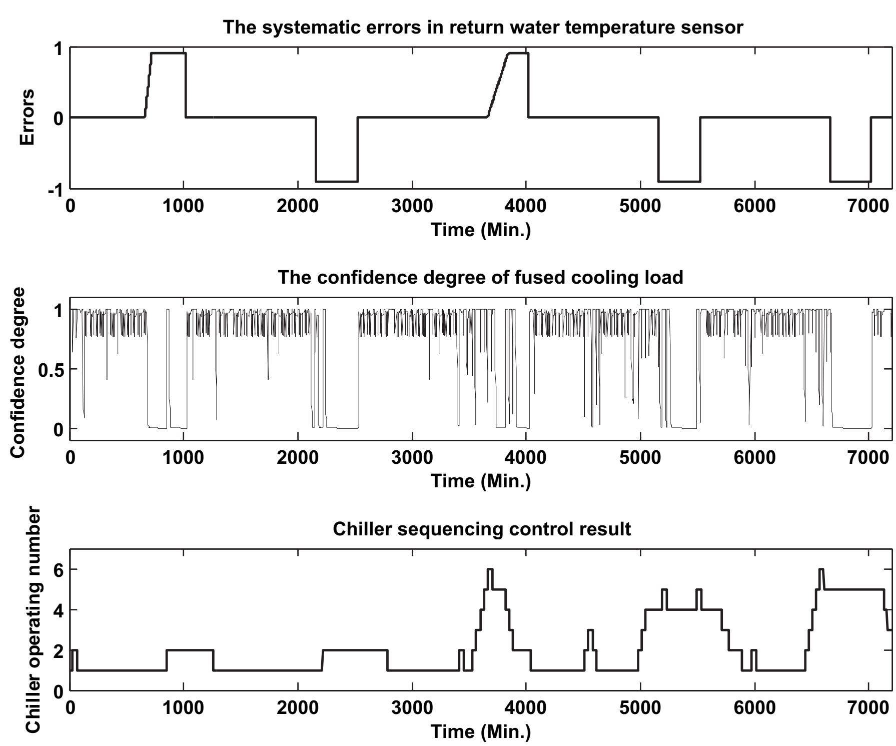

Fig. 10. The confidence degree and chiller sequencing control performance when faults only occurred in return water temperature sensor.

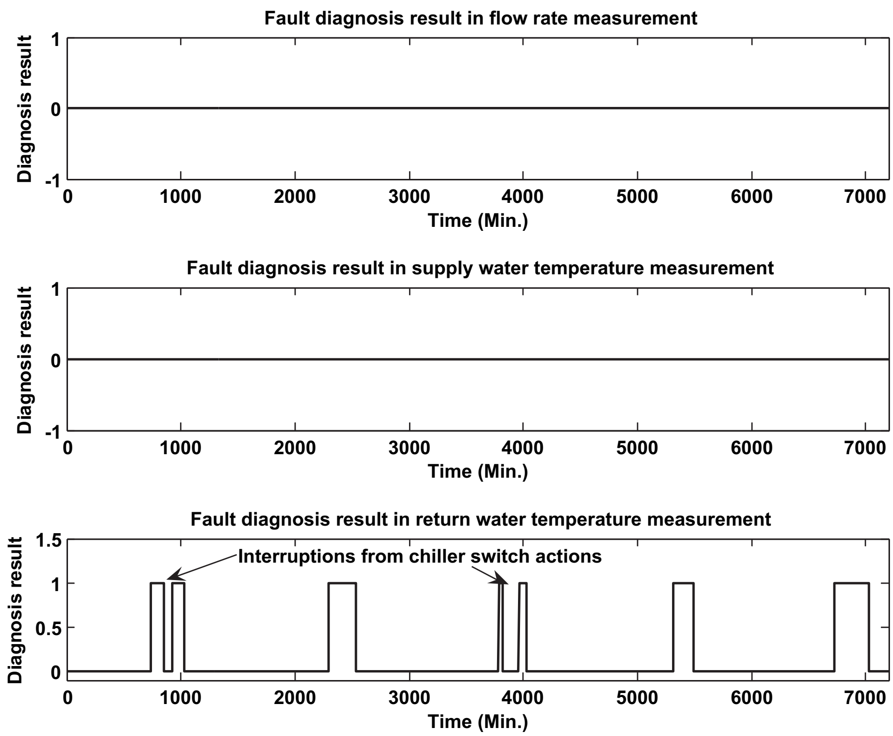

Fig. 11. The fault diagnosis results of the three measurements.

control. Fig. 11 shows the diagnosis results. Once again, the faults were isolated but with a slight delay. Note that in this case, diagnosis criterion 3 was used because there were no faults in both the chilled water flow measurements and the chilled supply water temperature measurements.

4.5. Case with multiple faults occurring in all three measurements

For fully testifying the fault diagnosis strategy, all of the measurements were added systematic errors, see Fig. 12 (the top three plots). Due to the simultaneous occurrence of these

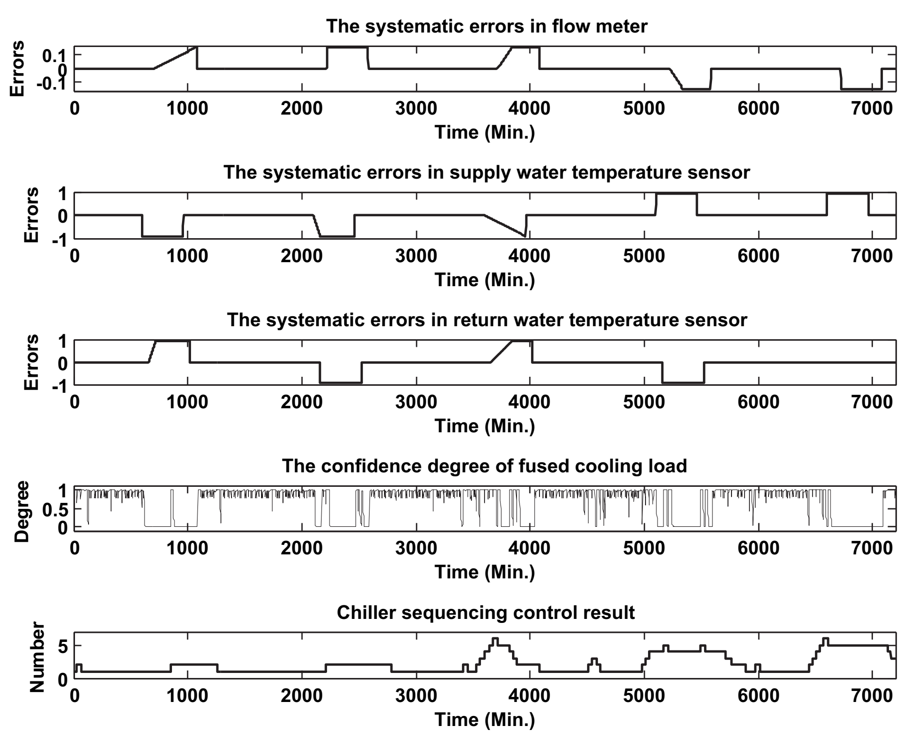

Fig. 12. The confidence degree and chiller sequencing control performance when faults occurred in all three measurements.

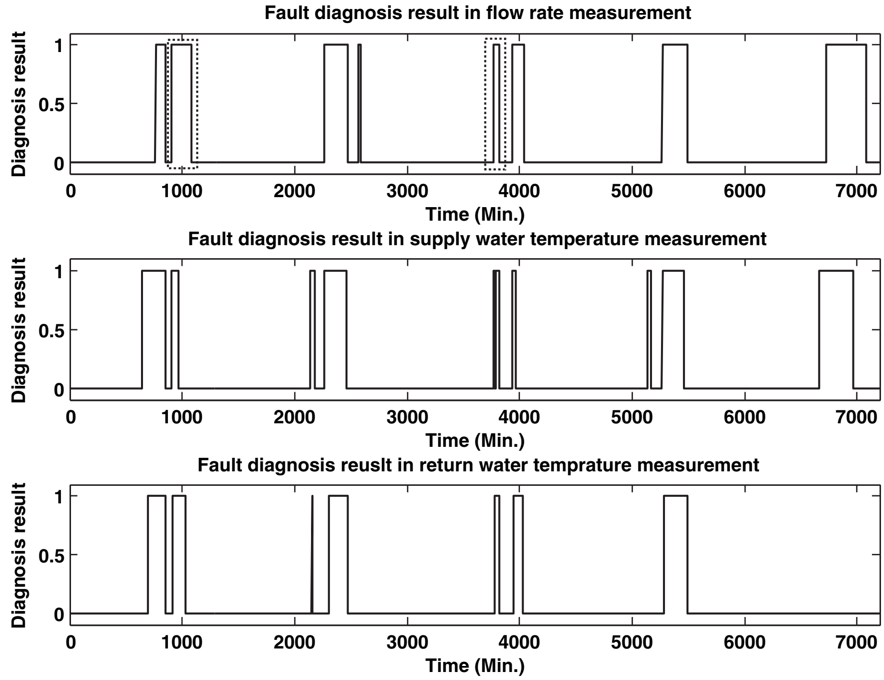

Fig. 13. The fault diagnosis results of the three measurements.

systematic errors, interruptions of chiller switching actions,the fault detection by the confidence degree became more difficult. However, these faults were detected by the confidence degree as shown in Fig. 12. Since there are faults in the chilled water flow and supply temperature measurements, diagnosis criterion 4 was used to diagnosis faults in the chilled water return temperature measurements. Fig. 13 presents the diagnosis results, which shows that these faults were also diagnosed correctly.

Although the errors in the chilled water flow measurements and in the chilled water supply temperature measurements were the same with those used in previous subsections, the diagnosis results given by diagnosis criterion 1 and diagnosis criterion 4 may be different due to the overlapping of these faults. For example, the first and the third fault diagnosed in the chilled water flow measurements in Fig. 7 were shorter than the corresponding faults shown in dotted box in Fig. 13. As many other diagnosis strategies, parameter setup is also significant for appropriate diagnosis in this strategy. Fig. 14 gives an example when $\Delta\widehat{Q}_{dm}$ used a different value, i.e., $\Delta\widehat{Q}_{dm} = 60$ kW. Misjudgment was observed as shown in the dotted box in the diagnosis result in the chilled water return temperature. Therefore, in

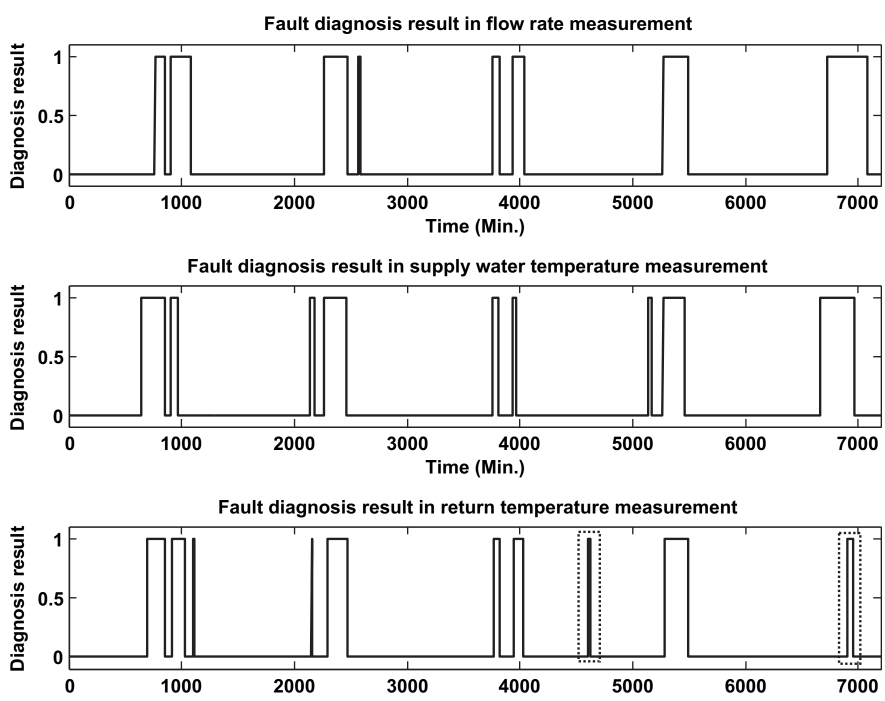

Fig. 14. The fault diagnosis results of the three measurements when $\Delta\widehat{Q}_{dm}$ was inappropriately set.

practical application, the parameters in these diagnosis criteria should be carefully set during commissioning.

5. Conclusion

An online sensor fault diagnosis strategy based on the data fusion technology has been presented to diagnose sensor faults in building cooling load direct measurement for improving the performance of chiller sequencing control. It has been shown that faults in the chilled water flow and supply temperature measurement can be efficiently diagnosed using the Moffat consistency test method since both measurements have an expected value while faults in the chilled water return temperature measurement can be diagnosed using the confidence degree reconstruction method.

Tests results showed that whether faults occurred solely or simultaneously in the three measurements, they can be successfully isolated by the proposed strategy. It will be helpful to inform the operator to repair/replace the faulty measuring instruments in time. Hence the healthy sensor measurements are guaranteed which will further enhance the reliability of chiller sequencing control for energy efficiency. It should be noted that the properly assigned values for the parameters used in the method are significant for ensuring a satisfactory diagnosis result. Therefore, careful parameters configuration in the commissioning period is required before the method is applied.

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Appendix A. Building cooling load fused measurements

Building cooling load fused measurements are obtained by merging the building cooling load direct measurements with the indirect measurements. The direct measurement Q_{dm} is computed by

$$Q_{dm} = C_w M_{hp}(T_{rtn} - T_{\sup}) \tag{A1}$$

where M_{hp} is the header pipe chilled water flow rate (kg/s), T_{rtn} is the chilled water return temperature, T_{sup} is the supply water temperature, C_w is the water specific thermal capacity (kJ/kg K). The indirect measurement Q_{im} is calculated based on the chiller power consumption P_{com}, evaporating temperature T_{ev} and condensing temperature T_{cd} using a chiller inverse model, which was developed in [23]

$$Q_{im} = \sum_i Q_{im}^{[i]} = \sum_i \frac{\left(P_{com}^{[i]} - \beta^{[i]}\right)\left(c_{pl}T_{cd}^{[i]} - c_{pg}T_{ev}^{[i]} - h_{fg}\right)}{\alpha^{[i]}c_{pg}\left(T_{ev}^{[i]} - T_{cd}^{[i]}\right)} \tag{A2}$$

where h_{fg} is the latent heat at reference state pressure; c_{pg} is the gaseous refrigerant specific heat at a constant pressure; c_{pl} is the liquid refrigerant specific heat at constant pressure; and all of them are constants. The superscript i denotes the ith chiller.

The fusion algorithm is developed based on the assumptions: (i) the sum of the direct measurements is more reliable than that of the indirect measurements and (ii) the cooling load variations provided by the indirect measurements are more reliable than those provided by the direct measurements [8]. Define a moving window with a horizon of N samples, which stores two groups of data. Group 1 consists of N continuous direct measurements when outliers are discarded and Group 2 consists of the corresponding indirect measurements.

$$\text{Group 1}: Q_{dm,1}^{\kappa}, \ldots, Q_{dm,N-1}^{\kappa}, Q_{dm,k};$$
$$\text{Group 2}: Q_{im,1}^{\kappa}, \ldots, Q_{im,N-1}^{\kappa}, Q_{im,k}$$

Here the subscript κ indicates the data at the current time instant. The building cooling load fused measurement is constructed by

$$Q_{im,k} = \left(S_{dm,k} + A^t \Pi_{im,k}\right)/N \tag{A3}$$

where $A_t = [N-1,\ldots,1]$, $S_{dm,k}$ and $\Pi_{im,k}$ are defined as

$$S_{dm,k} = \sum_{i=1}^{N-1} Q_{dm,i}^{\kappa} + Q_{dm,k},$$
$$\Pi_{im,k} = \left[\Delta Q_{im,k}^{\kappa}, \Delta Q_{im,N-1}^{\kappa}, \ldots, \Delta Q_{im,2}^{\kappa}\right]$$

where $\Delta Q_{im,i+1}^{\kappa} = Q_{im,i+1}^{\kappa} - Q_{im,i}^{\kappa}$, $i = 1,\ldots,N-1$ with $Q_{im,N}^{\kappa} = Q_{im,k}$.

The current direct measurement is considered as an outlier if the Moffat distance $d_{\Delta k}$, defined by $d_{\Delta,k} = |\Delta Q_{dm,k} - \Delta Q_{im,k}|/\Lambda_{\Delta,k}$, is larger than unity, where $\Lambda_{\Delta,k}$ is the uncertainty associated with $\Delta Q_{dm,k}$, which can be derived according to the characteristics of the direct measurement noises. In this case, the direct/indirect measurements are not added into the moving window and the fused measurement is given by

$$Q_{f,k} = Q_{f,k-1} + \Delta Q_{im,k}, \quad \Delta Q_{im,k} = Q_{im,k} - \Delta Q_{im,k-1} \tag{A4}$$

The differences between the fused measurements and the indirect measurements actually indicate the model errors introduced by the chiller inverse model, described by (A2). A normal range can be obtained when the indirect measurements suffer only from measurement noises during commissioning. Assume the normal range is $[E_L, E_U]$. When the fused measurement is outside this range, a systematic error in the direct measurements is believed to occur. In this case, the fusion formulation is

$$Q_{f,k} = Q_{im,k-1} + E, \quad E = (E_L + E_U)/2 \tag{A5}$$

The confidence degree γ_f is used to indicate the quality of the fused measurement. The confidence degree is defined as

$$\gamma_{f,k} = \begin{cases} \beta_1 \gamma_{f,k-1}, & \text{fused by (A4)} \\ \beta_2 \gamma_{f,k-1}, & \text{fused by (A5)} \\ 1 - (1-\beta_1)\zeta_k, & \text{fused by (A3)} \end{cases} \tag{A6}$$

where the parameter ζ_k is defined as $\zeta_k = |\Delta S_{im,k} - \Delta S_{dm,k}|/[(N-1)\Lambda_{\Delta,k}]$, in which $\Delta S_{im,k} = \sum_{i=1}^{N-1} \Delta Q_{im,i+1}^{\kappa}$ and $\Delta S_{dm,k} = \sum_{i=1}^{N-1}(Q_{dm,i+1}^{\kappa} - Q_{dm,i}^{\kappa})$ with $Q_{dm,N}^{\kappa} = Q_{dm,k}$; and β_1, β_2 satisfy $0 < \beta_2 < \beta_1 < 1$.

Appendix B. Definition of Moffat distance [18]

Given two measurements x_1 and x_2 with their uncertainties u_1 and u_2. Assume the measurements are representative of the same measurand, and then the Moffat distance is defined as

$$d_M = \frac{x_1 - x_2}{\sqrt{u_1^2 + u_2^2}}$$

The two measurements are consistent if $|d_M| < 1$.

References

[1] Y.C. Chang, J.K. Lin, M.H. Chuang, Optimal chiller loading by genetic algorithm for reducing energy consumption. Energy and Buildings 37 (2005) 147–155.
[2] R.J. Hackner, J.W. Mitchell, W.A. Beckman, HVAC system dynamics and energy use in buildings-Part I. ASHRAE Transactions 90 (1984) 523–535.

[3] Honeywell, Engineering Manual of Automatic Control for Commercial Buildings. Honeywell SI Edition, Minneapolis, MN, 1997.
[4] S.W. Wang, J.B. Wang, Automatic sensor evaluation in BMS commissioning of building refrigeration systems. Automation in Construction 11 (2002) 59–73.
[5] J.M. Gordon, K.C. Ng, H.T. Chua, Cool Thermodynamics. Cambridge International Science Publishing, UK, 2000.
[6] G.L. Ding, L. Fu, Performance analysis and improvement of air-to-water chiller for application in wide ambient temperature range. Applied Thermal Engineering 25 (2005) 135–145.
[7] Y.J. Sun, S.W. Wang, G.S. Huang, Chiller sequencing control with enhanced robustness for energy efficient operation. Energy and Buildings 41 (2009) 1246–1255.
[8] G.S. Huang, S.W. Wang, Y.J. Sun, Enhancing the reliability of chiller control using fused measurement of building cooling load. HVAC&R Research 14 (2008) 941–958.
[9] S.W. Wang, F. Xiao, Sensor fault detection and diagnosis of air-handling units using a condition-based adaptive statistical method. HVAC&R Research 12 (2006) 127–150.
[10] M.C. Comstock, J.E. Braun, Development of Analysis Tools for the Evaluation of Fault Detection and Diagnostics in Chillers Report HL99-20. Purdue University, Ray W. Herrick Laboratories, West Lafayette, IN, USA, 1999.
[11] H. Peitsman, V.E. Bakker, Application of black-box models to HVAC systems for fault detection. ASHRAE Transactions 102 (1996) 628–640.
[12] A.L. Dexter, D. Ngo, Fault diagnosis in HVAC systems: a multi-step fuzzy model-based approach. HVAC&R Research 7 (2001) 83–102.
[13] X. Hao, G. Zhang, Y. Chen, Fault-tolerant control and data recovery in HVAC monitoring system. Energy and Buildings 37 (2005) 175–180.
[14] X. Jin, Z. Du, Fault tolerant control of outdoor air and AHU supply air temperature in VAV air conditioning systems using PCA method. Applied Thermal Engineering 26 (2006) 1226–1237.
[15] D. Ngo, A.L. Dexter, A robust model-based approach to diagnosing faults in air-handling units. ASHRAE Transactions 105 (1999) 1078–1086.
[16] S.W. Wang, J.B. Wang, Law-based sensor fault diagnosis and validation for building air-conditioning systems. HVAC&R Research 5 (1999) 353–380.
[17] M.A. Piette, S.K. Kinney, H. Philip, Analysis of an information monitoring and diagnostic system to improve building operation. Energy and Buildings 33 (2001) 783–791.
[18] M. Duta, M. Henry, The fusion of redundant SEVA measurements. IEEE Transactions on Control Systems Technology 13 (2005) 173–184.
[19] R.J. Moffat, Contributions to the theory of single sample uncertainty analysis. ASME Journal of Fluids Engineering 104 (1982) 250–260.
[20] S.W. Wang, X.H. Xu, Z.J. Ma, Energy Performance Evaluation and Development of Control Strategies for the Air-conditioning Systems of a New Building at Construction Stage. IEA ECBCS Annex 47, Trondheim, Norway, 2006.
[21] S.W. Wang, Y.M. Chen, Sensor validation and reconstruction for building central chilling systems based on principal component analysis. Energy Conversion and Management 45 (2004) 673–695.
[22] Trnsys, Trnsys 16 Documentation (2004).http://sel.me.wisc.edu/trnsys.
[23] S.W. Wang, J.B. Wang, J. Burnett, Mechanistic model of centrifugal chillers for HVAC system dynamics simulation. Building Service Engineering Research and Technology 21 (2000) 73–83.