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RESEARCH ARTICLE

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SPC and Kalman filter-based fault detection and diagnosis for an air-cooled chiller

Abstract Buildings worldwide account for nearly 40% of global energy consumption. The biggest energy consumer in buildings is the heating, ventilation and air conditioning (HVAC) systems. In HVAC systems, chillers account for a major portion of the energy consumption. Maintaining chillers in good conditions through early fault detection and diagnosis is thus a critical issue.

In this paper, the fault detection and diagnosis for an air-cooled chiller with air coming from outside in variable flow rates is studied. The problem is difficult since the air-cooled chiller is operating under major uncertainties including the cooling load, and the air temperature and flow rate. A potential method to overcome the difficulty caused by the uncertainties is to perform fault detection and diagnosis based on a gray-box model with parameters regarded as constants. The method is developed and verified by us in another paper for a water-cooled chiller with the uncertainty of cooling load. The verification used a Kalman filter to predict parameters of a gray-box model and statistical process control (SPC) for measuring and analyzing their variations for fault detection and diagnosis. The gray-box model in the method, however, requires that the air temperature and flow rate be nearly constant. By introducing two new parameters and deleting data points with low air flow rate, the requirement can be satisfied and the method can then be applicable for an air-cooled chiller. The simulation results show that the method with the revised model and some data points dropped improved the fault detection and diagnosis (FDD) performance greatly. It can detect both sudden and gradual air-cooled chiller capacity degradation and sensor faults as well as their recoveries.

Keywords air-cooled chiller, fault detection and diagnosis (FDD), statistical process control (SPC), Kalman filter

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1 Introduction

Buildings worldwide account for nearly 40% of global energy consumption and a significant share of greenhouse gas emissions [1]. The biggest energy consumer in buildings is the heating, ventilation and air conditioning (HVAC) systems. HVAC also ranks top in terms of number of complaints by building tenants, way above the second ranked elevators. In HVAC systems, chillers account for a major portion of energy consumption. Maintaining chillers in good conditions is thus a critical issue. Sudden faults and gradual degradation of chillers and their associated sensors, however, may result in high energy consumption and large number of complaints from building tenants. Although regular maintenance can and should be scheduled, it may not be able to detect faults soon enough. To improve performance through early fault detection and diagnosis (FDD) is thus of great value [2].

Two kinds of chillers are in common use. One is cooled by air and the other by water. In Refs. [3,4], the fault detection and diagnosis for water-cooled chillers is discussed with the difficult that they worked under uncertain cooling load. In this paper, the FDD for air-cooled chillers and the related sensors are studied, including both sudden faults and gradual degradations. In a typical HVAC system with air-cooled chillers depicted in Fig. 1, three heat exchange processes are

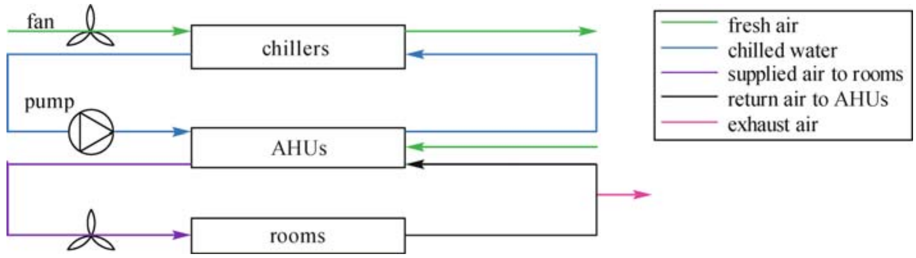

Fig. 1 Typical HVAC with air-cooled chillers

involved in taking extra heat out of rooms: 1) indoor air is cooled down by cooling air fed to rooms from air handling units (AHUs); 2) high temperature air returns from rooms to AHUs and is cooled down by chilled water supplied by chillers; 3) chilled water returns from AHUs to chillers, and extra heat in chilled water together with heat generated by chillers themselves is taken out of buildings by heat exchanging with outdoor air through refrigerant (e.g., Freon). The outdoor air is supplied to chillers through fans with varying speeds. FDD for an air-cooled chiller is difficult because the chiller is operating not only under uncertain cooling load as the water-cooled chiller did but also the uncertain air temperature and flow rate.

To overcome the difficulty caused by uncertainties, a potential method is to perform FDD based on a gray-box model with parameters that can be regarded as constants even under large uncertainties rather than based on a black-box model. That is because black-box models use only measured data to represent key characteristics of the air-cooled chiller, whereas gray-box models use physical knowledge in combination with measured data. Since parameters predicted by gray-box models tend to be more robust than those by black-box models, gray-box models have better potential for robust FDD, and can also provide insights and understanding of faults [5]. This method is developed and verified by us in another paper for a water-cooled chiller [3]. The verification was based on a simple and universal gray-box model that had parameters regarded as constants. It used a Kalman filter to predict the parameters and also their variance. These parameters were assumed to be constants so that statistical process control (SPC) could be used for measuring and analyzing their variations for fault detection and diagnosis. The method based on the gray-box model was tested by using the water-cooled chillers in a 420-m-high building, Jinmao Tower in Shanghai. The results showed that the method had good performance for detecting both sudden faults and gradual degradations. In Sect. 2, the method and the gray-box model are briefly introduced, together with some other methods in the literature.

The method can deal with the uncertainty of cooling load but not the uncertainties of the air temperature and flow rate which are specific for the air-cooled chiller. That is because the parameters in the gray-box model are required to be constants by the SPC and Kalman filter-based method. One of the parameters is a function of the air temperature and another parameter a function of the air flow rate. However, the air temperature and the air flow rate are both time varying. To satisfy the requirement for constant parameters so that the method can be applied, two different ways are carried out for the air temperature and the air flow rate in Sect. 3. The air temperature is separated out from the parameter by introducing another two new parameters. The two new parameters can be regarded as constants for FDD use. For the requirement on the air flow rate, we delete the data points with the fan not at the full speed since for most of the time the fan is at the full speed.

In Sect. 4, the method with the revised gray-box model and data pre-processing has been tested against a simulation model of air-cooled chiller in a building developed using the building simulation software — EnergyPlus (http://apps1.eere.energy.gov/buildings/energyplus). The results are good. It detects both sudden chiller capacity degradation and gradual sensor fault early enough; and also the recovery of faults. To see how much the FDD performance is improved by the model improvement and data pre-processing, respectively, the results with data pre-processing but using the original gray-box model and the results of using the revised method but not data pre-processing are presented. By comparing, it can be seen that both the model improvement and data pre-processing improved the FDD performance greatly.

2 Literature review

Various methods have been reported for chillers in the literature. Some of them are based on models, either black-box models [6–9] or gray-box ones [10], and others are not, e.g., using principal component analysis (PCA) [11,12]. However, most of FDD methods for air-cooled chillers are based on black-box models rather than gray-box models, which can provide insights and understanding of faults. The methods for air-cooled chillers are presented in Sect. 2.1. In Sect. 2.2, water-cooled chiller FDD methods, which are based on gray-box model and PCA and can be further extended for air-cooled chillers, are presented. In Sect. 2.3, an SPC and Kalman filter-based FDD method developed by us in another paper for a water-cooled chiller is presented. It was based on a gray-box model and had good FDD performance (It will be extended for an air-cooled chiller in Sect. 3).

2.1 FDD methods for an air-cooled chiller

Most of FDD methods for air-cooled chillers in the literature are based on black-box models. The general idea is to describe the correlations among input and output variables in air-cooled chillers by using black-box models. The black-box models can be used to predict the outputs based on measured inputs. Differences between measured outputs and predicted nominal model outputs are used as indicators for faults. The methods based on black-box models include multiple variable linear regression [6,7], artificial neural networks [8], gray forecasting [9], etc.

For example in Ref. [6], a black-box polynomial model fitted by linear regression based on training data was used to predict some temperatures of a chiller in a normal condition. These predicted temperatures were compared with measured ones to generate residuals. The means and standard deviations of residuals were used to perform fault detection by using a linear classifier. Based on patterns of directional temperature changes under several likely faults, another classifier was used to diagnose faults. Good FDD performance was reported in Refs. [7] and [13]. However, this method was sensitive to the order of polynomial and thresholds selected for classifiers. In addition, it required a large number of training data because of the large number of polynomial coefficients, e.g., 20 coefficients for a three-order polynomial in Ref. [7].

2.2 FDD methods for water-cooled chillers with capacity to be extended for air-cooled ones

The major difference between an air-cooled chiller and a water-cooled chiller is that the water-cooled chiller is cooled by water supplied from cooling towers rather than by air from outside as shown in Fig. 2. The water is cooled to a given set temperature by heat exchanging with outside air in cooling towers before supplied to chillers. In addition, the water is supplied to chillers by the pump with a constant speed. Therefore, FDD for the water-cooled chiller only needs to deal with the uncertainty of cooling load but not the uncertainties of the outside temperature and the air flow rate as for an air-cooled chiller.

Since most of the methods for air-cooled chillers are based on black-box models, we want to find if the water-cooled chiller FDD methods based on gray-box models or using PCA can be extended for air-cooled ones.

In Ref. [10], a mechanistic water-cooled chiller model was established and its parameters were estimated from measured data using least squares regression analysis. The model was used to predict outputs. Several chiller characteristic quantities (CQs), e.g., chiller coefficient of performance (COP), were derived as functions of model outputs for FDD purpose. Simulation results showed that CQs under faults deviated from their normal values. The method can be extended to air-cooled chillers since the refrigeration cycle is the same for both water-cooled chillers and air-cooled chillers. However, thresholds of deviations for fault detection were not easy to determine, especially when measurement noises and model inaccuracy were considered.

Unlike conventional model-based FDD methods using models to describe correlations between inputs and outputs, a PCA method considers correlations buried in data and uses pure mathematical data-driven model to derive some statistics. The statistics are then used to validate correlations for FDD. For example in Ref. [11], a strategy based on PCA was developed by using the Q statistic (i.e., squared prediction error (SPE)) to detect chiller sensor faults and by using the Q contribution plots. The PCA-based strategies were examined by using existing building chiller plant while various sensor faults were introduced. The method can be easily extended for an air-cooled chiller because the pure mathematical model is data-driven and does not care whether

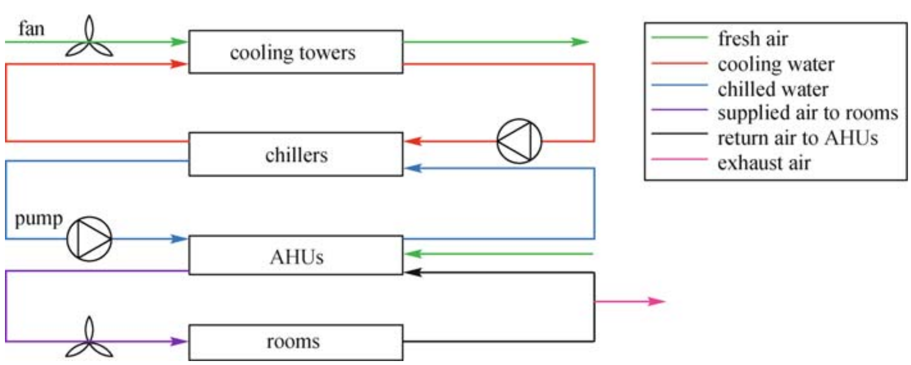

Fig. 2 Typical HVAC with water-cooled chillers

the data is from a water-cooled chiller or an air-cooled chiller. However, in view that PCA models generally do not have clear physical meanings, their abilities in fault isolation may be restricted.

2.3 SPC and Kalman filter-based method for a water-cooled chiller

In Refs. [3,4], we developed an FDD method which was data-driven and had good performance for water-cooled chillers. The method was based on gray-box models with insights and understanding of faults. It was a synergistic integration of proven techniques of 1) SPC for measuring and analyzing variations; and 2) Kalman filtering to provide predictions and to determine adaptive SPC thresholds.

A gray-box model was selected from literature where the state of the chiller was summarized by a few key model parameters. It is a simple and universal model developed by Gordon and Ng [14]:

$$\left(\frac{1}{\mathrm{COP}}+1\right)\frac{t_{\mathrm{chr}}}{t_{\mathrm{ci}}}-1=a_1\frac{t_{\mathrm{chr}}}{L_{\mathrm{ch}}}+a_2\frac{t_{\mathrm{ci}}-t_{\mathrm{chr}}}{t_{\mathrm{ci}}L_{\mathrm{ch}}}+a_3\left(\frac{1}{\mathrm{COP}}+1\right)\frac{L_{\mathrm{ch}}}{t_{\mathrm{ci}}}. \quad (1)$$

It has been proved to be accurate for a large number of chiller types and sizes [15]. In Eq. (1), a_1, a_2 and a_3 are three model parameters or state variables, with a_1 being the chiller internal entropy production rate; a_2 the heat losses (or gains) rate from (or into) the chiller; and a_3 the heat exchange thermal resistance. t_{chr} is return chilled water temperature from AHUs to the chiller and t_{ci} is the inlet water temperature from cooling towers to the chiller. COP is an indicator of the chiller's energy efficiency, and defined as the ratio of chiller cooling load L_{ch} divided by chiller electrical power P_{ch}. L_{ch} is calculated based on energy difference between return chilled water and supplied chilled water:

$$L_{\mathrm{ch}}=C_{\mathrm{w}}g_{\mathrm{wch}}\left(t_{\mathrm{chr}}-t_{\mathrm{chs}}\right), \quad (2)$$

where C_{w} is the water heat capacity, g_{wch} is the chilled water flow rate, and t_{chs} is the supplied chilled water temperature.

In Eq. (1), the three parameters are regarded to be constants under the uncertain cooling load and thus can be indicators of the chiller performance for FDD use. The state variables were then predicted and their standard deviations calculated by using Kalman filters. The standard deviations were used by SPC as adaptive thresholds around averaged state variable values over the past time period (e.g., 24 hours) for sudden fault detection. For gradual degradations, this idea was not work since gradual degradations could be buried within the adaptive averaging process. The idea was thus to perform SPC on state variables estimated by Kalman filters with fixed means and thresholds derived from manufacturer specifications or obtained from "good data" (collected when systems operated in good conditions). The method was tested against a simulation model of the famous Shanghai Jinmao Tower. The results showed that the method detected both sudden faults and gradual degradations and had good replicability and scalability. The method will be improved so that it can be extended for an air-cooled chiller in next section.

3 Gray-box model improvement and data pre-processing to satisfy FDD method

The gray-box model in Eq. (1) used for the FDD of water-cooled chillers [3] cannot be applied to an air-cooled chiller because of the time-varying air temperature and air flow rate. In Sect. 3.1, the gray-box model is improved so that the revised model is applicable for the time-varying air temperature. In Sect. 3.2, data points with variable air flow rates are pre-processed so that the revised model is applicable for the air-cooled chiller. With the revised gray-box model and data pre-processing, the SPC and Kalman filter-based FDD method for an air-cooled chiller is presented in Sect. 3.3.

3.1 Improvement of gray-box model

Based on model parameters of the gray-box models selected in Sect. 2, the idea of SPC and Kalman filter-based FDD method in Refs. [3,4] is to view these parameters as constant state variables, and estimate them by using a Kalman filter. If there is no fault, then the estimated state variables should not change rapidly. With a fault of the chiller or a related sensor, the estimated state variables may deviate from their normal values, causing the fault to be picked up by SPC [16]. Therefore, the three parameters in Eq. (1) should be regarded as constants for FDD use. However, a_2 is a function of the outside air temperature, which equals t_{ci}, as [14]

$$a_2=q_{\mathrm{leak,evap}}+\frac{q_{\mathrm{leak,comp}}t_{\mathrm{chr}}}{t_{\mathrm{ci}}-t_{\mathrm{chr}}}, \quad (3)$$

where $q_{\mathrm{leak,evap}}$ and $q_{\mathrm{leak,comp}}$ are the heat leaks from the evaporator and the compressor to the environment. The evaporator and the compressor are components in chillers. Since the outside temperature varies fast (high in the day and low at night), a_2 cannot be regarded as a constant. To make the gray-box model only consist of parameters that can be regarded as constants, a_2 is substituted into the model in Eq. (1) and $q_{\mathrm{leak,evap}}$ and $q_{\mathrm{leak,comp}}$ are defined as two new parameters. As a result, the outside air temperature t_{ci} is separated out from the parameter and the gray-box model consists of four parameters as

$$\left(\frac{1}{\mathrm{COP}}+1\right)\frac{t_{\mathrm{chr}}}{t_{\mathrm{ci}}}-1 = a_1\frac{t_{\mathrm{chr}}}{L_{\mathrm{ch}}}+a_2\frac{t_{\mathrm{ci}}-t_{\mathrm{chr}}}{t_{\mathrm{ci}}L_{\mathrm{ch}}}+a_3\frac{t_{\mathrm{chr}}}{t_{\mathrm{ci}}L_{\mathrm{ch}}} + a_4\left(\frac{1}{\mathrm{COP}}+1\right)\frac{L_{\mathrm{ch}}}{t_{\mathrm{ci}}}, \tag{4}$$

where a_1 is the chiller internal entropy production rate; a_2 is $q_{\mathrm{leak,evap}}$; a_3 is $q_{\mathrm{leak,comp}}$ and a_4 is the heat exchange thermal resistance.

3.2 Data pre-processing to satisfy FDD method

The revised model in Eq. (4) also requires the air flow rate g_{a} to be constant, since a_4, the heat exchange thermal resistance, is a function of g_{a} as

$$a_4 = R = \frac{1}{g_{\mathrm{a}}\left(CE\right)_{\mathrm{cond}}}+\frac{1}{g_{\mathrm{wch}}\left(CE\right)_{\mathrm{evap}}}, \tag{5}$$

where C is the specific heat, E is the heat exchange effectiveness, and the subscripts "evap" and "cond" represent evaporator and condenser, respectively. The air-cooled chiller studied in this paper, however, has variable fan speeds and thus variable air flow rates. Fortunately, the fan is at high speed for most of the time. Therefore, data points with the fan not at the high speed are dropped and then the remaining data points all have the same air flow rate for FDD use.

3.3 FDD method for an air-cooled chiller with revised gray-box model and data pre-processing

With four model parameters a_1, a_2, a_3, and a_4 viewed as four slow changing variables (they are not viewed as constants because they might be affected by cooling load, etc. [3,4]) contained in the state variable x and the left hand side of Eq. (4) as the measurement, the state at time k, x_k, is governed by the following linear system dynamics:

$$x_{k+1}-\bar{x}_{k+1}=x_k-\bar{x}_k+w_k, \tag{6}$$

where $\bar{x}_k$ is the mean of the estimated state $\hat{x}$ over the past several (e.g., 24) hours, and w_k is the process noise at time k. The means $\bar{x}_{k+1}$ and $\bar{x}_k$ in Eq. (6) are to account for slow varying patterns so as to have an accurate estimation of the covariance matrix of process noise w_k. The measurement at time k, z_k, is a linear function of x_k, i.e.,

$$z_k = H_k x_k + v_k, \tag{7}$$

with

$$H_k=\left[\frac{t_{\mathrm{chr},k}}{L_{\mathrm{ch},k}},\frac{t_{\mathrm{ci}}-t_{\mathrm{chr}}}{t_{\mathrm{ci}}L_{\mathrm{ch}}},\frac{t_{\mathrm{chr}}}{t_{\mathrm{ci}}L_{\mathrm{ch}}},\left(\frac{1}{\mathrm{COP}_k}+1\right)\frac{L_{\mathrm{ch},k}}{t_{\mathrm{ci},k}}\right],$$

where v_k is the measurement noise. The random variables w_k and v_k are assumed to be independent, white, zero mean and Gaussian. The matrix Q_{k-1} at time k–1 is calculated as the covariance of the estimated process noises $\hat{w}_j$, $j=k-1-l,\ldots,k-2$, over the past l (e.g., 240) hours. Upon initialization before the above l estimated process noises become available, Q_k is estimated based on experience. The matrix R_k is determined by using Monte Carlo simulation of the measurement (the left hand side of Eq. (1)) considering variance of sensor noises [3,4].

The estimated state $\hat{x}_{k+1}$ and its covariance matrix P_{k+1} at time k+1 are obtained by using the Kalman filter [17] based on state equation (6) and observation equation (7). The roots of diagonal elements of P_{k+1} are the standard deviations of model parameters.

For an air-cooled chiller fault, e.g., several sudden chiller capacity drops during July 31st to August 20th to be presented in Sect. 4, the FDD method with the revised gray-box model and data pre-process is applied. Since the fault can be viewed as a sudden fault and the state variables depend on the uncertain cooling loads, SPC control limits are not static but are dynamically adjusted based on state variables' standard deviations obtained dynamically by the Kalman filter.

The SPC control limits are calculated in the following way. The mean value of a model parameter over the past several hours (e.g., 24 hours) is used as the normal value of the parameter. The one- and two-sigma ranges are used as thresholds. Taking a_1 for a chiller as an example, it is defined as

$$\left[\mu_{1,k}-\sigma_{1,k},\mu_{1,k}+\sigma_{1,k}\right], \tag{8}$$

where $\mu_{1,k}$ is the mean of a_1 at time k, and $\sigma_{1,k}$ is the standard deviation of a_1 at time k. The two-sigma range is similarly defined.

One SPC rule used is that a fault is detected if n back-to-back points of a parameter fell outside the two-sigma range. The number of points, n, should be set to a value so that a fault is detected with a confidence level, e.g., 99.99%. That is when there is no fault, the possibility of n back-to-back points outside two-sigma range should be less than $1-99.99\%$. Therefore, to find the minimal n is equivalent to solve the problem:

$$\arg\min\{n\,|P\left(|a_{i,k}-\mu_{i,k}|>2\sigma_{i,k},\ldots, |a_{i,k+n-1}-\mu_{i,k+n-1}|>2\sigma_{i,k+n-1}\right)<1-99.99\%\}, \quad i=1,2,3,4, \tag{9}$$

where $a_{i,k}$ is a_i at time k, $\mu_{i,k}$ is the average value of a_i over the past j time steps as

$$\mu_{i,k}=\frac{1}{j}\sum_{l=k-j+1}^{k}a_{i,l}, \tag{10}$$

and the averaged standard deviation $\sigma_{i,k}$ at time k is averaged in the same way.

With the approximate assumption that $a_{i,k}, \dots, a_{i,k+n-1}$, $i = 1, 2, 3, 4$, are independent and Gaussian, the solution to Eq. (9) is $n = 3$. Therefore, a fault is detected if three back-to-back points of a parameter fall outside the two-sigma range.

Other SPC rules, e.g., m back-to-back points falling outside one-sigma range, can also be obtained in the same way. In the case study in next section, the SPC rule with three back-to-back points falling outside two-sigma range is used for FDD, i.e., a fault is detected if an estimated parameter is outside its two-sigma range for three back-to-back points.

In the above method, the means in Eq. (10) and also the standard deviations are adaptive and can be used for sudden fault. However, for a gradual fault, the thresholds in Eq. (8) are derived from fixed means and standard deviations which are obtained from good data when the chiller operates in good conditions. This, together with the FDD for a gradual sensor fault, will be represented in Sect. 4.

Note that after some data points are dropped to satisfy the method in the last subsection, the remaining data points are connected together. Therefore, the states at time k and $k+1$ in Eq. (6) might not be corresponding to two back-to-back data points. In addition, if the mean value of a model parameter is over the past 24 hours, then j in Eq. (10) is the number of the remaining data points in the past 24 hours.

4 Fault detection and diagnosis for an air-cooled chiller: A case study

In this section, the method with the improved gray-box model and data pre-processing is tested against a simulation model of an air-cooled chiller in a building developed in EnergyPlus (http://apps1.eere.energy.gov/buildings/energyplus). Two scenarios of chiller faults are then presented: 1) the chiller capacity drop in Sect. 4.1 and 2) the gradual sensor degradation in Sect. 4.2. Three criteria are used to evaluate the performance of our method when appropriate: 1) detection of faults and recovery, 2) delayed time for detection, and 3) number of false alarms. It will be demonstrated that the method can detect both chiller fault and sensor fault; both sudden faults and gradual degradations; and the recovery of faults. To see how much the FDD performance is improved by the revised model and data pre-processing, respectively, the results with data pre-processing but using the original gray-box model and the results of using the revised method but not data pre-processing are also presented in Sect. 4.2. By comparison, we can see that both the model improvement and data pre-processing improved the FDD performance greatly.

4.1 Chiller capacity reduction

The fault of chiller capacity reduction presented in Sect. 3.2 was generated in EnergyPlus by reducing chiller capacity as shown in Table 1. The fault is recovered on August 21st. During the detection process, we did not know what kind of the faults was or when it started and recovered in advance. The only thing we knew was that the fault was seeded between July and September.

Table 1 Fault of chiller capacity reduction

date	chiller capacity
July 31st to August 5th	80% of the full capacity
August 6th to August 10th	60% of the full capacity
August 11th to August 15th	40% of the full capacity
August 16th to August 20th	20% of the full capacity

In the chiller gray-box model in Eq. (4), the return chilled water temperature from AHUs to the chiller t_{chr}, the inlet air temperature from outside to the chiller t_{ci}, chiller electrical power P_{ch} were all measured from sensors for every 15 minutes. The chiller cooling load L_{ch} cannot be measured but can be calculated in Eq. (2), and therefore the chilled water flow rate g_{wch} and the supplied chilled water temperature t_{chs} were also measured. As presented in Sect. 3.2, data points with the fan not at high speed are taken out to satisfy the FDD method. As shown in Fig. 3, the fan was at the full speed for most of the time and data points dropped were almost at night or during weekends when cooling load is low.

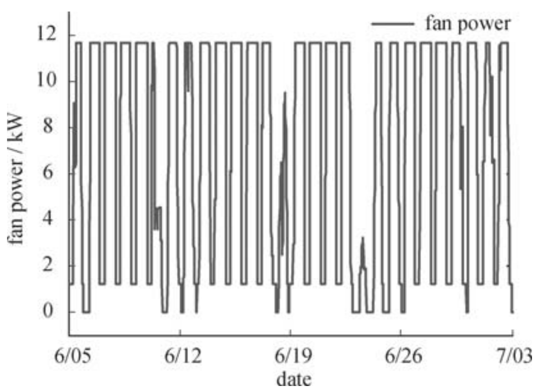

Fig. 3 Fan power. The higher the fan power is, the higher the fan speed is

Since we did not know whether it was a sudden fault or a gradual one, the FDD method with adaptive means and standard deviations was first applied to the air-cooled chiller and then the method with fixed ones was applied. For the first method, the adaptive means and standard deviations are averaged over the last 24 hours to obtain the thresholds.

The results of a_1, a_2, a_3 and a_4 are presented in Figs. 4–7, respectively. By using the SPC rule in Sect. 3.1, i.e., three back-to-back points (with no intermediate points dropped) outside two-sigma ranges, the time of detection of the fault was presented in Table 2. It can be seen that all the four parameters detected the fault early enough — in the morning on August 1st, only one day after the fault started on July 31st. From the column of a_4, we can see that the four reductions were all detected on August 1st, August 6th, August 11th, and August 16th, respectively. For a_1, a_2, and a_3, we cannot see the four reductions clearly since the fault was detected nearly every day from August 1st to August 21st. The reason might be that these three parameters could not converge easily within five days for which each reduction lasted.

The only two false alarms happened on July 19th and July 20th as shown in the first two rows in the column of a_4. By checking the outside temperature, it is found that the inlet air temperature to condenser t_{ci}, equal to outside temperature, reached its highest degree on July 19th.

Although no fault was detected after 17:30 on August 21st, we cannot say the fault was recovered. That is because if a fault happened and never recovered, the parameters and their means might converge to new values after a period of time and the parameters would no longer fall outside two-sigma ranges, either. For example, we can see from Fig. 7 that the fault was detected on August 11th by a_4, but in the following four days a_4 and its means converged since chiller capacity kept at 40% of full capacity.

By using the FDD method with fixed means and standard deviations obtained from the good data from July 19th to July 25th, the fault is detected by a_1, a_2, and a_3 at 8:15 on August 1st and a_4 at 13:15 on August 1st as shown in Figs. 8–11.

All the four parameters detected the recovery while no recovery is detected in the method with adaptive

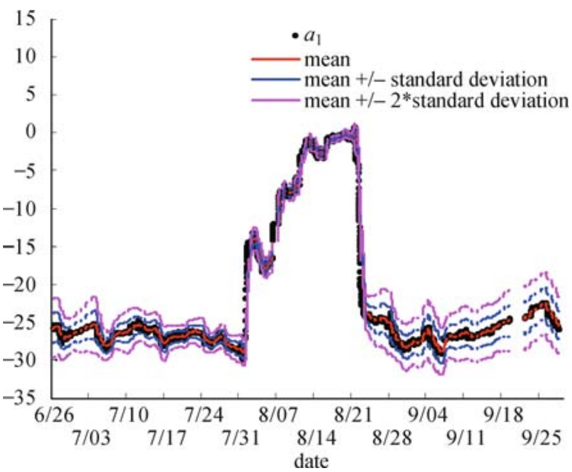

Fig. 4 Fault was detected by a_1 with means and standard deviations averaged over the past 24 hours after it fell outside two-sigma range for three back-to-back points

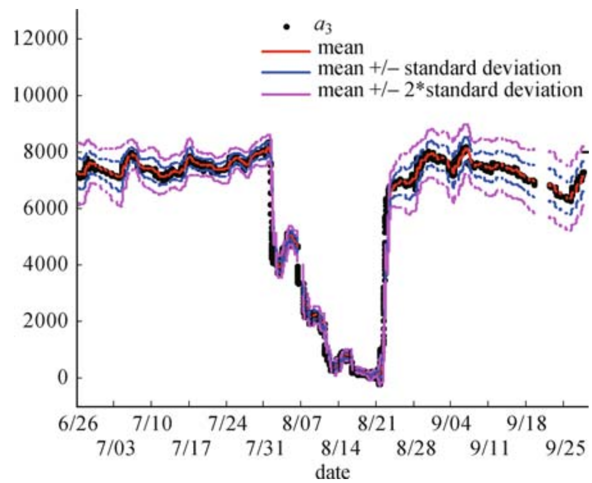

Fig. 6 Fault was detected by a_3 with means and standard deviations averaged over the past 24 hours after it fell outside two-sigma range for three back-to-back points

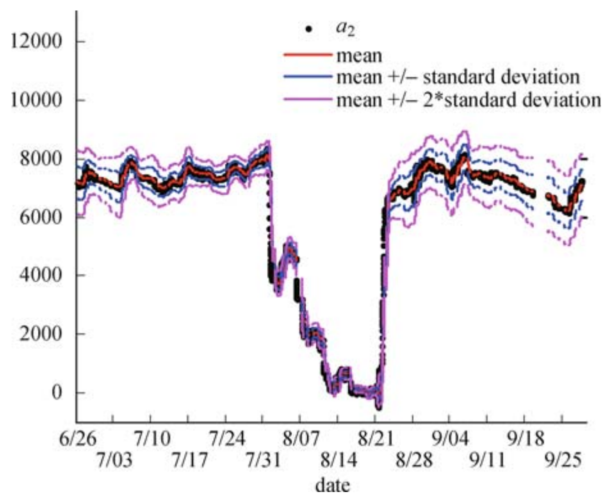

Fig. 5 Fault was detected by a_2 with means and standard deviations averaged over the past 24 hours after it fell outside two-sigma range for three back-to-back points

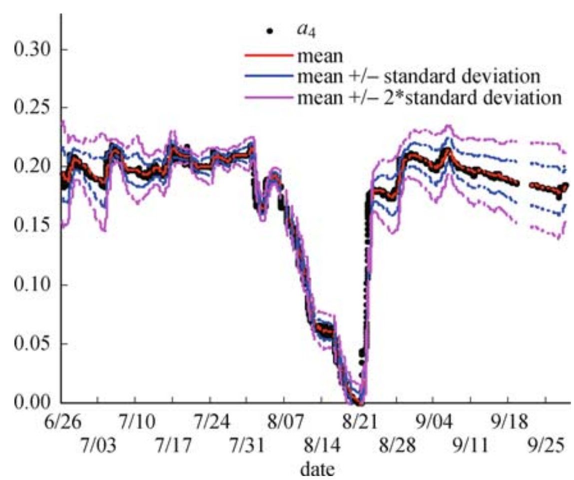

Fig. 7 Fault was detected by a_4 with means and standard deviations averaged over the past 24 hours after it fell outside two-sigma range for three back-to-back points

Table 2 Time when fault was detected by the four parameters

a_1		a_2		a_3		a_4	
8/01	**06:45**	8/01	06:45	8/01	06:45	7/19	14:30
8/03	**10:45**	8/03	10:45	8/03	10:45	7/20	08:15
8/04	**07:45**	8/04	06:45	8/04	07:30	8/01	07:45
8/04	**11:15**	8/04	07:45	8/04	11:15	8/03	10:45
8/05	**07:30**	8/05	07:45	8/05	07:45	8/06	07:45
8/06	**07:30**	8/06	07:45	8/06	07:45	8/11	08:45
8/10	**13:45**	8/10	15:45	8/10	14:45	8/11	19:30
8/10	**15:45**	8/11	07:30	8/10	15:45	8/16	13:00
8/11	**07:30**	8/13	13:15	8/11	07:30	8/16	15:45
8/13	**13:00**	8/14	08:30	8/13	13:00	8/21	08:45
8/14	**08:30**	8/14	13:45	8/14	08:30	8/21	13:45
8/14	**13:30**	8/14	15:00	8/14	13:45		
8/14	**17:00**	8/16	08:30	8/14	17:00		
8/16	**08:30**	8/19	08:45	8/16	08:30		
8/19	**08:30**	8/20	07:00	8/19	08:00		
8/20	**07:00**	8/20	20:45	8/20	07:00		
8/20	**20:30**	8/21	13:00	8/20	20:30		
8/21	**13:30**	8/21	16:00	8/21	13:30		
8/21	**17:30**	8/21	17:30	8/21	17:30		

thresholds. That was because with the fixed means and thresholds obtained from good data, parameters fell inside two-sigma ranges if and only if there was no fault. However we can also see that there is a false alarm for all the four parameters at the end of September. That might be because fixed means and standard deviations were season-dependent and good data should be chosen for each season. Another disadvantage of the method with fixed thresholds was that we could only detect the fault but could not differentiate the four reductions. That was because for the fixed thresholds a fault could be differentiated from another only when the second fault happened after the recovery of the first one.

To see how much the FDD performance is improved by the revised model and data pre-processing, respectively, the results with data pre-processing but using the original gray-box model and the results of using the revised method but not data pre-processing are also presented. By using the method with data pre-processing but using the original gray-box model to detect chiller capacity

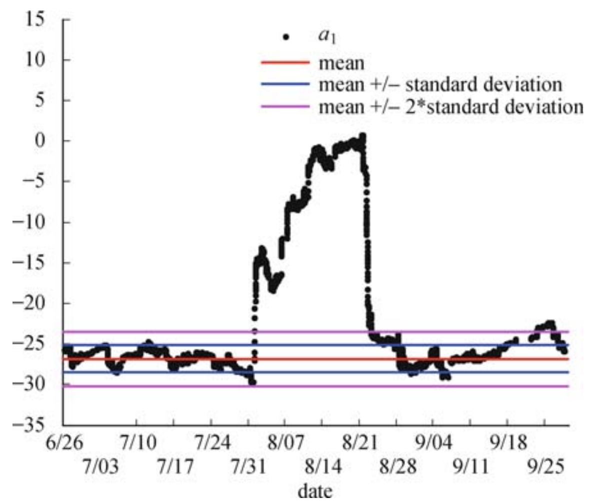

Fig. 8 Fault was detected by a_1 with fixed means and standard deviations

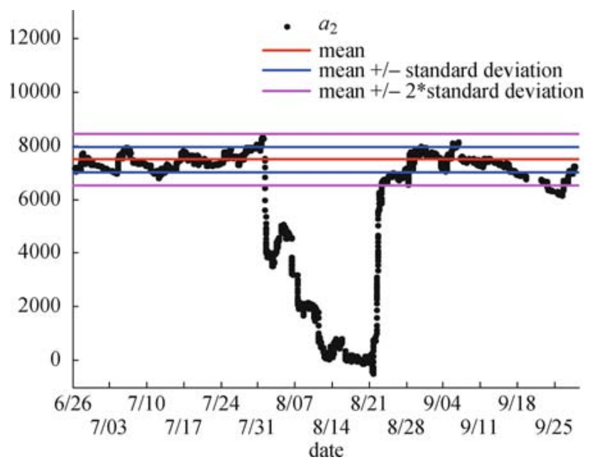

Fig. 9 Fault was detected by a_2 with fixed means and standard deviations

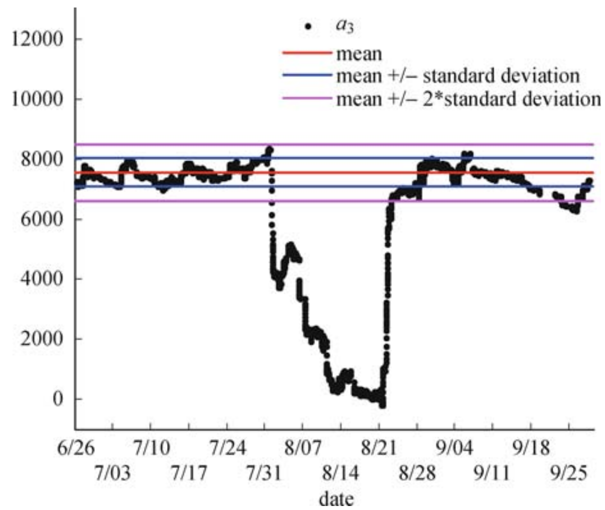

Fig. 10 Fault was detected by a_3 with fixed means and standard deviations

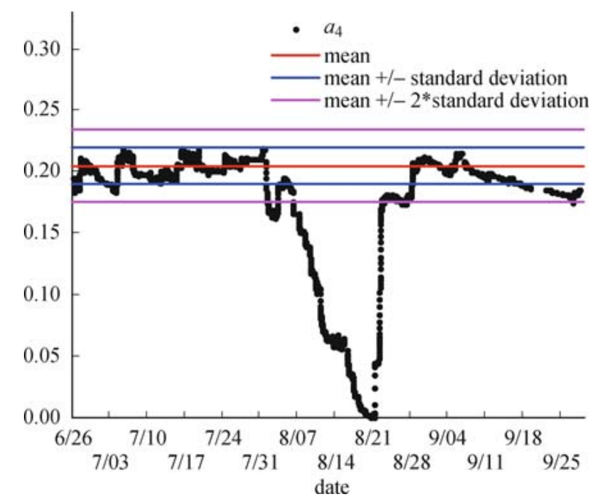

Fig. 11 Fault was detected by a_4 with fixed means and standard deviations

reduction, the plots of three parameters are shown in Figs. 12–14. In the three figures, the three parameters were all averaged over the past seven days; otherwise they would change so fast that they fell outside two-sigma ranges for most of the time. We can see that no fault was detected by a_1 or a_2, and a lot of false alarms by a_3. Furthermore, by comparing a_3 and the outside temperature which also averaged over the past seven days in Fig. 15, we can find that they almost had the same pattern. That means a_3 depended heavily on the outside air temperature, i.e., the inlet air temperature t_{ci}. It is a_3 but not a_2 that is heavily affected by the outside air temperature. That might be because a_1 and a_2 are correlated with a_3 in Eq. (1).

The fault was not detected and many false alarms happened if we did not revise the method. However, in the method with the revised model and data pre-processing, the fault was detected only one day after the fault happened. Therefore, we can say that the revised model greatly improved the FDD performance.

If the revised gray-box model was used but data points with the fan not at full speed were not dropped, the results for detecting the chiller capacity reduction fault are plotted in Figs. 16–19. Although the revised model was used, it can be seen that there were false alarms all the time. The reason is that a_4 is a function of the air flow rate and cannot converge if the flow rate is varying fast (high in the day and low at night). a_1, a_2, and a_3 also had many false alarms because they are correlated with a_4 in Eq. (4). Therefore we can say that the dropping of data points with the fan not at full speed is necessary and can improve the FDD performance greatly.

4.2 Gradual sensor fault

The sensor fault simulated here is the supplied chilled water temperature t_{chs} deviates from its true value gradually. From July 3rd, it takes two weeks to be 0.5 degree higher than its true value, i.e., it deviates about 0.0004 degree for every 15 minutes. The fault was generated by adding deviations to the temperature obtained from EnergyPlus under normal conditions.

In the FDD process, we had no idea it was a sudden or gradual fault, or when it started and recovered, so we performed FDD using both of the two methods — one with adaptive thresholds and the other with fixed

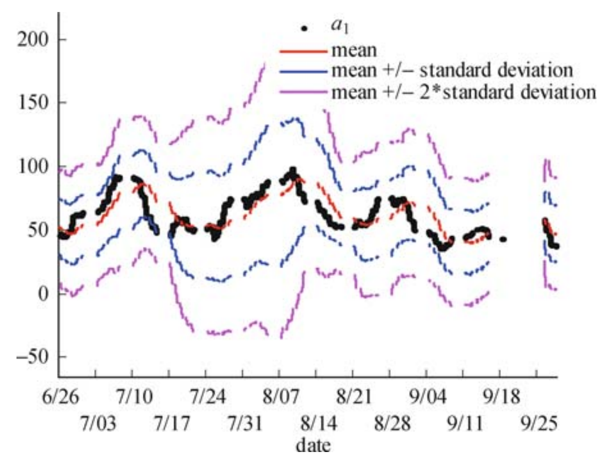

Fig. 12 No fault was detected by a_1

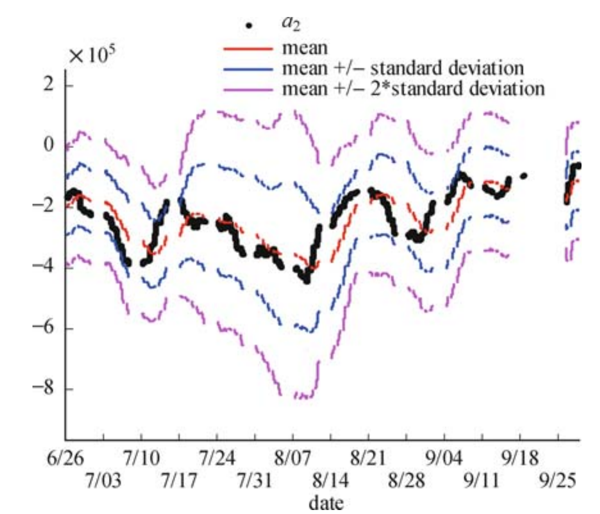

Fig. 13 No fault was detected by a_2

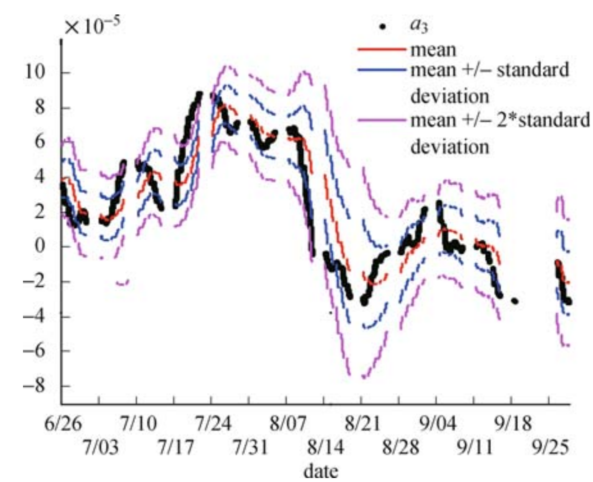

Fig. 14 A lot of false alarms were detected by a_3

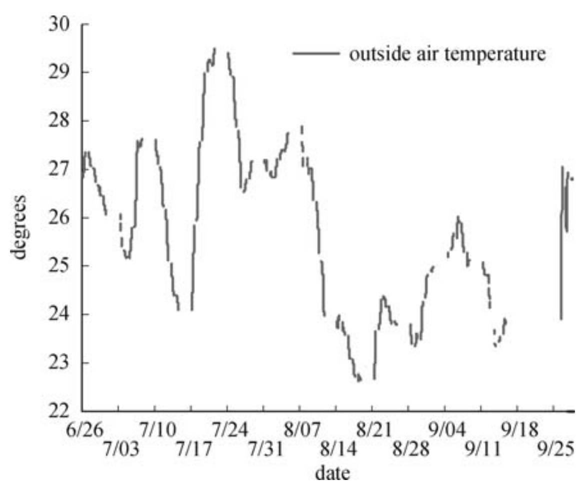

Fig. 15 Outside air temperature

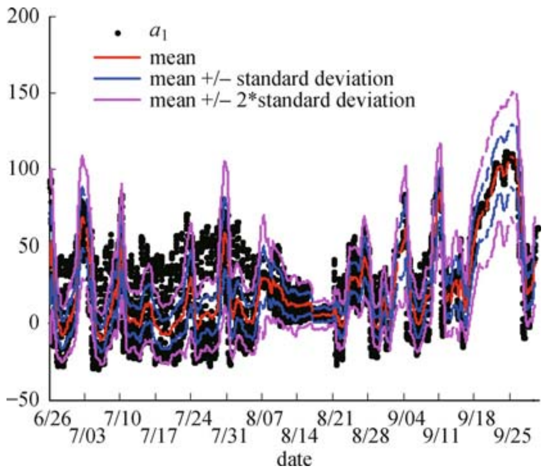

Fig. 16 A lot of false alarms detected by a_1 when the data points with the fan not at full speed were not dropped, although revised model was used

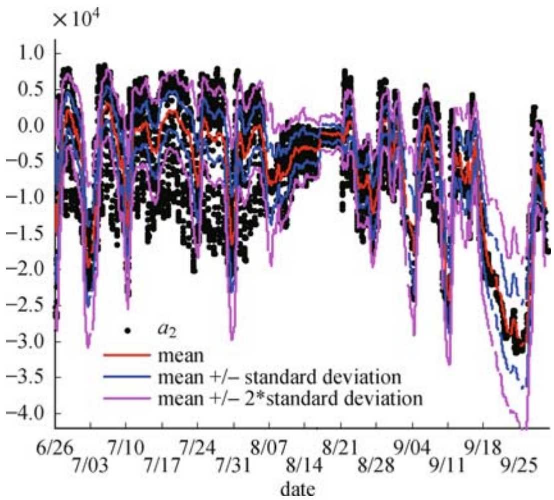

Fig. 17 A lot of false alarms detected by a_2 when the data points with the fan not at full speed were not dropped, although revised model was used

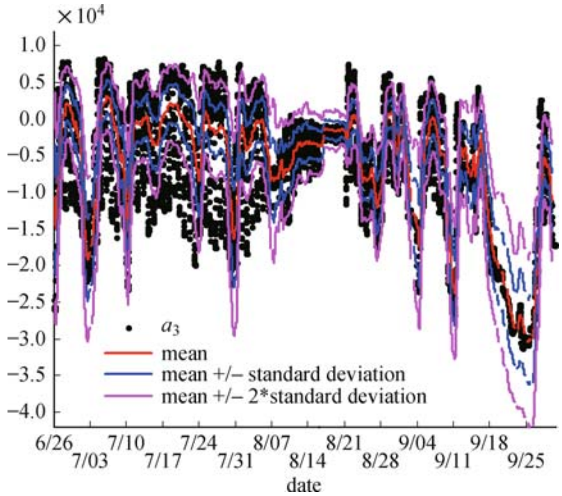

Fig. 18 A lot of false alarms detected by a_3 when the data points with the fan not at full speed were not dropped, although revised model was used

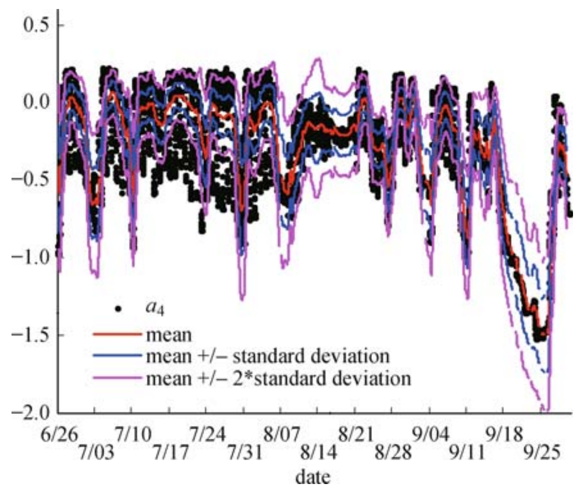

Fig. 19 A lot of false alarms detected by a_4 when the data points with the fan not at full speed were not dropped, although revised model was used

thresholds. Only the results using the method with fixed thresholds are plotted in Figs. 20–23 after we found that it was a gradual fault. It can be seen that the four parameters deviated from their normal values (the red lines) gradually. The fault was detected by all the four parameters early enough — only four days after it started. It can also been seen from the four figures that the fault recovered suddenly on July 18th.

5 Conclusion

In this paper, the FDD for an air-cooled chiller with air coming from outside in variable flow rates is studied. The problem is difficult since the air-cooled chiller is operating under major uncertainties including the cooling load, and the air temperature and flow rate. Our idea to overcome the difficulty is to perform FDD based on a gray-box model with parameters regarded as constants. It is verified by an SPC and Kalman filter-based method developed by us in another paper for water-cooled chillers. We revise the gray-box model and pre-process the data points so that the method is applicable for the air-cooled chiller. The method has been tested against a simulation model of a building with good results. It detects both chiller faults and sensor faults; both sudden faults and gradual faults; and also the recovery of faults. Our contribution is that we developed an FDD method for air-cooled chillers based on a gray-box model and it is robust and easy for online implementation.

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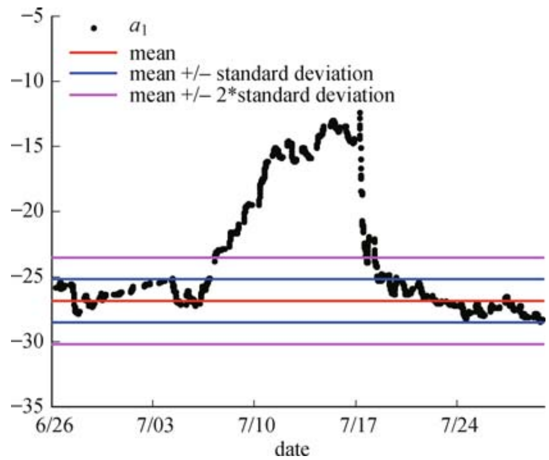

Fig. 20 Gradual sensor fault and its recovery were detected by a_1

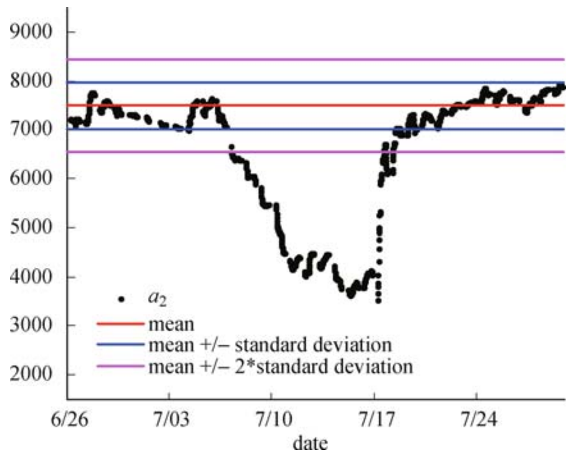

Fig. 21 Gradual sensor fault and its recovery were detected by a_2

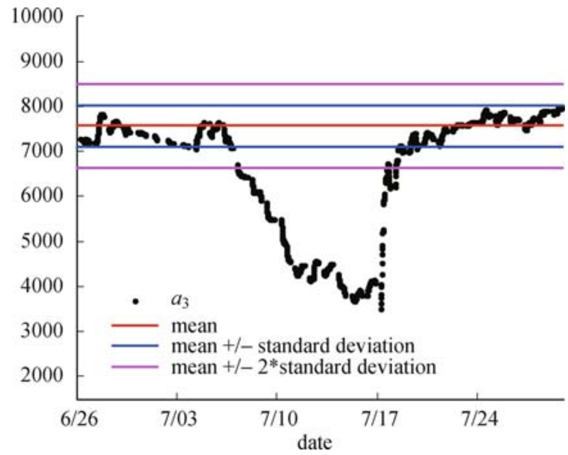

Fig. 22 Gradual sensor fault and its recovery were detected by a_3

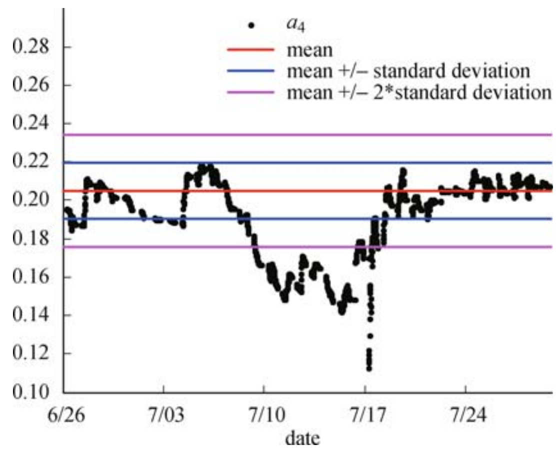

Fig. 23 Gradual sensor fault and its recovery were detected by a_4

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