Improving the Performance of PCA-Based Chiller Sensor Fault Detection by Sensitivity Analysis for the Training Data Set

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ABSTRACT

An improved approach of fault detection for chiller sensors is presented based on the sensitivity analysis for the original data set used to train the Principal Component Analysis (PCA) model. Sensor faults are inevitable due to the aging, environment, location and so on. Meanwhile, because of the wide range of operational conditions, the fault of a certain sensor is very difficult to be directly detected by its own historical data. PCA is a multivariate data-based statistical analysis method and it is very useful for the sensor fault detection in HVAC&R. The undetectable zone of a certain sensor by *Q*-statistic is derived from the definition of *Q*-statistic which is usually employed as a boundary to detect the sensor fault situation. Due to the similar style between *Q*-statistic and Hawkins' T_H^2, the undetectable zone by Hawkins' T_H^2 is also obtained. Undetectable zone is a predictive index to indicate the detectability of different sensors by different statistics. Since undetectable zone is the character of the original training data set, it can indicate the quality for the selected training data. One field data set is employed to validate the presented approach. Results show that the undetectable zone of a certain sensor by *Q*-statistic is quite different from that by Hawkins' T_H^2. Therefore, the undetectable zone can be used to improving the performance of PCA-based chiller sensor fault detection by choosing different fault detection statistics with less undetectable zone for different sensor.

1. INTRODUCTION

Due to long term operation and severely working environment, sensor faults are inevitable in HVAC&R. There are much disadvantage because of sensor fault, including ineffective control, unsafe operation, unreasonable energy consumption and so on (Lee and Yik, 2010; Yoon et al., 2011). For energy saving and conservation, researches on sensor fault detection, diagnosis and erroneous sensor data reconstruction (FDDR) for HVAC&R system have been paid more attention to in the last decade.

Usually, the model-based methods and the data-driven methods are the two typical classes of FDDR methods. Any faulty sensor cannot be easily identified just only from the historical data of its own. Thus, various multi-dimensional data-based methods have been introduced to the FDDR of HVAC&R system in the recent years, such as fuzzy inference systems(Kocyigit, 2015), data fusion(Sun et al., 2010), neural network(Du et al., 2014; Lee et al., 2004), support vector machine(Han et al., 2011), principal component analysis(Li et al., 2016), fisher discriminant analysis(Du et al., 2007), Bayesian network(Zhao et al., 2015), etc.

Recent years, principal component analysis (PCA) (Härdle and Simar, 2007; Jackson, 1991), a multivariate statistical analysis method, was presented in the sensor FDDR, including the whole system(Wang et al., 2010), AHU(Li and Wen, 2014; Xiao et al., 2009), VAV(Du et al., 2009), chiller(Chen and Lan, 2009; Hu et al., 2016; Xu et al., 2008) and so on. By the different assignment of sensors or the combination with other algorithms, PCA-based approaches were successfully applied into sensor FDDR for chiller.

Many researchers were dedicated in applying novel data-driven methods into the sensor FDDR of HVAC&R system. For any data-driven method, the analysis results highly depend on the character of the training data set. Because the fielded data relies on sampling interval, sampling location, measurement principles, and so on, the quality of training data is much worse. However, rare work was reported on how to predict the quality of the training data so as to enhance the FDDR results in detail. In this paper, the undetectable zone for each sensor assigned in PCA model is presented to evaluate the detectability for chiller sensor fault. It is derived from the training data and the definition of statistics employed as fault detection boundary. The undetectable zone for each sensor can be used to evaluate the fault detection ability and reliability with clear physical or thermodynamic meanings. A fielded data set of a real screw chiller was employed to validate the detectability of different statistics in detail.

2. PCA-BASED SENSOR FDDR

2.1 PCA-based sensor FDDR

In PCA method, the original data matrix $X^0 \in R^{m\times n}$ usually consists of *m* samples (rows) and *n* process variables (columns) obtained from the field measurements. The training data $X^0 \in \Re^{m\times n}$, which is consisted of the original measured data, is transferred to a normalized matrix $X=\{\vec{x}_1^T,\cdots,\vec{x}_m^T\}^T$ with zero mean and unit variance due to engineering units and orders of magnitude. After the eigenvalue decomposition of the covariance matrix, $R \approx X^T X/(n-1)$, any normalized samples $\vec{x}$ can be expressed as

$$\vec{x} = \hat{\vec{x}} + \tilde{\vec{x}} \tag{1}$$

where $\hat{\vec{x}}$, the estimation of $\vec{x}$, is the projection vector of $\vec{x}$ onto the PC subspace, and $\tilde{\vec{x}}$, the residual of $\vec{x}$, is the projection vectors of $\vec{x}$ onto the Residual subspace.

A common FDDR strategy for sensor fault based on PCA is illustrated as Figure 1. Its detailed structure can be referred in reference (Hu et al., 2012). It needs to emphasize that the original operational data used to train PCA model is included with many outliers inevitably due to measurement errors, hardware failure and so on. The aim of PCA modeling is to establish a fault boundary to detect whether there is a faulty sensor in system or not.

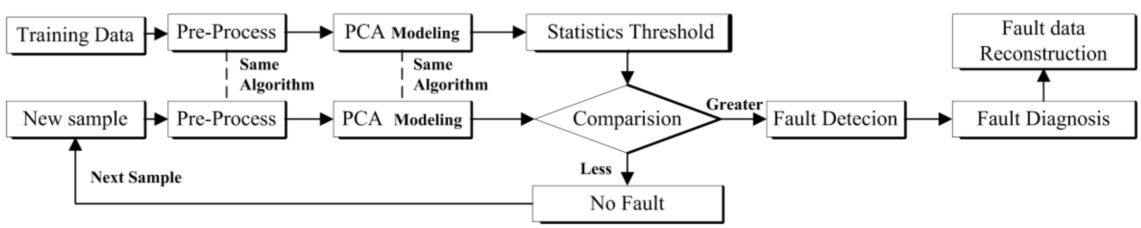


Figure 1: A common FDDR strategy for sensor fault based on PCA

Several statistics can be employed as the boundary to detect sensor fault, such as *Q*, Hawkins' T_H^2 and so on. When the value of statistics for the tested sample is greater than the boundary, the fault can be detected successfully. Therefore, the below equations mean the sensor fault cannot be detected.

$$Q \le Q_\alpha \tag{2}$$

$$T_H^2 \le \chi^2_{n-k;\alpha} \tag{3}$$

Where, Q_α is the threshold of *Q* statistic and $\chi^2_{n-k;\alpha}$ is the threshold of Hawkins' T_H^2.

2.2 Undetectable Zone by *Q*-statistic

If there is a faulty sensor, the measurement data of this sensor make the value of some statistic is greater than the threshold. Assuming the certain faulty sensor is the *i*th sensor, there must be a pair of limited upside and downside of *i*th sensor measurement data, which can just satisfy the Equation (1) or Equation (2). When the measurement data of the *i*th sensor is outside the pair of limitations, the fault can be detected. From the threshold and the other sensors measurement data, we derived the calculation of the limitations for the *i*th sensor not to be detected. Obviously, the pair of limitations is a predictive zone to demonstrate the fault detectability for the *i*th sensor.

Assuming the *j*th sensor is the faulty one, x_j, the *j*th entry of $\vec{x}$, is the erroneous measurement value. e_i, the *i*th entry of $\tilde{\vec{x}}$, can be rewritten as

$$e_i = y_{ij}^{RS} x_j + \sum_{k=1}^{j-1} y_{ik}^{RS} x_k + \sum_{k=j+1}^{n} y_{ik}^{RS} x_k = y_{ij}^{RS} x_j + Y_{i,:}^{RS} \Xi_j \vec{x} \tag{4}$$

Where, y_{ij}^{RS} is the *j*th entry of the *i*th row of Y^{RS}. $\boldsymbol{Y^{RS}}$ is the projection matrix of RS. Ξ_j is used to indicate the direction of the erroneous senor and be written as

$$\Xi_j = \begin{pmatrix} 1 & & 0 \\ & 0 & \\ 0 & & 1 \end{pmatrix}_{1,\cdots,j-1 \quad j \quad j+1,\cdots,n} \tag{5}$$

Therefore, *Q*-statistic can be derived as

$$Q = \left(\sum_{i=1}^{n} (y_{ij}^{RS})^2 \right) x_j^2 + (\sum_{i=1}^{n} 2 y_{ij}^{RS} (Y_{i,:}^{RS} \Xi_j \vec{x})) x_j + \sum_{i=1}^{n} (Y_{i,:}^{RS} \Xi_j \vec{x})^2 \tag{6}$$

Due to the *j*th sensor is faulty one, its *Q*-statistic will satisfy the following equation (7)

$$\left(\sum_{i=1}^{n} (y_{ij}^{RS})^2 \right) x_j^2 + (\sum_{i=1}^{n} 2 y_{ij}^{RS} (Y_{i,:}^{RS} \Xi_j \vec{x})) x_j + \sum_{i=1}^{n} (Y_{i,:}^{RS} \Xi_j \vec{x})^2 - Q_\alpha > 0 \tag{7}$$

From the style of Equation, it's a one-variable quadratic inequalities with the form of $ax^2 + bx + c > 0$. Where,

$$\begin{aligned} a &= \sum_{i=1}^{n} (y_{ij}^{RS})^2 \ , \\ b &= \sum_{i=1}^{n} 2 y_{ij}^{RS} (Y_{i,:}^{RS} \Xi_j \vec{x}) \ , \\ c &= \left(\sum_{i=1}^{n} (Y_{i,:}^{RS} \Xi_j \vec{x})^2 \right) \text{-} Q_\alpha \end{aligned} \tag{8}$$

The pair of solutions of Equation (7), $x_{j,min}$ and $x_{j,max}$, are the limitations for the normalized sensor fault boundary. A zone, $[x_{j,\min}^0, x_{j,\max}^0]$, can be obtained by de-normalizing. If the original measured data x_j^0 is outside of $[x_{j,\min}^0, x_{j,\max}^0]$, we can easily find the faulty sensor. Therefore, the area, $[x_{j,\min}^0, x_{j,\max}^0]$, can be defined as the undetectable zone of the *i*th sensor by *Q*-statistic. The undetectable zone can be employed as the index to evaluate the sensor fault detectability.

2.3 Undetectable Zone by T_H^2

Similar with the definition of *Q*-statistic, the Hawkins' T_H^2 can be rewritten as

$$T_H^2 = \left(\sum_{i=1}^{n} (y_{ij}^{\text{T2H}})^2 \right) x_j^2 + (\sum_{i=1}^{n} 2 y_{ij}^{\text{T2H}} (Y_{i,:}^{\text{T2H}} \Xi_j \vec{x})) x_j + \sum_{i=1}^{n} (Y_{i,:}^{\text{T2H}} \Xi_j \vec{x})^2 \tag{9}$$

Where, $Y^{T2H} = \Lambda_{k+1,m}^{-1/2} \tilde{P}^T$ is the projection matrix of Hawkins' T_H^2. Therefore, the undetectable zone of the *i*th sensor by Hawkins' T_H^2 can be the solutions with the style of $ax^2 + bx + c > 0$, where

$$a = \sum_{i=1}^{n} (y_{ij}^{\mathrm{T2H}})^2$$
$$b = \sum_{i=1}^{n} 2 y_{ij}^{\mathrm{T2H}} (Y_{i,:}^{\mathrm{T2H}} \Xi_j \vec{x}) \quad (10)$$
$$c = \left(\sum_{i=1}^{n} (Y_{i,:}^{\mathrm{T2H}} \Xi_j \vec{x})^2 \right) - \chi_{n-k;\alpha}^2$$

The undetectable zone by Hawkins' T_H^2 is quite different to that by Q-statistic. Therefore, the compared results can indicate the different sensitivity for these two different statistics.

2.4 PCA model for a water-cooled chiller

From the consideration of the energy balance principle, there are eight important sensors in the water-cooled chiller and its control logic. The PCA model of a typical water-cooled chiller is

$$X = \begin{bmatrix} T_{chw}^i & T_{chw}^o & M_{chw} & T_{cw}^i & T_{cw}^o & M_{cw} & W & V \end{bmatrix} \quad (11)$$

Where, T_{chw}^i and T_{chw}^o are the temperature sensors of inlet node and outlet node of evaporator, respectively. T_{cw}^i and T_{cw}^o are the condenser-water system inlet node temperature and outlet node temperature, respectively. M_{chw} is the water flowrate of chilled-water system and M_{cw} is the water flowrate of condenser-water system, respectively. W is the electrical power. V is the position of the slide valve to indicate the mass flowrate of the refrigerant into the screw compressor.

3. VALIDATION

3.1 Cases study

A fielded data (Hu et al., 2012; Hu et al., 2016) of a water-cooled screw chiller were used to validate the sensitivity of Q and Hawkins' T_H^2 for different sensors. The undetectable zones of different sensors by a same training data set were investigated. The results of sensor fault detection were used to validate the predictive ability of undetectable zone for the faulty sensor.

CASE I: T_{chw}^i with -1.5℃ bias fault

Undetectable zone of T_{chw}^i for the training data set is illustrated in the Figure 2.

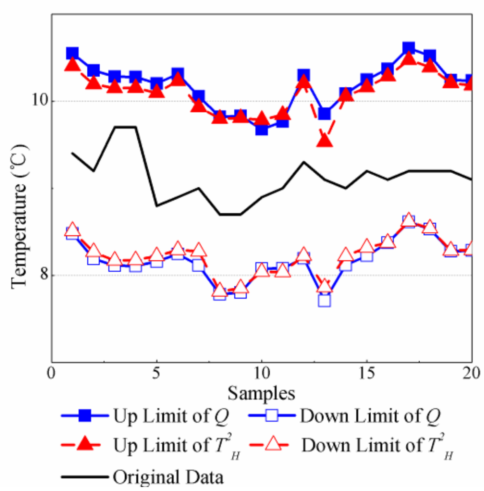


Figure 2: Undetectable zone of T_{chw}^i for the training data set

The up limits of undetectable zone by Q is almost equal to that by Hawkins' T_H^2, as well as the down limits of two statistics. Obviously, the fault detectability of T_{chw}^i by Q is equal to the ability by Hawkins' T_H^2. The undetectable zone of T_{chw}^i by Q is ±1.39 ℃, while that by Hawkins' T_H^2 is ±0.67℃.There are just the former 20 samples shown in the horizontal axis in order to make the figure clear.

A bias fault with -1.5℃ was introduced into T_{chw}^i to test the predictive ability. The fault detection results by Q and T_H^2 are illustrated in Figure 3 (a) and (b). All the Q-statistics values of tested samples are greater than the Q_α and the detection efficiency of sensor fault by Q is 100 %. Meanwhile, the -1.5℃ bias fault of T_{chw}^i is completely detected by Hawkins' T_H^2. Therefore, the detectability indicated by the undetectable zone of T_{chw}^i is according to the fault detection results of tested samples of T_{chw}^i. The undetectable zone successfully predicted the fault detection results.

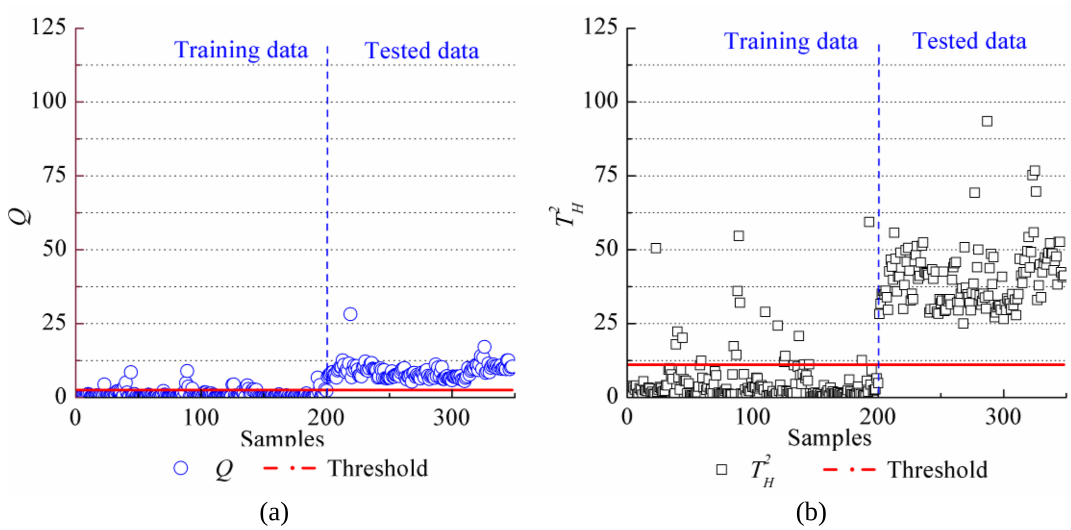


Figure 3: Fault detection for T_{chw}^i with -1.5℃ bias fault: (a) by Q (b) by T_H^2

CASE II: T_{cw}^o with -2.0℃ bias fault

Undetectable zone of T_{cw}^o for the training data set is illustrated in the Figure 4.

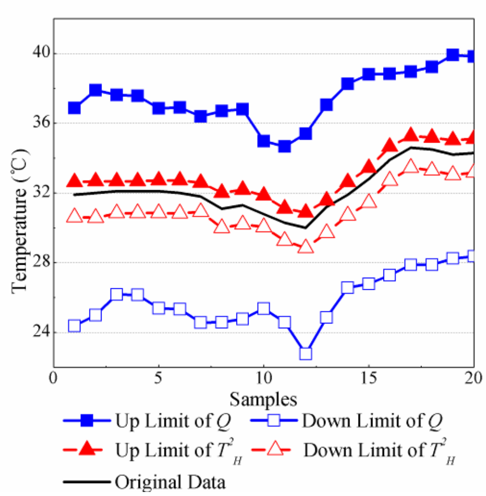


Figure 4: Undetectable zone of T_{cw}^o for the training data set

Unlike to the results of T_{chw}^{i}, the up and down limits of undetectable zone by Q is quite different to that by Hawkins' T_H^2. The undetectable zone by Q is much greater than that by Hawkins' T_H^2. The undetectable zone of T_{chw}^{i} by Q is over ±6.0 ℃, while that by Hawkins' T_H^2 is less than ±1℃. Consequently, the detectability of T_{cw}^{o} fault by Hawkins' T_H^2 is much better than the ability by Q.

The fault detection results by Q and T_H^2 are illustrated in Figure 5 and Figure 6, respectively, when a 2.0℃ bias fault was introduced into T_{cw}^{o}. There are only 21% of Q-statistics values in the tested samples are greater than the Q_α. It means that the fault detection by Q did not working. Meanwhile, the 2.0℃ bias fault of T_{cw}^{o} is completely detected by Hawkins' T_H^2. Due the introduced fault level, 2.0℃, is less than the undetectable zone by Q, ±6.0 ℃, the detectability by Q is completely worse than that by Hawkins' T_H^2. Therefore, it is better that the Hawkins' T_H^2 is employed to detect the T_{cw}^{o} fault.

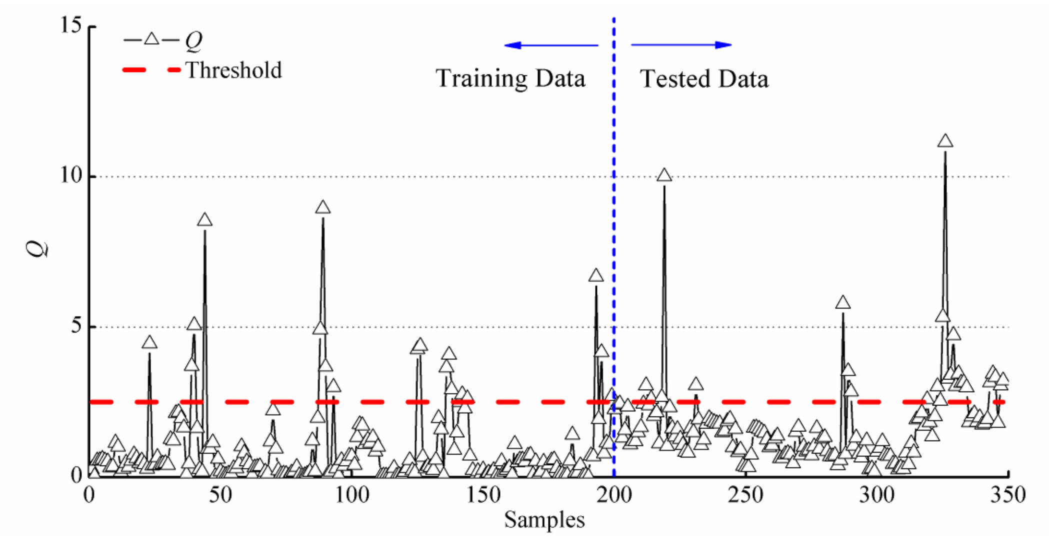


Figure 5: Fault detection for T_{cw}^{o} with 2.0℃ bias fault by Q

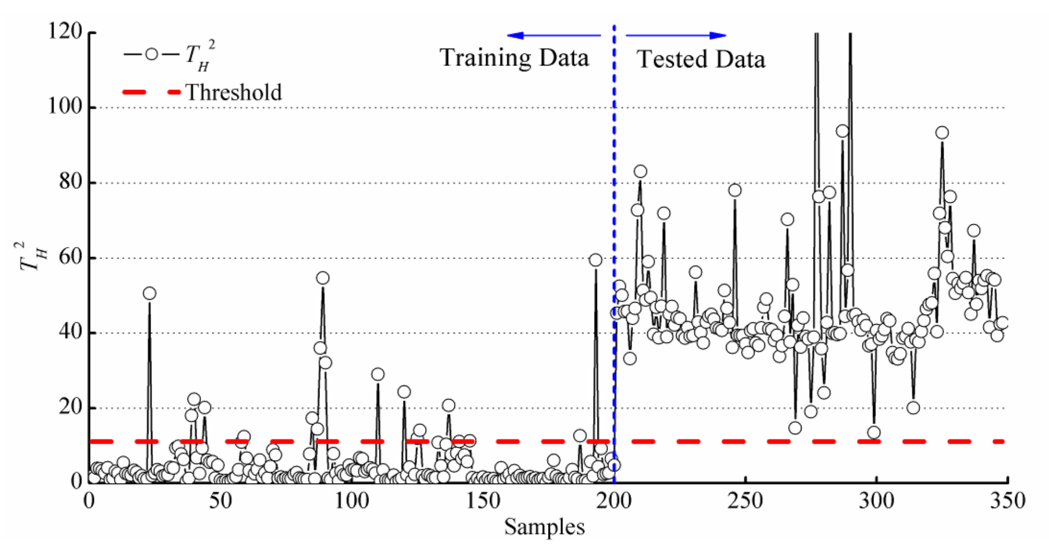


Figure 6: Fault detection for T_{cw}^{o} with 2.0℃ bias fault by T_H^2

CASE III: M_{cw} with +10% bias fault

The predictive results, undetectable zone, of M_{cw} for the training data set is illustrated in the Figure 7. Meanwhile the fault detection results of M_{cw} by Q and T_H^2 are illustrated in Figure 8. The undetectable zone by Q is nearly equal to that by Hawkins' T_H^2, so the fault detection results of M_{cw} by Q are in accordance with that by T_H^2.

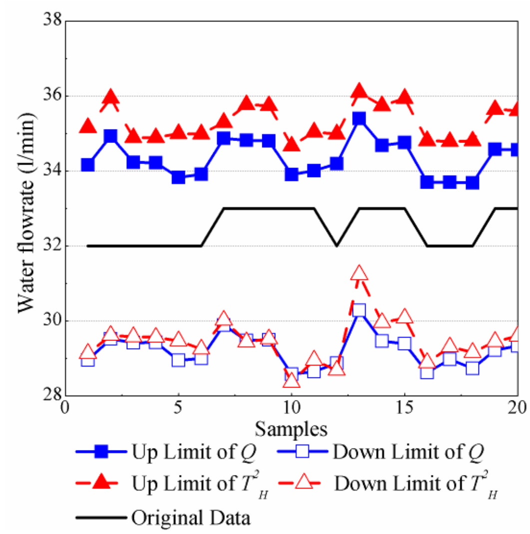
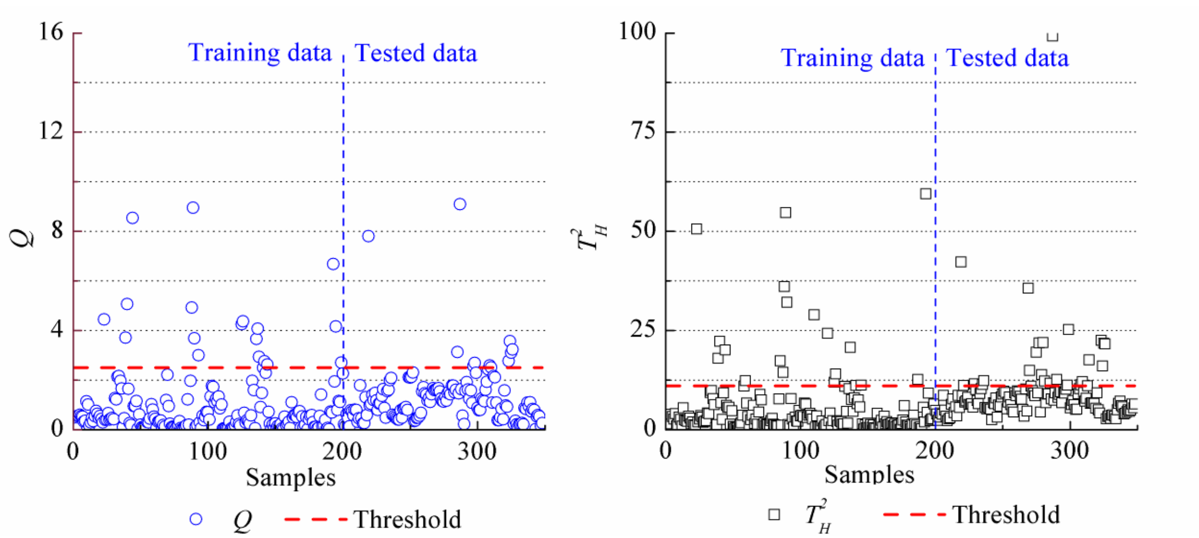


Figure 7: Undetectable zone of M_{cw} for the training data set



(a) (b)

Figure 8: Fault detection for M_{cw} with +10% bias fault: (a) by Q and (b) by T_H^2

3.2 Summary

The undetectable zones for all sensors in the PCA model by Q and by T_H^2 are summarized in the Table 1. The detection abilities for different sensor by Q and by T_H^2 are quite different. At the step for choosing the optimal statistics to obtain the fault boundary, the undetectable zone can directly predict the detection ability for the sensor by a certain statistics, such as Q or T_H^2. Therefore, the performance of PCA-based sensor Fault detection can be improved by choosing the statistics with higher fault detection efficiency by the sensitivity analysis for the certain training data set.

Table 1: Summary for all sensors' Undetectable zones by Q and by T_H^2

Sensor	Unit	Undetectable zone by Q	Undetectable zone by T_H^2
T_{chw}^o	℃	2.78 (±1.39)	1.74 (±0.67)
T_{chw}^i	℃	2.47 (±1.24)	1.68 (±0.84)
M_{chw}	l/min	6.28 (±3.14)	6.35 (±3.18)
T_{cw}^o	℃	11.77 (±5.89)	1.66 (±0.84)
T_{cw}^i	℃	12.77 (±6.39)	1.61 (±0.81)
M_{cw}	l/min	7.18 (±3.59)	5.30 (±2.65)
W	kW	137.84 (±68.92)	68.07 (±34.04)
M_{ref}	%	41.49 (±20.75)	20.33 (±10.17)

There is an important point illustrated by the case study and the summary. The solution of undetectable zone is derived from the matrix calculation process of different statistics. The results of undetectable zone only rely on the original training data. Therefore, the undetectable zone demonstrates the original feature of the training data.

4. CONCLUSIONS

Sensor fault detection, diagnosis and erroneous data reconstruction is the fundamental work for the thermodynamic fault isolation, the optimal control, the safety operation and so on. In this paper, an evaluation index, undetectable zone, is presented to predict the detectability of sensor fault so as to improve the performance of sensor fault detection. Different calculation algorithm is derived to obtain the undetectable zone by different statistics.

Undetectable zone can be employed as an index to predict and to evaluate the detectability of sensor fault by some statistics for a certain training data set. It can be used to choose the optimal statistics of fault detection for each sensor. From the evaluation of detectability for each sensor by different statistics, the online sensor fault detection can be more flexible by choosing the most sensitive statistics. Therefore, the detection efficiency can be promoted by the prediction of undetectable zone.

NOMENCLATURE

The nomenclature should be located at the end of the text using the following format:

T	temperature	(℃)
M	water flow rate	(l/min)
W	chiller electrical-power input	(kW)
V	position of the slide valve	(-)
$\boldsymbol{X}$	original matrix	(-)
$\boldsymbol{X}^0$	normalized original matrix	(-)
$\boldsymbol{R}$	covariance matrix	(-)
$\boldsymbol{U}$	eigen vector matrix	(-)
VE	variance explained	(-)
CV	cumulative contribution of variance	(-)
FDD	fault detection and diagnosis	(-)
FDDR	fault detection, diagnosis and reconstruction	(-)
HVAC&R	heating, ventilating, air-conditioning and refrigeration	(-)

PC	Principal Component	(-)
PCA	Principal Component Analysis	(-)
SPCA	Principal Component Analysis with a statistical data-cleaning	(-)
P	PC subspace projection matrix	(-)
$\tilde{P}$	Residual subspace projection matrix	(-)
Q_α	threshold of the Q-statistic	(-)
$\vec{x}$	a sample	(-)
$\hat{\vec{x}}$	estimate of a sample	(-)
$\tilde{\vec{x}}$	residual of a sample	(-)
$\vec{x}_{rc}$	reconstruction of a sample	(-)
x_j	the jth entry of $\vec{x}$	(-)
e_i	the ith entry of $\vec{e}$	(-)

Greek letters

μ	mean
σ	standard deviation
$\lambda_1, \cdots, \lambda_n$	eigenvalues

Superscript

i	inlet node
o	outlet node

Subscript

chw	chilled-water system
cw	condenser-water system

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