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User-friendly fault detection method for building chilled water flowmeters

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ABSTRACT

In building HVAC systems, chilled water flowmeter is an important sensor whose reading could be used to measure the real time cooling load, a critical variable for automated control of building HVAC systems. To maintain the reading data accurate, the fault detection and diagnosis (FDD) of flowmeters is necessary. Existing FD/FDD methods for chilled water flowmeters have several common shortcomings: (1) High requirements on sensor integrity: multiple sensors are usually involved to build energy balance models; (2) Complex methodology, the fault of any monitored sensor could trigger the detection hit, thus diagnosis procedure is unavoidable to isolate the faulty sensor; (3) the more sensors involved, the harder to collect fault-free historical data to build a fault-free benchmark. To tackle these existing problems, a user-friendly fault detection (FD) method for building chilled water flowmeters is proposed in this study. The proposed method requires three types of variables to function: pump frequency, pump power, and measured chilled water flowrate on the header pipe. The field data of a real HVAC system is used in the case study to validate the performance of the proposed method. Results of the validation case study suggest that the proposed method could reach high hit rates confronting different faults (bias, noise and drift) at different levels. Compared to existing FD methods, the simple workflow and low sensor requirements make the proposed method more feasible and user-friendly for engineering practice.

Keywords: Fault detection and diagnosis, Flowmeter, Chilled water pump, Affinity law, Random forest

1. INTRODUCTION

More than half of the total building energy consumption is caused by the heating, ventilation, and air-conditioning (HVAC) system [1]. The proper operation of HVAC systems is important to the building energy management and conservation. Moreover, the operation and automation of building systems highly depends on the sensor reading, thus rendering the importance of sensor maintenance. Most sensors in the HVAC system could be classified into three categories: thermometer, pressure meter and flowmeter. Different kinds of sensors are intended to monitor different regions of the whole system, such as AHUs, chillers, pumps; based on the collected data, building automation system (BAS) could control the system operation properly.

In order to maintain the sensor accuracy, a lot of works have been carried out in the field of sensor fault detection (FD) and diagnosis (FDD). Wang and Xiao [2] proposed an FDD method to diagnose the faults in AHU sensors. In their study, the data of 16 variables including temperature, humidity, air flowrate are split into two groups to build two matrixes, respectively. And two principal component analysis (PCA) models (heat balance model and pressure-flow balance model) are trained by the fault-free operational data in the matrix form. The trained PCA models are used to reconstruct the pending test data, and the residual between the reconstructed data and the original data could indicate the sensor condition.

In the field of sensor FDD, fault detection is usually intended to determine if any fault has occurred to the targeted system; if the system is detected faulty, then the diagnosis procedure would be conducted to isolate

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the faulty sensor. The FD procedure of existing FDD methods to the chilled water flowmeter have some defects on the feasibility and applicability:

High requirements of sensor integrity: A common feature of the studies reviewed above is that the FD of chilled water flowrate is usually bounded with the FD of other sensors especially temperature sensors (T_{chws} and T_{chwr}), because energy balance law is often used to build the fault-free benchmark [2]. Thus, a lack of sensors in real field application could affect the balance as well as the performance of these FDD method. This characteristic weakens the applicability of some FD/FDD methods in engineering practice [3].

Methodology complexity (weakened FD procedure): Another problem resulted from the sensor integrity is the complexity of the methodology. Due to the integrity of the benchmark model, any faults of any considered sensor would cause the gap between estimated indicator value and measured indicator value. In this case, if sensor faults are detected, the user has to identify the faulty sensor with a certain diagnosis process [2], which not only increases the method complexity, but also reduces the meaning of the FD procedure.

Difficulty of the acquisition of fault-free historical data: Model-based FD/FDD methods usually requires fault-free historical data to establish the benchmark model, which is used to estimate the true value of real-time sensor readings. Existing faults in historical data can evidently affect the accuracy of the benchmark model. However, because of the vulnerability of sensors [4], the more sensors involved, the harder to guarantee that the historical data is "fault-free".

To tackle the problems above, a user-friendly fault detection method for chilled water flowmeters is proposed in this paper. The proposed method is specifically targeted at flowmeters; the output of the proposed method could clearly infer the condition of the chilled water flowmeter on the header pipe (normal/abnormal), no need of faulty sensor isolation; the method has simple workflow and less requirements on system sensors, which enhances the feasibility of this method in real applications.

2. METHODOLOGY

2.1 Overview

As is illustrated in Fig. 1, the proposed method is realized by the following steps:

Off-line procedure:

A. Drop data items containing Null values. Then preprocess the historical fault-free data with Hoteling's T-square test (90% confidence level) to remove the extreme outliers [5].

B. Train the flowrate estimator with preprocessed historical fault-free data

On-line procedure:

C. Estimate the true value of real time flowrate with real time pump frequencies and pump powers

D. Calculate the real time threshold with measured real time data and preprocessed training data

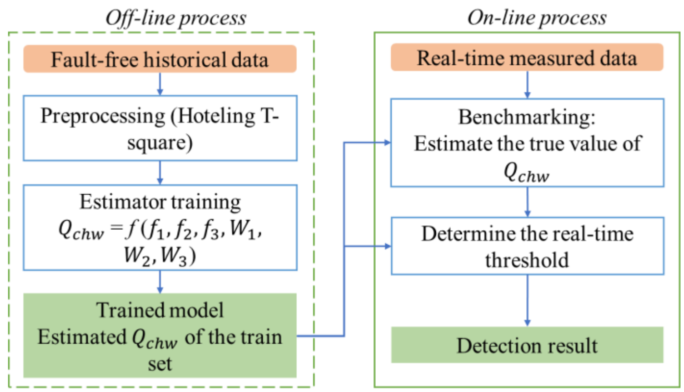

Fig 1. Method workflow

2.2 Data requirements and preprocessing

In this method, historical fault-free data of three months is required as the training data for the flowmeter estimator; and real time measured data is required for online fault detection. Both training process and detection process need the data of the same group of variables: (1) frequency of each chilled water pump, (2) input power of each chilled water pump, and (3) the measured chilled water flowrate on the chilled water header pipe.

As mentioned in Section 2.1, historical data need to be preprocessed before being applied to the training of the estimator. In this method, preprocessing is conducted in two steps: (1) the data items (rows) containing Null values should be dropped; (2) then the historical data need to be filtered with Hoteling T-square test at 90% confidence level (α=0.1) [5, 6].

2.3 Training of the flowrate estimator (random forest)

In this study, the random forest tool (Fig. 2) developed by sci-kit learn [7] is adopted and trained by the preprocessed fault-free data. When constructing the estimator, the frequency and input power of each chilled water pump are taken as input features (i.e., independent variables), and the measured chilled water flowrate is regarded as the output variable.

In this study, the model hyperparameters are specified in the following way: the tree number is defined 100, mean square error (MSE) is adopted as the criterion, tree depth and leaf nodes are not limited, no pruning conducted.

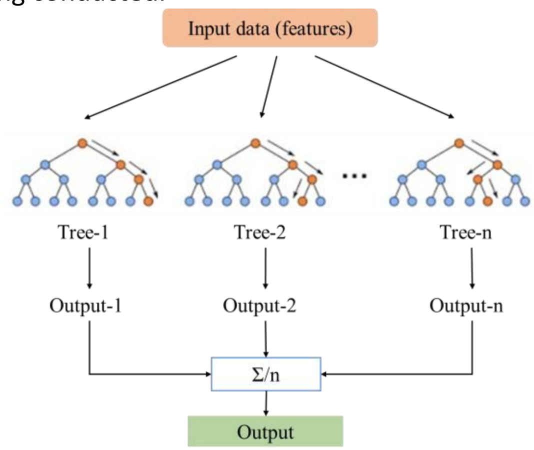

Fig 2. Prediction with trained random forest

After the offline training, the random forest regressor would be used online to estimate the true value of the real time chilled water flowrate.

2.4 *Threshold definition*

In this study, the threshold for fault detection is defined as Eq. (1) [8].

In Eq. (1), Th represents the upper/lower threshold, $t\alpha_{/2,n-m+1}$ is the quantile value of t distribution when the confidence level is (1-α) and the freedom degree equals (n-m+1), in this study α=0.1, n is the number of rows in the preprocessed training data, m is the number of features, $\tilde{\sigma}_Q^2$ is the estimated variance of the regression error, X is the matrix of the preprocessed training data, x_0 is the vector of real time input data (pump powers and frequencies), y_i the ith measured flowrate value, and $\hat{y}_i$ the ith estimated flowrate value.

$$Th = \pm t\alpha_{/2,n-m+1} \times \sqrt{\tilde{\sigma}_Q^2[1 + x_0^T(X^TX)^{-1}x_0]} \quad (1)$$

$$\tilde{\sigma}_Q^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n-m+1} \quad (2)$$

In each time of detection, the bias between the estimated flowrate value and the measured flowrate value is compared with the calculated threshold. If the bias exceeds the threshold, then this time of detection would be recorded as a hit.

3. VALIDATION CASE STUDY

3.1 *Case system*

The operation data of a real HVAC system is adopted for the case study. The layout of the case system is illustrated in Fig. 3. There are three identical CHWPs (1#, 2#, 3#) in this system. Field data (measured operation data) of this system from May to September is analyzed in this study.

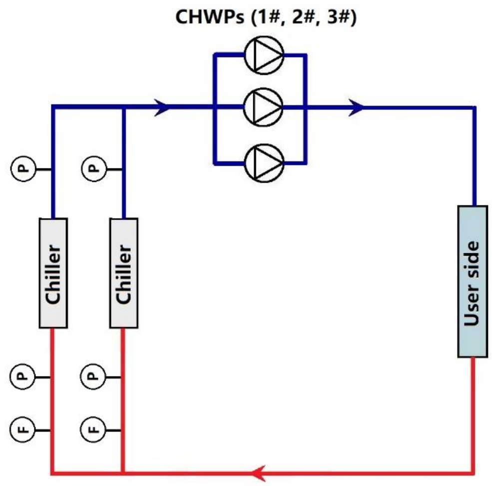

Fig 3. Case system

3.2 *Definition of faults*

As listed in Table 1, three types of typical faults: bias, noise, and drift, are investigated in this study [9, 10]. And errors are quantified to three different levels with the mean value (μ) and standard deviation (σ) of the fault-free flowrate data of this case study. Bias and drift errors are quantified according to the 3-σ principle of normal distribution. Noise errors are quantified according to uncertainty levels defined by Ref. [10]. In Table 1, σ_Q is the standard deviation of fault-free training data (data from May 31st to August 31st) of header pipe chilled water flowrate, μ_Q is the mean value, e_i is the error artificially added to the ith test data item, n is the number of test data items.

Table 1. Investigated sensor faults [9, 10]

Case No.	Fault name	Description	Parameter value (m³/h)
1#	Bias	$e_i = \delta$	$\delta = \sigma_Q = 49.55$
2#			$\delta = 2\sigma_Q = 99.10$
3#			$\delta = 3\sigma_Q = 148.65$
4#	Noise	$e_i = N(0, 0.01\mu_Q)$	$\mu_Q = 191.92$
5#		$e_i = N(0, 0.03\mu_Q)$	
6#		$e_i = N(0, 0.05\mu_Q)$	
7#	Drift	$e_i = e_{i-1} + \delta$	$\delta = \sigma_Q/n = 0.023$
8#			$\delta = 2\sigma_Q/n = 0.046$
9#			$\delta = 3\sigma_Q/n = 0.069$
10#	Fault-free	$e_i = 0$	

3.3 *Results and discussion*

The field data of the case system from May 31st to August 31st is adopted as fault-free data (train set) for model training and calibrating. Then, the fault-free data from September 1st to September 15th (test set) is used to test the accuracy of the flowrate estimator. Subsequently, the flowrate data of the test set is artificially added with errors to verify the FD performance of the proposed method. Results are discussed from two aspects: (1) accuracy of estimation; (2) FD performance.

Flowrate estimation results are illustrated in Fig. 4. The accuracy of the flowrate estimator is evaluated by coefficient of variation of the root mean square error (CV(RMSE)), the value of which is 4.10% (train dataset) and 5.60% (test dataset).

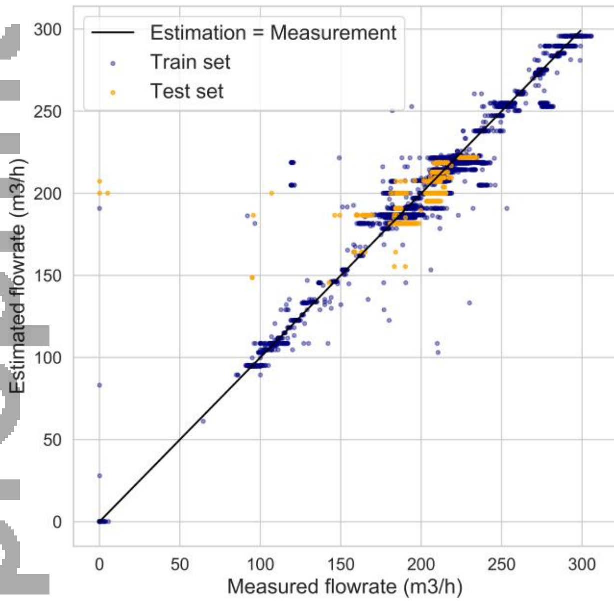

Fig 4. Estimator accuracy

In this study, the performance of the proposed method is evaluated by the detection rate calculated with Eq. (3) [11]. The denominator of Eq. (3) is the total number of tested time steps because in the test period, all data items of faulty data set are added with errors.

$$Hit\ rate = \frac{Number\ of\ hit\ times}{Total\ number\ of\ tested\ times} \tag{3}$$

The FD results of case 3#, 6#, 9# and 10# are illustrated in Fig. 5. Among three types of faults, the proposed method detects the bias better than drift and noise because (1) the bias fault could cause immediate error of the measurement while drift takes time to cause evident error of the sensor reading; (2) the noise fault is realized by adding a random value under normal distribution to the sensor reading; and the error caused by noise fault is not stable; in many time steps the error caused by the noise fault is not significantly enough to be detected.

Specifically, regarding the specification of detection thresholds, high confidence level (small α value) usually leads to big (loose) thresholds, which could reduce the amount of false hits with sacrifice on the detection sensitivity. Hence, the balance between detection sensitivity and false hit rate should be considered during the specification of FDD thresholds.

Table 2 FD performance

Case	Fault name	Hit rate
1#	Bias	29.46%
2#		99.91%
3#		100%
4#	Noise	7.25%
5#		20.13%
6#		32.50%
7#	Drift	5.59%
8#		50.83%
9#		67.82%
10#	Fault-free (false alarm/hit)	6.33%

CONCLUSION

A user-friendly FD method for chilled water flowmeters is proposed in this study. Compared with the existing FD method, the proposed method requires less sensors and simpler data processing to function. Validated with the measured data of a real system, the proposed method could effectively detect the bias and drift faults of the chilled water flowmeters.

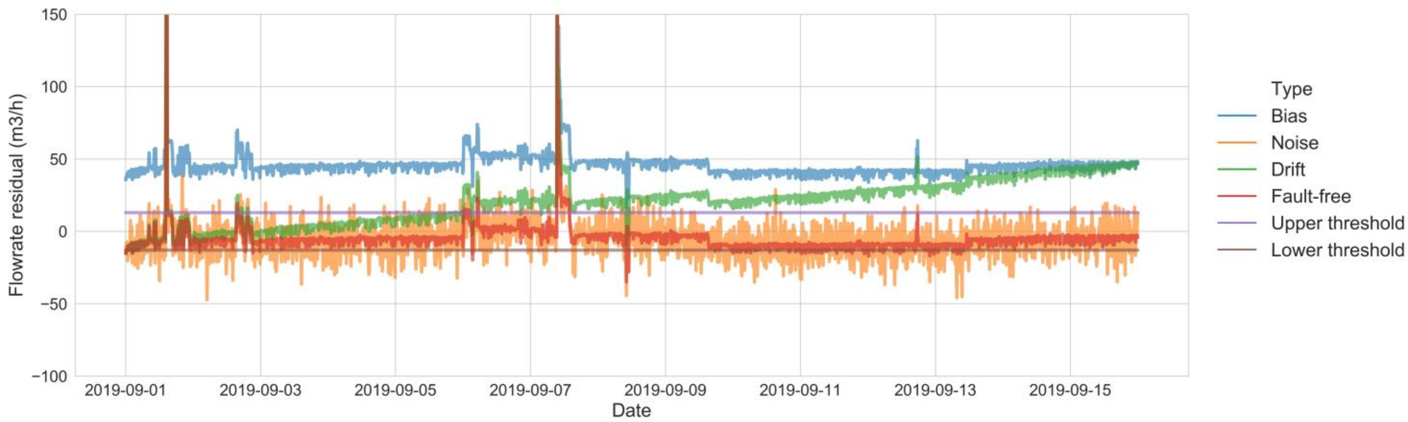

Fig 5. FD performance of Case 3#, 6#, 9#, and 10#

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