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A statistical fault detection and diagnosis method for centrifugal chillers based on exponentially-weighted moving average control charts and support vector regression

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HIGHLIGHTS

- ► A new FDD strategy combining EWMA control charts and Support Vector Regression (SVR) is proposed.
- ► EWMA control charts are used to overcome the shortcomings of the available statistic-based chiller FDD strategy, e.g. the *t*-statistic-based strategy.
- ► Support Vector Regression (SVR) is adopted to improve the accuracy of reference models.
- ► A new performance index was proposed to represent the effects of faults on the thermal performance of sub-cooling section.
- ► The proposed strategy improved the FDD performances significantly, especially on the faults at low severity levels.

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ABSTRACT

This paper presents a new fault detection and diagnosis (FDD) method for centrifugal chillers of building air-conditioning systems. Firstly, the Support Vector Regression (SVR) is adopted to develop the reference PI models. A new PI, namely the heat transfer efficiency of the sub-cooling section (ε_{sc}), is proposed to improve the FDD performance. Secondly, the Exponentially-Weighted Moving Average (EWMA) control charts are introduced to detect faults in a statistical way to improve the ratios of correctly detected points. Thirdly, when faults are detected, diagnosis follows which is based on a proposed FDD rule table. Six typical chiller component faults are concerned in this paper. This method is validated using the real-time experimental data from the ASHRAE RP-1043. Test results show that the combined use of SVR and EWMA can achieve the best performance. Results also show that significant improvements are achieved compared with a commonly used method using Multiple Linear Regression (MLR) and *t*-statistic.

1. Introduction

Chiller plants contribute to a large portion of the energy consumption of HVAC&R system of buildings [1]. It typically accounts for 35–40% of the total building electricity consumption in commercial buildings in Hong Kong [2]. Significant amount of energy is wasted in the case of chiller performance degradation and malfunctions. The chiller component faults account for around 42% of the service resources and around 26% of repair costs [3]. It is obvious that maintaining the chiller system in healthy conditions and identifying faults in time are beneficial to both building energy saving and operating costs saving.

Over the last decades, the development of automated fault detection and diagnosis (FDD) methods for chillers has been an area of active research. Detailed literature reviews on this subject can be found in the papers of Comstock et al. [3], Reddy et al. [4], Dexter and Pakanen [5], Katipamula and Brambley [6], Xiao et al. [7,8]. Among all of the methods, the methods, which use black-box approach to develop reference models and use *t*-statistic approach to detect faults, are efficient and widely used. Typical works can be found at Xiao et al. [7], Grimmelius et al. [9], McIntosh et al. [10], Chen and Braun [11] and Li and Braun [12], Jia and Reddy [13], Wang and Cui [14], Reddy [15]. Generally, these methods are developed as the following steps: 1) Reference PI models development. It is generally on the basis of physical chiller models [16,17] or black-box MLR (Multiple Linear Regression) models. 2) Confidence intervals (thresholds) calculation. They are usually gained through the *t*-statistic approach at a certain confidence level, e.g. 4.6% false alarm. 3) Fault detection. The residuals between

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Nomenclature

A	tube surface area (m^2)
c	specific heat capacity ($\mathrm{kJ\ kg^{-1}\ K^{-1}}$)
L	width of the control limits
LCL	lower control limit
n	amount of data in a sample group
PI	performance index
Q	chiller cooling load (kW)
R^2	R-square
T	temperature (°C)
TCA	condenser approach temperature (°C)
UA	overall heat transfer conductance ($\mathrm{W\ K^{-1}}$)
UCL	upper control limit
$\overline{X}$	group mean
Y	performance index value
Z	EWMA value

Greek symbols

σ	standard deviation
μ	expectation
ε	heat exchanger efficiency
λ	weighting factor
ξ	random error of regression

Subscripts

cd	condensing
chwr	returning chilled water
chws	supplying chilled water
cond	condenser
ecw	entering condenser water
evap	evaporator
sc	sub-cooling
w	water or water side

benchmark PIs and current ones are calculated. A fault is detected as soon as the residuals are out of the confidence intervals. 4) Fault diagnosis. The fault is diagnosed according to the fault pattern rule table. The lessons learned from the success of these methods can be concluded as follows. Firstly, the performance indexes (also named characteristic quantities or characteristic parameters in some studies) can account for existing chiller faults efficiently. Secondly, the statistical approaches are introduced to detect faults, which can properly handle the uncertainties of both model-fitting errors and measurement errors. In the end, the expert knowledge is used to diagnose fault using rule tables.

The low severity level is defined in this study as the level at which chiller performance is affected slightly. The available methods failed to detect and diagnose faults at low severity levels (SLs). For instance, the ratios of correctly diagnosed points were 0%, 0%, 0% at SL1 and 25%, 0%, 0% at SL2 respectively for the refrigerant leakage, condenser fouling and excess oil in Cui and Wang [14]. The MLR and t-statistic-based method in AHSRAE RP-1275 was reported that the ratios of correctly diagnosed points were 3.7%, 0%, 0% at SL1 and 7.4%, 0%, 0% at SL2 the refrigerant leakage, condenser fouling and refrigerant overcharge respectively [15]. It means that the operators have to wait for the fault alarms until the fault archives at a serious severity level. Obviously, significant amount of energy might have been wasted. The chiller might have been damaged. Hence, removing faults at low severity levels is crucial for chiller maintenance and costs saving.

Three major reasons are found in this study, which contribute to the poor FDD performances at low severity levels using available methods:

1) The Type II errors in the t-statistic-based approaches. Generally, a fault is detected when the residuals of PIs are outside of the confidence intervals. However, the residuals are still within the confidence interval at the low severity levels. This is the Type II error (more details can be found in Section 2.4).
2) The accuracy of MLR-based reference models. The MLR-based models have better accuracy than physical models in most of conditions. It is widely used, e.g., RP-1043 [18], Reddy [15], Cui and Wang [14], etc. However, MLR is still a linear regression approach. The chiller is a typical non-linearly system. The accuracy can be improved using non-linear regression approaches. The accuracy is important to the width of confidence interval. The lower the accuracy is, the wider the confidence interval will be, and then the FDD performance will be poor. In this way, the confidence interval can be narrowed obviously.
3) The improper performance index for the condenser fouling. The condenser fouling has similar fault patterns with the refrigerant overcharge and non-condensable gas. To distinguish it with other faults, it is generally assumed that the deviation of sub-cooling temperature is within conference intervals or a positive value. Actually, the deviation is sometimes positive (mostly in low severity levels) and sometimes negative (mostly in serious severity levels), as shown in RP-1043 data. Such assumptions always lead to higher false diagnosis ratios.

The objective of this study is to propose a robust statistical FDD method suitable for the detection and diagnosis of faults at low severity levels. Three innovations are adopted to overcome the shortcomings. Firstly, the Exponentially-Weighted Moving Average (EWMA) control charts are used to reduce the Type II errors. Secondly, Support Vector Regression (SVR) is implemented to develop reference models. Thirdly, a new performance index is introduced, which is named the heat transfer efficiency of the sub-cooling section (ε_{sc}). In the end, a new rule table is proposed. Both SVR and EWMA are statistical theories-based approaches and can efficiently handle uncertainties in FDD process. The proposed method is validated using the ASHRAE RP-1043 experimental data. Comparison is made with a typical FDD method from AHSRAE RP-1275.

2. Basic ideas and structure of the FDD method

2.1. Structure of the FDD method

The structure of the proposed FDD method is as shown in Fig. 1. It includes two parts, i.e. online chiller FDD and offline model training.

The offline model training consists of four steps. In the step of data pre-processing, the obvious outlying and dynamical data are filtered by the outlier detector and steady-state data filter respectively. In the step of performance indexes calculation, the four PIs are calculated using the filtered data. In the next step, SVR is adopted to develop the reference models. In the last step, the statistical characters of the reference models are calculated, i.e. μ (the expectation) and σ (the standard deviation), which are the requirements of the EWMA model.