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Data-driven based reliability evaluation for measurements of sensors in a vapor compression system

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ABSTRACT

Sensors play essential roles in the refrigeration and air conditioning systems. The faults of sensors may result in the decrease of system performance and waste of energy. It is not easy to discover the sensor bias, since its occurrence is always random and unpredictable. The data-driven based evaluation logic is proposed to assess the measurement reliability of sensors in the refrigeration and air conditioning systems. The subtractive clustering is presented to classify and recognize the various operation conditions adaptively. The principal component analysis models constructed upon the known conditions are developed to detect the measuring faults of sensors. Two statistics of T^2 and *SPE* are combined to evaluate the measurement reliability of variables, which are divided into monitoring-type and controlling-type according to their attributes in the control loops. Ten fault cases, which include the fixed and drifting biases of various temperature and pressure sensors, are tested in a real vapor compression system.

1. Introduction

Sensors and controllers play essential roles in the refrigeration and air conditioning (R&AC) systems. In the typical control process of R&AC systems, the sensors provide the operation information to the controllers continuously. With the feedback of current operation status, the controllers execute the PID (proportion, integration and differentiation) calculation and give the proper commands to modulate the actuators or components. If the sensors are not accurate, the controllers may be misled by the feedback information and give improper control commands. As a result, the parameter efficiency and system performance may be deviated to the unsatisfied points [1].

In real systems, it is difficult to maintain the high measurement precision for a sensor throughout its entire life cycle. The sensors are usually accurate at the stage of initial installation. After long term operation, unfortunately, they may be biased gradually because of the degradation of sensing element, signal inference or mechanical failure etc. The fault risk for a sensor is inevitably increased over the time. Therefore, the periodical or scheduled calibration for sensors is usually employed by the users. However, the occurrence of sensor bias is always random or unpredictable. The periodical calibration for sensor is neither the timely nor the low-cost approach, which cannot meet the requirement of continuous evaluation for the measurement reliability in real applications. Considering the costs, moreover, the calibration period varies from 1 to 2 years or even a longer period that relies on the willingness of users. Without the continuous reliability monitoring for measurements, the unwanted fault impacts cannot be removed in time. Before the next scheduled calibration, the potential loss cannot be saved, either. Therefore, it is necessary to develop a timely low-cost tool so as to continuously monitor the health rank of measurements in the R&AC systems.

Fault detection and diagnosis (FDD) is an efficient way that can provide the abnormity monitoring or health evaluation for the measurement and operation of various energy systems [2–8]. It has the potential to detect performance degradation early so as to increase equipment life, improve performance and efficiency, and avoid unscheduled loss of service [9]. FDD has gained more and more attention in the R&AC field recently, which can be classified into rules-based, model-based and data-driven approaches. The rules-based FDD approaches diagnose the faults according to the expertise knowledge and practical experience [10,11]. The rules designed for one specific system usually require some modifications when they are used in another system. Considering the diversification of R&AC systems, complete rules and robust inference are the key points in the real applications. The model-based methods [12–16] have been most widely developed, which

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Nomenclature

T	temperature (°C)
P	pressure (MPa)
M	mass flow rate (kg/s)
W	input power (kW)
f	frequency (Hz)
U	voltage (V)
I	current (A)
F	magnitude of fault
t	time
x, X	measurement vector
D	density or distance
m, $(n\text{-}m)$	variable number or degree of freedom
F_α	F distribution with confident limit α
COP	coefficient of performance
SPE	squared prediction error
T^2	Hotelling statistics
A, B	PCA model
S	covariance matrix
PID	proportion, integration and differentiation
R&AC	refrigeration and air conditioning
FDD	fault detection and diagnosis
PCA	principal component analysis
PCS	principal component subspace
RS	residual subspace

Greek symbols

ε	magnitude of fixed bias
ω	drifting factor
a, β	coefficients of adjacent field
σ	convergence coefficient of clustering
δ	threshold of Q statistics
Λ	eigenvalue matrix
τ	cumulative percent variance
λ	eigenvalue

Subscripts

l	principal component number
DIS	discharge of compressor
SUC	suction of compressor
LIQ	liquid line of refrigerant
GAS	gas line of refrigerant
IN	inlet of mixing tank
OUT	outlet of mixing tank
G	refrigerant gas
L	refrigerant liquid
OIL	lubricant oil
W	water
EV	evaporator
CD	condenser
SC	subcooling

detect the faults through comparing the measurement values with the predicted ones of model. The key point is to construct the accurate mathematical models matching the real physical process, which is never an easy task. Assumption or simplification of model for the purpose of fast solution may probably decrease the prediction precision. With the development of data mining technology, the data-driven FDD approaches [17–20] have received a great deal of attention recently. The data-driven FDD method does not require the detailed physical model. Instead, the data-driven model is usually constructed and trained using the historical operation data. Through the machine learning, FDD models can be used to distinguish the fault and fault-free operations.

Actually, the data-driven FDD method was originally from the statistical process control (also called statistical quality control) [21], which was popular applied in various industry fields. The early applications in R&AC systems include Shewhart control chart [22], contribution plots [23,24], cumulative sum control chart (CUSUM) [20,25], polynomial regression [26], partial least squares [27] etc. Recently, data mining technology has been frequently considered for the fault detection and diagnosis in the R&AC systems. Some novel data mining applications reveals the implicit characteristic of system or correlation between variables through collecting data, machine learning, inductive reasoning and recognizing potential patterns. Wang [28] and Beghi [29] developed the principal component analysis (PCA) strategies to detect the faults occurred in the chilled water systems. Du developed PCA based FDD models for the air handling unit [30] and variable air volume system [24]. Zhao developed the Bayesian belief networks to discover the faults of water-cooled centrifugal chillers [31]. In addition, neural networks [32], cluster analysis [33] and related methods [34,35] were also developed to diagnose the commonly occurred faults in the R&AC systems.

As to the evaluation of sensor reliability, it has two kinds of approaches: sensor-level and system-level. On one hand, the self-validating methods have been developed [36–38] for the sensors of flow rate and pressure etc. Advances in materials, construction of sensors and electronics are usually used to obtain better signal conditions. They can even check the sensor themselves to be sure they are operating properly. The self-validating approach is actually the sensor-level way to improve the measuring reliability of sensors themselves. Currently, the sensor with self-validating function is still seldom used in the real R&AC systems. The R&AC system usually requires lots of sensors, which means the higher costs to apply the self-validating sensors. On the other hand, system-level sensor FDD logic is usually based on the analysis of process characteristic and physical principle, which is a low cost way to evaluate the reliability of measurements.

The sensor FDD application in R&AC field was later than that in chemical, aerospace, nuclear etc. Some successful applications such as principal component analysis [39–42] showed well detection capacity in the industrial process monitoring. However, the R&AC systems usually illustrate the strong characteristics of nonlinearity and diversity. Even for the systems with same type, the component performance of different manufactures and control strategies may be quite different. Moreover, the load conditions (outdoor and indoor) always change continuously, which may lead to the various operation characteristics in R&AC systems. These factors may confuse the monitoring process inevitably that result in the unsatisfied diagnosis efficiency in the R&AC systems.

It can be found that rich historical data is the key point for the application of data-driven approaches. But the reliability evaluation method for the system measurements has not been well developed. The experimental tests about the sensor biases introduced into the real R&AC systems are not well investigated yet. In addition, the data-driven model is always sensitive to the operation conditions. But the recognition logic for the transformation of operation conditions is not well studied. The poor recognition capacity for operation conditions may decrease the detection capacity of data-driven FDD models.

It is not easy to detect the biases of sensors, which play essential