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Sensitivity analysis for PCA-based chiller sensor fault detection

Yunpeng Hu [a,b,c], Guannan Li [a], Huanxin Chen [a,*], Haorong Li [d], Jiangyan Liu [a]

[a] Department of Refrigeration and Cryogenic Engineering, School of Energy and Power Engineering, Huazhong University of Science and Technology, Wuhan 430074, China
[b] Wuhan Business University, Wuhan 430056, China
[c] State Key Laboratory of Compressor Technology, Hefei 230031, China
[d] Department of Architectural Engineering, University of Nebraska-Lincoln, PKI Room245 1110S, 67th Street, Omaha, NE 68182, United States

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ABSTRACT

This paper presents an algebraic solution of erroneous sensor's undetectable boundary to evaluate the sensitivity of chiller sensor fault detection based on principal component analysis. Q-statistic of PCA is normally applied as a collective statistical index to detect sensor fault by comparing its value with the threshold. However, Q-statistic has no specific physical meaning and cannot evaluate the sensitivity of the provided method for sensor fault detection. We analyzed the definition of Q-statistic and derived the numerical value of the minimum range not to detect sensor fault. Bias sensor fault of a fielded screw chiller was studied for each sensor in PCA model by introducing different severity levels. Results showed that each sensor has different fault detection sensitivity using the same PCA model. The undetectable boundary can be a criterion used to evaluate the detection sensitivity of PCA-based method easily.

Analyse sensorielle de la détection de défaut d'un capteur de refroidisseur fonctionnant par préconditionnement d'air (PCA)

Mots clés : Détection de défaut ; Refroidisseur ; Défaillance de capteur ; Analyse du composant principal ; Sensibilité

* *Corresponding author.* Tel.: +86 27 87558330; Fax: +86 27 87558330.
E-mail address: chenhuanxin@tsinghua.org.cn (H. Chen).

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Nomenclature

T_{chws}	chilled-water supply temperature [°C]
T_{chwr}	chilled-water return temperature [°C]
M_{chw}	chilled-water flow rate [m^3 min^{-1}]
T_{cws}	condenser-water supply temperature [°C]
T_{cwr}	condenser-water return temperature [°C]
M_{cw}	condenser-water flow rate [m^3 min^{-1}]
M_{ref}	mass flow rate of refrigerant [%]
W	chiller electrical-power input [kW]
$\mathbf{X}^0$	original matrix
$\mathbf{X}$	normalized original matrix
$\mathbf{R}$	covariance matrix
$\mathbf{U}$	eigen vector matrix
FDDR	fault detection, diagnosis and reconstruction
HVAC&R	heating, ventilating, air-conditioning and refrigeration
PC	principal component
PCA	principal component analysis
Q_α	threshold of the Q-statistic
$\vec{x}$	normalized sample column vector
$\vec{x}$	normalized sample vector
$\hat{\vec{x}}$	estimate of a sample
$\tilde{\vec{x}}$	residual of a sample
$\mathbf{P}$	PC subspace projection matrix
$\tilde{\mathbf{P}}$	Residual subspace projection matrix
$\mathbf{Y}^{RS}$	Residual subspace projection matrix
$Y^{RS}_{i,:}$	ith row vector of $\mathbf{Y}^{RS}$
Ξ	diagonal matrix
e_i	ith entry of residual
y^{RS}_{ij}	jth entry of the row vector $Y^{RS}_{i,:}$
x_i	ith entry of the normalized sample vector $\vec{x}$
ξ_{ij}	ith entry in the jth row of Ξ
Greek letters	
μ	mean
σ	standard deviation
$\lambda_1, \cdots, \lambda_n$	eigenvalues

1. Introduction

Sensor faults, including bias and drift, are inevitable situations that existed in the HVAC&R system due to long term operation and severe working environment. Because of the unreliable measurement data, the system would be controlled ineffectively and deviated from normal operation mode, which would lead to higher, unreasonable energy consumption (Kao and Pierce, 1983; Lee and Yik, 2010; Yoon et al., 2011). Therefore, research on sensor fault detection, diagnosis and erroneous sensor data reconstruction (FDDR) for HVAC&R system is of great importance and has been paid more attention to in the recent years.

FDDR can be simply classified as two typical methods, the model-based and the data-driven, respectively. Due to the difficulty in developing accurate models by model-based method in the real applications, the data-driven methods were applied in a wide range for the development of building energy management. Sensor data in HVACR&R system are highly coupled by following the principle of energy balance principle and some other basic principles. Due to the variation on the cooling load and the ambient conditions, HVACR&R system normally operates under a wide range. It is difficult to diagnose any faulty sensor just from the observation on the historical data. Therefore, various multi-dimensional data-based methods have been introduced to the FDDR of HVAC&R system in the recent years.

A common flowchart of a multi-dimensional data-driven sensor FDDR strategy is illustrated in Fig. 1. Firstly, training data are selected from original operational data before data pre-process, including data cleaning and normalization. Training data are used to establish fault indicators and corresponding boundary to detect a fault condition or diagnose any fault source in detail. Many data-driven FDDR methods were employed in

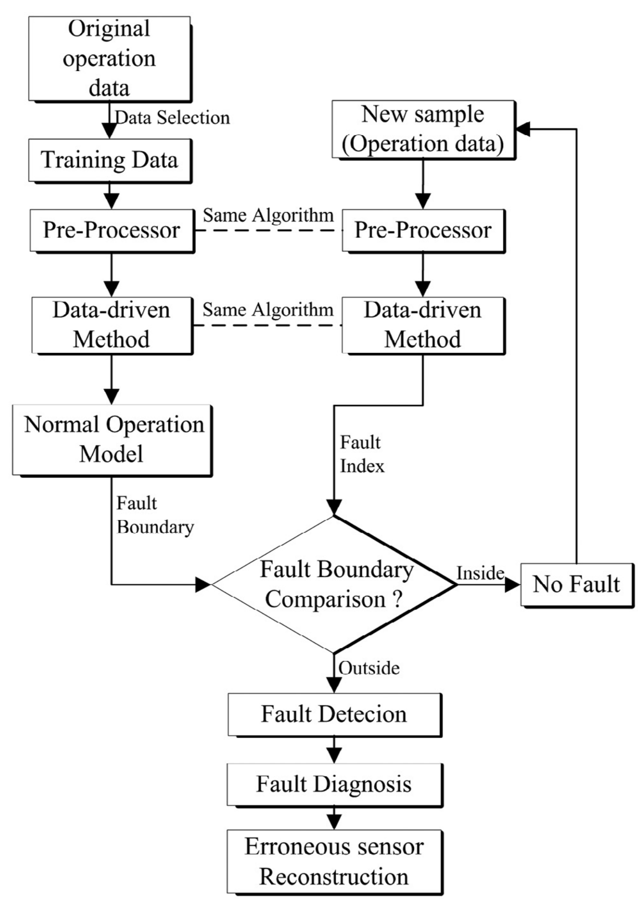

Fig. 1 – Flowchart of a data-based sensor fault detection, diagnosis and reconstruction.