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Research Paper

A robust online refrigerant charge fault diagnosis strategy for VRF systems based on virtual sensor technique and PCA-EWMA method

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HIGHLIGHTS

- VRC model can only identify VRF system charge faults at undercharge situation.
- PCA-EWMA method has shortcoming on detecting severe undercharge faults of VRF.
- A refrigerant charge fault diagnosis strategy is proposed based on VRC and PCA-EWMA.
- The proposed hybrid model showed high fault diagnosis accuracy and efficiency.

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ABSTRACT

The enhancement of fault detection and diagnosis (FDD) strategy for air-conditioning system is always a complex difficulty. In previous studies, the virtual refrigerant charge (VRC) sensor method and principal component analysis (PCA) based exponentially-weighted moving average (EWMA) method were proposed to identify refrigerant charge faults for variable refrigerant flow (VRF) systems, respectively. However, both methods had defects in some cases. On the basis of complementary advantages, this study employs the VRC model to detect the undercharge faults as it shown outstanding efficiency on identifying undercharge cases. Similarity, the PCA-EWMA model is used to detect the overcharge faults, since it is very sensitive to the little variation in the overcharge situations. Further, a novel online refrigerant charge fault diagnosis strategy is proposed based on two fault detection methods, i.e. VRC method and PCA-EWMA method. The new hybrid model overcomes the defects of two previous methods appropriately and well inherits the advantages of both. Finally, the robustness of the proposed refrigerant charge fault diagnosis strategy is verified using the experimental data and online data collected from different type of VRF systems.

1. Introduction

Variable refrigerant flow (VRF) systems are growing more popular in the light commercial and commercial buildings. The VRF market widely distributes in Asia, Europe and South America as it reached 1.3 million units with a corresponding value of US $ 9.7 billion in the world [1]. Moreover, the VRF shared 41.94% of the Chinese total central air-conditioning market in 2015 [2]. Compared to splits units, windows/through the wall units and indoor packaged air-conditioning systems etc. the proportion of household VRF system in the residential buildings is also increasing rapidly. However, the energy consumption of the air-conditioning system is non-negligible and worrying since it accounts for more than 50% of building energy usage [3]. Hence, numerous researches and techniques were implemented focusing on improving the VRF performance and reducing its energy consumption.

Recent development of VRF are mainly focus on experimental and numerical studies, steady-state or dynamic modeling studies, advanced control strategy exploitations, etc. [4]. Much of researches suggested that the VRF system not only has lower power dissipation than common air conditioning systems (e.g. variable air volume, fan-coil plus fresh air) under the same condition, but also provides better indoor thermal comfort [5–7]. However, in a real case, VRF systems are usually installed in the unstable indoor/outdoor environment rather than the laboratory chambers. It is vulnerable to the erosion of the rain and dust, as well as mechanical damages from the nature or individuals. Moreover, improper operation, employment or service give rise

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Nomenclature

C	covariance matrix
CV	cumulative proportion of variance
E	residual matrix
EXV_{subc}	openness of the electronic expansion valve of subcooler
f	compressor operating frequency
FDD	fault detection and diagnosis
I	compressor current
k	principal component number
$K_{dsh/sc}$	constant characteristic of a given system
K_{ch}	empirical constant
K_{sc}	constant related to condenser subcooling
K_{sh}	constant related to evaporator superheat
$K_{sh/sc}$	empirical constant
$K_{x/sc}$	constant characteristic of a given system
K_x	constant characteristic of a given system
LCL	lower control limit
L	control limit width
m	rows of original observation matrix
M_{total}	total refrigerant charge of a given system
$M_{total.rated}$	total refrigerant charge of a given system at rated condition
n	columns of original observation matrix, variable number
NC	normal charge
OC	overcharge
OEM	original equipment manufacturer
P	loading matrix
PC	principal component
RCL	refrigerant charge level
SL	severity level
T_{cond}	condensing saturation temperature
T_{evap}	evaporating saturation temperature
T_{shell}	compressor shell temperature
T_{sc}	liquid line subcooling
$T_{sc.rated}$	liquid line subcooling at rated condition
T_{sh}	suction superheat
$T_{sh.rated}$	suction superheat at rated condition
$T_{sh.com.suc}$	compressor suction superheat temperature
$T_{subc.out.L}$	liquid refrigerant temperature at the subcooler outlet pipe
$T_{subc.out.V}$	vapor refrigerant temperature at the subcooler outlet pipe
$T_{accu.out}$	accumulator outlet pipe temperature
UC	undercharge
UCL	upper control limit
VRC	virtual refrigerant charge
VRF	variable refrigerant flow
X	original observation matrix
$\bar{X}$	principal component matrix
y	number of the test observations
y_{cor}	number of the correctly detected test observations
z	total number of test data
z_c	total number of specified category data
z_{cor}	number of test data correctly classified
$z_{cor.c}$	number of specified category data correctly classified.
Z	EWMA value

Greek symbols

γ	EWMA weight factor
$\lambda_1, \ldots, \lambda_n$	Eigenvalues
δ	correctly detected ratio
θ	classification accuracy
ε	classification sensitivity

Subscripts

accu	accumulator
cond	condenser
dsh	discharge superheat of compressor
evap	evaporator
in	inlet
out	outlet
sc	subcooling
sh	superheat
shell	compressor shell
subc	subcooler
suc	compressor suction

to drastically performance degradation of the system. Therefore, it is highly possible that the performance would be quite different from its rated performance after years of operation. To automatically identify possible faults of the VRF system, e.g. refrigerant undercharge (UC) or overcharge (OC), evaporator/condenser fouling, fan stuck, compressor liquid floodback, temperature/pressure sensor faults and valve sticking, it is very necessary to develop fault detection and diagnosis (FDD) techniques for VRF systems. However, less literatures about the VRF FDD are presented in recent years.

Previous studies on the VRF FDD are as follows: Kim and Cho [8] employed a regression method to identify the evaporator air blockage faults of multi-heat pump system. The algorithm shown good performance to detect the faults when the multi-units operating in faulty cases. Shin et al. [9] investigated the heat exchanger fouling faults and valve stuck faults of a multi-split VRF system. Two model based fault detection strategy were proposed to identify faults above mentioned. For the VRF refrigerant charge fault detection and diagnosis, Li et al. [10] found that the traditional physical model based virtual refrigerant charge sensor (VRC) performed well at undercharge cases but conducted large prediction errors at overcharge cases in the VRF system. They employed a data based method, support vector regression (SVR), to improve the performance of the VRC for the overcharge situations. The SVR-VRC method promoted the VRC models and extended the application in the VRF system. However, the prediction results of the SVR-VRC were still undesirable in high-level overcharge cases. Liu et al. [11] proposed a data-driven method to detect the refrigerant charge faults for VRF system based on principal component analysis (PCA) and exponentially-weighted moving average (EWMA). The PCA method extracts the residual matrix from the original data as the input of the EWMA control charts. The fault detection strategy showed good efficiency on detecting overcharge faults and part of undercharge faults. Unfortunately, it failed to reject the severe undercharge fault. Liu et al. [12] also employed a data mining method, classification and regression tree (CART), to diagnosis the refrigerant charge faults of VRF system. Results showed that the CART method was sensitive to undercharge faults but failed to reject overcharge faults. Sun et al. [13] and Shi et al. [14] used support vector machine (SVM) based method and Bayesian artificial neural network (ANN) based method to diagnosis the refrigerant charge faults for VRF systems, respectively. The importance of variable number was analyzed in both researches while the proposed methods achieved high fault diagnosis accuracy. However, as data mining method, both SVM and ANN models had complex algorithm structure so that they were time-consuming in the train-