Energy and Buildings 94 (2015) 43–51

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Lab test of three fault detection and diagnostic methods' capability of diagnosing multiple simultaneous faults in chillers

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ARTICLE INFO

Article history:
Received 10 December 2014
Received in revised form 24 January 2015
Accepted 16 February 2015
Available online 25 February 2015

Keywords:
Chiller
Fault detection and diagnosis (FDD)
Multiple simultaneous faults
Decoupling-based FDD method

ABSTRACT

Chillers are large energy consumers which account for 20% to 40% of a facility's total energy consumption. The performance of chiller is often affected by faults introduced during initial installation or developed in routine operation. Over last two decades, much research has been performed on automated fault detection and diagnosis (AFDD) for the chiller systems. In the real world, a chiller is often affected by multiple faults. This research was for the first time to evaluate three promising FDD methods' capacity of diagnosing multiple simultaneous faults in chillers. First, the three FDD methods were introduced, including the multiple linear regression (MLR) black-box model-based FDD method, the simple linear regression (SLR) model-based FDD method, and the decoupling-based (DB) FDD method. Second, multiple simultaneous faults test was conducted on a 90-t centrifugal chiller installed in a laboratory. Several common chiller faults were introduced into the test chiller. Third, the three FDD methods were tested to detect and diagnose multiple faults. And then, a detailed evaluation of the three FDD methods was performed. The test and evaluation results show that the decoupling-based (DB) FDD method has the best performance in dealing with multiple simultaneous faults.

1. Introduction

Centrifugal chillers are large contributors of energy usage and maintenance costs for building energy systems, which can account for 20% to 40% of a facility's total energy consumption. The chiller systems often do not function as well as expected due to faults introduced during initial installation or developed in routine operation. A centrifugal chiller can lose as much as 30% efficiency and still appear to be operating satisfactorily. Automated fault detection and diagnosis (AFDD) technology has potential to reduce energy penalties and equipment downtime due to faulty operation and to provide building owners with sufficient information to prioritize maintenance job orders to reduce maintenance costs.

Over the last two decades alone, much research has been performed on AFDD for the chiller systems [1–8]. In response to the demand for a comprehensive study of AFDD for chillers, ASHRAE initiated a three-phase research project aiming at identifying the chiller AFDD methods for filed implementation and commercial generalization. The first phase 1043-RP [4] identified the common chiller faults in the real world and built a database of chiller performance for normal operation and with faults at different levels of severity and under different operating conditions on a 90-t laboratory centrifugal chiller. In 2003, the second phase 1275-RP [6] was conducted to evaluate the effectiveness and robustness of four promising FDD methods using the database provided by Phase I and to further identify the most promising of those for follow-up field evaluation and adoption. A general evaluation methodology, completed in this study, was developed to assess the overall performance of the FDD methods and tools. Based on this evaluation methodology, a five-characteristic-parameters-based multiple linear regression (MLR) black-box innovations for FDD table was determined as the best method. Reddy [9] extended the research of 1275-RP [6] and presented a simple linear regression (SLR) model-based method to do FDD for chillers.

A decoupling-based FDD method which can deal with multiple-simultaneous chiller faults was developed by Zhao et al. [10] and evaluated using the database provided by Comstock and Braun [4]. The test results showed that the proposed decoupling features for each fault are independent of driving conditions and all other chiller faults. It is worth noticing that fault tests data used for evaluation are individual fault tests instead of multiple-simultaneous faults test.

In summary, the literature review showed that previous research has evaluated the capability of FDD methods to handle

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http://dx.doi.org/10.1016/j.enbuild.2015.02.039
0378-7788/

Nomenclature

$\mathrm{CONDT}^*_{\mathrm{appr}}$	a pseudo condenser approach temperature which excludes the impact of refrigerant charge faults
CONDT_i	condenser water inlet temperature
CONDT_o	condenser water outlet temperature
EVAPT_o	evaporator water outlet temperature
C_p	specific heat of water at constant pressure
K_{sc}	slope of refrigerant charge vs. liquid line subcooling
K_{sh}	slope of refrigerant charge vs. suction line superheat
$\dot{m}_{\mathrm{cond}}$	condenser water flow rate
Q_{ev}	chiller cooling capacity
$T_{\mathrm{cond,cl}}$	calculated condensing temperature from condenser pressure
$T_{\mathrm{cond,ms}}$	actual measured condensing temperature
T_{sc}	liquid line subcooling
$T^*_{\mathrm{sc,rated}}$	model predictions which describing how rated subcooling vary under different driving conditions
T_{sh}	suction line superheat
$T^*_{\mathrm{sh,rated}}$	model predictions which describing how rated superheat vary under different driving conditions
UA	condenser overall heat conductance
UA^*	a pseudo condenser overall heat conductance that excludes the influence of refrigerant charge faults
ΔT	condenser water temperature difference
$\Delta T^-_{\mathrm{sc-sh}}$	a decoupling feature for low refrigerant charge fault
$\Delta T^+_{\mathrm{sc-sh}}$	a decoupling feature for refrigerant overcharge fault
ΔT_{cond}	a decoupling feature for non-condensable gas fault

individual faults in chillers, but generally has not investigated the ability of the FDD method to deal with multiple-simultaneous chiller faults.

The objective of this study is to perform lab tests to evaluate the capability of three promising methods of detecting multiple simultaneous faults. To be more specific, one method is the five characteristic-parameters-based multiple linear regression (MLR) black-box innovations for fault detection with diagnosis table, determined as the best method from Phase II research project [6]. The second method is the simple linear regression (SLR) model-based FDD method [9]. The third method is the decoupling-based FDD method [10].

The methodologies of the three evaluated FDD methods are summarized in this paper. The multiple simultaneous faults tests were conducted on a 90-t centrifugal chiller to test and evaluate the capability of the three evaluated FDD methods to handle common faults in chillers. The lab test results show that the decoupling-based FDD method has potential to be incorporated within commercial FDD products or embedded into the control system onboard the chiller to monitor the health of the chiller's operation.

2. The three evaluated FDD methods

2.1. Multiple linear regression (MLR) black-box model-based FDD methodology

Based on the results of 1275-RP [6], the MLR black-box model-based FDD method was determined as the best method among four promising evaluated FDD methods for chiller system. Five characteristic parameters are used in the MLR black-box model-based FDD method and shown as follows: evaporator water temperature difference (CQ1), condenser water temperature difference (CQ2), refrigerant condenser subcooling (CQ5), condenser approach temperature (CQ6), and overall condenser heat loss coefficient (CP1). The proposed FDD method is based on insights gathered from an exploratory analysis of the fault-free and faulty data sets of RP-1043 [4], which revealed that the above five characteristic features (CFs) are the most influential and useful for FDD application [6].

Basically, the FDD strategy includes two steps (detection and diagnosis): (1) a fault is flagged if a statistical test of the residuals (difference between actual characteristic features' value derived from measurements and expected value obtained from a reference model) exceeds predefined thresholds. (2) a qualitative fault classifier table based on the fault impacts on characteristic features is used to identify the specific fault in the system. The reference model (MLR model) uses three regressors to predict the characteristic features' values in normal operating conditions. The three regressors are the chiller cooling load (Q_{ev}), the condenser water inlet temperature (CONDT_i), and the evaporator water outlet temperature (EVAPT_o) respectively. The investigator of 1275-RP [6] suggested that the reference model can take the following forms:

(i) Use all terms in the MLR model. The form of the MLR model using all terms is shown as follows:

$$\begin{aligned} y = {} & a_0 + a_1\,\mathrm{CONDT}_i + a_2\,\mathrm{EVAPT}_o + a_3\,Q_{\mathrm{ev}} + a_4\,\mathrm{CONDT}_i^2 \\ & + a_5\,\mathrm{EVAPT}_o^2 + a_6 Q_{\mathrm{ev}}^2 + a_7\,\mathrm{CONDT}_i\,\mathrm{EVAPT}_o \\ & + a_8\,\mathrm{CONDT}_i\,Q_{\mathrm{ev}} + a_9\,\mathrm{CONDT}_o \end{aligned} \tag{1}$$

where 'y' is any characteristic feature pertinent to the chiller system and 'a' are the coefficients determined from the regression analysis.

(ii) Use a forward stepwise regression approach based on the F-statistic test method to determine the parameters to enter into the MLR model [6].

Table 1 presents the forward step-wise multiple linear regression model coefficients using a normal test data set in 1043-RP [4] along with their goodness-of-fit indices. The coefficients in the table were used for the evaluations of the MLR FDD method with the laboratory test data.

The following is a summary of the implementation steps of the MLR FDD method:

- Calculate the five characteristic feature values (CQ1, CQ2, CQ5, CQ6, and CP1) based on actual sensor measurements.

Table 1
MLR regression model coefficients identified from a normal data set of 1043-RP (Comstock and Braun [4]).

CF	Model	R^2%	RMSE
CQ1	$0.00310568 + 0.0176299 \cdot Q_{\mathrm{ev}} - 0.00000942766 \cdot \mathrm{EVAPT}_o \cdot Q_{\mathrm{ev}}$	99.99	0.0067
CQ2	$0.329792 + 0.0106599 \cdot \mathrm{CONDT}_i - 0.0298881 \cdot \mathrm{EVAPT}_o + 0.0135795 \cdot Q_{\mathrm{ev}} + 0.00000486393 \cdot (Q_{\mathrm{ev}})^2 + 0.0000541527 \cdot \mathrm{EVAPT}_o \times Q_{\mathrm{ev}}$	99.98	0.0227
CQ5	$0.69061 + 0.0684609 \times \mathrm{CONDT}_\mathrm{i} + 0.0171009 \cdot Q_{\mathrm{ev}} - 0.000176183 \times \mathrm{CONDT}_\mathrm{i} \times Q_{\mathrm{ev}}$	99.80	0.1290
CQ6	$0.131555 + 0.0111733 \cdot Q_{\mathrm{ev}} - 0.0000955529 \cdot \mathrm{CONDT}_i \times Q_{\mathrm{ev}}$	97.80	0.1210
CP1	$66.4296 + 0.0097447 \cdot (\mathrm{CONDT}_i)^2$	31.98	2.7300