Proceedings of ES2008
Energy Sustainability 2008
August 10-14, 2008, Jacksonville, Florida USA

ES2008-54002

COMPARISON OF TWO MODEL BASED AUTOMATED FAULT DETECTION AND DIAGNOSIS METHODS FOR CENTRIFUGAL CHILLERS

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ABSTRACT

Research has been ongoing during the last several years on developing robust automated fault detecting and diagnosing (FDD) methods applicable for process faults in chillers used in commercial buildings. These FDD methods involve using sensor data from available thermal, pressure and electrical measurements from commercial chillers to compute characteristic features (CF) which allow more robust and sensitive fault detection than using the basic sensor data itself. One of the proposed methods is based on the analytical redundancy approach using polynomial black-box multiple linear regression models for each CF that are identified from fault-free data in conjunction with a diagnosis table. The second method is based on a classification approach involving linear discriminant analysis to identify the classification models whereby both the detection and diagnosis can be done simultaneously. This paper describes the mathematical basis of both methods, illustrates how they are to be tuned using the same fault-free data set in conjunction with limited faulty data, and then compares their performance when applied to different fault severity levels. The relative advantages and disadvantages of each method are highlighted and future development needs are pointed out.

Keywords: centrifugal chillers, fault detection and diagnosis, model based automated fault detection methods.

Background

Faults in heating, ventilating, air-conditioning and refrigeration (HVAC&R) equipment result in excessive energy consumption. Faulty operation also leads to equipment wear and non-compliance of the design conditions of the process or space to be conditioned, which could result in litigation. Existing Building Automation Systems (BAS) are primarily meant to control or manage various building mechanical and electrical equipment so as to achieve optimal energy use or minimum operating costs. Such systems to-date lack sophisticated detection and sequence control capability of equipment such as chillers. On the other hand, the control and fault detection systems which manufacturers provide in their chillers are primarily meant to prevent catastrophic failures.

There are numerous research papers and about a dozen textbooks which specifically pertain to fault detection and diagnosis (FDD) in engineering systems (for example, Himmelblau, 1978; Pau, 1975; Patton et al., 1989; Pouliezos and Stravrakakis, 1994; Gertler, 1998; and Chen and Patton, 1999). Many of these techniques have been evaluated for adoption to FDD of HVAC&R equipment and systems. From the last 20 years, the development of robust automated fault detection and diagnosis (FDD) methods applicable to HVAC&R equipment has been an area of active research, and several papers have been written on this issue (see literature review papers by Comstock et al., 1999; Katipamula and Brambley, 2005a,b; Reddy, 2006).

A basic requirement for the widespread use of model-based FDD (as against one based on heuristic or rule-based approach) is the ability to identify an accurate performance model of the chiller characterizing its fault-free operation. Such a model can then be used to detect faulty operation by tracking the deviation of the residuals (or innovations) between model predictions and actual performance, and flagging occurrences of faults when these deviations exceed pre-selected thresholds. The numerical values of these thresholds can be selected based on statistical considerations (for example, the 99% confidence limits), fuzzy logic or heuristics.

Traditional FDD methods adopted in the HVAC&R area generally involve measuring numerous performance variables, determining if one or more performance features show a statistically significant deviation as against a baseline or fault-free state (this is the fault detection process), and then comparing the relative direction of change against pre-defined patterns embedded in a diagnostic classifier database (which is the fault diagnosis phase). Such an approach requires that fault detection be performed on numerous measured and/or derived data channels (which is a statistically challenging step), but more importantly, that a diagnostic classifier database be generated and available for fault diagnosis. The latter is usually done on a generic type of equipment or system by a series of intrusive tests during which known faults are intentionally introduced, which are then assumed to apply to other allied systems as well.

Objective and Scope

The focus of this paper is limited to FDD methods applicable to large centrifugal chillers which are typically the single most expensive piece of equipment in HVAC&R systems. They are well suited for this purpose where the economic benefits of proper operation and control may justify the added cost of the FDD system.

The objectives of this study were to compare the performance of two different model-based FDD methods when applied to the same data sets involving fault-free and intentionally introduced faults in a centrifugal chiller. A previously proposed evaluation methodology, fully described in another paper (Reddy, 2007) is used for the evaluation of the two FDD methods. Large chiller plants of the same type may consist of different sizes of individual components and subsystems (such as heat exchangers, compressor,…), and hence a certain amount of customization is necessary; how this has been done is also described in this paper.

The scope of the proposed research was limited to process fault detection and did not include sensor faults (see for example, Wang and Cui, 2006) or actuator faults or control loop or controller faults. Also, the FDD processes were to rely on continuous thermal/pressure/electrical measurements as against one-time diagnostic measurements or other tests (such as vibration and electrical signature analysis, visual inspection checks, oil wear debris analysis, surface and internal defect detection tests as described in Davies, 1998). Further, the scope of this research was limited to FDD methods which are based on steady-state data, which is consistent with most of the FDD work to-date in the HVAC&R area.

Medium to large chillers come equipped with elaborate safety control mechanisms for critical/catastrophic faults. This study is not targeted towards such faults or to the detection of hard faults (such as fan belt breakage, or a burnt motor) but towards incipient faults which lead to energy wastage and gradually damage equipment. Further, such medium to large chillers come equipped with numerous sensors, usually temperature, pressure, and electrical, on individual sub-components and loops such as the condenser and evaporator loops, refrigerant loop, and cooling oil loop. Thus, any FDD method should explicitly make use of such data-rich environment, for which <u>component isolation methods</u> (McIntosh et al., 2000; Jia and Reddy, 2003; Wang and Cui, 2006) seem particularly appropriate. On the other hand, calibrated simulation model approaches for FDD are deemed best suited for systems where limited sensor data are available (such as those for unitary roof-top cooling equipment studied by Rossi and Braun,1997; Brueker and Braun,1998a,b and Castro, 2002).

Chiller Faults and Data Sets

This study used the extensive performance data gathered by Comstock and Braun (1999) within the framework of a research project funded by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) for a centrifugal water cooled chiller of 90 Ton. Experimental data were collected under: (a) eight different chiller faults (however, only data from six faults are used in this study since an earlier study by Reddy (2006) found certain limitations with data collected under excess oil faults and faulty thermostatic expansion valve operation); (b) each fault was introduced at four levels of severity (10-40% fault levels in increments of about 10%); (c) the faults were tested at 27 different operating conditions of chiller thermal load (Q_{ev}), chilled water outlet temperature from chiller evaporator (T_{evo}) and condenser water inlet temperature (T_{cdi}). Each steady-state performance condition collected included the four entering and leaving water temperatures, the sub-cooling, suction and discharge temperatures of the refrigerant, the water flow rates in the evaporator and condenser, the refrigerant pressures in the evaporator and condenser, the heat transfer rates in the condenser and evaporator, and the compressor power consumption. Table 1 summarizes the numerous sets of tests performed under each of the six different faults under benchmark (or normal or fault-free or baseline conditions) and under four different fault severity levels (SL). Note that several replicate sets of tests had to be performed under fault-free conditions in order to re-establish the baseline each time a specific fault, which was previously introduced, had to be rectified prior to introducing another fault. Three such fault-free data sets were used in this study (Normal 1, Normal 2 and Normal CF). Table 1 also specifies the range of variation in the magnitude of the faults compared to the baseline condition.

Table 1. Summary of Lab Chiller Data sets (Comstock and Braun, 1999).

	Description of Fault	Normal Operatio	SL1	SL2	SL3	SL4
1	*Reduced Condenser water flow*	270 gpm 0.98-1.0	0.87-0.93	0.77-0.81	0.69-0.70	0.59-0.61
2	*Reduced evap. water flow*	216 gpm 0.99-1.0	0.90-0.91	0.81-0.82	0.72-0.72	0.63-0.65
3	*Refrigerant leak*	300 lb	0.1	0.2	0.3	0.4
4	*Refrigerant overcharge*	300 lb	0.1	0.2	0.3	0.4
5	*Condenser fouling*	164 tube in total	0.06	0.12	0.20	0.30
6	*Non-condensables i system(by volume)*	No nitrogen	0.01	0.017	0.024	0.057

Note: Fractional values indicate the level of fault severity. For example, the range 0.59-0.61 under SL4 for reduced condenser water flow indicates that flow was reduced to about 60% of the normal value.

Types of Variables

Experience gained from past studies (for example, Comstock and Braun, 1999; McIntosh et al., 2000; Wang and Cui, 2006) indicates that fault detection can be more sensitive if certain characteristic quantities (CQ) or characteristic parameters (CP) are used instead of the basic sensor measurements themselves. These CPs and CQs can be directly deduced from the sensor measurements using arithmetic operations and thermodynamic refrigerant property tables or correlations. A supposedly distinguishing trait between CPs and CQs is that the former are those which in some manner better capture the performance of the internal state of the system or its components than do the latter in response to specific values of forcing functions. Hence, we have also adopted the terminology characteristic features (CF) which would include both CQs and CPs. Definitions of the seven CQs and seven CPs subsequently used in this research are provided in Table 2 along with their symbols and computational definitions. The overall chiller Coefficient of Performance (COP) is also considered as an additional CF.

Since, basic knowledge necessary to propose a fault diagnosis table is lacking, we have used data from fault severity level 4 (highest level) for each fault along with fault-free data to extract fault features, i.e., determine association of a specific CF to a particular fault and codify the diagnosis rules.

Developing and Customizing the FDD Methods

(1) FDD-MLR (Multiple Linear Regression) approach

The procedure adopted consists of the following steps:

(A) Pre-processing: Polynomial black-box MLR models for each CF have been identified from the fault-free data consisting of 27 individual performance data points. Though we realize that physical models would have been preferable because of the parsimony they provide along with capturing the basic physics of the processes, developing such models is not straightforward and would depend on the geometric configuration of the specific chiller. Black-box models are, in that sense, easier to identify for a practical situation, and hence, their widespread use. Identification of the most suitable (parsimonious model) is an issue. One can consider two different MLR black-box polynomial model identification techniques:

(i) use all terms in the model- this is not parsimonious but is easy to implement

$$y = \alpha + \underbrace{\beta_1 T_{cdi}}_{A} + \underbrace{\beta_2 T_{evo}}_{B} + \underbrace{\beta_3 Q_{ch}}_{C} + \underbrace{\beta_4 T_{cdi}^2}_{D} + \underbrace{\beta_5 T_{evo}^2}_{E} + \underbrace{\beta_6 Q_{ch}^2}_{F} + \underbrace{\beta_7 T_{cdi} T_{evo}}_{G} + \underbrace{\beta_8 T_{cdi} Q_{ch}}_{H} + \underbrace{\beta_9 T_{evo} Q_{ch}}_{I} \qquad (1)$$

where y denote the various CFs and the terms in the model by letters A-I. Books on statistics caution that though this model may give excellent fits to the data used for training, it is likely to be unstable and perform poorly for extrapolation. This aspect has also been investigated for chillers (for example, Reddy and Anderson, 2002).

(ii) adopt a forward stepwise regression approach (refer to any appropriate statistical textbook, for example Manly, 2005) using a F-statistic = 4 (corresponding to a confidence level of 99%) for a parameter to enter the model. Note that we have also compared this approach to another regression approach where all possible permutations are evaluated and the parsimonious model identified following the Mallow c_p statistic (Manly, 2005). We find the results of both approaches to be very similar, and since stepwise regression is the better known method, we have adopted this approach here. It must be cautioned that stepwise regression is likely to suffer from unstable model identification, i.e., different terms in the model given by eq. (1) are likely to be retained when different training sets are used. This is well documented in the statistical literature, and has also been illustrated with chiller data (Reddy and Anderson, 2001). Because of the paucity of data (only 27 data points), we could not perform validation tests involving breaking the performance data set into training and testing sets.

We have used the forward stepwise regression approach as the basis for identifying models of the various CFs during fault-free chiller operation. Table 3 indicates which terms in eq.(1) have been retained during the forward step-wise regression model identification using Normal2 data set along with their goodness-of-fit indices. Figure 1 depicts the goodness of fit (x-y plot) and residual plots of fitting fault-free chiller COP using a quadratic polynomial model (which is an excellent model), while Fig. 2 illustrates that for a poor model (the condenser UA model).

Table 3. Forward stepwise regression model coefficients identified from Normal 2 data for the MLR approach.

CF	Influential model parameters (*)	Adj-R2	RMSE
COP	ACFHI	99.8%	0.0342
CQ1	CI	99.99	0.0067
CQ2	ABCFI	99.98	0.0227
CQ3	ABCDEI	99.7	0.092
CQ4	BCFI	99.2	0.661
CQ5	ACH	99.8	0.129
CQ6	CH	97.8	0.121
CQ7	ABCDF	98.5	0.137
CP1	D	31.98	2.730
CP2	BEGH	96.6	2.269
CP3	ABCDFHI	99.7	0.008
CP4	ABCDFHI	99.7	0.008
CP5	ABCDFGH	99.98	0.004
CP6	ACDGHI	99.8	0.049
CP7	BCFI	97.3	0.005

- The model parameters are specified in eq. (1)

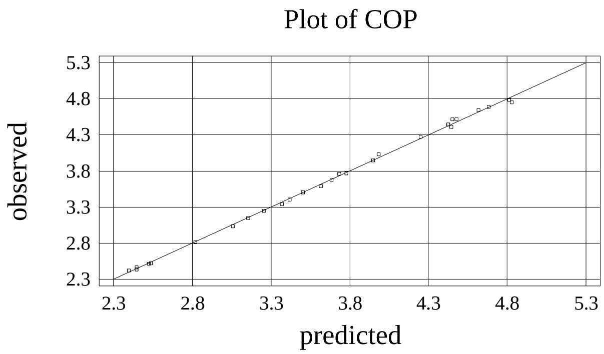

Figure 1. Goodness of fit plot of fitting the fault-free chiller COP using a quadratic polynomial model (good model)

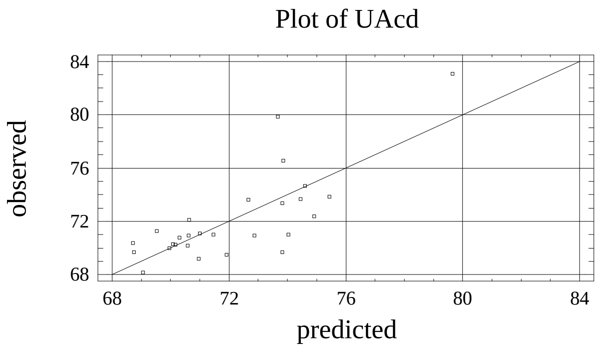

Figure 2. Goodness of fit plot of fitting fault-free chiller condenser UA value (poor model)

(B) Fault detection: Analytical redundancy (see any appropriate FDD textbook, for example, Himmelblau, 1978) is used for calculating innovations or model residuals. For a specific chiller operating condition, the particular models are used to predict the values of the various CFs from which the residual for each CF is normalized by the fault-free model root mean square error (RMSE) so as to provide the well known Student t-statistic:

$$t-statistic=\frac{(y_{meas,i}-\hat{y}_{model,i})}{RMSE} \qquad (2)$$

The numerical value of this statistic can be directly interpreted in statistical measures provided the student t distribution of the model errors applies.

(C) Fault diagnosis: Several CFs are likely to be impacted whenever a fault occurs. In order to simplify the diagnosis while reducing the probability of a wrong diagnosis, we have elected to identify only those CFs affected most strongly by a particular fault and use these rules for diagnosis. The fault diagnosis rules have been identified as follows. At each of the 27 operating points under each fault condition, we have calculated the model t-values with respect to the baseline model. Unfortunately, these values vary greatly with operating conditions specified by the two fluid temperatures and the thermal load which is detrimental to the robustness of this FDD method. Instead of computing the mean value (which will be affected by extreme values) we have computed the median, minimum and maximum values of the t-values as shown in Table 4. It is interesting to point out that the mean and median values are close in most cases, and also that the distribution of t-residuals are near-normal distribution

A diagnosis rule would be considered robust when all three residuals (median, min and max) are of the same sign and have large numerical values (in absolute terms). Unfortunately, not all faults had this behavior, as can be noted in Table 4. We have identified the combinations of strong association between CFs and faults which are then cast as diagnostic rules as shown in Table 5. A detailed analysis (see Reddy 2006) showed that the last two CFs in Table 5, namely CP5 and CP6, which only impact non-condensable fault (F6), are not crucial since they do not have much impact on either the sensitivity or the robustness of the method. The results presented in this paper are, consequently, based on using five CFs only. To summarize, fault detection will involve the following steps:

(i) Calculate the five CF values (CQ1, CQ2, CQ5, CQ6, CP1) from primary sensor measurements.
(ii) Predict fault-free values for each of these CF using the models shown in Table 3.
(iii) Compute the t-statistic for each of these five CF using the RMSE value shown in Table 3.
(iv) If the absolute t-value of any single CF exceeds a pre-set value, flag occurrence of a fault. The more sensitive (i.e., lower the numerical value) the threshold selected, the greater the false alarms, resulting in the operator disabling the FDD system altogether. Thus, one has to balance FDD sensitivity against false alarm rates. The current thinking is that, false alarm rates of 5% seems to be acceptable; however, we have performed the analysis with three other false alarm rates as well (described below). The FD thresholds involve calibrating the t-values of the fault-free innovations so as to achieve the pre-selected false alarm rates.

Table 5. Fault diagnosis table proposed for FDD-MLR approach using Table 4 results. The + and – signs indicate directional change of the t-statistic with increasing fault severity. For example, as the condenser water flow rate decreases, the t-statistic for CQ2 will increase.

Fault code	Fault description	**CQ1**	**CQ2**	**CQ5**	**CQ6**	**CP1**
F1	Reduced condenser water flow rate		+			
F2	Reduced evaporator Water flow rate	+				
F3	Refrigerant leak			-	-	+
F4	Refrigerant overcharge			+	+	-
F5	Condenser fouling			0	+	-
F6	Non-condensables in System			+	+	-

Fault diagnosis will be done using the association rules shown in Table 5. We shall use five CFs (CQ1, CQ2, CQ5, CQ6 and CP1) with a statistical test done on CQ5 to ascertain whether it is zero or not for fault F5.

(2) FDD-LDC: Linear Discrimination and Classification Approach

Discriminant analysis and classification approaches are multivariate techniques concerned with separating distinct objects or observations and with allocating new ones to previously defined groups (see any appropriate textbook, for example, Manly, 2005). This allows the association of faults and CFs to be identified simply, while allowing easy implementation. Techniques which involve linear models are called linear discriminate and classification (LDC) methods. Discriminant analysis provides the necessary methodology to statistically distinguish or "discriminate" differences between two or more groups when one knows beforehand that such groupings exist in the data set provided. Subsequently, it can be used to assign, allocate or classify a future observation into a specific group. Hence it can be used to train the data with known fault-free and faulty data sets, and then to conveniently determine whether a particular performance condition datum is faulty or not. Analyzing and interpreting the results from discriminant analysis is similar to multiple linear regression analysis except that here the dependent variable is categorical (either 0 or 1- i.e., fault-free or faulty). One could also code the various fault data by say, denoting 0 for fault-free, 1 to F1, 2 to F2 and so on. Moreover, unlike MLR, no underlying probability distribution is assumed and in that sense it can be viewed as a nonparametric method. One can use these functions to predict the group into which an observation is placed. The function that yields the largest value for an observation indicates that the particular datum is best classified in that particular group or fault condition. It will be noted that LDC approach is similar to the artificial neural network approach (except that the latter are non-linear models, of course), but the computational effort involved is substantially reduced. Another advantage of the discriminant approach is that data need not be standardized to have zero mean and unit variance (as usually done in principal component analysis). The results are not affected by scaling of the individual variables.

We have used the 15 CFs variables (with 27 observations) from Normal2 data (the dependent categorical variable is coded as 0) along with those from each of the faulty data sets at fault severity level 4 of the lab chiller data (the categorical variable coded from 1-6 are for the six faults) to develop linear discriminant models using forward stepwise model identification. It was found that the FDD results with 15 CFs were very similar to those using the same 5 CFs selected in the FDD-MLR approach (see Reddy, 2006). Thus, for consistency, we have only presented results for LDC models identified using the same five CFs as in the previous method. The linear discriminate function coefficients are shown in Table 6 for each of the 6 faults considered. For example, the model would be a linear polynomial model with the model coefficients for fault code "0" (representing fault-free operation) listed in the column underneath pertinent to each of the 5 CFs (CQ1…CP1). The models are excellent with 100% classification accuracy. These functions can be used to predict the group into which a future observation can be placed. The function that yields the largest value for an incoming future observation represents the predicted group. Figure 3 is a three dimensional scatterplot which plots the fault-free and faulty observations by the three CFs influencing non-condensables in system fault.

No preprocessing of data is necessary except to calculate the CFs. Fault detection will involve calculating the various sets of classification functions for all the faults and determining whether the observation can be classified as faultfree or faulty. Fault detection will be signaled even if one of the classifiers assigns the incoming observation as a fault. Fault classification is immediately indicated by the classifier.

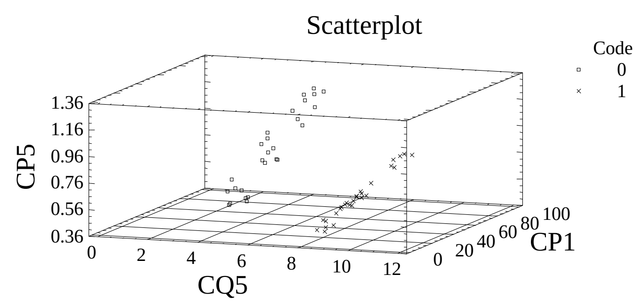

Figure 3. Three-dimensional scatter plot showing how the fault-free and the faulty observations are distinctly different w.r.t. the three CFs for the non-condensables in system fault.

Table 6. One set of classification functions identified from RP1043 lab chiller data using only 5 CFs with Normal2 data paired with each of the faulty data at fault severity level 4.

Fault Code	0	1	2	3	4	5	6
CQ1	2.39535	-6.41338	10.6924	2.35117	-1.28958	0.67205	-4.86291
CQ2	-4.41552	5.55096	-12.2459	-2.43625	-6.05917	-2.80707	-7.13599
CQ5	6.30166	7.84475	8.63203	3.0633	7.36913	3.09112	0.418812
CQ6	-1.96295	-6.33261	-6.19201	0.468244	5.22512	2.95793	23.7959
CP1	1.54869	1.22362	1.57676	2.31821	1.14769	1.35378	0.986011
Cte	-63.9133	-54.198	-75.4632	-138.518	-51.37	-49.5048	-84.3367

FDD Evaluation Methodology

A previously proposed methodology to evaluate different chiller FDD tools (Reddy, 2007) will be used to evaluate the two methods. The methodology suggested involved developing analytical expressions for the FDD evaluation which is cast into an objective function of two competing considerations (cost associated with false alarms, and penalties associated with the onset of faults). Further, a special effort was made to determine the types of penalties associated with various faults in chiller installations (energy increase, loss of cooling capacity, reduced life,…). After discussion with service personnel of a large chiller company, it was decided to limit the FDD evaluation to the energy penalty alone. It was also pointed out that from a practical viewpoint, FDD evaluation should be based on two criteria:

(i) the **normalized fault detection index** resulting in a normalized score or rank between 0 and 1 (where the basis of evaluation is with respect to an ideal detector with score of unity and with no false alarms whatsoever) :

$$\Phi_{Detect,s} = \sum_{f=1}^{N_F} [P_f . \Delta E_f . (1 - F_{N,f})] / \sum_{f=1}^{N_F} (P_f . \Delta E_f) \tag{3}$$

where

$F_{N,f}$	false negative rate for fault f, i.e., missed opportunity rate
f	index for fault type
N_F	total number of possible faults in system
P_f	probability of occurrence of fault type f
ΔE_f	extra electric power required to provide necessary cooling due to performance degradation as a result of fault type f

(ii) the **combined fault detection and fault diagnosis index** which consists of four different diagnosis outcomes (correct and unique diagnosis, correct but non-unique, unable to diagnose, incorrect diagnosis) all of which have different implications in terms of the time taken (and hence the cost) for the technician or the serviceman to diagnose the fault, and then evaluate its implication and chose an appropriate course of action.

$$\Phi_{FDD} = \sum_{f=1}^{N_F} [P_f . \Delta E_f . (w_{cu} . r_{cu,f} + w_{cn} . r_{cn,f} + w_{ic} . r_{ic,f} + w_{ud} . r_{ud,f})] / \sum_{f=1}^{N_F} [P_f . \Delta E_f] \tag{4}$$

where the terms are defined in the nomenclature.

Numerical values of various quantities appearing in the above expressions are shown in Table 8, and have been determined based on discussions with chiller service personnel (Reddy, 2007). The energy penalties for the six faults at different SL values are shown in Table 7. We note that these vary greatly across a specific SL category. Hence, we have selected a composite fault severity level category (CFS) which is made up of different SL categories for different faults selected such that the energy penalties are as close as possible. Even then, the energy penalties differ appreciably. This, however, is not a major issue since the normalized expressions for FD and FDD rating (given by eqs. 3 and 4) do allow for this possibility since they include a weight for this energy penalty term.

Table 8. Weights assigned to the four different diagnoses outcomes.

Outcome	Symbol	Base Weights
Correct and unique	w_cu	1.00
Correct but non-unique	w_cn	0.75
Unable to diagnose	w_ud	0.50
Incorrect diagnosis	w_ic	0.40

Analysis and discussion of Results

(a) Raw data generation: The first step in the analysis involves identifying the number of instances when the FDD-MLR and FDD-LDC methods signaled faults when applied to the data sets consisting of 27 performance points each. Table 9 assembles these values for FDD-MLR with the FD thresholds tuned using N2 data set so as to yield a correct fault-free detection rate of 95%. We note that one fault has been erroneously detected under N1, while for reduced condenser flow and reduced evaporator flow faults, all 27 occurrences have been correctly identified as faults (these are shown bolded). However, the FD process is much poorer for refrigerant leak fault where for example, under SL1, only 1 out of 27 fault occurrences have been signaled as faulty. The other values in this table can be interpreted accordingly.

(b) Evaluating fault detection capability: The second step in the analysis involves condensing the information contained in Table 9 into a form more convenient for evaluating the fault detection capability of the various FDD methods. This is provided in Figs. 4 and 5 for the detection phase and the diagnosis phase respectively. The fault detection rates (in %) for each fault F1 through F6 for two FDD methods are shown as cumulative bar plots in Fig.4 for the CFS weighting scheme. This provides a visual comparison for the two methods, and suggests that FDD-MLR is slightly better than FDD-LDC.

(c) Evaluation of the fault diagnosis capability: The third stage of the analysis involves comparing the diagnosis capability of the two methods in terms of the four diagnosis categories shown in Table 8. The results for the FDD-MLR approach only are shown in Fig.5. The trouble with making an overall inference is that there are several numbers to consider, and this supports our suggestion of deriving one or two representative normalized performance indices as given by eqs. (3) and (4).

(d) Evaluation overall FDD capability: The final step in the analysis involves computing the normalized overall FD and FDD indices given by eqs. (3) and (4). Figure 6 plots the results of our analysis comparing the two FDD methods with the FD thresholds tuned to four different false alarm states. The values are normalized scores, which can be evaluated against an ideal FDD (i.e., one which detects and diagnoses perfectly) with a score of 1.0. One concludes that fault detection capability is generally excellent (about 90% as against an ideal detector), while the overall FDD capability is much poorer, about 50% only. Also, the same general conclusions can be drawn as previously: FDD-MLR is slightly superior to the FDD-LDC method. We have also found the same conclusion when different sensitivity tests using different diagnosis weights, as well as with and without inclusion of energy penalties, were performed (see Reddy, 2006).

Summary and Conclusions

This paper reports the results of evaluating two different model-based FDD methods when applied to the same data set. How the two methods evaluated, the MLR and the LDC methods, have been customized in a consistent manner is first described. Subsequently, we present both the evaluation methodology and the results when applied to the same data sets, and we show that the MLR method is slightly superior in both its FD and FDD capabilities. This paper presents the analysis performed in a clear and methodical manner so that future researchers could replicate, and perhaps refine, specific aspects of the evaluation methodology and rate future FDD methods and tools in a rational manner.

Acknowledgments

We acknowledge advice and helpful feedback from Ashish Singhal, John Seem, Bill McQuade, Justin Kauffman, Dennis Dietz and John House. The lab chiller data has been supplied by J. Braun which is greatly appreciated.

NOMENCLATURE

C_dA_0	expansion valve blockage coefficient
COP	coefficient of performance of chiller
C_p	specific heat at constant pressure
E	electric power input to compressor
$F_{N,f}$	false negative rate for fault f
F_P	false positive rate
f	index for fault type
h	enthalpy
m	mass flow rate
N_F	total number of possible faults in system
P_f	probability of occurrence or frequency weight of fault type f
P	pressure
Q_{ev}	thermal heat load or capacity
r_{cu}	correct and unique diagnosis rate expressed as a fraction of the signaled faulty data
r_{cn}	correct but non-unique diagnosis rate
r_{ic}	incorrect diagnosis rate
r_{ud}	unable to diagnose rate
T	temperature
T_c	saturated refrigerant temperature in condenser
T_{cdi}	condenser water inlet temperature
T_{cdo}	condenser water outlet temperature
T_{co}	refrigerant temperature leaving condenser
T_{cpi}	refrigerant temperature entering compressor or leaving evaporator
T_{cpo}	refrigerant temperature at compressor discharge
T_e	saturated refrigerant temperature in evaporator
T_{evi}	evaporator water inlet temperature
T_{evo}	evaporator water outlet temperature
t-value	student t-statistic
UA	overall heat conductance of heat exchanger
w_{cu}	weighting factor for correct and unique diagnosis rate (same for each fault type)
w_{cn}	weighting factor for correct but non-unique diagnosis rate
w_{ic}	weighting factor for incorrect diagnosis
w_{ud}	weighting factor for unable to diagnose
x	regressor variable
y	response variable
ΔE_f	extra electric power required to provide necessary cooling due to performance degradation as a result of fault f
ν	specific volume
η	efficiency
ϕ	normalized rating index for FD and FDD defined by equations (3) and (4)
1,2,3,4	refrigerant state points on the pressure-enthalpy diagram indicating inlet to compressor, exit from compressor, exit from condenser and inlet to evaporator

Subscripts

cd	condenser
ch	chiller, evaporator
ev	evaporator
r	refrigerant
s	index for fault severity level

Acronyms

CF	characteristic feature
CFS	composite fault severity
CP	characteristic parameter
CQ	characteristic quantity
FD	fault detection
FDD	fault detection and diagnosis
LDC	linear discriminant and classification method
MLR	multiple linear regression method
RMSE	root mean square error
SL	severity level of a fault

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Table 2. Characteristic quantities and parameters evaluated.

	Description	Symbol	Computed as
-	Chiller overall COP	COP_overall	Q_{ev}/E
CQ1	Evaporator water temperature difference	T_evi-T_evo	$T_{evi} - T_{evo}$
CQ2	Condenser water temperature difference	T_cdo-T_cdi	$T_{cdo} - T_{cdi}$
CQ3	Refrigerant compressor suction superheat	T_cpis	$T_{cpi} - T_e$
CQ4	Refrigerant compressor discharge superheat	T_cpos	$T_{cpo} - T_c$
CQ5	Refrigerant condenser subcooling	T_cds	$T_{co} - T_c$
CQ6	Condenser approach temperature	T_c-T_cdo	$T_c - T_{cdo}$
CQ7	Evaporator approach temperature	T_evo-T_e	$T_{evo} - T_e$
CP1	Overall condenser heat loss coefficient	UA_cd	$(UA)_{cd} = C_p \dot{m}_{cd} \ln(\frac{T_{cdo} - T_c}{T_{cdi} - T_c})$
CP2	Overall evaporator heat loss coefficient	UA_ev	$(UA)_{ch} = C_p \dot{m}_{ch} \ln(\frac{T_{cho} - T_e}{T_{chi} - T_e})$
CP3	Polytropic efficiency of the compressor	Effy_Poly	$\eta_p = \frac{(P_2 v_2 - P_1 v_1)\ln(P_2 / P_1)}{(h_2 - h_1)\ln((P_2 v_2)/(P_1 v_1))}$
CP4	Isentropic efficiency of the compressor	Effy-Isen	$= \frac{h''_2 - h_1}{h_2 - h_1}$
CP5	Expansion valve blockage coefficient	Cd.A0*10^6	$C_d A_0 = \frac{\dot{m}_r \upsilon_3}{2\sqrt{P_3 - P_4}}$
CP6	COP of the thermodynamic cycle	COP_cycle	$= \frac{h_1 - h_4}{h_2 - h_1}$
CP7	Motor efficiency	Effy_motor-drive	$= \frac{COP_{overall}}{COP_{cycle}}$

- m_r is the refrigerant mass flow rate calculated from an energy balance on the evaporator $= Q_{ev} / h_1 - h_4$
- P, v and h are the refrigerant absolute pressure, specific volume and enthalpy respectively

Table 4. Table used to identify association rules of specific faults and CFs for MLR model based approach. The values shown in each cell are the median, minimum and maximum values of the t-values (following eq.2) of the 27 different operating states at severity level 4. Normal2 data set was used to identify the fault-free performance models. The combinations of strong association between CFs and faults are shown bolded.

Characteristic Features		CQ1	CQ2	CQ3	CQ4	CQ5	CQ6	CQ7	CP1	CP2	CP3	CP4	CP5	CP6	CP7
		T_evi-T_evo	T_cdo-T_cdi	T_cpis	T_cpos	T_cds	T_c-T_cdo	T_evo-T_e	UA_cd	UA_ev	Effy_Poly	Effy-Isen	Cd.Ao* 10^6	COP_Cycle	Effy_motor
Units		C	C	C	C	C	C	C	$kW/m^2.C$	$kW/m^2.C$	-	-		-	-
F1- Reduced condenser flow	Median	0.41	**82.50**	-4.07	0.52	14.58	3.00	-3.17	-6.92	1.97	1.17	1.02	-7.49	-4.97	-1.95
	Min	-0.42	**35.36**	-6.61	-1.96	-6.32	-4.71	-6.08	-8.47	-2.20	-1.56	-1.59	-23.00	-13.85	-7.36
	Max	2.46	**167.62**	-0.52	8.86	25.22	4.94	-1.19	12.54	7.31	4.54	4.44	1.56	-0.04	1.93
F2- Reduced evaporator flow	Median	**242.09**	1.61	-2.65	-0.88	-0.11	0.07	1.33	0.09	-2.67	1.23	1.31	-0.54	0.52	-2.78
	Min	**102.86**	-1.25	-9.08	-4.84	-4.24	-3.04	-1.29	-1.52	-5.85	-1.23	-1.27	-3.18	-1.99	-6.89
	Max	**386.88**	4.61	1.15	1.59	3.40	1.21	4.24	9.39	-0.65	4.03	4.59	2.09	3.17	2.20
F3- Refrigerant leak	Median	1.32	0.03	0.35	-0.25	**-14.75**	**-9.05**	0.25	**15.86**	0.00	-0.60	-0.50	9.01	2.17	-0.10
	Min	-0.43	-2.19	-2.94	-2.11	**-37.97**	**-15.50**	-3.26	**9.53**	-3.07	-3.57	-3.53	1.62	-1.68	-5.07
	Max	3.91	1.88	4.64	1.58	**-9.03**	**-3.14**	3.02	**25.89**	1.58	2.62	3.09	24.48	9.51	3.67
F4-Refrig overcharge	Median	1.09	16.99	0.70	0.97	**31.35**	**23.59**	-0.01	**-11.43**	0.28	2.29	2.10	-16.52	-9.26	0.53
	Min	-0.22	1.29	-3.69	-2.78	**5.96**	**4.79**	-3.08	**-13.13**	-1.72	-0.82	-1.01	-36.22	-17.18	-1.78
	Max	3.90	27.09	5.23	2.78	**48.44**	**36.33**	4.21	**-5.79**	2.19	5.37	5.37	-0.77	-0.85	2.75
F5- Condenser fouling	Median	1.35	4.85	-1.24	-0.30	0.90	**3.77**	-0.75	**-3.80**	0.65	0.44	0.38	-1.45	-1.72	0.00
	Min	-1.20	-0.01	-11.66	-1.21	-9.31	**-2.17**	-4.50	**-6.79**	-2.40	-2.70	-3.06	-9.45	-8.08	-7.41
	Max	3.84	10.64	3.34	2.16	8.05	**11.73**	2.36	**2.24**	4.24	3.66	4.42	5.56	1.10	1.68
F6-Non-condensables	Median	1.29	6.47	-1.58	1.20	**44.29**	**44.35**	-2.11	**-16.83**	1.17	3.80	3.35	**-21.53**	**-15.26**	0.72
	Min	-1.66	1.74	-6.16	-0.42	**38.64**	**40.52**	-4.98	**-19.11**	-1.32	-2.35	-2.91	**-36.17**	**-21.35**	-1.66
	Max	2.94	10.21	7.06	3.97	**49.31**	**50.58**	5.21	**-14.32**	3.37	8.47	8.05	**-14.46**	**-10.50**	4.33

Table 7. Values used in the FDD evaluation for excess electric energy use (%) of different faults at different severity levels along with their frequency weights which include their occurrence and their impact.

	Fault	Energy Penalty (ΔE_f) SL 1 %	SL 2 %	SL 3 %	SL 4 %	CFS* %		Frequency Weights (P_f)
		%	%	%	%	Fault dataset	Assumed Value %	
F1	Reduced condenser water flow	0.70	1.9	3.0	5.3	SL3	3.0	1.0
F2	Reduced evaporator water low	0.0	0.0	0.40	0.90	SL4	0.90	2.0
F3	Refrigerant leak	0.14	0.31	0.47	0.71	SL4	0.71	1.5
F4	Refrigerant Overcharge	0.80	0.94	3.8	7.6	SL3	3.8	0.25
F5	Condenser Fouling	0.50	0.50	0.50	1.8	SL4	1.8	1.0
F6	Non-Conden. in refrigerant	4.5	6.2	7.4	15.6	SL1	4.5	0.5

* CFS (composite fault severity level). Different severity levels were selected for different faults so that a composite SL could be generated with an associated increased energy use as close to 1-3 % as permitted by data. The corresponding fault data sets for different CFS faults are also shown.

Table 9. Summary results of FDD-MLR . The t-value threshold have been adjusted so that the correct fault-free detection rate = 95.4%.

Fault Type	Normal Operation				Reduced Cond flow				Reduced Evap flow				Refrigerant Leak			
	N2	N1	NCF	NR1	SL1	SL2	SL3	SL4	SL1	SL2	SL3	SL4	SL1	SL2	SL3	SL4
Faults detected	**0**	**1**	**2**	**2**	27	27	27	27	27	27	27	27	4	7	24	27
Unable to diagnose	0	0	2	2	0	0	0	0	0	0	0	0	3	5	14	6
Reduced condenser flow	0	0	0	0	**27**	**27**	**27**	**27**	0	0	0	0	0	0	0	0
Reduced evaporator flow	0	0	0	0	0	0	0	0	**27**	**27**	**27**	**27**	0	0	0	0
Refrigerant Leak	0	1	0	0	0	0	0	0	1	1	0	0	**1**	**2**	**10**	**21**
Refrigerant Overcharge	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Condenser Fouling	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Non-condensables	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fault Type	Refrigerant Overcharge				Condenser Fouling				Non-condensable			
	SL1	SL2	SL3	SL4	SL1	SL2	SL3	SL4	SL1	SL2	SL3	SL4
Faults detected	14	21	24	27	5	2	9	13	27	27	27	27
Unable to diagnose	14	21	4	2	4	2	1	2	0	0	0	0
Reduced condenser flow	0	0	14	25	1	0	8	10	0	0	5	17
Reduced evaporator flow	0	0	0	0	0	0	0	0	0	0	0	0
Refrigerant Leak	0	0	0	0	0	0	0	0	0	0	0	0
Refrigerant Overcharge	**0**	**0**	**20**	**25**	0	0	0	1	27	27	27	27
Condenser Fouling	0	0	0	0	**0**	**0**	**0**	**1**	0	0	0	0
Non-condensables	0	0	20	25	0	0	0	1	**27**	**27**	**27**	**27**

Note: Numbers in each cell indicate the number of times fault has been signaled in each of the 27 operating conditions

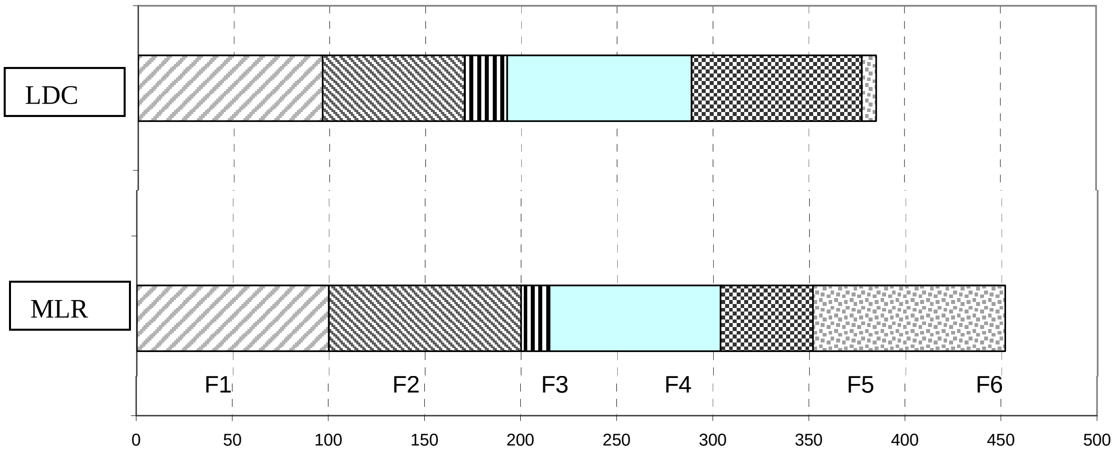

Figure 4. Cumulative fault detection rates (in %) for each fault (F1 through F6) for the two FDD methods using the composite fault severity level (CSL). The fault detection thresholds have been tuned to 5% false alarm rate.

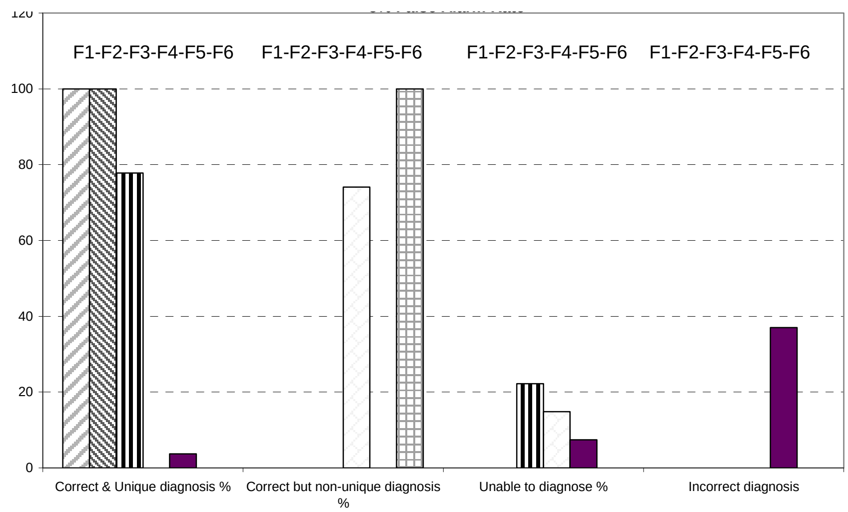

Figure 5. Percentage scores of different categories of diagnosis rates for the FDD-MLR approach using the composite fault severity (CFS) level. The fault detection thresholds have been tuned to 5% false alarm rate.

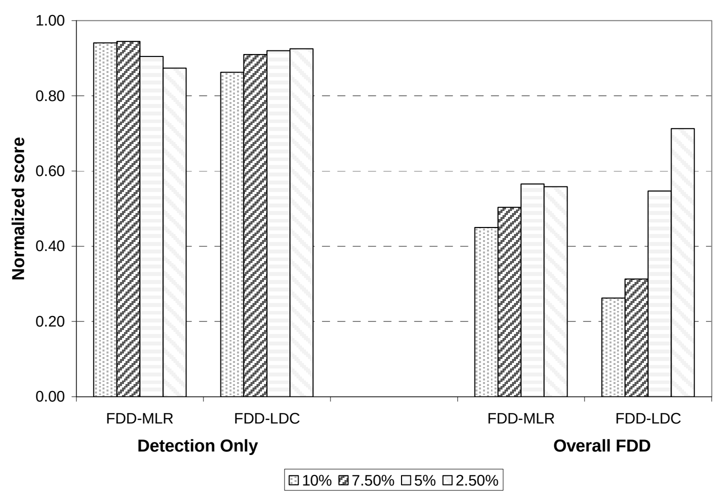

Figure 6. Normalized scores for fault detection only (eq.3) and for overall FDD (eq.4) for both FDD methods with FD threshold tuned at four different false alarms rates and using the composite fault severity (CFS) level.