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ABSTRACT

Existing methods addressing automated fault detection and diagnosis (FDD) for vapor compression air conditioning system have good performance for faults that occur individually, but they have difficulty in handling multiple-simultaneous faults. In addition, the methods require measurements over a wide range of conditions for training reference models, the development of which can be time consuming and cost-prohibitive. This paper demonstrates that decoupling is the key to handle multiple-simultaneous faults. To eliminate cost-prohibitive overall system modeling, a mathematical decoupling methodology is developed. During the mathematical development, a previously developed FDD method, termed the statistical rule-based (SRB) method, is re-examined and cast within the general mathematical framework. The method is evaluated using laboratory data and demonstrated using a field application.

1. Introduction

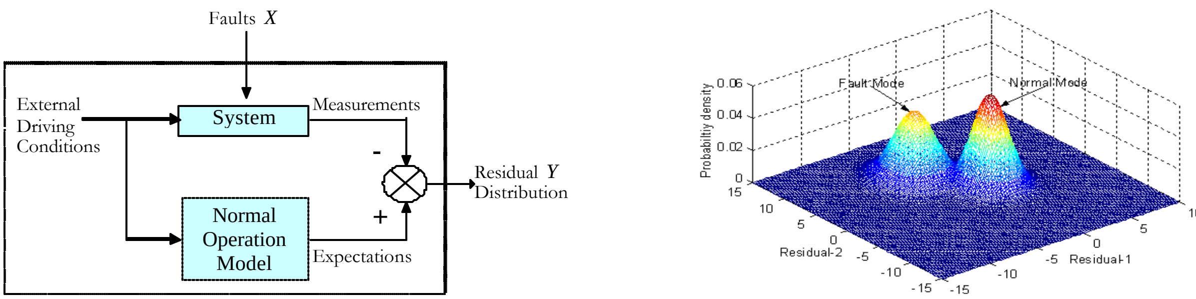
HVAC systems often do not function as well as expected due to faults introduced during initial installation or developed in routine operation. Rooftop and other packaged air conditioners are used extensively throughout small commercial and institutional buildings, but compared to larger systems, they tend to be not well maintained. As a result, widespread application of automated FDD will significantly reduce energy use & peak electrical demand, down time and maintenance costs. Unlike critical systems, FDD for HVAC systems, especially for small packaged air conditioners, is subject to very significant economic constraints.

Rossi and Braun (1997) originally proposed the statistical rule-based (SRB) FDD technique and applied it to vapor compression systems. This technique uses only low-cost sensors: nine temperatures and one relative humidity. Following this research, Breuker and Braun (1998a, 1998b) first identified important faults and their impacts on rooftop air conditioners through interactions with industry personnel, and then did a detailed evaluation of the performance of the SRB FDD technique. Laboratory results based on a 3-ton fixed orifice system showed that refrigerant leakage, condenser fouling, and liquid line restriction faults could be detected and diagnosed before an 8% reduction in COP occurred; compressor valve leakage was detected and diagnosed before a 12% reduction occurred. Chen (2000) found that the fault characteristics on a system with a TXV are different from those with a fixed orifice for which Rossi and Braun originally developed the SRB technique, and modified and evaluated the original FDD technique for a 5-ton rooftop unit with a TXV as the expansion device. Li and Braun (2003) thoroughly reexamined the SRB FDD technique and proposed new detection and diagnosis classifiers and modeling methods. Performance with the new components was improved significantly. However, the SRB method can not handle multiple-simultaneous faults and requires an overall system model to do diagnosis which is cost prohibitive, especially for retrofit applications.

This paper first formulates model-based FDD techniques in a general mathematical way and finds that the methodology of decoupling is the key to handle general multiple-input and multiple-output issues. In order to fit the decoupling methodology to non-critical HVAC&R systems, a mathematical decoupling methodology is developed that eliminates cost-prohibitive overall system model. Finally, the proposed decoupling-based FDD is validated using laboratory data and demonstrated using a field application.

2. Mathematical Formulation of Model-based FDD

The thermodynamic states of a RTU system are functions of external driving conditions and various faults, as is shown in Figure 1a. It is important for fault detection and diagnosis (FDD) not to misinterpret variations in thermodynamic state-variables caused by changes in the driving conditions for faults. If measurements are classified directly, the classification has to be complicated to consider the effect of external driving conditions. In order to simplify classification and improve overall FDD performance, normal operation models are used to predict expected values for these measurements under normal operation in terms of measured external driving conditions. For any steady-state measurement, the difference between expected and actual measurement values (residuals) should have a zero mean when there are no faults (see Figure 1b) and a probability distribution that is a weak function of driving conditions but dominantly dependent on faults.



(a) System incorporated with a normal operation model

(b) 2-dimensional residual distribution

Figure 1. Role of Model in FDD

The input-output relationship of the system after being incorporated with a normal operation model can be described approximately as follows,

$$Y = F(X) \quad (1).$$

where, $X = [x_1, x_2 \ldots x_n]^T$, $Y = [y_1, y_2, \ldots y_m]^T$, and $F(X) = [f_1(X), f_2(X), \ldots f_m(X)]^T$. X is the fault vector with each entry x_i representing a measure of the fault level for fault. Y is the state variable residual vector, with each entry y_i representing a particular state-variable residual. $F(X)$ is a nonlinear function vector with each individual nonlinear function $f_i(x_1, x_2, \cdots, x_n)$ defining the relationship between different faults at different levels and the state-variable residuals Y. n is the number of fault types considered, and m is the number of chosen state variables.

2.1. Fault Detection

Fault detection, which is to indicate whether the system is normal or not, can be done essentially just by looking into whether the resulting Y in Equation (1) is zero or not in a statistical sense. Li and Braun (2003) presented details of a normalized distance fault detection classifier that can be used for both individual and multiple-simultaneous faults. The classifier evaluates the following inequality,

$$(Y - M_{normal})^T S_{normal}^{-1} (Y - M_{normal}) \underset{w_2:Faulty}{\overset{w_1:Normal}{\lesseqgtr}} (c^2)^{-1}\{(1-a), m\} \quad (2).$$

where $(Y - M_{normal})^T S_{normal}^{-1} (Y - M_{normal})$ is the normalized distance, $(c^2)^{-1}\{(1-a), m\}$ is the threshold of normalized distance for normal operation, $(c^2)^{-1}\{,\}$ is the inverse of the chi-square cumulative distribution function, a is the false alarm rate, and m is the degree of freedom or dimension which is equal to the number of chosen state variables. Class w_1, normal operation, is selected if the left-hand-side is less than right-hand-side and class w_2, faulty operation, is selected otherwise. Due to modeling error M_{normal} is not exactly zero, so Equation (2) takes modeling error into account to statistically evaluate whether Y is zero or not.

The above fault detection scheme can be illustrated using Figure 2. The residual distribution of normal operation can be characterized in terms of the covariance matrix S_{normal} and mean vector M_{normal} and depicted in the residual space plane as in Figure 2. In the residual space plane, any operating states (points) outside the normal operating region are classified as faulty while those inside the normal operation region are classified as normal. The normal operating ellipse is the fault detection boundary.

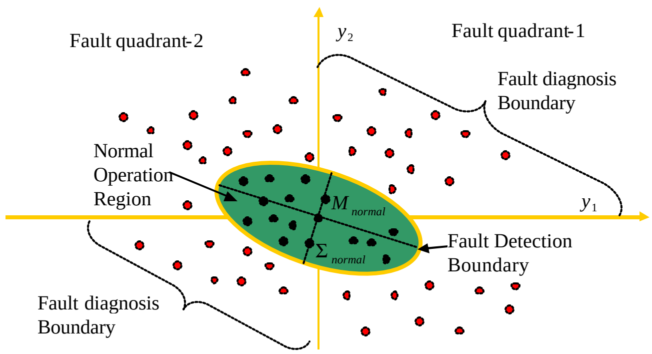


Figure 2. Illustration of FDD strategy

2.2. Fault Diagnosis

Fault diagnosis, which entails the determination of the kind and location of the detected fault from a list of possibilities, needs to use the resulting Y (knowns) to find the causes X (unknowns) qualitatively or quantitatively. The nonlinear Equation (1) can not get unique solutions for X for a given Y if $m < n$ and may result in inconsistencies if $m > n$, but it would not lose any generality to assume $m = n$. If $F(X)$ is known, multiple-simultaneous fault diagnosis becomes easy. However, it is very difficult, if not impossible, to find $F(X)$. To simplify Equation (1), the first two items of Maclaurin's series can be used to linearize the nonlinear Equation.

$$Y = F(0) + \frac{\partial F}{\partial X}(0)(X - 0) = JX \tag{3}$$

where, $F(0) = 0$, $J = \frac{\partial F}{\partial X}(0)$ is the Jacobian matrix of $F(X)$ evaluated at 0. Compared to $F(X)$, J is much easier to estimate by experiment, which requires n^2 tests. After J is estimated, diagnosis can be done more easily by,

$$X = J^{-1}Y \tag{4}$$

It should be pointed out that a nonsingular matrix J is a necessary and sufficient condition for the above Equation. For a practical engineering problem, this condition is readily guarantied if the given set of state variables Y can be used to uniquely describe the system under the possible fault vector X. It is not difficult at all to find such a set of state variables Y with the help of physical knowledge.

2.2.1. Original SRB Fault Diagnosis Method

Although J can be estimated approximately by experiment, it is still not generic because different units of the same type may have different values of J. Estimation of J for individual systems is only practical for large or critical systems. Instead of estimating J, the rule-based FDD method proposed by Rossi and Braun (1997) is equivalent to using the sign of J to do fault diagnosis,

$$J_{sign} = sign(J).$$

If faults occur individually, for example, only individual fault i happens at some time,

$$X_{sign} = sign(X) = sign([0,\ldots,x_i,\ldots,0]^T) = [0,\ldots,1,\ldots,0]^T$$

and then,

$$Y_{sign} = J_{sign}X_{sign} = sign([\frac{\partial f_1}{\partial x_i}, \frac{\partial f_2}{\partial x_i}, \ldots, \frac{\partial f_n}{\partial x_i}]^T).$$

So, if a fault happens individually, for a given matrix J_{sign}, Y_{sign} is determined uniquely by X_{sign} and vice versa. Inversely, this can be used to do fault diagnosis by comparing Y_{sign} with the column of J_{sign} in the statistical sense or mathematically by,

$$X_{sign} = sign\left(J_{sign}{}^T Y_{sign} - [n, n, \ldots, n]^T\right) \tag{5}$$

By determining which entry of vector X_{sign} is 1, the fault diagnosis classifier can make a decision. The advantages of this method are that: 1) it is very easy to infer the J_{sign} accurately by n simple tests or from experience, compared to n^2 well- designed tests to estimate J roughly; 2) J_{sign} is generic at least for the same type of system, compared to different J 's for different systems, because there is no linearization approximation for J_{sign}; 3) this diagnosis method uses direction change pattern (sign) to convert an infinite classification problem (infinite number of fault levels for an individual type of fault) into a multiple classification one. The drawback is that it can only handle individual faults. Corresponding to the SRB fault diagnosis terminology, J_{sign} is equivalent to the fault diagnosis rules, which are expressed as positive and negative changes in residuals, so that each fault type corresponds to a unique quadrant of a multi-dimensional residual space. To decide which fault is the most probable is equivalent to identifying which quadrant the current measurement belongs to. Combined with the normal operating ellipse, coordinate axes form the fault diagnosis boundary (see Figure 2). To eliminate the independence assumption and improve fault diagnosis performance, a simple distance fault diagnosis classifier, which does not require integration of the probability distributions, was developed and validated by Li and Braun (2003). This method has good sensitivity for diagnosing faults and is relatively insensitive to the choice of parameters and different operating conditions over a wide range.

2.2.2 Decoupling-Based Fault Diagnosis Method

In order to extend the easily-implemented SRB fault diagnosis idea to handle multiple-simultaneous faults, Equation (3) can be further transformed as follows,

$$PY = PJX$$

$$Z = LX = [l_1 x_1, l_2 x_2, \ldots, l_n x_n]^T$$

where, $L = PJ = Diag([l_1, l_2, \ldots, l_n])$, $Z = PY$ is the transformed feature vector, and $P = LJ^{-1}$ is the transformation matrix to make L diagonal. There exists infinite number of transformation combinations of L, P and Z by arbitrarily choosing a diagonal L if matrix J is non-singular (this can be guaranteed by proper choice of Y physically). This transformation decouples interactions among the different faults and makes each entry of the feature vector Z only correspond to unique fault entries of the fault vector X and vice versa.

$$X = L^{-1}Z = [\frac{z_1}{l_1}, \frac{z_2}{l_2}, \ldots, \frac{z_n}{l_n}]^T \tag{6}$$

To eliminate impacts of the linearization operation and driving-condition-independence assumption on diagnosis, the signum operation is applied to both sides of Equation (6). Since Z, based on actual measurement or virtual estimate, is corrupted by measurement noise, system disturbance and modeling error, it should be statistically evaluated by the signum operation. So, the $n-dimensional$ FDD problem has been decoupled to be n $1-dimensional$ SRB FDD problems,

$$sign(X) = sign(L^{-1})sign\_stat(Z)$$

where, $sign\_stat(z)$ is a signum operation in a statistical sense, such that

$$sign\_stat(z) = \begin{cases} -1, & if\,(z < -cs_z) \\ 0, & if\,(|z| < cs_z) \\ 1, & if\,(z > cs_z) \end{cases}$$

where, c is a constant, say, 3.

$$X_{sign} = [\frac{sign\_stat(z_1)}{sign(l_1)}, \frac{sign\_stat(z_2)}{sign(l_2)}, \ldots, \frac{sign\_stat(z_n)}{sign(l_n)}]^T \tag{7}$$

Equation (7) can be easily used to do multiple-simultaneous fault diagnosis. Although the impacts of the linearization operation and driving-condition-independence assumption on diagnosis are eliminated and multiple-simultaneous faults diagnosis can be handled, P and Z depend on J. If J is not known, P and Z can not be determined mathematically. Since there exists infinite number of transformation combinations of L, P and Z, from the mathematical viewpoint, it can be supposed without proof that there exists at least one Z which has physical meaning. So, if some Z can be found physically or empirically, the sign of L can also be decided empirically. Consequently, the methodology to physically construct the decoupled feature vector Z becomes the key point of this approach. In addition to the previous advantages listed for the SRB fault diagnosis method, the decoupling-based diagnosis method:

1) Simplifies fault detection from a high-D problem to n 1-D ones. Equation (2) boils down to following n 1-D Equations,

$$sign\_stat(|z_i|) = \left\{ \frac{(z_i - m_{i,normal})^2}{s^2_{i,normal}} > (c^2)^{-1}\{(1-a),1\} \right\} \tag{8}$$

2) Automatically achieves fault diagnosis without any extra computation immediately after fault detection is finished, because Equation (8) have obtained what Equation (7) needs. So the fault diagnosis classifier is not required.

$$x_{i,sign} = \frac{sign\_stat(z_i)}{sign(l_i)} = \frac{sign(z_i) sign\_stat(|z_i|)}{sign(l_i)} = sign\_stat(|z_i|)$$

3) Overcomes the drawback of the SRB diagnosis method and handles multiple-simultaneous faults diagnosis.
4) Becomes more generic and system-independent and does not require complicated rules, which depend on the system.

3. Decoupling RTU Faults

The approach proposed in the previous section is based on decoupled features. Mathematically, infinite number of decoupled features can be constructed, but for HVAC systems only those with intuitive physical meaning and those that are readily available (low-cost) are practical. This section develops a methodology or guidelines to find these kinds of features.

Philosophically, any problem could be approached microscopically or macroscopically or both to obtain required results with different details. A macroscopic approach uses external and overall information to interpret the observed phenomenon or predict a coming phenomenon, while a microscopic approach uses internal and component information to interpret or predict phenomenon. In some situations, a macroscopic approach is preferred and unnecessary details are often ignored to simplify a complicated problem to be a manageable one at the cost of losing some information. For example, statistical thermodynamics considers the physical models at the level of particles while classical thermodynamics focuses on macroscopic and overall behavior of the particle system. FDD is not an exception. The original SRB method approaches the FDD problem from the overall system point of view. It considers the thermodynamic impact of different faults on overall system state variables, and uses models to predict normal operation state variables according to the overall system driving conditions, and then statistically evaluates the overall system state residuals to do FDD. The merit of this method is that it is simple and systematic, while the drawback is that it has difficulty in handling multiple-simultaneous faults and also depends on components which constitute the system. Multiple-simultaneous faults have almost infinite combinations with different fault types and levels and each combination has an overall impact on the overall system behavior. So it is almost impossible to extract so many system-level rules to do FDD with multiple-simultaneous faults. In addition, system-level rules depend on the composition or structure of the system. So these two drawbacks are inherent. To overcome these two drawbacks, an approach is developed that is based on individual components, which leads to identification of decoupled features.

3.1. Taxonomy of Faults

Taxonomy always is based on and also conversely contributes to the understanding of a subject. For the SRB FDD method, all the faults are treated equally and only the overall impacts of them on the overall system state variables are discriminated. For example, from the macroscopic and overall system point of view, the only discrimination among the 7 faults of refrigerant leakage, compressor valve leakage, condenser fouling, evaporator fouling, liquid-line restriction, refrigerant overcharge and non-condensable gas is the directional change of the overall system state variables' residuals. However, from microscopic and macroscopic points of view, the seven faults can be divided into two classes: component-level and system-level faults. If classified from the view of fault cause, they can be divided into: operational and service faults. The characteristic of a component-level fault is that its source impact is confined to a specific location or component and all the other impacts on the system originate from this source impact. On the contrary, the source impact of a system-level fault cannot be confined to a specific location or component. Operational faults usually develop through running and occur randomly or gradually, while service faults are introduced with service.

For example, compressor valve leakage is a component-level and operational fault. Although it impacts the overall system performance such as discharge temperature and condensing temperature, these impacts are indirectly related to a compressor volumetric efficiency reduction, which is directly impacted by valve leakage. A loss of compressor volumetric efficiency results in the reduction of refrigerant flow rate and increasing power consumption per refrigerant flow rate and discharge pressure and temperature, and other changes of system variables, whose direction and intensity depend on the expansion device used. Physically, this source impact can be confined to the compressor component. Since a compressor valve is normally damaged when the system is running, it is classified to be an operational fault.

Low or high refrigerant charge is a system-level fault because it can occur anywhere and its direct impact cannot be confined to a particular location. Refrigerant overcharge only happens during service, so it is a service fault. Low refrigerant charge has two possible causes: refrigerant is undercharged when service was done or there is a refrigerant leakage. Therefore, low charge can be a system-level operational or service fault. Classification for all the other RTU faults is provided by Li (2004) and summarized in Figure 3.

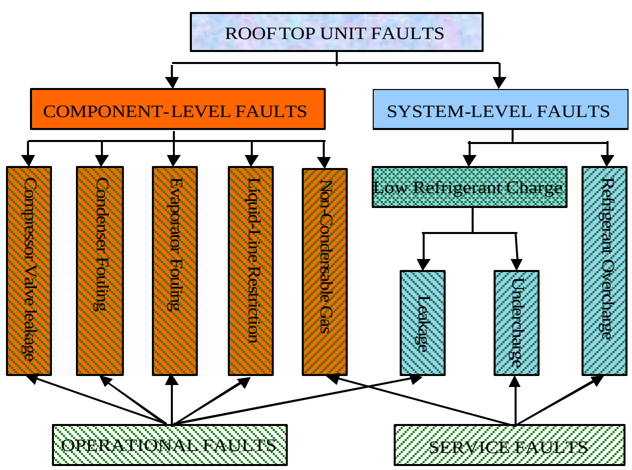


Figure 3 Taxonomy of Rooftop Faults

3.2. Decoupling Features

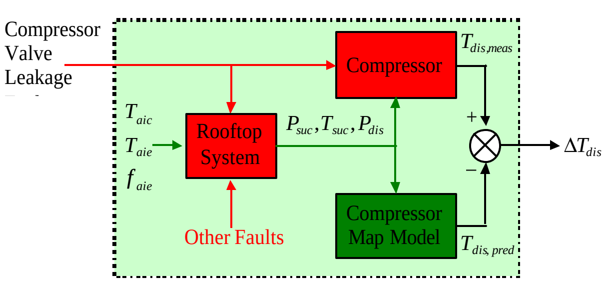
As a component-level operational fault, a decoupling feature for compressor leakage can be found by analyzing the physics of the compressor. A compressor pumps a certain flow rate of refrigerant with certain thermodynamic state to the whole system. At steady state, the compressor is mainly driven by three conditions: any two independent thermodynamic parameters of the compressor inlet conditions, say pressure P_{suc} and temperature T_{suc}, and compressor outlet pressure P_{dis}. These three driving conditions determine all the outlet thermodynamic parameters and refrigerant mass flow rate $\dot{m}_{ref,pred}$. For a certain set of driving conditions: P_{suc}, T_{suc} and P_{dis},

$$T_{dis,pred} = ref(P_{dis}, h_{dis,pred})$$

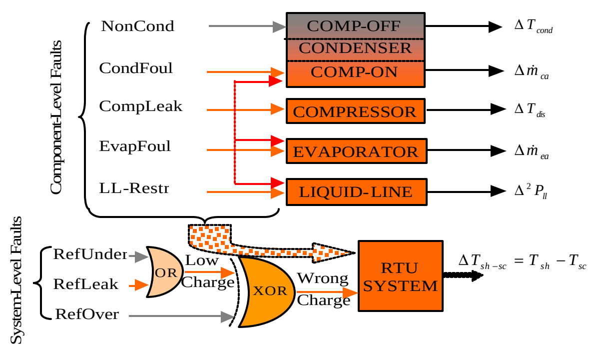
$$h_{dis,pred}(P_{suc}, T_{suc}, P_{dis}) = h_{suc}(P_{suc}, T_{suc}) + w_{pred}(P_{suc}, T_{suc}, P_{dis}) - Q_{loss}$$

where, $w_{pred}(P_{suc}, T_{suc}, P_{dis}) = \dfrac{\dot{W}_{pred}(P_{suc}, T_{suc}, P_{dis})}{\dot{m}_{ref,pred}(P_{suc}, T_{suc}, P_{dis})}$ is the compressor specific power consumption, $h_{dis,pred}$ is the predicted discharge line refrigerant enthalpy, T_{dis} is discharge line temperature, h_{suc} is suction line refrigerant enthalpy, and Q_{loss} is the compressor heat loss. For packaged systems, Q_{loss} is around 5% of the compressor specific power consumption and can be neglected. When a compressor valve has leakage, the compressor volumetric efficiency η_v decreases compared to the given set of driving conditions. The decrease of volumetric efficiency η_v causes the refrigerant mass flow rate $\dot{m}_{ref}$ to decrease compared to the normal value for the given set of driving conditions. Although the power consumption $\dot{W}$ may increase or decrease, w, power consumption per mass flow rate, would increase compared to the normal value. As a result, the compressor discharge line enthalpy h_{dis} would increase significantly. Since, at a given pressure P_{dis}, the discharge line temperature T_{dis} monotonically increases with h_{dis}, the discharge line temperature would increase significantly due to a compressor valve leakage fault. Using a compressor map, $w_{pred}(P_{suc}, T_{suc}, P_{dis})$ can be predicted and then $T_{dis,pred}$ can be calculated. Using this model, the residual DT_{dis} between predicted $T_{dis,pred}$ and measured $T_{dis,meas}$ would be a function of compressor valve leakage independent of operating conditions and faults in other components. Figure 4a shows the decoupling scheme. It can be seen that the residual DT_{dis} is only impacted by compressor faults and all the other factors including other component faults and overall system driving conditions have been taken into account by P_{suc}, T_{suc} and P_{dis}.

Similarly, Li (2004) developed the decoupling features for all the other faults. Figure 4b summarizes the decoupling scheme for RTU faults. Equation (9) formulates the decoupling scheme and results of all the rooftop faults. It can be seen the matrix L of Equation (9) is sparse and lower triangular. The algorithm developed by Li (2004) can solve this unilateral decoupled problem.



(a) Compressor Valve Leakage Decoupling Scheme



(b) Decoupling Scheme of Rooftop System Faults

Figure 4 The Decoupling Scheme of Rooftop System Faults

$$\begin{bmatrix} DT_{sat} \\ DT_{dis} \\ D^2 P_{ll} \\ D\dot{m}_{ca} \\ D\dot{m}_{ea} \\ T_{sh-sc} \end{bmatrix} = Z = LX = \begin{bmatrix} l_{11} & & & & & \\ & l_{22} & & & & \\ & l_{32} & l_{33} & & & \\ & l_{42} & & l_{44} & & \\ & l_{52} & & & l_{55} & \\ l_{61} & l_{62} & l_{63} & l_{64} & l_{65} & l_{66} \end{bmatrix} \begin{bmatrix} NonCond \\ CompLeak \\ LLRestr \\ CondFoul \\ EvapFoul \\ RefCharge \end{bmatrix} \quad (9)$$

where, DT_{cond} is the temperature difference between the condensing temperature and saturated temperature based on condensing pressure, $D\dot{m}_{ca}$ is condenser air mass flow rate residual, $D\dot{m}_{ea}$ is evaporator air mass flow rate residual, D^2P_{ll} is the liquid line pressure drop residual, DT_{sh-sc} is the difference between suction line superheat and liquid line subcooling, *NonCond* denotes non-condensable gas fault, *CompLeak* denotes compressor valve leakage fault, *LLRestr* denotes liquid-line restriction fault, *CondFoul* denotes condenser fouling fault, *EvapFoul* denotes evaporator fouling fault, and *RefCharge* denotes refrigerant charge faults including low charge and overcharge.

4. Validation

Li (2004) verified the decoupling features were using laboratory data of a fixed-orifice system and demonstrated the capability of the proposed technique to handle multiple-simultaneous faults using a demonstration prototype built for the Purdue field emulation site. Li and Braun (2004) presented its application to light commercial equipments in California. Its sensitivity and robustness evaluation was presented in following sections.

4.1. Sensitivity

The sensitivity of the FDD technique is defined as the lowest fault level which needed to be introduced to the system for it to be successfully detected and diagnosed. Since there are infinite combinations of multiple faults with different fault levels, sensitivity can only be evaluated on individual faults. Table 2 tabulates the method of implementing faults and corresponding fault levels simulated. Six faults are implemented in the Purdue field site: compressor valve leakage, condenser fouling, evaporator fouling, liquid-line restriction, refrigerant low charge, and refrigerant over charge. Except for refrigerant charge and compressor leakage faults for which five fault levels are introduced, four fault levels are introduced for the other three faults.

Table 2 Method of implementing faults and corresponding fault levels simulated

Faults	Simulation Method	Fault Level Expression	Fault Level Simulated					
			0	1	2	3	4	5
Compressor Leakage	Partially open a bypass valve between discharge and suction lines	% refrigerant mass flow rate bypass	0%	8%	18%	33%	44%	56%
Condenser fouling	Block certain condenser air flow with paper	% reduction of air volume flow rate	0%	3%	10%	13%	16%	
Evaporator fouling	Block certain evaporator air flow with paper	% reduction of air volume flow rate	0%	5%	9%	16%	31%	
Liquid-line restriction	Partially close the needle valve on the liquid line	% of the pressure drop from high to low sides	0%	5%	10%	13%	19%	
Refrigerant low charge	Under-charge the system	% reduction of charge	0%	11%	16%	21%	26%	32%
Refrigerant over charge	Over-charge the system	% increase of charge	0%	11%	16%	21%	26%	32%

Table 3 summarizes the FDD sensitivity results in terms of physical level, cooling capacity degradation (d_{cap}), energy efficiency ratio (EER) degradation (d_{EER}) and sensible heat ratio (SHR) degradation (d_{SHR}). In terms of the physical fault level, compressor valve leakage and evaporator fouling faults have the highest sensitivities while refrigerant overcharge has the lowest sensitivity. In terms of performance degradations in cooling capacity and EER and SHR, the technique has comparable good sensitivities in all faults.

False alarm is an indication of a fault when in actuality a fault has not occurred. For a given technique, there is an inherent tradeoff between minimizing the false alarms and maximizing sensitivity. Table 4 lists the theoretical false alarm rates calculated from the fault indicator standard deviation. Except for the liquid-line restriction, all the other faults have very small false alarm rate. Since the sensitivity of liquid-line restriction is high, it seems that there is some potential to reduce its false alarm rate by means of raising the FDD threshold further. However, robustness tests show that it is impractical to raise the FDD threshold.

Table 3 FDD sensitivity of individual faults

Faults	Sensitivity				
	Simulated Level	Physical Level	d_{cap}	d_{EER}	d_{SHR}
Compressor Leakage	1st	8%	5%	3%	-3%
Condenser fouling	2nd	10%	3%	4%	0%
Evaporator fouling	2nd	9%	5%	4%	4%
Liquid-line restriction	2nd	10%	3%	1%	2%
Refrigerant low charge	1st	11%	3%	1%	5%
Refrigerant over charge	2nd	16%	2%	2%	0%

Table 4 Normalized fault indicator standard deviations of normal operations and false alarm rates

Fault Name	Compleak	Condfoul	Evapfoul	Llrestr	Reflow	Refover
FDD Threshold	0.2	0.2	0.2	0.2	0.2	-0.2
Standard Deviation	0.072	0.074	0.091	0.133	0.066	0.066
False Alarm Rate	0.003	0.004	0.014	0.067	0.005	0.005

4.2. Robustness

To verify the robustness, multiple-simultaneous faults for combinations of six faults are performed for the fault levels given in Table 5. Only one fault level is implemented for one combination, because there are infinite combinations if fault level is considered. Except for compressor leakage, all the other faults are implemented at the levels that are slightly greater than the lowest detectable levels given in Table 3. Higher levels of compressor leakage faults are better for robustness tests of other faults. Fault levels of condenser fouling and liquid-line restriction and refrigerant overcharge are fixed, while two fault levels of refrigerant leakage and evaporator fouling are simulated.

All the possible forty-one combinations were considered. For reference, indicators for the different faults and the range of faults implemented are given in Table 5. Figure 5 shows the different combinations of faults implemented for the forty-one different cases and also shows differences between binary indicators (1=fault, 0=no fault) for individual diagnosed and implemented faults. A '-1' denotes a missed diagnosis or sensitivity loss for one fault and a '1' denotes a false alarm. There are two false alarms and two missed diagnoses (lost sensitivity) for combinations with a liquid-line restriction. The reason for worse robustness in this case is that more uncertainties are introduced to do FDD for liquid line restriction due to the use of virtual sensors (models built from manufacturers data) for estimating: 1) refrigerant mass flow rate, 2) condenser outlet refrigerant, and 3) pressure drop across TXV. Pressure drop across TXV is estimated using a TXV model which is pretty sensitive to superheat measurement noise and refrigerant mass flow rate estimation. In addition, when the operation is out of the control range of the TXV, the TXV model will not have good performance. There are two situations where this can occur: 1) when the refrigerant charge is lower than a certain value, the TXV is saturated and will cause abnormally high superheat, and 2) when there is a compressor leakage fault, the evaporating pressure may be high enough to trigger the TXV maximum operation pressure (MOP). In addition to more uncertainties, the pressure drop across the clogged filter/drier itself varies according to refrigerant mass flow rate and refrigerant state even for the same physical fault level. Since both false alarm and sensitivity loss occur, the idea suggested in the prior section that false alarm rate can be reduced by means of raising diagnosis threshold to reduce some sensitivity can not be entertained. A possible way to reduce false alarm rate but keep good sensitivity is to use one more pressure sensor in the liquid-line. More detailed analysis of the robustness was provided by Li (2004).

Table 5 Fault levels implemented for multiple-simultaneous faults and corresponding fault indicator numbers

Fault name	CompLeak	Condfoul	Evapfoul	Llrestr	Reflow	Refover
Level	20~35%	11%	12%&16%	12%	11%&14%	21%
Indicator number	1	2	3	4	5	6

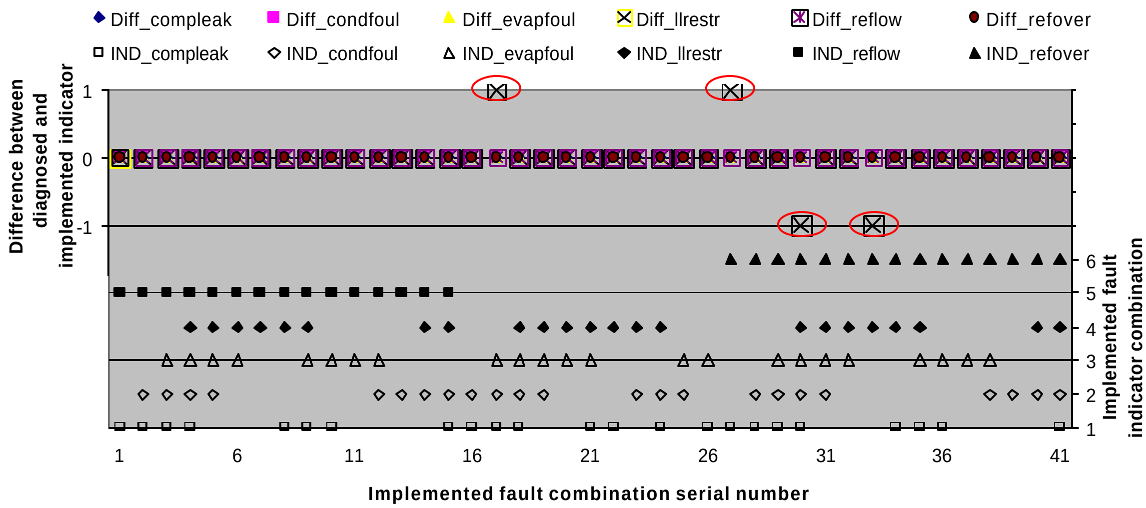


Figure 5 Robustness test for multiple-simultaneous-fault FDD

5. Conclusions

A general mathematical framework was formulated and the SRB FDD technique was cast within it, which contributes to further systematic investigation of FDD. A decoupling strategy was introduced to handle multiple-simultaneous faults. A decoupling-based FDD technique for vapor compression system was developed and validated. The proposed technique is practical and low-cost for implementation and capable of handling multiple-simultaneous faults. Sensitivity tests show that all the individual faults can be identified before they cause 5% of degradation in cooling capacity, EER and SHR. Robustness tests of forty-one multiple-simultaneous-fault combinations showed that false alarms and sensitivity loss only occurred in a couple of cases for a liquid-line restriction.

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