

DEVELOPMENT OF FAULT DETECTION AND DIAGNOSIS METHOD FOR WATER CHILLER

Young-Soo, Chang, Dong-Won, Han**, Senior Researcher*, Researcher**
Korea Institute of Science and Technology,
39-1, Hawolgok-dong, Seongbuk-gu, Seoul, 136-791, Korea*

Abstract: When operating a complex facility, Fault Detection and Diagnosis (FDD) system is beneficial in equipment management to provide the operator with tools which can help find out a failure of the system. In this research, FDD algorithm was developed using the general pattern recognition method that can be applied to water chiller system. The simulation model for water chiller system was developed in order to obtain characteristic data of water chiller system under normal and faulty operation. We tested FDD algorithm of a water chiller using data from simulation model. Comparisons were conducted between Bayes classifier method and normalized distance method. Sensitivity analysis of fault detection was carried out with respect to fault progress. More than 7 parameters are recommended to detect failure modes of this study accurately. FDD algorithm developed in this study was found to indicate each failure modes accurately.

Key Words: *Fault detection and diagnosis, Water chiller, Bayes classifier*

1 INTRODUCTION

For many years, FDD has been an active area of research and development in the aerospace, process controls, automotive, manufacturing, nuclear, and national defense fields and continues to be today. Automated FDD for HVAC systems have the potential to reduce energy and maintenance costs and improve comfort and reliability of HVAC. Water chiller constitutes a largest portion of commercial and industrial refrigeration capacity and account for an important portion of energy consumption in these sectors. In large office buildings, it is estimated that 10% to 25% of the total electricity consumption can be attributed to cooling systems alone (Huang et al. 1991). Moreover, these percentages can be significantly higher if a cooling system is operating at low performance levels due to the presence of faults (Herzog and LaVine 1992).

Faults of water chiller system can be divided into two categories; hard failures that occur abruptly and cause the system to stop functioning such as compressor and electrical faults. These kinds of faults can be easily detected and diagnosed by electrical on/off relays and an alarm signals. However, soft failures, such as a slow loss of refrigerant or fouling of a heat exchanger, are more difficult to detect and diagnose. Even though soft faults do not bring the system to a halt, they lead to a loss in comfort, or excessive energy consumption, and consequently, fatal failure of components. Therefore, this research is focused on evaluation of an FDD system to detect and diagnose soft failures.

Fault detection and diagnosis in refrigeration equipment has been discussed previously in Grimmeliuss et al. (1994), Rossi and Braun (1995), and Stylianou and Nikanpour (1996). The first two studies used steady-state data to perform fault detection and diagnosis, whereas the third one used a combination of steady-state and start-up transient data to accomplish the task. Grimmeliuss et al. (1994) developed a matrix of symptoms with respect to failure modes. The symptoms were deviations of selected parameters from the values predicted using a nonlinear statistical chiller model. These symptoms were then used to identify particular fault

patterns using a fuzzy classifier. Rossi and Braun (1995) used a two-step approach. The first step determined whether the unit was operating normally or not using statistical pattern recognition. Once a faulty operation was identified, the diagnostic classifier used a matrix similar to the one described in the study of Grimmeli et al. (1994) to diagnose the faults. Stylianou and Nikanpour (1996) used a rule-based approach to diagnose faults based on the start-up temperature variations. In addition, a steady-state module was used to detect and diagnose faults using a second rule base that employed a matrix similar to the one described above.

In this research, we compared the Bayes classifier method and the normalized distance method about FDD performance.

2. FAULT DETECTION AND DIAGNOSIS SYSTEM FOR WATER CHILLER

In this research, FDD algorithm was developed using the general pattern recognition method that can apply to water chiller system.

2.1 Application system of FDD algorithm

Figure 1 shows schematic diagram of water chiller system with two stage compression. Two stage compression water chiller system is composed of five main components; condenser, evaporator, compressor (primary compressor and secondary compressor), economizer, expansion device (primary orifice and secondary orifice).

The evaporator and condenser are shell and tube type heat exchangers with one shell pass and two tube passes where the water flows through the tubes and the refrigerant boils or condenses on the outside of tubes.

Compressor is centrifugal compression type. Inlet guide vanes (IGV) are used as means of capacity control which allows the machines to operate down to about 10% of the rated load capacity. The capacity control of the chiller is performed by adjusting IGV open degree depending on the chilled water outlet temperature.

FDD algorithm parameters constitute eleven parameters; nine temperature parameters, one electric current parameter, IGV open rate as shown in Table 1.

Table 1; FDD algorithm parameters

Symbol	Parameter	Unit	Symbol	Parameter	Unit
T1	Compressor outlet temperature	°C	T7	Cooling water outlet temperature	°C
T2	Condenser saturation temperature	°C	T8	Chilled water inlet temperature	°C
T3	Condenser outlet temperature	°C	T9	Chilled water outlet temperature	°C
T4	Evaporator saturation temperature	°C	A	electric current at compressor	A
T5	Evaporator outlet temperature	°C	α	Inlet Guide Vane open degrees	degrees
T6	Cooling water inlet temperature	°C			

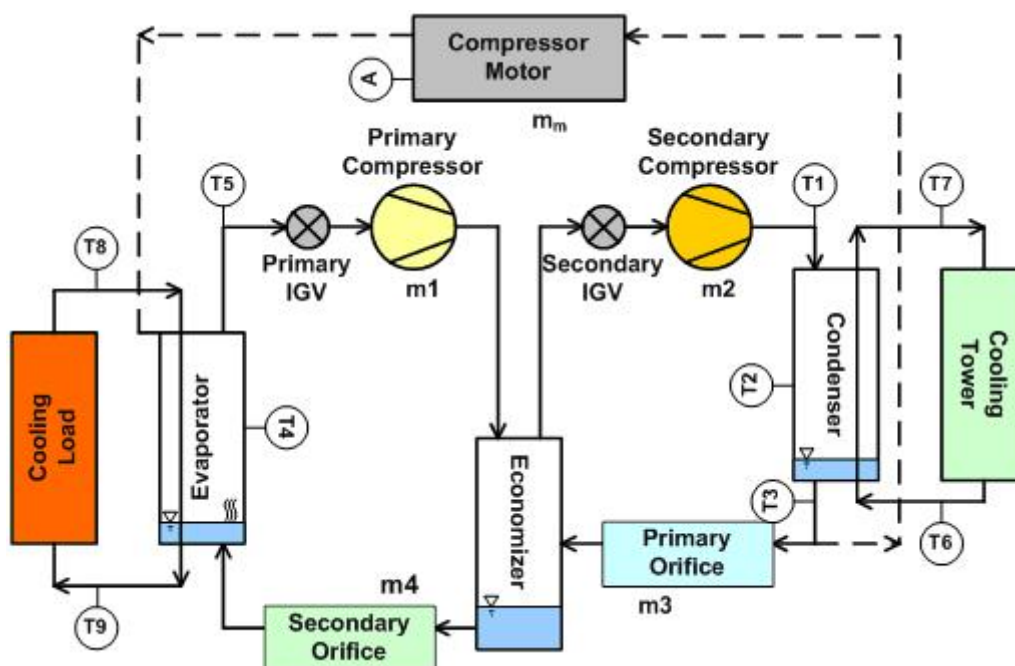


Figure 1: 2 stage compression water-chiller (R-123)

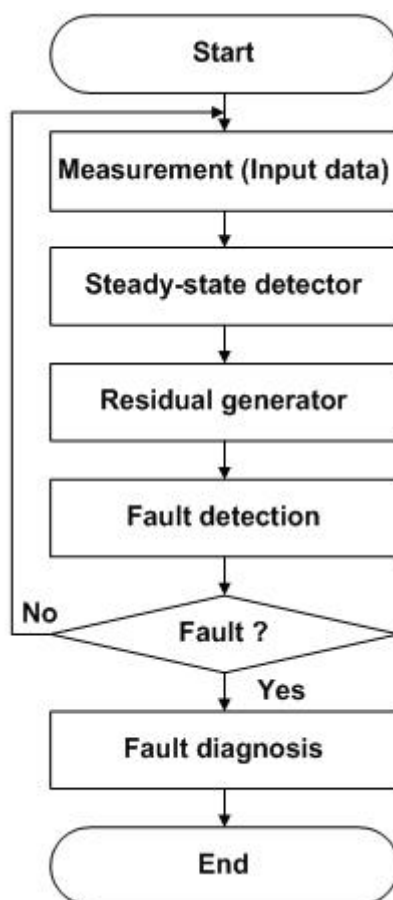


Figure 2: FDD algorithm flow chart

2.2 Fault detection and diagnosis algorithm for water chiller

Figure 2 shows flow chart of FDD algorithm. Measured data from target system are fed into the steady-state detector. The steady-state detector determines whether the system is considered to be at a steady-state and thus filters the transient data. Steady-state reference model is composed using normal operation data. The residuals between measured current data and predicted by steady-state reference model are used to detect whether the system is operating with a fault. If the system operation is faulty, residuals are further used to diagnose the fault type.

2.2.1 Steady-state detector

Most FDD schemes applied to various types of equipments detect and diagnose faults during steady-state operation. In this research, we envision the FDD process to be performed when the system is in a steady-state, or when the system is statistically identified to be nearly in a steady state.

A steady-state detector determines whether the system operates in a steady state. There are many different ways to design a steady-state detector, which adopt simple method of averaging over a predefined moving time window.

Steady-state classifier is given as

$$|\sigma_k| \leq |\sigma_s| \quad (1)$$

$$|a_1| \leq \frac{2\sigma_s}{t} \quad (2)$$

If standard deviation (σ_k) and the slope of linear regression analysis (a_1) in moving window data are satisfied with eq. (1) and (2), it is assumed to be a steady-state.

2.2.2 Multivariate polynomial reference model

In this research the chilled water inlet temperature (T_{chwi}), cooling water inlet temperature (T_{cwi}), and chilled water outlet temperature (T_{chwo}) are selected as independent variables defining operating conditions. The other system parameters(X) can be explicitly described by multivariate polynomials correlated with the no-fault data. (eq. (3))

$$X = a_0 + a_1 \cdot T_{chwi} + a_2 \cdot T_{cwi} + a_3 \cdot T_{chwo} + a_4 \cdot T_{chwi} \cdot T_{cwi} + a_5 \cdot T_{cwi} \cdot T_{chwo} + a_6 \cdot T_{chwo} \cdot T_{chwi} + a_7 \cdot T_{chwi}^2 + a_8 \cdot T_{cwi}^2 + a_9 \cdot T_{chwo}^2 \quad (3)$$

The first order polynomial equation offers a rough estimate of the reference state (no-fault). The third order polynomial equation has too many coefficients. So, in this research, all the features selected are correlated using second order polynomials with 10 coefficients which estimate the reference state with acceptable accuracy.

2.2.3 Fault detection classifier

The detection classifier uses residuals to determine whether the current equipment behavior is normal or faulty. The residuals are calculated by comparing the current values of parameters with the estimated values generated by a steady-state model of equation 3.

When the current residuals are statistically different from the expected residuals (zero residual), a fault is identified.

In this research, we adopted two statistical methods for fault detection classifier; probability method and normalized distance method. (Figure 3)

In probability method, the uncertainties of the residuals are assumed to follow a Gaussian distribution. The integrated overlap of the two distributions (residuals of parameters on normal and faulty state), which indicates the likelihood that the faulty distribution of residuals is judged by normal operation, and vice versa, is termed as classification error. A fault in the system will cause bias in the mean values from normal residuals. As the fault becomes progressively worse, the bias increases and the classification error (ε) decreases. Once the classification error drops below a threshold value, a fault is indicated by the detection classifier. (eq. 4)

$$\varepsilon = s \int_{-M_N / \sigma_N}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx + (1-s) \int_{-\infty}^{-M_c / \sigma_c} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx \quad (4)$$

We tried to adopt normalized distance method for fault detection classifier. This method requires very little computation and memory compared with Bayes classifier. Equation 5 present details of a normalized distance fault detection classifier that can be used for both individual and multiple-simultaneous faults simply.

$$prob(d_X^2 < d_{\max}^2) = 1 - \alpha \quad (5)$$

Where $d_X^2 = (X - M_N)^T \Sigma_N^{-1} (X - M_N)$ is normalized distance, α is the false alarm rate.

In the residual space plane, any operating points outside the normal operating region are classified as fault while those inside the normal operation region are classifier as normal.

Practically, normal operation information, such as the mean and covariance matrix, is more accessible and more reliable compared to faulty operation data. The advantage of this method is that the fault detection decision is based on individual points rather than on a distribution, so it is more computational efficient for online application.

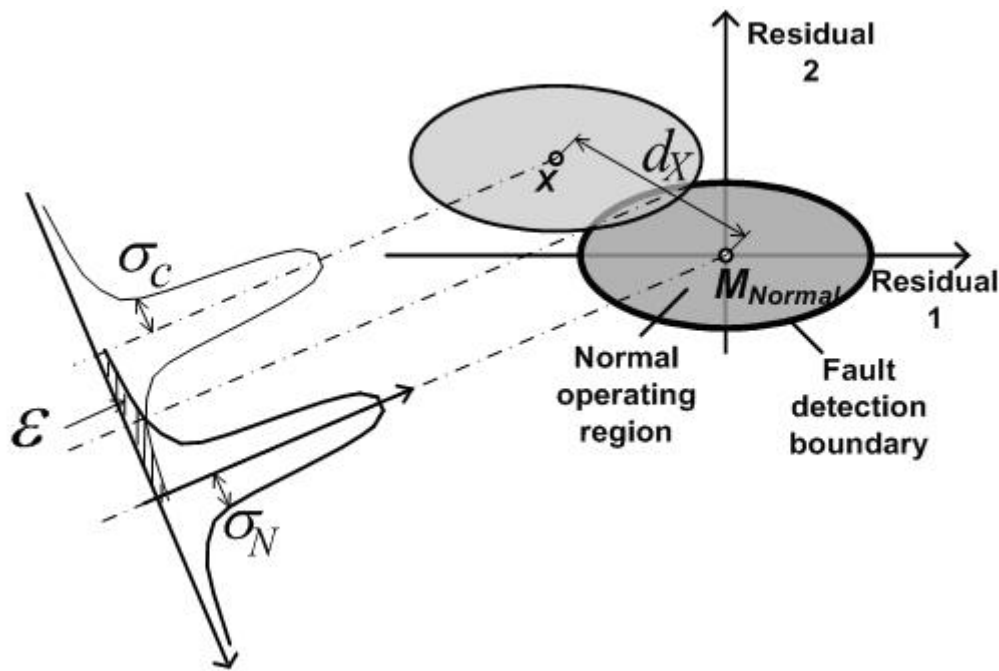


Figure 3: Compare the probability method with the normalized distance method
2.2.4 Fault diagnosis classifier

Diagnostic classifier by probability method in the FDD system determines the most likely explanation of the faulty behavior occurred in the system using a set of diagnosis rules. Rossi and Braun (1997) developed a set of rules related with the faults of interest through simulation modeling and tested the rules using experimental data.

$$w_j = \prod_{k=1}^m \frac{1}{2} \left[1 + C_{jk} \operatorname{erf} \left(\frac{M_C(k) - M_N(k)}{\sqrt{2 \Sigma_C(k, k)}} \right) \right] \quad (6)$$

Where

$C_{jk} = 1$ if $M_C(k) - M_N(k)$ has the same sign as d_{jk} , $C_{jk} = -1$, otherwise.

3. DEVELOPMENT OF SIMULATION MODEL FOR WATER CHILLER SYSTEM

The pattern recognition method for a FDD algorithm needs a reference model trained using steady-state data. In this research, we developed a simulation model by various principles like conservation of energy and mass and heat transfer. Table 2 shows input and output variables in each component model. Figure 4 shows a structure of the simulation model. The water chiller system is divided into five component groups; compressor, condenser, evaporator, economizer, expansion device. System parameters in Figure 4 are calculated until convergence is obtained.

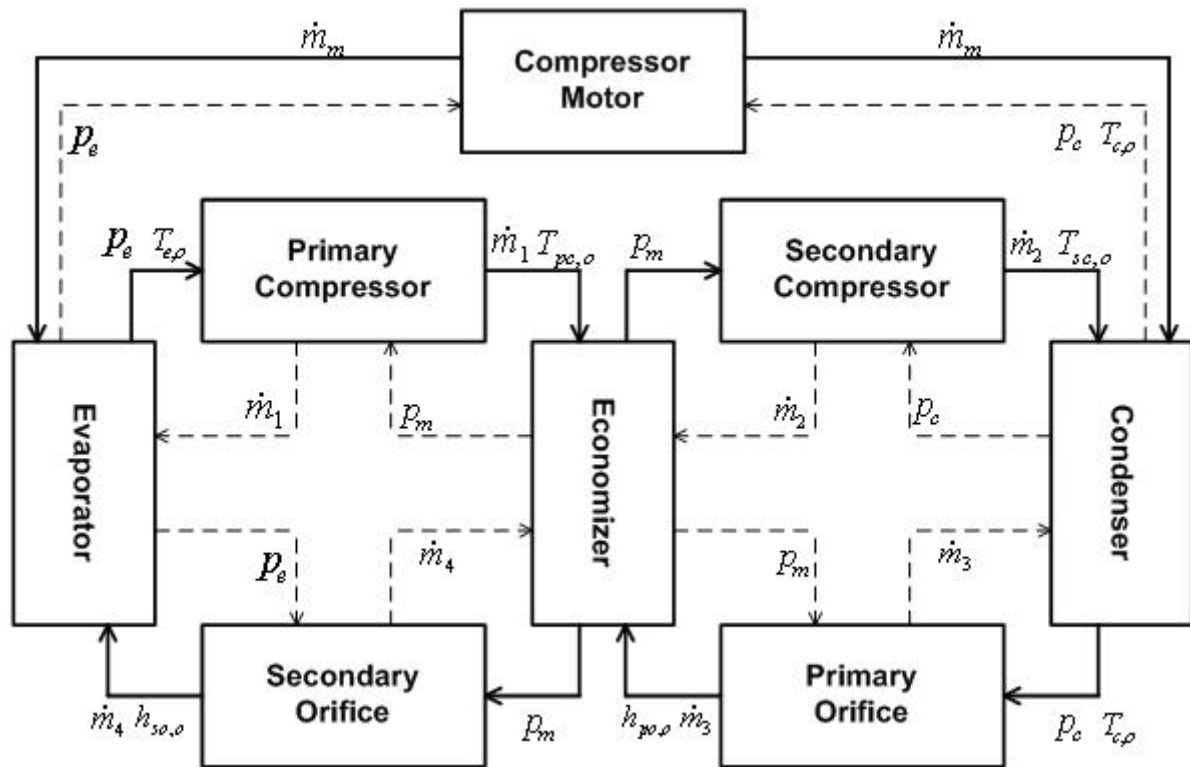


Figure 4: Structure of the simulation model

Table 2; Component models

Component		Principle models
Compressor	Primary compressor	$[m_1, T_{pc,o}] = f(p_e, T_{e,o}, p_m)$
	Secondary compressor	$[m_2, T_{sc,o}] = f(p_m, T_{p,o}, p_c)$
Condenser		$[p_c, T_{c,o}] = f(m_2, T_{sc,o}, m_3, m_m)$
Evaporator		$[p_e, T_{e,o}] = f(m_1, m_4, h_{po,o}, m_m)$
Economizer		$[p_m] = f(m_1, T_{pc,o}, m_2, h_{po,o}, m_3, m_4)$
Expansion Device	Primary orifice	$[m_3, h_{po,o}] = f(p_c, T_{c,o}, p_m)$
	Secondary orifice	$[m_4, h_{so,o}] = f(p_m, p_e)$
Compressor motor		$[m_m] = f(p_e, p_c, T_{c,o})$

4. FDD ALGORITHM USING THE SIMULATION MODEL

4.1 Possible simulated failure modes and failure symptom table

The reference model of FDD algorithm was trained using steady-state data from water chiller simulation model. Table 3 shows possible simulated failures. The simulation model calculated the variations of output variables for various failure modes in Table 3, which were compared to reference values. By analyzing biased output values from reference model, symptom table was made.

Table 3; Simulated failure modes

No.	Failure mode	Implementation	Fault factor (<i>ff</i>)
1	Condenser fouling	Increase fouling factor/ Reduce heat transfer area	$R_f = R_f^*(1+ff)$ $A_f = A_f^*(1-ff)$
2	Refrigerant leaking	Reduce refrigerant	$m_r = m_r^*(1-ff)$
3	Decrease cooling water	Reduce cooling water mass flow rate	$m_{cw} = m_{cw}^*(1-ff)$
4	Decrease chilled water	Reduce chilled water mass flow rate	$m_{chw} = m_{chw}^*(1-ff)$
5	Sensor error 1	measurement sensor error : Cooling water inlet temperature(Low)	$T_{cwi} = T_{cwi}^*(1+ff)$
6	Sensor error 2	measurement sensor error : Cooling water inlet temperature(High)	$T_{cwi} = T_{cwi}^*(1-ff)$
7	Sensor error 3	measurement sensor error : Chilled water outlet temperature(Low)	$T_{chwo} = T_{chwo}^*(1+ff)$
8	Sensor error 4	measurement sensor error : Chilled water outlet temperature(High)	$T_{chwo} = T_{chwo}^*(1-ff)$

4.2 Comparing fault detection methods

We compared the performances of FDD classifier methods; the Bayes classifier method and normalized distance method. Figure 5 (a) and (b) shows the variation of the classification error(ϵ) and normalized distance (d) when cooling water mass flow rate was decreased according to fault level increase. The classification error decreases rapidly on first fault level, but normalized distance changes gradually.

FDD system must detect faults in an early stage as soon as possible and accurately because the primary objective of the FDD system is enabling correction of the faults before additional damage to the system or loss of service occurs.

Therefore, the Bayes classifier method (classification error method) is better than normalized distance method for the fault detection algorithm.

4.3 Fault detection sensitivity

There are several effective parameters on FDD algorithm sensitivity, such as a standard deviation, number of FDD parameters and measurement noise etc. In this study, sensitivity analysis for fault detection was conducted with respect to number of parameters and standard deviation of reference model used for fault detection and diagnosis.

Figure 5 (b) shows the variation of fault detection sensitivity when the number of fault detection parameter was decreased from seven parameters to five parameters. The number of fault detection parameter has an effect on initial fault detection level. The fault detection level decreased from 0.8 to 1.3 when the number of fault detection parameter decreased from seven parameters to five parameters. As the number of parameters gets smaller, the sensitivity of fault detection becomes lower.

Figure 6 (a) shows effect of standard deviation on FDD algorithm sensitivity. Standard deviation 2(SD2) is larger than standard deviation 1(SD1) by twice and the fault detection of SD1 is faster than that of SD2 for all failure modes. Figure 6 (b) shows effect of number of FDD parameters on FDD algorithm sensitivity. Fault detection sensitivity with 10 parameters is similar with 7 parameters but fault detection sensitivity with 5 parameters becomes lower. More than 7 parameters are recommended to be used to detect failure modes of this study accurately.

4.4 Results of fault diagnosis

Table 5 shows fault diagnosis results according to failure progress for some failure modes. The class probabilities (ω_i) were diagnosed well about the each failure modes. FDD algorithm indicated well each failure mode.

Table 5; FDD performance for decreasing cooling water mass flow rate

Fault level	Classification Error (ε)	Diagnosis	Class probabilities (ω_i) (Failure modes)							
			1	2	3	4	5	6	7	8
1	2.53 E-04	Fault 3	0.00	0.00	0.30	0.01	0.09	0.00	0.00	0.00
2	0.00	Fault 3	0.00	0.00	0.52	0.00	0.03	0.00	0.00	0.00
3	0.00	Fault 3	0.00	0.00	0.67	0.00	0.00	0.00	0.00	0.00
4	0.00	Fault 3	0.00	0.00	0.76	0.00	0.00	0.00	0.00	0.00
5	0.00	Fault 3	0.00	0.00	0.82	0.00	0.00	0.00	0.00	0.00
6	0.00	Fault 3	0.00	0.00	0.87	0.00	0.00	0.00	0.00	0.00

5. CONCLUSIONS

In this research, we tested FDD algorithm of a water chiller using data from simulation model. We compared the Bayes classifier method and normalized distance method about the performances of FDD classifier. The Bayes classifier method is better than normalized distance method when apply the fault detection algorithm. Because of the Bayes classifier method detect faults in an early stage. We study effect of standard deviation and number of fault detection parameter on FDD algorithm sensitivity. If standard deviation of an initial model is unsuitable, the sensitivity of fault detection becomes lower. Also, as the number of parameters gets smaller, the sensitivity of fault detection becomes lower. So, we have need of suitable standard deviation and number of fault detection parameter. More than 7 parameters are recommended to be used to detect failure modes of this study accurately. A fault was indicated whenever the classification error was below 0.001. The class probability of current occurred fault (failure mode 3) was increased with fault level but the other class probability (in special, failure mode 5) was decreased. FDD algorithm developed in this study was found to indicate each failure modes accurately.

6. ACKNOWLEDEMENTS

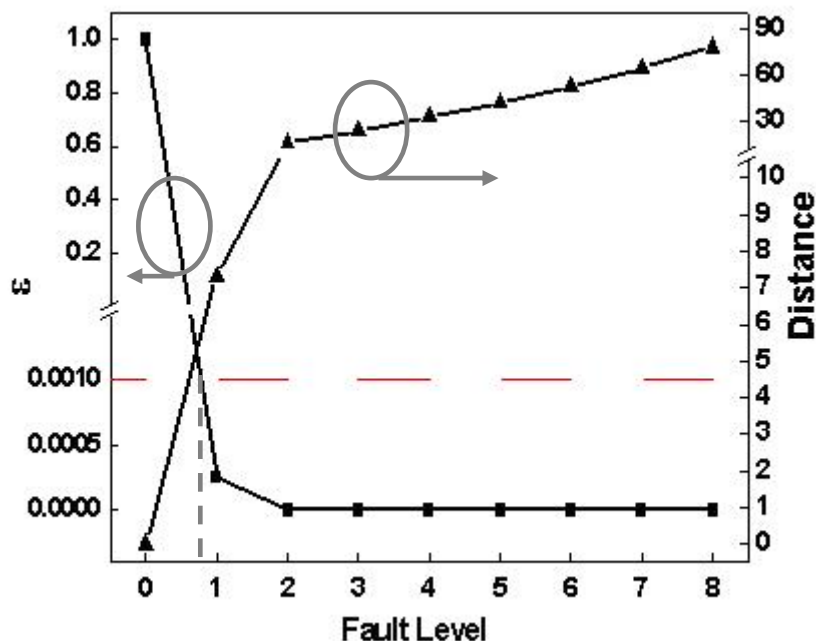
The research described in this paper was sponsored by Ministry of Commerce, Industry and Energy 『2006 Energy · Resource Technology Development Enterprise (Subject No. 2006-E-BD11-P-03)』

7. NOMENCLATURE

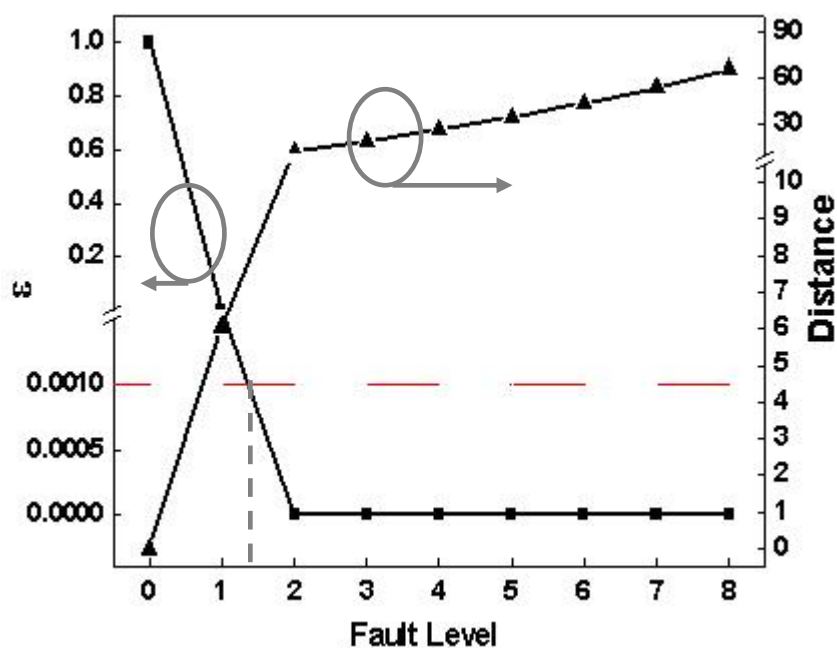
v	variance	(-)	M	mean vector
σ	deviation	(-)	Σ	covariance matrix
T	temperature	(°C)		
p	pressure	(kg/cm ²)		
P	consumption power	(kW)		
Subscripts				
k	current time		C	current
s	steady-state		N	normal

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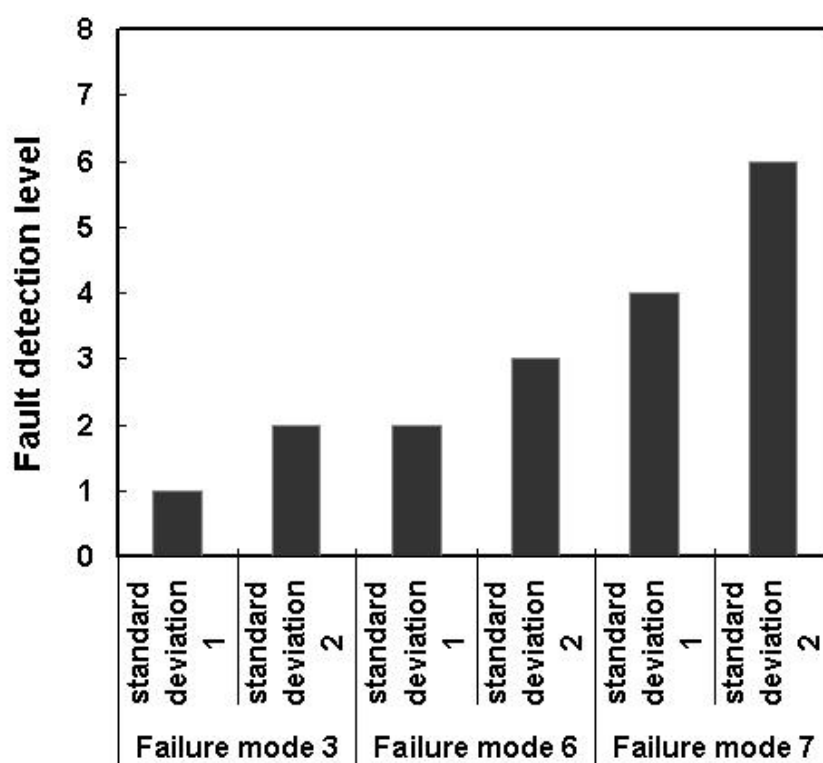


(a) The variation of the classification error and normalized distance (7 parameters)

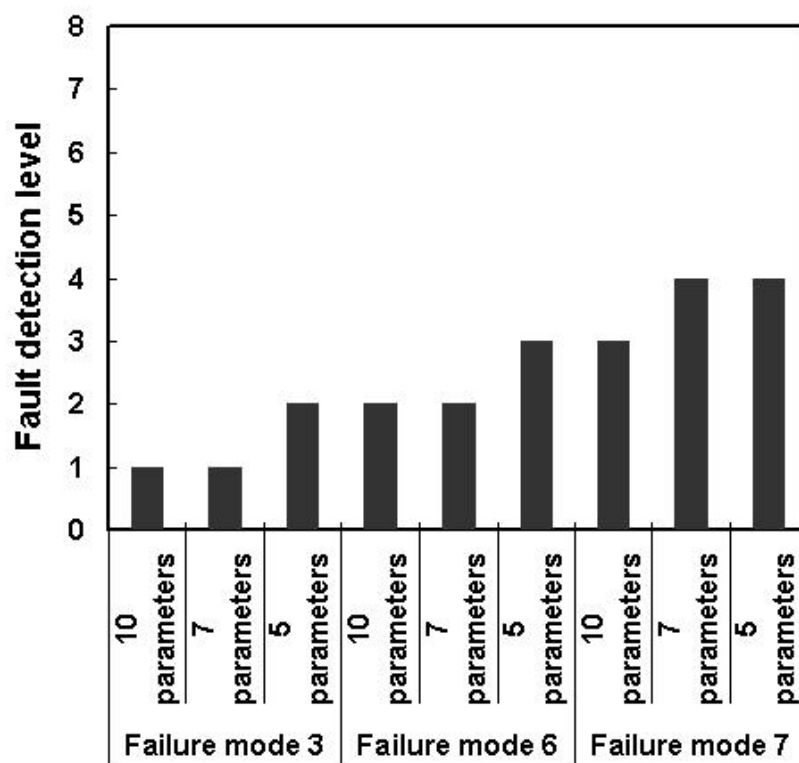


(b) The variation of the classification error and normalized distance (5 parameters)

Figure 5: Compared both FDD classifier methods



(a) Effect of standard deviation about fault detection sensitivity



(b) Effect of number of parameters about fault detection sensitivity

Figure 6: Comparison fault detection sensitivity