퍼지논리를 이용한 다중관측자 구조 FDIS의 성능개선

論 文
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Performance Improvement of Multiple Observer based FDIS using Fuzzy Logic

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Abstract - A diagnostic rule-base design method for enhancing fault detection and isolation performance of multiple observer based fault detection isolation schemes (FDIS) is presented. The diagnostic rule-base has a hierarchical framework to perform detection and isolation of faults of interest, and diagnosis of process faults. The decision unit comprises a rule base and a fuzzy inference engine and removes some difficulties of conventional decision unit which includes crisp logic with threshold values. Emphasis is placed on the design and evaluation methods of the diagnostic rule-base. The suggested scheme is applied to the FDIS design for a DC motor driven centrifugal pump system.

Key Words : fault detection and isolation scheme, decision unit, fuzzy inference, diagnostic rule-base

1. Introduction

Automated large scale systems are characterized by an increase in desired level of system reliability. And achievement of the desired reliability becomes more difficult than ever. Among various methods to enhance system reliability, fault detection and isolation schemes (FDIS) can be considered to be the most promising. FDIS can be classified into many categories according to the type of process model, the method of residual generation and the diagnostic algorithm adopted in the scheme. According to the type of process model, the FDIS can be classified into the following groups:

(a) Analytic Redundancy Method (ARM) [1][2]
(b) Rule (Knowledge) based approaches [3]
(c) Techniques based on the data structure [4]

In the ARM group, there are two typical approaches: a) state estimation based and b) parameter estimation based [1][5]. Although more attention has been paid to the observer approach than to the parameter estimation approach, the practical applicability of the scheme is very restrictive due to following well-known reasons. First, observer schemes require an exact mathematical model of the process to be diagnosed. Second, the FDI schemes fail to provide reasonable decisions when some uncertainties, such as unmodelled dynamics, or unknown external disturbances are introduced. Two major approaches, active and passive, have been developed to remove these difficulties. The active approach is to design a residual generator which is insensitive to modelling errors and disturbances while sensitive to the fault of interest.[6] The passive approach includes the use of adaptive thresholds and the design of more reliable decision logic unit using artificial intelligence tools such as fuzzy logic and artificial neural networks[7], and the approach is useful whenever the robust design of the residual generator is impossible.

In this paper, a new concept of decision logic design for multiple observer scheme(MOS) is suggested. The decision logic unit has a hierarchical framework to perform fault detection, isolation of faults, failed sensor identification, and diagnosis of process faults. The proposed scheme employs a fuzzy rule base and a fuzzy inference engine and doesn't require threshold values. One of important contribution of this paper is the suggestion of the design and evaluation method of the diagnostic rule base. The design concepts are applied to the design of a multiple observer based FDIS for a DC motor driven centrifugal pump system.

2. Residual Generation for MOS type FDIS

The residuals contain the information that will be used directly for fault detection and diagnosis. The quality of the information carried by the residuals influences the diagnostic performance. In order to define and explain the residuals, we consider the dedicated observer scheme

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(DOS)[1][2] in which conventional observer theory is adopted. We also assume a linear process model for brevity.

$$\begin{aligned} \dot{\boldsymbol{x}}(t) &= \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t) + \boldsymbol{D}\boldsymbol{f}_p(t) \\ \boldsymbol{y}(t) &= \boldsymbol{C}\boldsymbol{x}(t) + \boldsymbol{E}\boldsymbol{f}_s(t) \end{aligned} \tag{1}$$

where $\boldsymbol{x}(t)$ is state vector, $\boldsymbol{u}(t)$ is input vector, $\boldsymbol{y}(t)$ is output vector, $\boldsymbol{f}_p(t)$ is process fault vector, and $\boldsymbol{f}_s(t)$ is sensor fault vector. In (1), assume that the output matrix $\boldsymbol{C}$ has the following form

$$\boldsymbol{C} = \begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_p \end{bmatrix} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \tag{2}$$

and the system is observable from each output. In DOS, kth observer is driven by kth measurement output $y_k = \boldsymbol{C}_k\boldsymbol{x}$ only, then p dedicated observers are given as follows

$$\begin{aligned} \dot{\hat{\boldsymbol{x}}}^k &= (\boldsymbol{A} - \boldsymbol{L}_k\boldsymbol{C}_k)\,\hat{\boldsymbol{x}}^k + \boldsymbol{L}_k y_k + \boldsymbol{B}\boldsymbol{u} \\ \hat{\boldsymbol{y}}^k &= \boldsymbol{C}\,\hat{\boldsymbol{x}}^k \qquad (k = 1, 2, \cdots, p) \end{aligned} \tag{3}$$

where $\boldsymbol{L}_k$ is the gain matrix of kth observer. The state observer has the asymptotic convergence property, which means that the observation error defined by $\boldsymbol{e}^k = \boldsymbol{x} - \hat{\boldsymbol{x}}^k$ converges to zero if and only if all observer poles have negative real part, i. e.,

$$\lim_{t\to\infty} \boldsymbol{e}^k(t) = 0 \tag{4}$$

In the case of ith sensor fault the observation error of the ith dedicated observer converges to

$$\lim_{t\to\infty} \boldsymbol{e}^i(t) = -(\boldsymbol{A} - \boldsymbol{L}_i\boldsymbol{C}_i)^{-1}\boldsymbol{L}_i(\boldsymbol{E}_i\boldsymbol{f}_s) \tag{5}$$

with the measurement output, $y_i = \boldsymbol{C}_i\boldsymbol{x}^i + \boldsymbol{E}_i\boldsymbol{f}_s$, whereas other observers have zero steady state errors. In the case of a process fault, the estimation errors converges to non-zero steady state values

$$\lim_{t\to\infty} \boldsymbol{e}^i(t) = -(\boldsymbol{A} - \boldsymbol{L}_i\boldsymbol{C}_i)^{-1}\boldsymbol{D}\boldsymbol{f}_{ps} \tag{6}$$

for all state observers, where the subscript s indicates steady state.

Residuals can be defined in various ways since the dedicated observer bank provides redundant information. Two typical residuals are defined as

$$R_{jk} = y_j - \hat{y}_j^{\,k} \qquad (j, k = 1, 2, \cdots, p) \tag{7}$$

$$RE_i^{jk} = |\, \hat{x}_i^{\,j} - \hat{x}_i^{\,k} | \tag{8}$$
$$(i = 1, 2, \cdots, n\ ;\ j, k = 1, 2, \cdots, p\ ;\ j \neq k)$$

where $\hat{x}_i^{\,j}$ is the estimate of x_i from the jth observer. Some function of residuals may be chosen as the condition variables. In order to design more reliable decision rules, following residuals are defined.

$$RT_{jk} = \sum_{i=1}^{n} RE_i^{jk} \tag{9}$$

where RT_{jk} gives the total difference between the estimated vectors provided by the i th observer and the k th observer. The total number of residuals RT_{ij} is limited to $p(p-1)/2$.

3. Design and evaluation criterion of diagnostic rule-base

3.1 Decision rules for sensor faults

In the following explanations, assume that sensor faults and process faults are not occurred simultaneously. Once the condition variables were selected, the rule-base for sensor fault detection and isolation is readily obtained.

Detection and Localization Rules:
In the conventional DOS using threshold test, detection of any fault can be performed by the rule:

If ($RT_{12} > TH_{12}$ OR $RT_{23} > TH_{23}$ OR $\cdots$ OR $R_{p1} > TH_{p1}$),
Then a fault occurred

And sensor faults and process faults can be localized by a rule such as:

If ($RT_{12} > TH_{12}$ AND $RT_{23} > TH_{23}$ AND $\cdots$ AND $RT_{p1} > TH_{p1}$), Then process fault.
Otherwise, sensor fault.

Above rules take crisp binary logic where TH_{xx}s are threshold values. The threshold test can be considered as an operation by which quantitative information is transferred to binary information. With the test, almost all the quantitative information carried by the residuals will be lost. The selection of appropriate threshold values is well known to be one of the most difficult job in the design of the detection and localization logic. Even with properly selected threshold values the crisp logic does not allow any competition between the diagnostic results; if any one among those conditions in a rule is mismatched due to noises and/or uncertainties, the rule provides incorrect decision. All this difficulties come mainly from the rigidity of crisp logic and can be resolved by employing a fuzzy rules. For example, the detection rule and the localization logic mentioned in earlier part of this section can be transformed to following rules.

If ($RT_{12} = PO$ OR $RT_{23} = PO$ OR $\cdots$ OR $R_{p1} = PO$), Then a fault occurred.

If ($RT_{12} = PO$ AND $RT_{23} = PO$ AND $\cdots$ AND $RT_{p1} = PO$), Then process fault.
Otherwise, sensor fault.

The mean of linguistic values used in this paper is given in Table A1 in the Appendix. We will not give any description about fuzzy set theory for brevity and the conventional rules will be omitted.

Rules for identification of a failed sensor:
The residuals RT_{ij}s can also be employed for the identification of a failed sensor. The identification rules are obtained in a logical way. Let us assume an ith sensor fault. Then, the residuals RT_{ij}s and RT_{ki}s have non-zero values, while other residuals have zero values.

Rule 1 : If($RT_{12}, RT_{23}, \cdots, RT_{p1}$)=($PO, AZ, AZ, \cdots, PO$), Then sensor 1 fault

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Rule p : If($RT_{12}, RT_{23}, \cdots, RT_{p1}$)=($AZ, \cdots, AZ, PO, PO$), Then sensor p fault

Unfortunately, there is no logical way to design rule-base for process fault detection. An evaluation criterion which helps the design of rule-base based on the analysis of fault data, is described in next subsection.

3.2 Evaluation criterion for the rule-base design

The rule-base is at the core of the proposed FDIS and determines the performance of the FDIS. To design an effective rule-base and an inference engine, the following design procedure can be employed.

Step 1: Fault data collection and analysis
Step 2: Add expert and theoretic knowledge
Step 3: Select condition variables in the rules
Step 4: Build fuzzy-subsets for the selected variables
Step 5: Select fuzzy composition operator

In all MOSs, observers provide excessive redundant information, and there is some degree of freedom in the selection of condition variables, which leads to different rule-bases. So, we need a criterion by which the quality of the linguistic rule-base can be evaluated. To suggest an evaluation criterion, let us make following definitions.

Definition 1. [Distance between two terms] :
For a fuzzy variable X with term set or linguistic values $[v_1 \ v_2 \ \cdots \ v_p]$, the distance between two terms is defined as:

$$d_X(v_i , v_j) = | \ i - j \ | \tag{9}$$

Definition 2. [Distance between two rules] :
Consider two rules with same condition variables $[x_1 \ x_2 \ \cdots \ x_n]$, where each fuzzy variable, x_i, has term set $[v_{i1} \ v_{i2} \ \cdots \ v_{ip}]$. Assume following two rules.

Rule i : If (x_1 *is* v_{1i}) AND (x_2 *is* v_{2i}) AND $\cdots$ (x_n *is* v_{ni}), Then fault i
Rule j : If (x_1 *is* v_{1j}) AND (x_2 *is* v_{2j}) AND $\cdots$ (x_n *is* v_{nj}), Then fault j

The distance between two rules is defined as:

$$D_{ij} = \sum_{k=1}^{n} d_{X_k}(v_{ki}, v_{kj}) \tag{10}$$

The distance is a measure of distinguishability of two faults, ith fault and jth fault, when two rules, ith rule and jth rule, are employed.

Definition 3. [Score of a rule] :
The score of the $i$the rule in a rule-base is defined as the sum of the distances from ith rule to each other rule:

$$S_i = \sum_j D_{ij} \ , \ j \neq i \tag{11}$$

Definition 4. [Score of a rule-base] :
The score of a rule-base is defined as the sum of all the distances between every two rules in the rule-base.

$$S_{RBk} = \sum_i \sum_j D_{ij} \qquad (12)$$

The distance and the score have following properties.

- The addition of a significant condition variable increases the distance between a rule pair and the score of the rule-base and the converse is also true.
- If the minimum of distances D_{ij} between two rule-bases are same, then high score implies improved distinguishability and low score means conflict.
- Distance between terms is defined for a variable, not for different variables.

Quality of rule-bases is a relative concept, so the evaluation of given rule-bases is performed as follows:

Step 1. For every rule pair, calculate the distances D_{ij} for all i and j.

Step 2. For every rule, calculate the score of the rule S_i.

Step 3. Calculate the score of the kth rule-base S_{RB_k}.

Step 4. Compare S_{RB_k}, S_i, and minimum D_{ij} with those of other rule-base that is obtained from the same data.

For illustration, consider the following two rule-bases in table 1 that are built from a set of fault data. Our problem is to determine the rule-base which gives higher score. It is assumed that the premises in each rule are connected with 'and' operator.

Evaluation of those rule-bases starts by calculating distance D_{ij}. Let us assume that the term set of each residual is chosen as {NB, NS, AZ, PS, PB}. Two distance maps in table 2 are generated. If there is a zero entry, it means that the corresponding two faults cannot be isolated. In such cases, the condition variables must be changed or added to produce non-zero distances. If there is no zero entry, find the score of the rule-base. In this example, the score and the minimum distance of the rule-base 1 are 46 and 1, and those of rule-base 2 are 36 and 2, respectively. So, it can be concluded that rule-base 2 is superior to rule-base 1 in diagnostic ability.

Table 1 Rule-Base[1] Rule-Base[2]

Rule NO.	R_{12}	R_{13}	R_{31}	R_{12}	R_{23}	R_{31}	Fault NO.
1	NS	NS	PS	NS	AZ	PS	1
2	PS	PS	NS	PS	AZ	NS	2
3	AZ	NS	PB	AZ	AZ	PB	3
4	AZ	PS	NB	AZ	AZ	NB	4
5	AZ	NB	PB	AZ	PB	PB	5

Table 2 Distance maps for rule-base 1 and 2

Rule-Base[1]

Rule NO.	2	3	4	5
1	6	2	6	3
2	x	6	2	7
3	x	x	6	1
4	x	x	x	7

Rule-Base[2]

Rule NO.	2	3	4	5
1	4	2	4	4
2	x	4	2	4
3	x	x	4	2
4	x	x	x	6

In rule-base 2, there may be some conflicts between fault 1 and 3, fault 2 and 4, and fault 3 and 5, since they got the minimum distance. It is noteworthy that the evaluation criterion indicates the diagnostic ability of the given rule-base, provides an useful selection criterion of condition variables and the degree of usefulness of each condition variable.

4. An application to a DC motor driven pump system

4.1 A motor-pump system

The proposed FDIS is applied to a DC motor driven centrifugal pump system. Such motor-pump systems are widely used for the transportation of all kinds of liquids. The state variables and the outputs are defined as

$$x^T = [\varDelta I_a(t) \ \varDelta w(t) \ \varDelta \dot{M}(t)] \qquad (13)$$

$$y^T = [y_1 \ y_2 \ y_3] = [x_1 \ x_2 \ x_3] \qquad (14)$$

$$u = [\varDelta u_a] \qquad (15)$$

where x_1 is the armature current of the motor, x_2 is the angular velocity of the motor-pump shaft, x_3 is the mass flow rate of the fluid, and u is the applied armature voltage. The linear model is then defined by following parameter matrices[8].

$$A = \begin{bmatrix} -\dfrac{R_a}{L_a} & -\dfrac{K_b}{L_a} & 0 \\ \dfrac{K_b}{J} & -\dfrac{(C_f+K_p)}{J} & -\dfrac{K_m}{J} \\ 0 & \dfrac{H_p}{A_{ac}} & -\dfrac{(A_r+H_m)}{A_{ac}} \end{bmatrix}$$

$$B = \begin{bmatrix} \dfrac{1}{L_a} \\ 0 \\ 0 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

The process parameter values employed to obtain this linearized model are taken from [8] and listed in Table A2 and Table A3 in the Appendix. In Table 3, the relations between the faults and the corresponding process parameter variations are defined. These relations are taken from Isermann [9].

Table3 Faults and parameter variations.

Fault1 : Brush fault	R_a increase
Fault2 : Short circuit of armature coil	R_a decrease L_a decrease
Fault3 : Excess of lubrication oil on ball-bearing.	C_f decrease K_p decrease
Fault4 : Dirt on ball-bearing	C_f increase K_p decrease
Fault5 : Impeller degradation	A_r increase H_p decrease K_p decrease

4.2 Rule-Base of the FDIS

The rule-base includes; a rule-base for sensor faults, a rule-base for process faults, and the rules for localizing sensor fault and process fault. Detection itself is very simple because any non-zero RT indicates a fault. Unfortunately, the simple rule for localization of sensor faults and process faults in section 3.1 cannot be used.

Table 4 Rule-base with $\{\ |R_{31}|\ , RT_{12}, RT_{23}, RT_{31}\}$

Fault	$\lvert R_{31}\rvert$	RT_{12}	RT_{23}	RT_{31}
Sensor 1	PB	PM	AZ	PM
Sensor 2	AZ	PB	PB	AZ
Sensor 3	AZ	AZ	PM	PM
Process 1,2	PS	PM	PM	PS
Process 3,4,5	PB	AZ	PM	PM

Table 5 The distance map for rule-base with $\{\ |R_{31}|\ , RT_{12}, RT_{23}, RT_{31}\}$

Rule No.	2	3	4	5
1	7	4	3	2
2	x	5	4	7
3	x	x	3	2
4	x	x	x	3

Table 6 A rule-base for the proposed scheme

Failed sensor Identification & Isolation of sensor fault/	RS1: IF($\lvert R_{31}\rvert$,RT_{12},RT_{23},RT_{31})=(PB,PM,AZ,PM), Then SF1 RS2: IF($\lvert R_{31}\rvert$,RT_{12},RT_{23},RT_{31})=(AZ,PB,PB,AZ), Then SF2 RS3: IF($\lvert R_{31}\rvert$,RT_{12},RT_{23},RT_{31})=(AZ,AZ,PM,PM), Then SF3 RP : If($\lvert R_{31}\rvert$,RT_{12},RT_{23},RT_{31})=(PS,PM,PM,PS) OR (PB,AZ, PM, PM), Then PF
Process fault Diagnosis	RP1: IF(R_{12},R_{23},R_{31}) =(NS,AZ,PS), Then PF 1 RP2: IF(R_{12},R_{23},R_{31}) =(PS,AZ,NS), Then PF 2 RP3: IF(R_{12},R_{23},R_{31}) =(AZ,AZ,PB), Then PF 3 RP4: IF(R_{12},R_{23},R_{31}) =(AZ,AZ,NB), Then PF 4 RP5: IF(R_{12},R_{23},R_{31}) =(AZ,PB,PB), Then PF 5

※ RS and RP mean Rule for Sensor and Rule for Processor fault detection. Also, SF and PF are stand for Sensor Fault and Process Fault, respectively.

The identification of sensor 3 fault and process faults is impossible in the rule. In order to identify these faults, a residual set $\{\ |R_{31}|\ , RT_{12}, RT_{23}, RT_{31}\}$ is chosen. The rule-base and the corresponding distance map are given in Table 4 and Table 5, respectively. A complete rule-base given in Table 6. Because of the large number of faults to be detected and isolated, residual R_{ij} s, together with RT_{jk}, are chosen to form the rule-base of Table 6.

4.3 Simulation study

Three observers with the eigenvalues (-60, -50, -40) are designed for residual generation. Fuzzy subsets of each selected condition variables in the rule-base are defined as shown in Table 7. One-sided and two-sided triangular membership functions and trapezoidal form membership function are employed. They are distinguished by the number of representative points.

Table 7 Linguistic values and membership functions

Residual	Linguistic Values and Membership Functions
R_{12}	NB(-3.7 -0.3], NS[-1.4 -0.3 0.0], AZ[-0.05 0 0.05], PS[0.0 0.3 1.4], PB[0.3 3.7)
R_{23}	NB(-0.42 -0.1], AZ[-0.2 0 0.2], PB[0.1 0.42)
R_{31}	{NB(-2.3 -0.05], NS[-1.0 -0.15 0], AZ[-0.15 0 0.15], PS[0.0 0.15 1.0], PB[0.05 2.3)}
$\lvert R_{31}\rvert$	{AZ[0.0 0.15], PS[0.0 0.15 1.0], PB[0.05 2.3)}
RT_{12}	AZ[0.0 2.0], PM[0.3 2.7 22.0] , PB[2.7 35.0)
RT_{23}	AZ[0.0 1.2], PM[0.1 2.5 10 18], PB[2.5 31.0)
RT_{31}	AZ[0.0 0.8], PS[0.2 0.9 1.8], PM[0.9 2.0 7.5], PB[1.0 11.0)

Triangular membership functions have three representative points and trapezoidal membership functions have four representative points. The notation '(' or ')' represent the open-tail membership function which has membership value '1' for all input values 'smaller' or 'larger' than the number specified as left argument or right argument. Mamdani's Max-Min operator is employed for the fuzzy inference. The output of the inference engine of the FDI subsystem is the membership value which means the possibility of the fault and the compatibility of the observed data with the premise of corresponding rule.

In the simulation, an input $\Delta u_a = 10$[V] is applied to the motor-pump system. The pump characteristic coefficient H_p is varied from 95 percent to 105 percent of its nominal value to verify the robust property of the FDIS against parameter variations. It is assumed that the variation is represented by the equation, $H_p = H_{pn}(1 + 0.05\sin(100t))$, where H_{pn} is nominal parameter value. Also, to show the property of the FDIS against measurement noise, white noise of variance 0.01 is added in each output, and that each fault occurs at 5 second. For comparative study, simulations for the conventional DOS are performed under same situations. The diagnostic rule-base given in Table A4 in Appendix is employed for the conventional scheme. Generally, the threshold values should be chosen so that the FDIS can cover the effects of noises and parameter variations in normal operation, and detects as small faults as possible. The threshold values in Table A4 have been chosen on the basis of data obtained by numerous simulations.

Fig. 1 and Fig. 2 show the diagnostic results of the FDIS with proposed fuzzy rule-base, and Fig. 3 and Fig. 4 show those of the FDIS with conventional crisp rule-base. The first in each figure shows the possibility of each sensor fault and process fault. An important aspect of the proposed FDIS subsystem is that the scheme allows the competition among all possible faults. so final decision is made by taking the fault of highest possibility. Remember that each fault was assumed to occur at 5 sec, and the system is in normal operation before the time in all simulations. Fig. 1 and Fig. 2 show that the proposed FDI subsystem gives correct diagnostic results. On the other hand the isolation of sensor 3 fault and process fault is impossible in the conventional scheme as shown in Fig. 3. The second in each figure shows the diagnostic result of process fault, which shows the possibilities of process faults to be isolated. In all cases the effect of introducing the proposed scheme can be clearly recognized.

It should be noticed that an assumption, that the maximum degree of fault should be limited to the 30% variation of corresponding parameters, has been made for this development. It means that our concern is the detection of incipient fault. Although the FDI subsystem was designed based on the fault data for the range of 5% to 30%, the subsystem works very well even for 50% or larger magnitude of faults.

5. Conclusions

In this paper, a fuzzy logic based diagnostic unit for MOS type FDIS is to improve the diagnostic performance. The FDIS with the diagnostic unit, the difficulties of conventional MOS can be removed, because it doesn't require threshold values, and provides reasonable decisions even in uncertain environments. The design and evaluation of diagnostic rule-base is illustrated and a new evaluation method with which the quality of rule-base can be evaluated, is suggested. The application of this evaluation criterion to the selection of condition variables and diagnostic rules is described. In contrast to the conventional ARM based FDI schemes, it is always possible to introduce human knowledge in the design stage and external information that cannot be represented in terms of state variables may be included in the rule-base. It is noteworthy that there is a strong relationship between the severity of a fault and the membership grade. The design concepts are applied to a DC motor driven centrifugal pump system. In the proposed scheme, a diagnostic rule-base is implemented by using Mamdani's Max-Min operator. However, if the residuals are perturbed, the decision reliability could be decreased in this type implementation. The further researches such as how to choose an other type operator and how to optimize the membership functions have been performed.

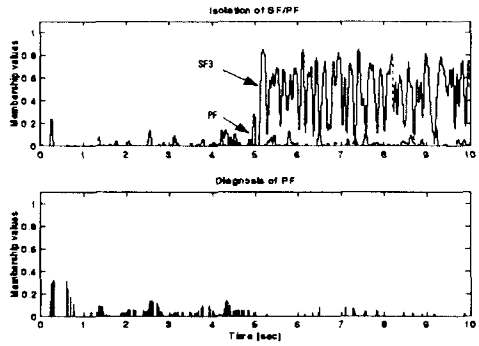

Fig. 1 The diagnostic result of the proposed scheme (10% additive fault of mass flow rate sensor).

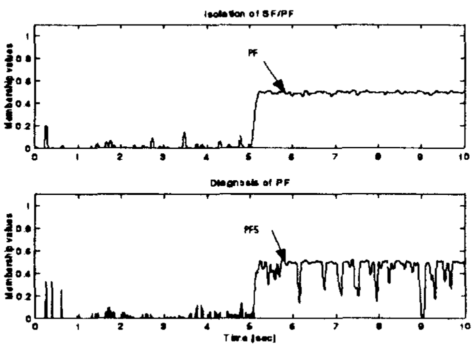

Fig. 2 The diagnostic result of the proposed scheme (10 % impeller degradation).

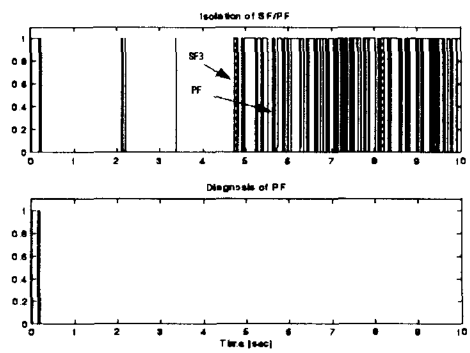

Fig. 3 The diagnostic result of the conventional scheme (10% additive fault of mass flow rate sensor).

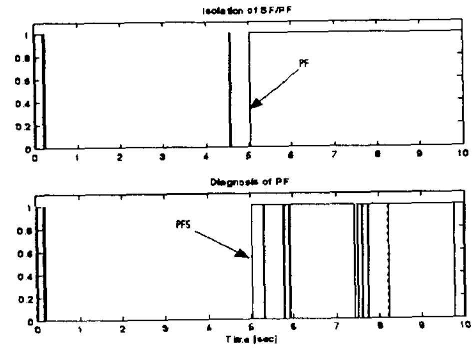

Fig. 4 The diagnostic result of the conventional scheme (10% impeller degradation).

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Appendix

Table A1 The mean of linguistic values.

Linguistic value	Mean
PO	Positive
NB	Negative Big
NS	Negative Small
AZ	Approximate Zero
PS	Positive Small
PM	Positive Medium
PB	Positive Big

Table A2 DC motor rating[DM30]

Maximum Power	3.52 [kW]	Rated Power	3.0 [kW]
Maximum Speed	1250 [rpm]	Rated Speed	1000 [rpm]
Rated Armature Voltage	160 [V]	Rated Armature Current	22 [A]

Table A3 Parameters in steady-state.

R_a	Armature Resistance	0.45 [Ω]
L_a	Armature Inductance	0.0054 [H]
K_b	Back Electromotive Force Constant	1.433 [Vsec/rad]
J	Moment of Inertia	0.398[kg · m^2]
C_f	Adhesive Friction Coefficient	0.02 [Nmsec/rad]
K_m	Motor Torque Coefficient	0.1459 [Nm/A]
K_p	Pump Torque Coefficient	0.2736 [Nmsec/rad]
H_m	Motor Characteristic Coefficient	0.015 [m^2/kgsec]
H_p	Pump Characteristic Coefficient	0.564 [m^2/radsec]
A_{ac}	Acceleration Coefficient of Fluid	17.13 [m^2/kg]
A_r	Resistance Coefficient of Fluid	13.704 [m^2/kgsec]

Table A4 A rule-base for the conventional scheme.

Failed sensor Identification & Isolation of sensor fault/ process fault	RS1: IF($\|R_{31}\|>0.08$) AND ($RT_{12}>1.0$) AND ($RT_{23}<1.5$) AND ($RT_{31}>1.0$), Then SF1 RS2: IF($\|R_{31}\|<0.08$) AND ($RT_{12}>1.0$) AND ($RT_{23}>1.5$) AND ($RT_{31}<1.0$), Then SF2 RS3: IF($\|R_{31}\|<0.08$) AND ($RT_{12}<1.0$) AND ($RT_{23}>1.5$) AND ($RT_{31}>1.0$), Then SF3 RP: IF(($\|R_{31}\|>0.08$) AND ($RT_{12}>1.0$) AND ($RT_{23}>1.5$) AND ($RT_{31}>1.0$)) OR (($\|R_{31}\|>0.08$) AND ($RT_{12}<1.0$) AND ($RT_{23}>1.5$) AND ($RT_{31}>1.0$)), Then PF
Process fault Diagnosis	RP1: IF($R_{12}<-0.05$) AND ($\|R_{23}\|<0.2$) AND ($R_{31}>0.06$), Then PF 1 RP2: IF($R_{12}>0.05$) AND ($\|R_{23}\|<0.2$) AND ($R_{31}<-0.06$), Then PF 2 RP3: IF($\|R_{12}\|<0.05$) AND ($\|R_{23}\|<0.2$) AND ($R_{31}>0.06$), Then PF 3 RP4: IF($\|R_{12}\|<0.05$) AND ($\|R_{23}\|<0.2$) AND ($R_{31}<-0.06$), Then PF 4 RP5: IF($\|R_{12}\|<0.05$) AND ($R_{23}>0.2$) AND ($R_{31}>0.06$), Then PF 5

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