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Fuzzy Fault Detection and Diagnosis under Severely Noisy Conditions using Feature-based Approaches

Y. Ganjdanesh*, Y. S. Manjili**, M. Vafaei*, E. Zamanizadeh**, E. Jahanshahi**
* Islamic Azad University, Saveh Branch
** Department of Automation and Instrumentation Engineering, Petroleum University of Technology (PUT), Tehran, Iran

Abstract—This paper introduces an approach to fault detection and diagnosis scheme which uses fuzzy reference models to describe the symptoms of both faulty and fault-free plant operation. Recently, some approaches have been combined with fuzzy logic to enhance its performance in particular applications such as fault detection and diagnosis. The reference models are generated from training data which are produced by computer simulation of typical plant. A fuzzy matching scheme compares the parameters of a fuzzy partial model, identified using on-line data collected from the real plant, with the parameters of the reference models. The reference models are also compared to each other to take account of the ambiguity which arises at some operating points when the symptoms of correct and faulty operations are similar. Independent Components Analysis (ICA) is used to extract the exact data from variables under severe noisy conditions. A Fuzzy Self Organizing Feature Map is applied to the data obtained from ICA for obtaining more accurate and precise features representing different conditions of the system. The results are then applied to the model-based fuzzy procedure for diagnosis goals. Results are presented which demonstrate the applicability of the scheme.

I. Introduction

After the birth of fuzzy logic, a rapid growth in its popularity made a revolutionary transient era in science and especially in engineering which has lasted up to now. Recently, some approaches have been combined with Fuzzy to enhance its performance in particular applications such as fault detection and diagnosis. Fault detection and diagnosis usually requires a knowledge-based treatment [1] since, in practice, it is very difficult to obtain adequate representations of the complex and often highly nonlinear behavior of faulty plant using quantitative models. The use of fuzzy qualitative models can take account of the uncertainties associated with describing the behavior and more easily incorporate what expert knowledge is available about the symptoms of faults [10]. Both implicit (shallow knowledge) fuzzy models and explicit (deep knowledge) fuzzy models are used for fault diagnosis [5]. Terpstra et al. [8] uses an implicit fuzzy model (a fuzzy rule base) to analyze qualitative statements of the differences between the actual values and those predicted by quantitative models of the behavior of the system with and without faults. Schneider and Frank [6] and Sauter et al. [10] describe similar observer based fault detection schemes in which fuzzy rules adapt the threshold for evaluating the residuals according to the current operating conditions. Ulieru [9] identifies faults using a fuzzy inter-relational diagnostic model which is constructed from fuzzy relations based on expert opinion that map symptoms to faults. The possibility of each fault given the detected symptoms is calculated and the diagnosis is based on fuzzy pattern recognition. Kang et al. [2] proposes an analytical intelligent approach which diagnoses faults via fuzzy inferencing based on expert rules. Some explicit approaches are proposed by Marcu and Voicu [4], who train a fuzzy classifier to detect and isolate faults using data generated by simulation, and by Sauter et al. [7] who use fuzzy clustering in residual space to locate faults in systems which have multiple sensors.

This paper describes a parameter estimation rather than an innovative approach to fuzzy model-based fault diagnosis. The use of ICA as a powerful tool for denoising can also be considered as an innovation for improving the efficiency of the proposed method under severe noisy conditions. Although the data obtained from ICA, which are in-fact the real inputs and outputs of plant whose signal to noise ratio has been increased to a very good level, are at an acceptable range of noisiness, they still need treatment of some feature-based methods for giving the best possible information to the fuzzy network. FSOM is employed here as a suitable clustering method which enhances the quality of data given to fuzzy system by extracting centers of the ICA output.

The fuzzy matching is based on the same measure of similarity as that used by Wang et al. [11] to match fuzzy propositions. The fuzzy measures of similarity are used to calculate a set of basic assignments which indicate the strength of the evidence that the system is operating correctly or has a particular fault. The method of diagnosis has been developed to detect and diagnose faults in continuous stirred-tank reactor (CSTR). The detection of

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Y. Ganjdanesh is with the Department of Engineering at Islamic Azad University, Saveh Branch, Saveh, Iran. (Corresponding author to provide phone: +98-9123703074; e-mail: ganjdanesh@yahoo.com).

Y. S. Manjili is with the Department of Automation and Instrumentation Engineering, Petroleum University of Technology (PUT), Tehran, Iran.

M. Vafaei is with the Department of Engineering at Islamic Azad University, Saveh Branch, Saveh, Iran.

E. Zamanizadeh is with the Department of Automation and Instrumentation Engineering, Petroleum University of Technology (PUT), Tehran, Iran

E. Jahanshahi is with the Department of Automation and Instrumentation Engineering, Petroleum University of Technology (PUT), Tehran, Iran.

four common faults associated with the operation of the whole unit is used to demonstrate the applicability of the scheme.

II. Fuzzy Fault Detection and Diagnosis

The fuzzy reference models are made up from IF-THEN rules which describe the symptoms of faulty and fault-free operation in terms of predefined fuzzy reference sets. A particular model is defined by specifying the values of the elements of its associated fuzzy relational array. Each element of the array is a measure of the credibility or confidence that the associated rule correctly describes the behavior of the system around a particular operating point. The models can be based on expert knowledge or learned offline from training data produced by computer simulation of typical plant, with and without the faults. The degree to which a fault, or correct operation, is present is determined by comparing the rules of the reference models with the rules of a partial fuzzy model identified using normal operating data collected on-line from the real plant (see Fig. 1). A fuzzy measure of similarity is used to calculate the belief that the fault condition associated with each of the reference models has occurred in the real plant.

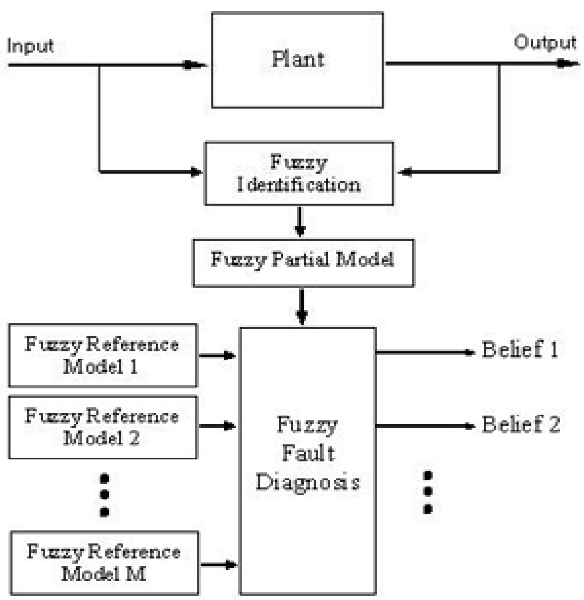


Fig. 1 Schematic of fault detection and diagnosis using fuzzy models

A. Fuzzy equality

The equality of two fuzzy sets A and B can be assessed by calculating the degree to which $A \subset B$ and $B \subset A$. One measure of the grade of equality or similarity $Sim_{A,B}$ of A and B [3] is given by

$$Sim_{A,B} = \frac{\sum_{i=1}^{N} MIN\,[(\mu_A(i)\alpha\mu_B(i), \mu_B(i)\alpha\mu_A(i))]}{MAX\,\{\sum_{i=1}^{N}\mu_A(i), \sum_{i=1}^{N}\mu_B(i)\}} \quad (1)$$

Where μ_A is the membership function for fuzzy set A, μ_B is the membership function for fuzzy set B, α is the fuzzy inclusion operator:

$$\begin{aligned} \mu_A(i)\alpha\mu_B(i) &= 1 \quad if\ \mu_A(i) \le \mu_B(i) \\ &= \mu_B(i)\ otherwise \end{aligned} \quad (2)$$

and N is the number of elements defined on the discrete universe of discourse. The similarity measure can be simplified [3, 11] when the fuzzy sets are generated from measured data, since exact equality $\mu_A(i) = \mu_B(i)$ is unlikely to occur in practice. In this case,

$$Sim_{A,B} = \frac{\sum_{i=1}^{N} MIN\,\{\mu_A(i), \mu_B(i)\}}{MAX\,\{\sum_{i=1}^{N}\mu_A(i), \sum_{i=1}^{N}\mu_B(i)\}} \quad (3)$$

B. Fuzzy matching

The same similarity measure can be used to compare the partial fuzzy model with the reference models, if all of the fuzzy models have the same structure and they are considered as level two fuzzy sets whose membership values are given by the credibilities of their rules. In this case the measure of the similarity Sim_{S_P, S_i} between the partial fuzzy model representing the current state of the system S_P, and the fuzzy reference model representing the behavior of the system if it were in state S_i, is given by:

$$Sim_{S_P,S_i} = \frac{\sum_{n=1}^{N_r} MIN\,\{C_{S_P}(n), C_{S_i}(n)\}}{\sum_{n=1}^{N_r} C_{S_P}(n)} \quad (4)$$

Where Csp(n) is the credibility of the nth rule in the partial fuzzy model, Csi(n) the credibility of the equivalent rule in the ith fuzzy reference model describing the behavior of the system when it is in state S_i, and Nr is the number of rules that are compared. Since a partial model can only describe the symptoms of operation around the current operating point, the rules of the partial fuzzy model are only compared with rules in the fuzzy reference models that have the same antecedents as rules with nonzero credibility in the partial model, and the sum of the credibilities in the partial fuzzy model is used to normalize the result.

III. Case Study

System has got four inputs which we use in addition to four outputs as the primary input data for fuzzy logic to determine system status. Outputs of the system are exactly its four state variables which are known as follows in the literature and in software programs used for simulation: Input1: u1, Mass flow rate of substance A (symbolic Fi) Input2: u2, Concentration of substance A (symbolic C_{Ai}) Input3: u3, Temperature of the substance A (symbolic Ti) Input4: u4, Temperature of the coolant (symbolic Tc) State1: x1, Volume of liquid in CSTR (symbolic V) State2: x2, Concentration of substance B (symbolic C_A) State3: x3, The temperature of substance B (symbolic T) State4: x4, The temperature of Jacket (symbolic Tj)

A. Specifications of Faults

Among the various possible faults to be defined in this system, some were realistic and practically more common. Below, there is a list of different types of fault considered to train the fuzzy models for the case under study:

Fault1: Leakage in the flow rate of input material A (Fi) Fault2: deposition in the jacket which results in reduction of heat transfer coefficient (U) Fault3: Low efficiency of compressor which causes the input temperature of the coolant to increase (Tc) Fault4: Sensor Fault which results in an offset when measuring output temperature of the material B (T)

Fault4 in-fact is a false-alarm which represents that there is some problem in measuring devices not in the process or the plant itself. Therefore, when Fault4 is activated by the FDD system, there is no need for shut-down, but the only action necessary is to replace the output sensor of variable x3 by a new calibrated one.

IV. Simulation & Results

Simulations have been performed using Matlab package and Simulink. The steady-state value of inputs and outputs will be subtracted from the measured values of the system variables to make the problem easier. The centers of fuzzy sets will be chosen around zero according to the deviations that system variables will have due to the condition which includes the presence of each fault or the fault-free condition. This way the faults can be detected and diagnosed at the same time and, on the other hand, the false alarms considered in this case study will also be detected properly which avoids the system from being shut down and helps the quality of the products and the amount of energy consumption to be kept at desired level.

An example of membership functions chosen for variables of the system is shown in fig.2. We've considered 3 MFs for each of the input variables due to their range of deviation. The terms "nlarge" (Negative Large Values) and "plarge" (Positive Large Values) in fig. 5-a represent high amounts of deviation or change in the input variable which can be caused by both a fault (in this case: sensor fault, compressor fault, etc.) or a change in the set-point of the system. MF named "small" represents small changes or deviations in the temperature of the coolant which can be caused by some noise or because of some non-fault reasons. Therefore, whenever the values of the input u4 are under the membership "small" the condition of this input should be identified as "normal". We refer to the MF "small" as the MF "Z" from this moment on. The MFs "nlarge" & "plarge" will also be referred to as "N" & "P".

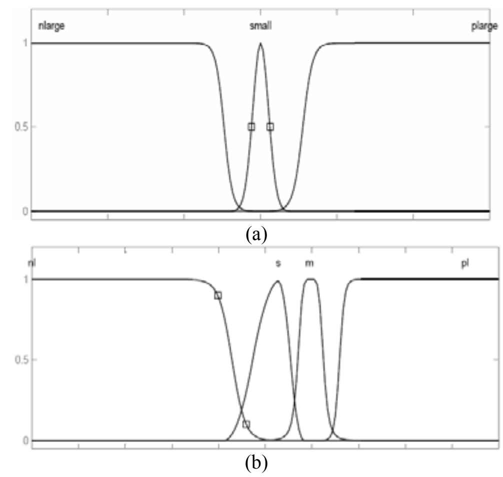
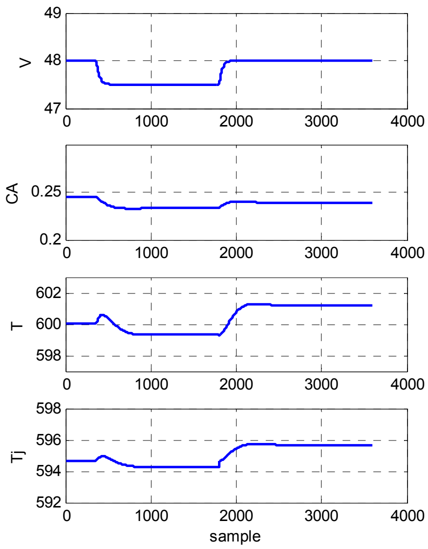


Fig. 2. Membership Functions.
(a) Input temperature of coolant or u4 (symbolic Tc)
(b) Output temperature of substance B or x3 (symbolic T)

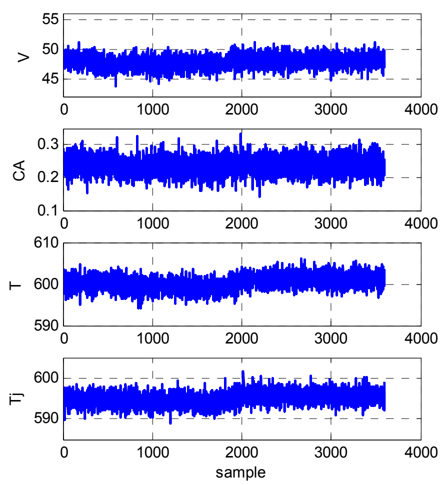
We refer to the values of the u1, u2, u3, u4, x1, x2, x3, x4 as the difference values of the variables. Therefore, u1=0 or u1 is "Z" means that the main value of the variable u1 is constant and doesn't have any change or deviation. Regarding the definition mentioned here we can introduce the basic fuzzy rules as follows:

1. If u1, u2, u3, u4 are "Z" and x1, x2, x3, x4 are "Z" then the status is "Normal"
2. If u1, u2, u3, u4 are "Z" and x1, x2, x3, x4 are "N" then the status is "Fault1"
3. If u1, u2, u3, u4 are "Z" and x1 is "Z" and x2 is "N" and x3 is "P" and x4 are "N" then the status is "Fault2"
4. If u1, u2, u3 are "Z" and u4 is "P" and x1 is "Z" and x2 is "N" and x3, x4 are "P" then the status is "Fault3"
5. If u1, u2, u3 are "Z" and u4 is "P" and x1, x2 are "Z" and x3 is "N" and x4 is "Z" then the status is "Fault4"

Fig. 3 shows one example of test data which represent the presence of Normal steady-state at the beginning after which Fault 1 has been occurred. The last part of the diagrams (after sample 1750) shows the presence of Fault3 and removal of Fault1.



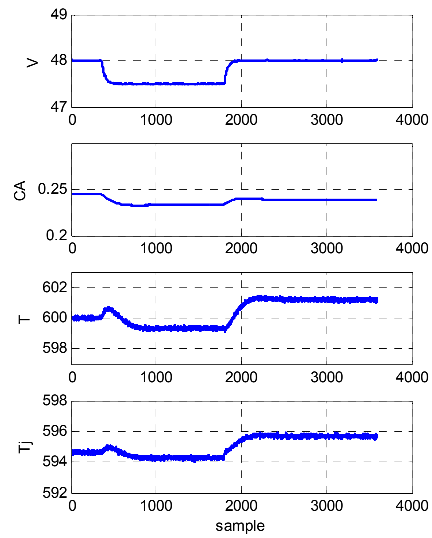
(a)



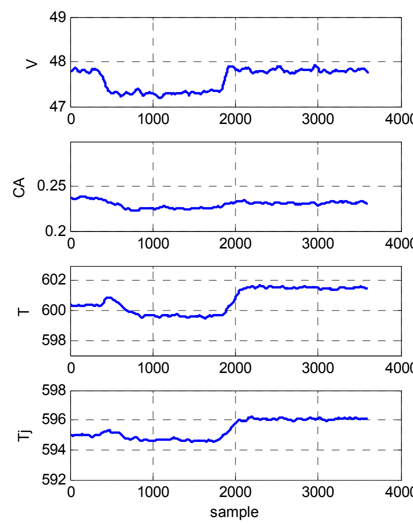
(b)

Fig. 3. Test status of the system is Normal-Fault1-Fault3 (a) noiseless (b) very noisy (Sampling time = 10 s, total of 3600 samples for 10 hours)

The data have been sampled from a computer simulation under noiseless condition (a), and severe noisy condition (b). As one can easily see here, the noisy measurements can reveal approximately nothing for the user. It seems that there only exist some high amplitude noise which is recorded because of some critical fault in sensors or the data transmission line, etc. The inherent ability of ICA in denoising helps us in this case. Although there are some approaches used for reproducing the two source signals from one mixed signal [12] using wavelet decompositions, we just had the simple assumption of having a hardware redundancy for the system. There should be two sensors for measuring each of the variables, the effect of noise on each of the sensors is different from the other. This way there'll be two mixed signals which are given to the ICA method for the two sources to be separated. The method used for implementing Independent Components Analysis is the FastICA algorithm [13].



(a)

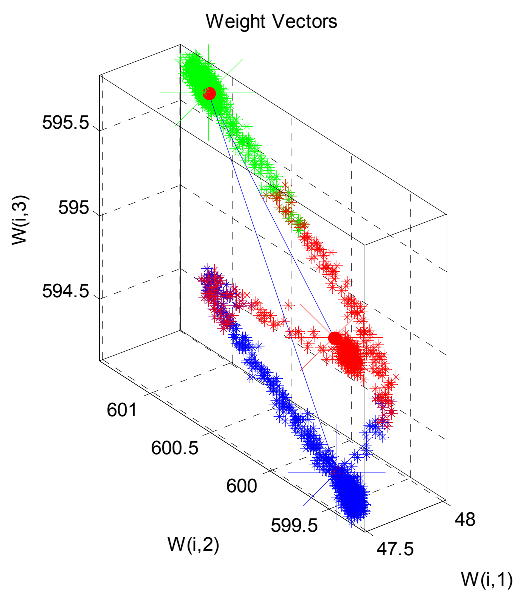


(b)

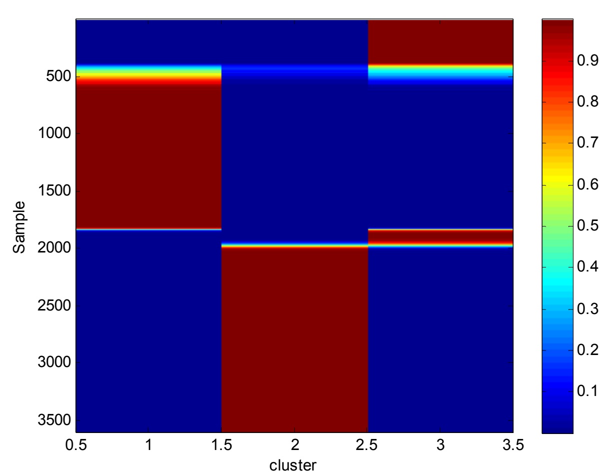
Fig. 4. Separation results: (a) Main data extracted by ICA (b) Main data obtained using LPF (Sampling time = 10 s, total of 3600 samples for 10 hours)

Fig. 4a shows the main independent source separated using the ICA method. As one can see here, the noise and the main data have been successfully separated. Diagram of Noise is not shown in this figure because it contains no information of the plant behavior. Results of using a very powerful Low-Pass Filter (LPF) are also shown in fig. 4b for comparison with those of ICA. The main data will be used for the rest of the procedure.

The best possible separation results for an LPF obtained by order of two and the cut frequency of 100 (Hz). Diagrams have shown in Fig. 4 for comparison. If one is to compare the results of Fig. 4 with the data shown in fig. 3a it will be easily seen that the ICA has proven itself much more powerful than LPF in this case. Output of ICA is at a good level of noisiness, but for more accurate decision-making, we need to use another approach to extract features of the data in different working conditions of the plant, including transition and steady-state. For obtaining this result, we chose an FSOM method which is based on c-Means algorithm [13, 15].



(a)



(b)

Fig. 5. Results of clustering using FSOM:
(a) 3D view of clusters (b) Samples vs. clusters
(Sampling time = 10 s, total of 3600 samples for 10 hours)

The results of the clustering procedure are shown in fig 5.

The mentioned data are used to investigate the fuzzy method proposed in this paper which is based on fuzzy modeling and a fuzzy matching of the test data with models in addition to fuzzy of the fuzzy models to each other to extract a strength factor for credibility of each rule.

Fig. 5a represents the weight vectors which are in-fact the three denoised inputs to the FSOM. Different values of inputs have some effects on the place of centers used for clustering. Here the simulation is done using three centers to result in three different clusters. Different clusters are represented by different colors in the 3D map of Fig. 5a. In Fig. 5b a 2D map of samples vs. clusters is drawn. It can be easily seen here that to which cluster each sample belongs. Cluster 3 represents the first steady-state condition under which the plant behaves normally. Cluster 1 is the symbol of second steady-state condition during which fault1 is present in the plant. Cluster 2 shows the last steady-state condition of the system during which plant is under the effect of fault3 solely. There can a confusion be detected in the diagram of Fig. 5b which refers to the transient condition of plant outputs during the change from fault1 to fault3. The FSOM just detects the status of plant as normal for the samples 1800 to 2000 because of their exact value whereas the actual status of the plant should be detected fault1 and fault3 with some percentage for each of them during this transitory condition. Another confusion is also detected in the 2D map for samples 450 to 550 during which the FSOM can not detect the plant status properly due to the similarity of values of inputs to the clustering method.

After obtaining the centers of the data using FSOM the normal steady-state value of each variable will be subtracted from its measured value. Using fuzzy rules and credibilities introduced before we'll be able to calculate the degrees of similarity for ambiguous data according to the fuzzy memberships for all of the universes of discourse. The result of the plant status detection and diagnosis under severe noisy condition is shown in fig. 6 which represents condition of the system for each sample of data. Data have been sampled by the sampling time of 10 (sec) for 10 hours. So there are totally 3600 samples studied in this simulation.

As one can easily see here, the results are clearly distinguishable. The specifications of Normal and faulty conditions have been introduced in section 3.1 of this paper.

For the steady-state condition, this approach gives a reliable and accurate response even under severe noisy conditions which is impossible for ordinary and common fuzzy approaches. For the test status data the diagram of which is given in fig. 6a we've got a precise and accurate response for detecting and diagnosing the plant status by using the proposed method in fig. 6b during steady-state conditions.

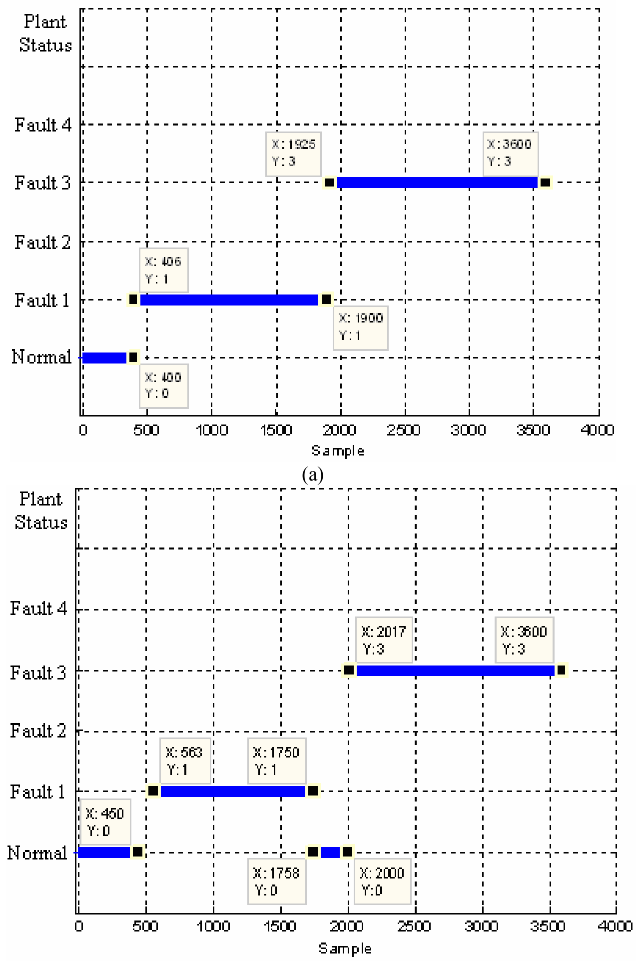


Fig. 6. Diagrams of plant status:
(a) Real Plant Status
(b) Results of the proposed method under severe noisy condition
(Sampling time = 10 s, total of 3600 samples for 10 hours)

V. CONCLUSION

An innovative method of fault detection and diagnosis has been developed which is based on fuzzy matching of fuzzy reference models generated from simulation data. The method of diagnosis calculates a measure of the underlying ambiguity associated with the diagnosis and generates a confidence interval for each of the possible diagnoses. The scheme is computationally efficient since the identification of a partial fuzzy model and the fuzzy matching of the models require relatively little processing power. To enhance the ability of fuzzy fault detection and diagnosis under severe noisy conditions, the method of ICA was employed. The method of FSOM was also used to extract the features of the data obtained by ICA for more accurate and precise fuzzy decision making. The results have shown that the scheme can successfully diagnose correct operation in an industrial example of continuous stirred-tank reactor. Work is now being undertaken to examine the sensitivity of the diagnosis to the structure of the models and to investigate ways of producing generic reference models which can be used to represent the operating characteristics of a range of plants of similar design.

REFERENCES

[1] ISERMANN, R 'On the aDolicabi1itv of model-based fault detection for technical process&', Proceedings of the 12th IFAC world congress, Sydney, Australia, 1993, Vol 9, pp 195-200
[2] KANG,H , CHENG, J , KIM, I , and VACHTSEVANOS, G 'An application of fuzzy logic and Dempster-Shafer Theory to failure detection and identification', Proceedings of the 30th IEEE conference on decision and control, Brighton, UK, 1991, pp 1555-1 560
[3] LEE, K -M , SEONG, K -A , and LEE-KWANG, H 'Fuzzy matching and fuzzy comparison in fuzzy expert systems', Proceedings of the 2nd international conference on fuzzy logic and neural networks, Iizuka, Japan, 1992, pp 3 13-3 16
[4] MARCU,T., and VOICU,M. 'Fuzzy weighted clustering and classification for process fault detection', Proceedings of the IFACIIFIPSIIMACS international symposium on AI in real-time control, Delft, Netherlands, 1992, pp 275-280
[5] QUEK,C , and LEITCH,R R 'Using energy constraints to generate fault candidates in model based diagnosis', Proceedings of the IEE conference on intelligent rhythms engineering, Edinburgh, 1992. nn 159-164
[6] SCHNEIDER,H., and FRANK,P.M.: 'Fuzzy logic based threshold adaptation for fault detection in robots'. Proceedings of the 3rd IEEE conference on control applications, Glasgow, U'K, 1994, Vol. 2, pp. 1127-1132
[7] SAUTER,D., MARY,N., SIROU,F., and THIELTGEN,A. 'Fault diagnosis in systems using fuzzy logic', Proceedings of the 3rd IEEE conference on control applications. Glasgow. UK. 1994. Val 2,pp 883-888
[8] TERPSTRA,V J , VERBRUGGEN,H B , HOOGLAND,M W , and FICKE,R.A E: 'A real-time, fuzzy, deep-knowledge based fault-diagnosis system for a CSTR', Proceedings of the IFAC symposium on online fault detection and supervision in the chemical process industries, Newark, Delaware, USA, 1992, pp 26-31
[9] ULIERU, M 'Processing fault-trees by approximate reasoning in solving the technical diagnostic problem', Proceedings of the 12th IFAC world congress, Sydney, Australla, 1993, Vol 9, pp 221- 224
[10] VACHKOV,G 'Identification or fuzzy rule based system for fault diagnosis in chemical plant', Proceedings of the IFAC symposium on online fault detection and supervision in chemical process industries, Newark, Delaware, USA, 1992, pp 315-318
[11] WANG,J T , SEHM1,A S , JONES,N B , and DE BONO,D P 'A knowledge-based system for fuzzy ECG interpretation', Proceedings of the IEE conference on intelligent systems engineering, Edinburgh, 1992, pp 238-243
[12] MING J. ZUO_, JING LIN, XIANGFENG FAN 'Feature separation using ICA for a one-dimensional time series and its application in fault detection', Journal of Sound and Vibration, 287 (2005) 614–624
[13] A. HYVARINEN, E. OJA, Independent component analysis: algorithms and applications, Neural Networks 13 (4–5) (2000) 411–430.
[14] JAMES C. BEZDEK, ERIC CHEN-KUO TSAO and NIKHIL R. Pal 'FUZZY KOHONEN CLUSTERING NETWORKS' Research supported by NSF Grant RI-9003252 0-7803-0236-2 192 $3.00 8 1992 IEEE
[15] WEIMING HU, DAN XIE, TIENIU TAN, and STEVE MAVBANK 'Learning Activity Patterns Using Fuzzy Self-Organizing Neural Network' IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART B: CYBERNETICS, VOL. 34, NO. 3, JUNE 2004