A Study on the Development of Robust Fault Diagnostic System Based on Neuro-Fuzzy Scheme

Sung-Ho Kim and SSang-Yoon Lee

Abstract : FCM(Fuzzy Cognitive Map) is proposed for representing causal reasoning. Its structure allows systematic causal reasoning through a forward inference. By using the FCM, authors have proposed FCM-based fault diagnostic algorithm. However, it can offer multiple interpretations for a single fault. In process engineering, as experience accumulated, some form of quantitative process knowledge is available. If this information can be integrated into the FCM-based fault diagnosis, the diagnostic resolution can be further improved. The purpose of this paper is to propose an enhanced FCM-based fault diagnostic scheme. Firstly, the membership function of fuzzy set theory is used to integrate quantitative knowledge into the FCM-based diagnostic scheme. Secondly, modified TAM recall procedure is proposed. Considering that the integration of quantitative knowledge into FCM-based diagnosis requires a great deal of engineering efforts, thirdly, an automated procedure for fusing the quantitative knowledge into FCM-based diagnosis is proposed by utilizing self-learning feature of neural network. Finally, the proposed diagnostic scheme has been tested by simulation on the two-tank system.

Keywords : fuzzy cognitive map, fault diagnosis, qualitative approach, neural network

I. Introduction

In recent years, the complexity of modern industrial processes and the availability of inexpensive computer hardware prompted us to develop automated fault diagnostic systems instead of conventional diagnosis. Generally, depending on the rigorousness of the process model employed, existing fault diagnostic schemes can be classified into quantitative, qualitative and qualitative/quantitative approaches. Quantitative approaches which have been studied by Clark and Willsky are based on the analytical redundancy generated by the use of estimators such as Kalman filter, state observer, and detection filters [1][2]. It can accurately find out the fault origin. However, it is too time-consuming and requires as precise a model as possible to get a good diagnostic result. Qualitative approaches, on the other hand, only consider the signs of coefficients in all governing equations. The SDG (Signed Directed Graph) is a typical example. Upon diagnosis, the consistency of the branches of a given fault origin is checked to validate the hypothesis and all possible origins are screened. In many cases, it simply gives multiple interpretations for a single event. This is an inherent limitation of the qualitative approaches. Since only qualitative knowledge is employed, the diagnostic resolution can only be improved to a certain degree.

Another one is the qualitative/quantitative approaches proposed by Yu and Lee where they integrated quantitative knowledge into a qualitative model to improve the diagnostic resolution[3].

Recently, concept of fuzzy cognitive map is proposed by Kosko for representing causal reasoning [4]. Its structure allows systematic causal reasoning through a forward-evolved inference. Since forward inference behaves as temporal associative memories (TAM), it is possible to reason with FCM as we recall with TAM. By utilizing the FCM, author has already proposed two FCM-based fault diagnostic algorithms [5][6]. The first one is an on-line fault diagnostic scheme based on FCM where an important concept, the TAM recall property of FCM, is utilized. It can also be considered as a simple transition of Shiozaki's SDG-based diagnostic approach to FCM framework. The second one is an application study of FCM-based diagnostic scheme to a hierarchical fault diagnosis where an FCM's feature of composibility/decomposility is used. Generally, proposed FCM-based fault diagnostic algorithm can be effectively used in on-line fault diagnosis owing to its self-generated **"fault FCM models"** which can generate predicted pattern sequences. However, FCM-based diagnosis is a qualitative approach in nature. Therefore, it can offer multiple interpretations for a single fault: in diagnosis, this implies that the diagnostic system provides more possible fault interpretations in addition to the true one. This is an inherent limitation of the qualitative approaches. In process engineering, as experience accumulated, some form of quantitative process knowledge is available, e.g., steady-state gain between process variables. If this information can be integrated into the FCM-based fault diagnosis, the diagnostic resolution can be further improved.

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The purpose of this work is to propose an enhanced FCM-based fault diagnostic scheme. Firstly, the membership function of fuzzy set theory is used to integrate quantitative knowledge into the FCM-based diagnostic scheme. Secondly, modified TAM recall procedure based on **"extended fault FCM models"** which can effectively deal with quantitative knowledge is proposed. Generally, the integration of quantitative knowledge into FCM-based diagnosis requires a great deal of engineering efforts, even when all process data are available. Furthermore, quantitative knowledge is varying according as operating conditions of process and the magnitude of faults are changed. Therefore, some automated procedure for fusing the quantitative knowledge into FCM-based diagnosis is required. For this, self-learning feature of neural network is utilized. The self-learning procedure is based on reinforcement learning of the neural network [7].

This paper is organized as follows: Concept of FCM and FCM-based diagnostic algorithm are outlined in section II and III, respectively. The detailed procedure for integration of fuzzy set theory into FCM-based diagnosis is described in section IV. In section V, self-learning feature to the FCM-based diagnosis is considered. Finally, simulation study for the two-tank system is given to illustrate the feasibility of the proposed diagnostic scheme.

II. Fuzzy cognitive map

1. Basic of fuzzy cognitive map

FCM was proposed by Kosko to store uncertain causal knowledge. It is a fuzzy signed directed graph with feedback. FCM consists of nodes and branches. The nodes of the FCM correspond to variables and branches represent the causal influences between nodes. The influences are represented by [-1,1] on the arcs, indicating that the cause and effect variables tend to change in the same or opposite direction. Using Kosko's convention, Values -1 and 1 represent full causality, zero denotes no causal effects, and all other values correspond to different fuzzy level of causal effect. If the permissible values assigned to the directed branches are restricted only to the set {-1,0,+1}, it is called a simple FCM.

2. Simple FCM-based fault diagnostic algorithm

Basic fault diagnostic algorithm based on the simple FCM is outlined in this section. The more detailed description can be found in [5].

2.1 FCM-based fault diagnostic algorithm

The proposed FCM-based diagnostic algorithm is based on Shiozaki's consistent rooted trees method, which is built upon the concept of SDG (Signed Direted Graph). The inherent assumption in his approach was that a single root cause which can explain the given abnormal situation can be found. Concept of Shiozaki's algorithm is as follows: Nodes which have a sign other than '0' are known as valid nodes, while branches for which the product of the signs on the initial and terminal nodes is the same as the sign of the branch are known as consistent branches. The graph which is composed of valid nodes and consistent branches is called a cause and effect (*CE*) graph. If there is an elementary path from a node on the SDG to all valid observed nodes, and if all the branches on these paths are consistent branches, then the tree which is composed of such a node and such consistent paths is known as a 'consistent rooted tree'. A 'root node' is any node in the CE graph which has at least one consistent branch connecting it to an effect node and no consistent branch connecting it to a cause node. The idea of consistent rooted-tree method is that a root node which is the maximal strongly connected component of the CE graph is the candidate of the fault.

Let FCM matrix for a system, E and the observed pattern vector W be given. In what follows is the detailed FCM-based diagnostic algorithm.

Step 1 : Calculating CR matrix

$$WE = Diag(W) \cdot E \cdot Diag(W) \tag{1}$$

$$CR(i,j) = T(WE(i,j)) \tag{2}$$

where Diag(W) represents a square matrix whose diagonal elements are those of W and all other elements off the diagonal are zero, and T is the threshold function with a threshold selected to be zero. According to Shiozaki's consistent rooted tree method, (1) can be thought of as the process of generating all possible paths. Threshold function in (2) plays the role of removing inconsistent paths from WE.

Step 2 : Identifying the origin of the fault.

In order to find out the origin of the fault, we should find a maximal strongly connected node. This can be done as follows.

1) Calculate the column sum of CR matrix which represents the number of concepts causally impinging on concept C_i.

$$\mathrm{IN}(C_i) = \sum_{k=1}^{n} CR(k,i) \tag{3}$$

2) Calculate the row sum which represents the number of concepts concept C_i causally impinges on.

$$OUT(C_i) = \sum_{k=1}^{n} CR(i,k) \tag{4}$$

3) By using the concept of Shiozaki's algorithm, a root node which corresponds to maximal strongly connected component can be thought of the one having **zero column sum and non zero row sum.**

2.2 Generation of fault FCM model

If an FCM and steady-state observed patterns are given, the origin of fault can be easily found out. Furthermore, if we take advantage of CR matrix, we can easily obtain fault FCM models. In general, the task of constructing fault models in other diagnostic schemes such as fault tree analysis is time-consumming and burdensome process. Detailed procedure for generating fault FCM model is as follows:

Step 1 : Apply steady-state observed pattern for a known fault to the basic FCM-based diagnostic algorithm and derive its *CR* matrix.

Step 2 : Superimpose a sign onto each non-zero elements of the *CR* matrix. The signs are borrowed from the original FCM matrix for the system.

Fault FCM models obtained by the above process are stored into **fault model-base** for TAM recall and pattern matching.

2.3 TAM recall process

TAM recall is an inference process which can successively predict a future behavior. If this property is utilized in the fault diagnosis, it is possible to infer how primary fault effect is propagated through the whole system. In FCM-based fault diagnosis, simulation tree method is used: If the non-zero element within the observed pattern vector is initially detected, TAM recall process as in (5) is triggered for obtaining the predicted propagation of that initial deviation.

$$PW(k+1) = PW(k) \cdot FCM_{x_i} \qquad (5)$$

where FCM_{x_i} denotes each fault FCM models with state variable x_i being an origin of fault. Generally, it is impossible to know which fault FCM model is the right candidate for that deviation in beforehand. Therefore, it is required to obtain each predicted pattern sequences associated with each fault FCM models stored in **Fault Model-Base.** These predicted pattern sequenceses are compared with actually observed patterns in latter pattern matching phase to find out the true origin of fault.

III. Extended fault FCM model and modified tam recall process

Pattern matching based on TAM recall is performed between qualitative observations and qualitative predictions. In any realistic situation, quantitative observations are available. As the qualitative nature of the FCM-based diagnosis, we ignore some given information because of the limitation of the fault FCM models employed. This entails lower diagnostic resolution compared with quantitative ones. For this, a method is devised to integrate quantitative knowledge into the fault FCM models.

1. Extended fault FCM model

Consider a branch in a fault FCM model as in Fig.

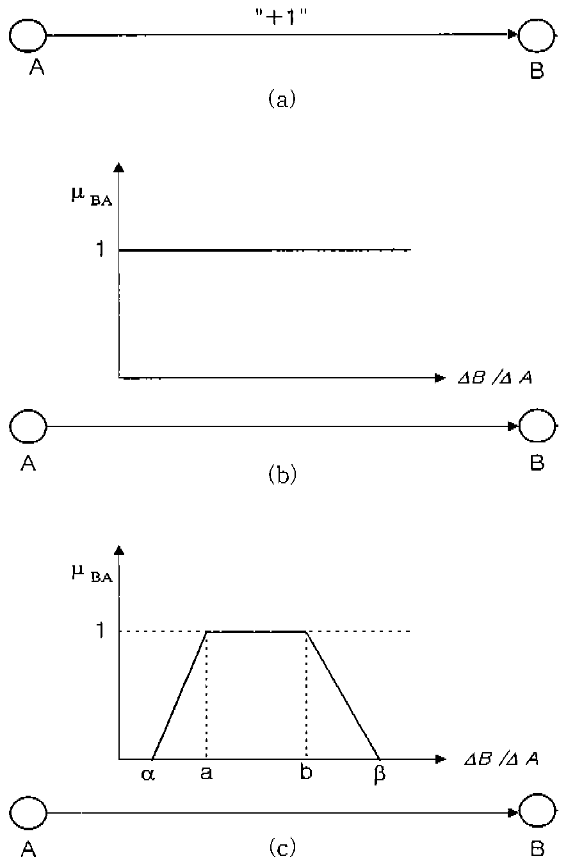


Fig. 1. Membership functions for qualitative and quantitative knowledge.

1(a). The binary relationship(+1) between A and B can also be described by the ratio $\Delta B/\Delta A$ taking the value from 0^+ to infinity by using membership function as in Fig. 1(b). If some quantitative information is known, e.g., the steady-state gain between A and B, we can shape the membership function as in Fig. 1(c).

The membership function of the fuzzy set theory provides a efficient way of dealing with the quantitative knowledge, i.e., the transfer gains between process variables as shown in Fig. 1(c). The most common form of membership function is a trapezoidal fuzzy number. Its graph has a form of a trapezoid and x-coordinates of its four vertices $\alpha \leq a \leq b \leq \beta$.

$$C = (a, b, \alpha, \beta) \qquad (6)$$

If we substitute non-zero elements in an fault FCM model with the fuzzy number, we can obtain the extended fault FCM models which can effectively represent the transfer gains between process variables. These **extended fault FCM models** are stored into **fault FCM model-base** for modified TAM recall and pattern matching. However, most processes include many different types of measured variables with different magnitude orders. Fuzzified transfer gains can be inordinate owing to the division operation among the variables having different magnitude orders. For this, a certain normalization should be required. To get a reasonable transfer gains, firstly, the following normalized deviation of process variables is introduced.

$$\Delta X_N = \frac{X - X_s}{X_{MAX} - X_{MIN}} \qquad (7)$$

where X_{MAX} and X_{MIN} are maximum and minimum value which the state variable X can take and X_S represents the magnitude of normal operating value. We can obtain ΔX_N which takes the value ranging from -1 to 1. By using the above normalization scheme, we can finally obtain reasonable transfer gains having reasonable magnitude.

2. Modified TAM recall

Modified TAM recall based on the extended fault FCM models can be represented as in (8).

$$P(k+1) = P(k) \bigstar EFCM_{x_i} \qquad (8)$$

where $P(k)$ is row vector which has trapezoidal fuzzy number as its element. $EFCM_{x_i}$ is selected from the fault FCM model-base. The operator ★ represents vector and matrix multiplication. In this work, we use the following fuzzy addition(⊕) and fuzzy multiplication(⊗) operators.

$$(a,b,\tau,\beta) \otimes (c,d,\gamma,\delta) =$$

$$\begin{cases} (ac, bd, a\gamma + c\tau - \tau\gamma, b\delta + d\beta + \beta\delta) & m >_0 0, n >_0 0 \\ (ad, bc, d\tau - a\delta + \tau\delta, -b\gamma + c\beta - \beta\gamma) & m <_0 0, n >_0 0 \\ (bc, ad, b\gamma - c\beta + \beta\gamma, -d\tau + a\delta - \tau\delta) & m >_0 0, n <_0 0 \\ (bd, ac, -b\delta - d\beta - \beta\delta, -a\gamma - c\tau + \tau\gamma) & m <_0 0, n <_0 0 \end{cases} \qquad (9)$$

$$(a,b,\tau,\beta) \oplus (c,d,\gamma,\delta) = (a+c, b+d, \tau+\gamma, \beta+\delta) \qquad (10)$$

The i th element, $p_i(k+1)$ in $P(k+1)$ is calculated as follows:

$$p_i(k+1) = (p_1(k) \otimes \mu_{i1}) \oplus (p_2(k) \otimes \mu_{i2}), \cdots, (p_N(k) \otimes \mu_{iN}) \qquad (11)$$

where μ_{ij} represents the ij-th trapezoidal fuzzy number in the extended fault FCM model, $EFCM_x$.

3. Fault diagnosis based on pattern matching

To perform fault diagnosis using modified TAM recall, we suggest that whenever non-zero deviation in the process variables is detected, the contribution of each extended fault FCM models to that deviation should be checked to find out cause of the fault. If the observed state vector with non-zero deviation is utilized in the modifed TAM recall process, we can obtain each possible predicted pattern sequences corresponding to each extended fault FCM models. In general, it is natural to pick up the extended fault FCM model as a origin of fault which can generate the future fault

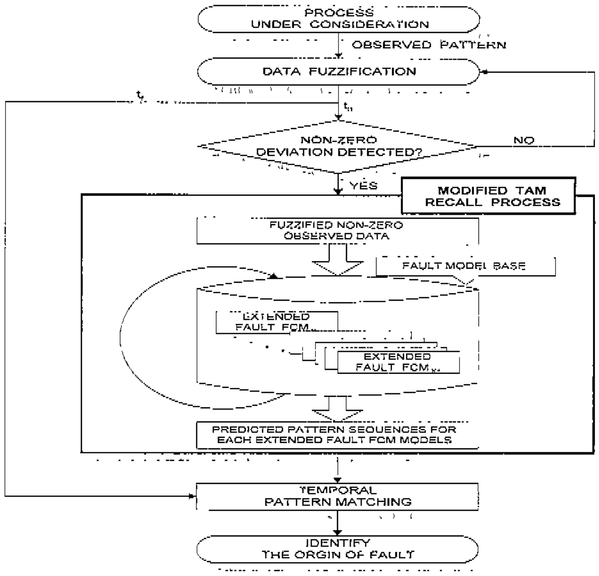


Fig. 2. Block diagram for the fault diagnosis based on modified TAM recall.

propagation. For their verification, measure of compatibility is required to calculate the fitness between predicted and observed patterns. For this, compatibility of two fuzzy sets proposed by Zadeh is utilized. Compatibility, τ between two fuzzy sets, A and B is defined as follows.

$$\mu_\tau(u) = \lim_{x: u = \mu_A(x)} \mu_B(x), \forall u \in [0,1] \qquad (12)$$

By utilizing the compatibility, we can calculate the fitness of each candidate at each steps as follows.

$$\mu_{EFCM_{x_i}}(k) = \min[p_{1k}(m_1(k)), \cdots, p_{Nk}(m_N(k))] \qquad (13)$$

where p_{ik} represents the i-th predicted fuzzy number at the k-th step and $m_i(k)$ represents center of the i-th observed fuzzy number at the k-th step. Finally, we can get the total compatibility for the extended fault FCM model, e.g., $EFCM_{x_i}$.

$$Confidence\ \deg_{EFCM_{x_i}} = \min[\mu_{EFCM_{x_i}}(1), \cdots, \mu_{EFCM_{x_i}}(K)] \qquad (14)$$

The schematic diagram for fault diagnosis based on extended fault FCM models is depicted in Fig. 2.

Ⅳ. Self-Learning Feature to the FCM-based diagnosis

The construction of the extended fault FCM model requires a great deal of engineering effort. In general, the steady-state gains between process variables need to be modified as the operating conditions and the magnitude of faults are changed. The trapezoidal fuzzy number is adequate for representing varying transfer gains. One important property related with the fault FCM model is that its structure remains the same under almost all possible operating conditions. There-

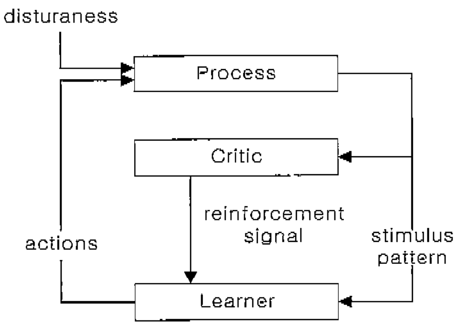


Fig. 3. Structure of reinforcement learning.

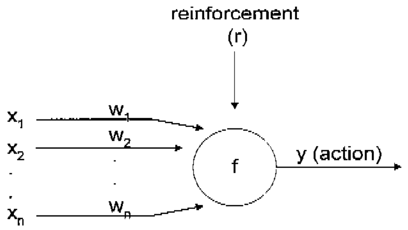


Fig. 4. Structure of ASE.

fore, all we have to do is to tune the shape of the membership function.

1. Associative reinforcement learning

In this work, neural network scheme is employed to automatically acquire the extended fault FCM models. We consider an associative reinforcement learning scheme shown in Fig. 3.

In the associative reinforcement learning problem, the learning system receives stimulus patterns as input in addition to the reinforcement signal. The optimal action on any trial depends on the stimulus patterns presented on that trial. Several associative reinforcement learning rules for neuron-like units have been studied. Fig. 4 shows a neuron-like unit called Associative Searching Element(ASE). The unit has a reinforcement input pathway, n-pathways for non-reinforcement input signals, and a single output pathway.

The element's output $y(t)$ is determined from the input vector $X(t)=[x_1(t), x_2(t), \cdots, x_n(t)]$.

$$y(t)=f(\sum_{i=1}^{n} w_i(t)x_i(t)) \tag{15}$$

where f is the following threshold function.

$$f(x)=\begin{cases} +1 & \text{if } x \geq 0 \\ -1 & \text{if } x < 0 \end{cases} \tag{16}$$

The weight w_i's are changed according to

$$w_i(t+1)=w_i(t)+\alpha r(t)e_i(t) \tag{17}$$

$$e_i(t+1)=\delta e_i(t)+(1-\delta)y(t)x_i(t) \tag{18}$$

where α = learning rate, δ = trace decay ratio, $r(t)$ = reinforcement signal at time t, $e_i(t)$ = eligibility at time t of input pathway i, and $x_i(t)$ = input vector at time t.

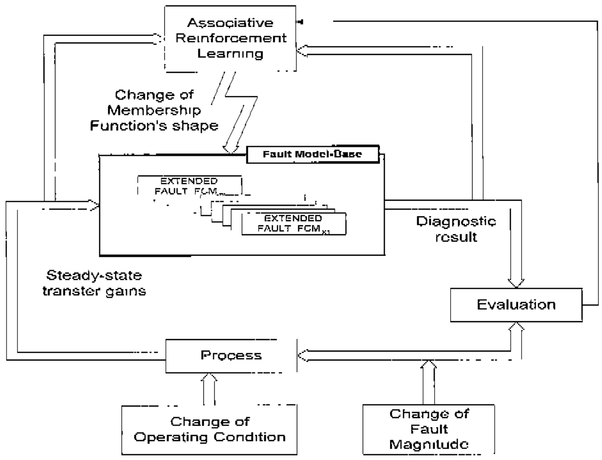


Fig. 5. Schematic diagram for self-learning of extended fault FCM models via ASE.

2. Tuning of membership function via ASE

Self-learning of extended fault FCM models via ASE is shown in Fig. 5. For a known fault origin, we can obtain the steady-state observed patterns and the steady-state transfer gains from process simulation. These measurements are fed into the corresponding extended fault FCM model selected from the fault model-base. If the compatibility between the steady-state observed pattern and the predicted steady-state pattern is not satisfactory, i.e., $\mu_{FCM_i} \neq 1$, reinforcement learning is triggered and the measurements and the diagnostic result (compatibility) are fed to the corresponding ASE. Subsequently, the shape and location of the membership function is tuned until a satisfactory diagnostic result is found. Let's consider a steady-state gain between A and B in a certain extended fault FCM model and its corresponding ASE as in Fig. 6. The shape of initial membership function is triangular and its center is located according to the measurement $\Delta B/\Delta A$. This value corresponds to the full membership, i.e., $\mu_{BA}(\Delta B/\Delta A)=1$. If another set of measurement (caused by change of operating conditions or change in magnitude of fault) is available and the result is not satisfactory, then the system responds with a reinforcement signal $r=1$. This indicates the location and the shape of the membership function is incorrect. Therefore, the ASE automatically tunes the shape of membership function according to new $\Delta B/\Delta A$ and compatibility of its extended fault FCM model until a right diagnosis is achieved. The membership function is relocated according to the weight change Δw. In this work, the weight w is changed as follows (Hsu and Yu,1992).

$$w(t+1)=w(t)+\alpha r(t)e(t) \tag{19}$$

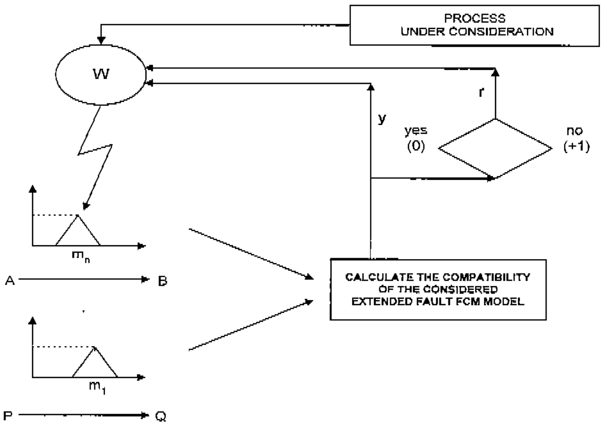
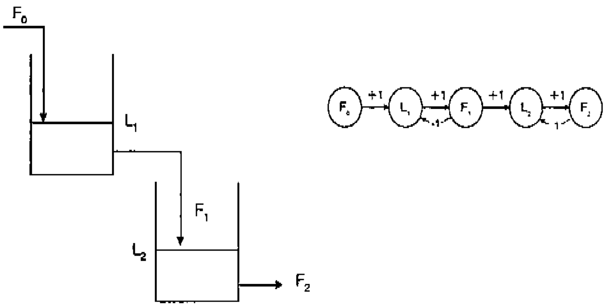


Fig. 6. Schematic diagram of changing the shape of membership function.



(a) (b)

Fig. 7. The simplified process flow diagram of a two-tank system(a) and its signed directed graph(b).

$$e(t+1) = \delta e(t) + (1-\delta)(1-y(t))x(t) \tag{20}$$

The ASE adjusts the location and shape of the membership function in the following way.

$$f(x) = \begin{cases} |\delta w| & \text{if } x > b_f \\ 0 & \text{if } b_i < x < b_f \\ -|\delta w| & \text{if } b_i > x \end{cases} \tag{21}$$

where b_i and b_f are the initial value of the steady-state transfer gain satisfying $y = 1$.

V. Simulation study

To demonstrate the performance of the proposed diagnostic system, we consider the two tank system shown in Fig. 7(a).

FCM for the two-tank system can be obtained as follows from the SDG shown in fig. 7(b).

$$E = \begin{array}{c} \\ F_0 \\ L_1 \\ F_1 \\ L_2 \\ F_2 \end{array} \begin{array}{c} \begin{array}{ccccc} F_0 & L_1 & F_1 & L_2 & F_2 \end{array} \\ \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & -1 & 0 \end{bmatrix} \end{array}$$

The task is to detect and diagnose faults in the system. The investigated faults are:

Fault 1: Blockage of the upper pipeline
Fault 2: Leakage of the upper tank
Fault 3: Blockage of the lower pipeline
Fault 4: Leakage of the lower tank

Fault FCM models for each faults can be obtained as follows by using the procedure described in section III.

$$FCM_{fault_1} = \begin{array}{c} \\ F_0 \\ L_1 \\ F_1 \\ L_2 \\ F_2 \end{array} \begin{array}{c} \begin{array}{ccccc} F_0 & L_1 & F_1 & L_2 & F_2 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array} \quad FCM_{fault_2} = \begin{array}{c} \\ F_0 \\ L_1 \\ F_1 \\ L_2 \\ F_2 \end{array} \begin{array}{c} \begin{array}{ccccc} F_0 & L_1 & F_1 & L_2 & F_2 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

$$FCM_{fault_3} = \begin{array}{c} \\ F_0 \\ L_1 \\ F_1 \\ L_2 \\ F_2 \end{array} \begin{array}{c} \begin{array}{ccccc} F_0 & L_1 & F_1 & L_2 & F_2 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 \end{bmatrix} \end{array} \quad FCM_{fault_4} = \begin{array}{c} \\ F_0 \\ L_1 \\ F_1 \\ L_2 \\ F_2 \end{array} \begin{array}{c} \begin{array}{ccccc} F_0 & L_1 & F_1 & L_2 & F_2 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

To obtain the extended fault FCM models, some quantitative process knowledge are required. For the simulation studies, we consider the following differential equation for the two-tank system:

$$A_1 \frac{dL_1}{dt} = F_0 - F_1 - C_{l1}\sqrt{L_1} \tag{22}$$

$$\frac{dF_1}{dt} = \frac{\pi d^2}{4\rho l}\left[\rho g L_1 - (f + f_{r1})\frac{8\rho l F_1 |F_1|}{\pi^2 d^5}\right] \tag{23}$$

$$A_2 \frac{dL_2}{dt} = F_1 - F_2 - C_{l2}\sqrt{L_2} \tag{24}$$

$$\frac{dF_2}{dt} = \frac{\pi d^2}{4\rho l}\left[\rho g L_2 - (f + f_{r2})\frac{8\rho l F_2 |F_2|}{\pi^2 d^5}\right] \tag{25}$$

where A_1, A_2 represent each cross-sectional area of two tanks, L_1, L_2 is the height of the liquid levels, and F_0, F_1, F_2 denote the inlet and outlet flow rate of the upper tank and outlet flow rate of lower tank, respectively. d and l represent the diameter and length of the upper and lower tank's pipe. c_{l1}, c_{l2} are parameters that characterize the leakage of each tanks and f_{r1}, f_{r2} denote the additional friction caused by a change in the valve position and/or partial blockage in upper and lower pipeline.

Finally, applying the self-learning procedure, each extended fault FCM models can be obtained as follows.

EFCMF1 =

	F_0	L_1	F_1	L_2	F_2
F_0	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]
L_1	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]
F_1	[0 0 0 0]	[.1 -7.55 -.89 .1]	[0 0 0 0]	[.1 2031.68 .1]	[0 0 0 0]
L_2	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[.1 .49 .59 .1]
F_2	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]

EFCMF2 =

	F_0	L_1	F_1	L_2	F_2
F_0	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]
L_1	[0 0 0 0]	[0 0 0 0]	[.1 .65 .82 .1]	[0 0 0 0]	[0 0 0 0]
F_1	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[.1 1.25 1.54 .1]	[0 0 0 0]
L_2	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[.1 .65 .81 .1]
F_2	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]

EFCMF3 =

	F_0	L_1	F_1	L_2	F_2
F_0	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]
L_1	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]
F_1	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]
L_2	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]
F_2	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[.1 −7.55 −.81 .1]	[0 0 0 0]

EFCMF4 =

	F_0	L_1	F_1	L_2	F_2
F_0	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]
L_1	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]
F_1	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]
L_2	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[.1 .65 .81 .1]
F_2	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]	[0 0 0 0]

Each trapezoidal fuzzy numbers in the extended fault FCM models are obtained via reinforcement learning by using a set of simulation data under the circumstances that both operating conditions and magnitude of faults are changed. In case of the two-tank system, the operating points are determined by the input flow rate, F_0. The considered operating points are varying between 0.9 and 1.1 and the magnitude of faults concerned with pipeline blockage and tank leakage are shown in Table 1.

Table 1. Parameter values for fault condition.

Fault	Parameter	Value
Fault 1	f_{r1}	≥0.6
Fault 2	C_{l1}	≥0.7
Fault 3	f_{r2}	≥0.6
Fault 4	C_{l2}	≥0.7

Let's assume that the following observed pattern is initially detected. In general, it is quite natural to think that the decrease in F_1 can be thought of the primary deviation caused by blockage of the upper pipeline (in this case: f_{r1} = 0.8).

	F_0	L_1	F_1	L_2	F_2
W_0=	[[0 .0 .0 .0]	[0 .0 .0 .0]	[.1 −.18 −.18 .1]	[0 .0 .0 .0]	[0 .0 .0 .0]]

If we successively applies this pattern to the modified TAM recall process, each predicted pattern sequences associated with each extended fault FCM models can be obtained as follows.

Pr*edicted pattern sequences* for $EFCM_{F_1}$:

F_0	L_1	F_1	L_2	F_2
[.0 0 .0 .0]	[.0 .0 0 .0]	[.1 −.18 − 18 .1]	[.0 .0 0 .0]	[0 0 .0 .0]
[0 0 0 .0]	[.1 .16 1.36 76]	[1 −.18 − 18 1]	[23 −.36 −.30 .17]	[.0 .0 .0 .0]
[0 0 .0 0]	[1 16 1 36 76]	[.1 − 18 − 18 1]	[23 − 36 −.30 .17]	[2 −.22 −.15 .08]

Pr*edicted pattern sequences* for $EFCM_{F_2}$:

F_0	L_1	F_1	L_2	F_2
[0 0 0 0]	[0 0 0 0]	[1 − 18 − 18 1]	[0 0 0 0]	[0 0 .0 0]
[0 0 0 0]	[0 0 0 0]	[1 − 18 − 18 1]	[18 − 28 − 22 12]	[0 0 0 0]
[0 0 0 0]	[0 .0 0 0]	[1 − 18 − 18 1]	[18 − 28 − 22 12]	[.19 − 22 − 15 08]

Pr*edicted pattern sequences* for $EFCM_{F_3}$:

F_0	L_1	F_1	L_2	F_2
[0 0 0 0]	[0 0 0 0]	[1 − 18 − 18 .0]	[0 0 0 .0]	[.0 .0 .0 .0]
[.0 0 0 .0]	[.0 .0 .0 .0]	[.1 − .18 − 18 .0]	[0 .0 0 0]	[.0 0 .0 .0]

Pr*edicted pattern sequences* for $EFCM_{F_4}$:

F_0	L_1	F_1	L_2	F_2
[0 0 0 0]	[.0 0 0 .0]	[1 − 18 −.18 .0]	[.0 .0 .0 .0]	[.0 .0 .0 .0]
[.0 0 0 0]	[0 0 0 0]	[1 − 18 − 18 .0]	[0 .0 .0 .0]	[.0 .0 .0 .0]

We consider the two cases: Case 1 is that magnitude of blockage in upper pipeline is f_{r1} = 0.8 at the operating condition of F_0 = 1. Case 2 is that magnitude of blockage in upper pipeline is f_{r1} = 0.9 under the operating condition of F_0=1.1. In these cases, each actually pattern sequences can be obtained as follows by process simulations.

Actually obtained pattern sequences for *the decrease of upper* pipe *blockage* (f_{r1} = 0.8 F_0 = 1.) :

F_0	L_1	F_1	L_2	F_2
[0 0 .0 0]	[0 0 0 0]	[1 −.18 .18 1]	[.0 0 .0 .0]	[0 0 .0 .0]
[.0 .0 0 .0]	[1 2 2 1]	[1 −.18 - .18 .1]	[.1 −.33 −.33 .1]	[.0 .0 0 .0]
[0 0 0 .0]	[.1 2 .2 1]	[1 −.18 −.18 1]	[.1 −.33 −.33 .1]	[.1 −.18 − 18 .1]

Actually obtained pattern sequences for *the decrease of upper* pipe *blockage* (f_{r1} = 0.9 F_0 = 1.1) :

F_0	L_1	F_1	L_2	F_2
[0 0 0 0]	[0 0 0 0]	[1 −.202 − 202 1]	[.0 0 0 .0]	[.0 0 .0 .0]
[0 0 0 0]	[1 2 .2 .1]	[.1 −.202 − 202 1]	[.1 − 36 − 36 .1]	[.0 .0 0 .0]
[0 .0 .0 .0]	[1 .2 .2 1]	[.1 − 202 −.202 1]	[1 −.36 −.36 .1]	[.1 −.202 −.202 1]

If we compare the observed pattern with each predicted ones which are obtained from the TAM recall based on each extended fault FCM models, the following compatibilities are obtained.

	$EFCM_{F_1}$	$EFCM_{F_2}$	$EFCM_{F_3}$	$EFCM_{F_4}$
$compatibility_{case1}$	1	0	0	0
$compatibility_{case2}$	.9	0	0	0

From the above example, we can get a better diagnostic resolution in the face of the changes in magnitude of fault and operating conditions. Modified

TAM recall is a very useful characteristic of FCM because it can generate the future fault propagation sequences compared with actual ones. However, it is very important to notice that modified TAM recall can only provide conceptually ordered fault pattern sequences. In engineering processes, the propagation delays are induced by the dynamics of the process and may vary with variables involved. Disregarding such propagation delays can lead to erroneous diagnostic results.

VI. Conclusion

In this paper a new approach to FCM-based fault diagnosis has been proposed. The proposed diagnostic scheme incorporates the fuzzy set theory and neural network scheme to overcome the problem of low diagnostic resolution associated with FCM-based diagnosis. Through the simulation studies, it can be verified that trapezoidal fuzzy number can be effectively utilized for representing the steady-state transfer gains between process variables in the non-linear systems and reinforcement learning scheme can be used for automatic generation of the extended fault FCM models. However, in this work, we only considered the simple two-tank system to verify its effectiveness. It is desirable to apply the proposed diagnostic scheme to more complex non-linear processes for its better applicability.

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