Fault Diagnostic System Based on Fuzzy Time Cognitive Map

Kee-Sang Lee and Sung-Ho Kim

Abstract : FCM (Fuzzy Cognitive Map) is proposed for representing causal reasoning. Its structure allows systematic causal reasoning through a forward inference. Authors have already proposed a diagnostic system based on FCM to perform on-line fault diagnosis. In FCM-based fault diagnosis, Temporal Associative Memories (TAM) recall of FCM is utilized to identify the true origin of fault by on-line pattern match where predicted pattern sequences obtained from TAM recall of fault FCM models are compared with actually observed ones. In engineering processes, the propagation delays are induced by the dynamics of processes and may vary with variables involved. However, disregarding such propagation delays in FCM-based fault diagnosis may lead to erroneous diagnostic results. To solve the problem, a concept of FTCM (Fuzzy Time Cognitive Map) is introduced into FCM-based fault diagnosis in this work. Especially, translation method of FTCM makes it possible to diagnose the fault for some discrete time. Simulation studies through two-tank system is carried out to verify the effectiveness of the proposed diagnostic scheme.

Keywords : fuzzy cognitive map, fault diagnosis, temporal associative memory, fuzzy time cognitive map

I. Introduction

Recent industrial processes can be characterized by large-scale and complex structure. Therefore, for guaranteeing the desired stability and reliability of the processes, some high performance fault diagnostic systems should be developed. There are several different ways of approaching the fault diagnosis problem. Generally speaking, existing schemes can be classified into two broad categories according to the type of model on which they are based: quantitative approaches and qualitative 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]-[3]. This kind of approaches can accurately find out the fault origin. However, it generally requires as precise a model as possible in order to get a good diagnostic result. This requirement limits the versatility of the quantitative approaches.

As pointed out by many AI researchers, human operators appear to use a qualitative causal calculus in reasoning about the behavior of a physical system. Therefore, this kind of reasoning scheme qualitatively representing the operation of a physical system can be employed to diagnose system malfunctions. Depending on the type of knowledge employed, the qualitative approaches can be further divided into shallow and deep knowledge-based diagnostic system [4]. Shallow knowledge-based system describes the empirical relationships between irregularities in the system behavior and faults. Accordingly, it can be thought of as the expert system, which is composed of knowledge base and inference engine. These schemes are effectively applied to the medical fields where the underlying mechanisms can not be described exactly or are completely unknown. The main pitfalls of the shallow knowledge-based approaches include as follows: Difficulty in knowledge acquisition and incompleteness in knowledge and so on. All disadvantages of the shallow knowledge-based approaches do not exist in the deep knowledge-based approaches. Deep knowledge-based systems can infer the propagation of malfunctions or predict the effect of the fault utilizing extensive knowledge about system behaviors. To name some of the representative deep knowledge-based schemes, we can mention causal search techniques, constraint suspension techniques, and signed directed graph (SDG) method. Especially, SDG which has been extensively studied by Kramer and Shiozaki can be considered as a typical schemes among the deep knowledge-based approaches [5][6].

Recently, concept of fuzzy cognitive map is proposed by Kosko for representing causal reasoning [7]. FCM is a fuzzy graph structure allowing hazy degrees of causality between causal concepts. Its structure allows systematic causal reasoning through a forward-evolved inference. Therefore, we can think of FCM as a dynamical system which has its equilibrium behavior as 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, authors have already proposed two FCM-based fault diagnostic algorithms [8][9]. One can be considered as a simple transition of

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Shiozaki's SDG-based diagnostic approach to FCM framework. The other is an extended version of the basic diagnostic algorithm where an FCM's important property, i.e., TAM recall, is utilized. It can be effec tively utilized in on-line fault diagnosis owing to its self-generated **fault FCM models** which can generate predicted pattern sequence for pattern match with observed one. TAM recall based on fault FCM model is a very useful characteristic because the predicted fault pattern sequences to be compared with actually observed ones are easily obtained. However, it is very important to notice that TAM recall procedure based on fault FCM models can only provide conceptually ordered fault pattern sequences. In engineering processes, the propagation delays in TAM recall process can lead to erroneous diagnostic results. To solve the problem, a certain technique for incorporating timing information into the fault FCM models is required. There have been a number of authors who have addressed this problem. Among them, Park and Kim proposed a concept of fuzzy time cognitive map (FTCM) for efficient treatment of timing relations existing in an FCM [10]. In this work, concept of FTCM is integrated into the fault FCM models for effective treatment of propagation delays of fault. This paper is organized as follows. Firstly, the fundamentals of FCM and basic diagnostic algorithm based on FCM-algebra are presented. Secondly, generation of fault FCM model and TAM recall process are briefly described. Thirdly, the concept of FTCM and its application to fault FCM model are presented. Finally, simulation studies through two-tank system is carried out to verify the effectiveness of the proposed diagnostic algorithm.

Ⅱ. Fuzzy cognitive map and its property

The FCM was proposed by Kosko to store uncertain causal knowledge. An FCM which consists of nodes and branches is a fuzzy directed graph with feedback. Each node represents one concept (state), C_k, $k=1,2,\Lambda,N$, that can have measurable levels of intensity. The branch e_{ij} connecting any two nodes C_i and C_j is directed from node C_i to node C_j, and is positive if a level increase of C_i results in a causal increase of C_j, and is negative if it results in a causal decrease of C_j. Using Kosko's convention e_{ij} has a value in [-1,1]. Values -1 and 1 represent full causality, zero denotes no causal effects, and all other values correspond to different fuzzy level of causal effect. In general, FCM is described by a connection matrix E whose elements are connection weights e_{ij}. The *ith* row and the *jth* column of E contains respectively the connection weights of the branches directed out of C_i, and the connection weights of the branches directed into C_j. If the value of the directed branch of FCM takes only {-1,0,1}, it is called a simple FCM. FCM - based expert system may have the following merits comparing to the expert systems based on various tree structures. First, trees are originally forward structure and can not express feedback loops in the system. However, FCM can easily accom modate physical or conceptual feedback loops. Second, tree method is not suitable for large scale systems because searching time is increased exponentially with the augmentation of the tree, whereas FCM inference can be carried out by simple vector-matrix operations. Third, the future behavior of the system can be predicted with FCM inference because FCM is a kind of dynamical system and has a special property of temporal associative memories.

Ⅲ. Basic fault diagnostic algorithm based on simple FCM

Basic fault algorithm based on the simple FCM is briefly described in this section. Detailed explanation can be found in reference [8].

1.Generation of the fault pattern vector

The first step for fault diagnosis is a generation of observed pattern vectors for some faults. First, we define DI (Deviation Index) and NOV (Normal Operating Value) to obtain the elements w_i in the observed pattern vector W as in (1) and (2).

$$DI_i = \frac{MeasuredValue_i - NOV_i}{\Delta \cdot NOV_i} \tag{1}$$

where subscript i indicates the *ith* state variable of the system and △ represents the normal operating band, i.e., thresholds to be used to distinguish normal and abnormal operation. For normal operation, DI_i has its within [-1,1]. Thus, w_i of the observed pattern vector is determined as follows.

$$w_i = \begin{cases} 1 & if\ \ DI_i \geq 1 \\ 0 & if\ |DI_i| < 1 \\ -1 & if\ \ DI_i \leq -1 \end{cases} \tag{2}$$

2. FCM-based fault diagnostic algorithm

The FCM-based fault diagnostic algorithm is based on Shiozaki's consistent rooted tree method, which is built upon the concept of SDG. SDG has the same structure as FCM. That is, it consists of nodes and directed branches, and signs attached to the directed branches. The sign on a directed branch in SDG has the same meaning as that in FCM. 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', and the node is its 'root'. The idea of consistent rooted-tree method is that the node which is the maximal strongly connected component of the CE graph is the candidate of the fault.

Let the connection matrix E and the observed pattern vector W be given. In general, connection matrix E can be simply obtained by (1) plant operation data and/or experienced operator and (2) a mathematical model of the process or process simulation. In what follows is the detailed basic diagnostic algorithm based on simple FCM.

Step 1. Calculating CR matrix

$$WE = Diag(W) \cdot E \cdot Diag(W) \tag{3}$$

$$CR(i,j) = T(WE(i,j)) \tag{4}$$

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, (3) can be thought of as the process of generating all possible paths. Threshold function in (4) plays the role of removing inconsistent paths from WE. Therefore, after removing all inconsistent paths, the remaining information in CR matrix is about nodes satisfying $w_i \cdot E(i,j) \cdot w_f \geq 0$. The CR matrix is used for identifying the origin of fault and it can be calculated as in (5)

$$CR(i,j) = \begin{cases} 1 & \text{if } WE(i,j) \geq 0 \\ 0 & \text{if } WE(i,j) < 0 \end{cases} \tag{5}$$

Step 2. Identifying the origin of the fault

In order to find out the origin of the fault, we must calculate the root of the CR matrix, i.e., find the maximal 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.

$$IN(C_i) = \sum_{k=1}^{n} CR(k,i) \tag{6}$$

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

$$OUT(C_i) = \sum_{k=1}^{n} CR(i,k) \tag{7}$$

3) Find the origin of fault corresponding to the maximal strongly-connected concept which has zero column sum and non-zero row sum.

The pseudo program for the above steps is as follows.

```
Initial:
        OUT(i)=0, IN(j)=o;
Loop:
    for(i=1 to n) { for(j=1 to n) {
      if(CR(i,j)=1) then OUT(i)=OUT(i)+1; }}
    for(j=1 to n) { for(i=1 to n) {
      if(CR(i,j)=1) then IN(j)=IN(j)+1; }}
Diagnosis:
    for(k=1 to n) {
      if(OUT(k) >= 1 and IN(k)=0)
        then k'th node is the origin of the fault; }
      if(number of the failure source >=2)
        then further diagnostic algorithm is triggered.
```

Ⅳ. ON-lind fault diagnostic algorithm

1. Fault FCM model and TAM recall property

If FCM for a system is given, the basic diagnostic algorithm described in Section Ⅲ can be effectively applied. FCM-based fault diagnosis can easily find out the origin of the fault if steady-state observed patterns could only be obtained at the end of the propagation of faults. In fact, considering that one of the important roles of the diagnostic system is to take rapid remedial actions to prevent the propagation of faults, the pitfall of not being able to detect incipient faults must be overcome. Since FCM has special features of forward evolved inference and TAM recall, this concept can be further extended to on-line incipient fault diagnosis which can accommodate incipient fault diagnosis.

2. Generation of fault FCM model

Fault models represented by FCM form the core of on-line fault diagnosis system. If steady-state patterns for each faults are available beforehand, fault FCM models can be obtained by applying these steady-state patterns to the basic diagnostic algorithm in Section Ⅲ.

Step 1 : Apply steady-state observed pattern for a known fault to the basic diagnostic algorithm in Section Ⅲ 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 considered system.

The CR matrix obtained from step 1 contains the information branches for the known fault. In general, it was considered that a fault propagates along consistent branches. Therefore, in order to precisely represent the direction of each node, the sign assignment into the CR matrix is required. The above steps should be repeated for all known fault origins. Once fault FCM models are available, we will be able to predict future behavior of patterns(symptoms) under a fault condition. Fault FCM models generated by the

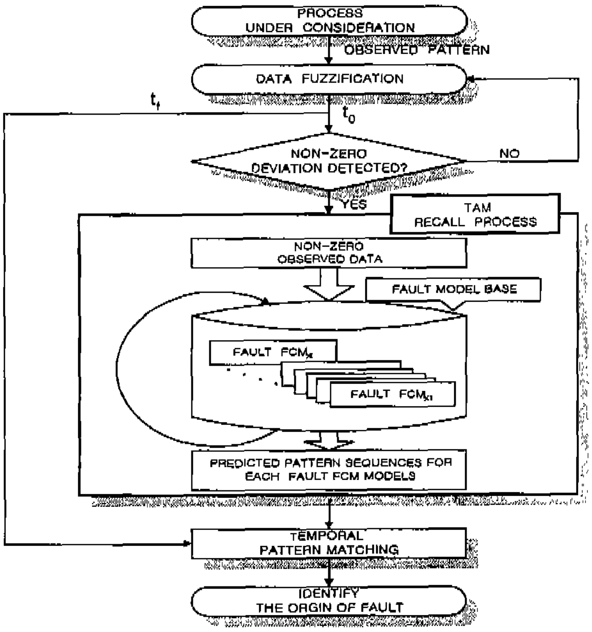

Fig. 1. Block diagram for the fault diagnosis based on TAM recall and pattern match.

above steps are stored into the fault FCM model base for TAM recall and pattern matching schemes.

3. TAM recall process based on fault FCM model

TAM recall is an inference procedure which can successively predict a fault propagation based on the current one. If this property is utilized in the fault diagnostic fields, it is possible to infer how fault effects are propagated through the whole system. The detailed procedure for fault diagnosis based on TAM recall process is as follows. If the observed state vector with non-zero deviation is initially detected, each predicted pattern sequences generated from each corresponding fault FCM models can be obtained by TAM recall as in (8) beforehand. From that time on, each predicted pattern sequences are compared with really observed ones to select the right fault FCM model which can best describe the actual behavior of the fault.

where $FCM\ x_i$ denotes a fault FCM model with state variable x_i being an origin of origin. W_0 is the detected incipient fault pattern vector and PW(0) is the same as W_0. W_0 in (8) plays the role of persistently firing the detected fault, i.e., clamp this state until the end of the TAM recall process.

V. Enhanced FCM-based diagnostic schemes based on FTCM

TAM recall is a very useful characteristic of FCM because we can obtain the predicted fault pattern sequences to be compared with actually observed ones. However, it is very important to notice that TAM recall procedure based on fault FCM models can only provide conceptually ordered fault pattern sequences.

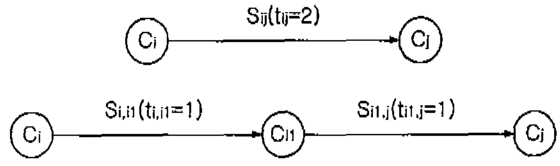

Fig. 2. Value preserving translation by using dummy nodes.

In engineering processes, the propagation delays are induced by the dynamics of processes and may vary with variables involved. Disregarding such different time relations (caused by propagation delays) in a certain fault FCM model can lead to erroneous diagnostic results. Therefore, a certain technique for incorporating timing information into the fault FCM models and TAM recall procedure is required. There have been a number of authors who have addressed this problem. Among them, Park and Kim proposed a concept of fuzzy time cognitive map (FTCM) for efficient treatment of timing relations existing in an FCM [10]. A brief description of FTCM is as follows.

1. Concept of fuzzy time cognitive map[10]

An FTCM is a directed graph $G=(C, E)$ which consists of a finite set C of N nodes, $C=\{i\}_{i=1}^{N}$, and a set E of edges e_{ij} $i, j \in C$, $E \in C \times C$ Each edge e_{ij} of the FTCM has two kinds of relative causalities: the strength $S_{ij} \in [-1,1]$ and the time lag (timing information) $t_{ij} \in [a,b]$, where a and b are constants and $0 < a \leq b$. For example, if the time lag involved before a change in node i has an effect on node j, $t(i \to j) = 6$ minutes, then we can assign as $t_{ij} = 6$. Finally, the FTCM can be identified by C, $S = \| s_{ij} \|_{N \times N}$, and $T = \| t_{ij} \|_{N \times N}$. Generally, it has a different time lag on each edge e_{ij}. Therefore, it is required that all edges must be translated into the edges with one unit-time lag for its direct applicability to causal inference as in (8). A technique for translating time lags into one unit-time lag is as follows.

For deriving the causal strength per one unit-time, S_{ij}, on an edge e_{ij}, simply the arithmetic division might be considered. But it would be misleading. The reason is that large time lag on an edge can not lead to adequate causal strength on it. Therefore, a value-preserving translation is required. For value-preserving translation, concept of dummy nodes are introduced. For example, as shown in Fig. 2, if a node C_i influences a node C_j through two delay unit, then one dummy node C_{i1} is inserted between node C_i and node C_j so that the edge e_{ij} of the initial FTCM is splited into two edges, $e_{i,i1}$ and e_{i1j} of new FTCM. Thus, each time lag on the edges of new FTCM becomes on unit-time. The name of node C_{i1} equals to the name of the original node C_i. It can be illustrated as follows: the causality of node C_i stays at node C_{i1}, since one unit time is elapsed. After two unit-time elapsed, the causality of C_{i1} imparts to C_j. Above observation is easily generalized as follows: if the time lag on t_{ij} is m delay units, then m-1 dummy nodes which are the equal name with node C_i are introduced. Each time lag on the new edges is one unit-time and an appropriate strength on the new edges, $\{S_{i,i1}, S_{i1,i2}, \Lambda, S_{i(m-1),j}\}$ are assigned by many methods such as t-norm method.

2. Introduction of FTCM into fault FCM model

If the concept of value-preserving translation in the FTCM is utilized in the basic FCM-based fault diagnosis, problems associated with propagation delays in the TAM recall can be easily overcome. Furthermore, value-preserving translation can be further simplified because we only consider the simple FCM. Detailed value-preserving translation in FCM-based fault diagnosis as follows. Let's consider the sign assignment process of the new edges, $\{S_{i,i1}, S_{i1,i2}, \Lambda, S_{i(m-1),j}\}$ on an edge e_{ij} having m delay until (t_{ij} = m). To identify the signs of the new edges, the following four cases are considered:

1) sign(e_{ij}) = +, and m is an odd number,

2) sign(e_{ij}) = +, and m is an even number,

3) sign(e_{ij}) = −, and m is an odd number,

4) sign(e_{ij}) = −, and m is an even number.

In case of 1) through 3), $S_{i,i1} = sign(e_{ij})$ for $p \in (i_1, \Lambda\ i_{m-1})$. In the case of 4), the number of minus signs on the must be an odd number. Although this method increase the size of fault FCM model specially when the process has not only fast modes but also very slow modes, we can remove the aforementioned problem by introducing the dummy nodes into each fault FCM models. Remember the automatic generation of each fault FCM models can be applied only when the steady state fault pattern is obtained from the practical operation data and/or simulation. In these cases, some amount of information about the propagation delays are available and can be used for the generation of fault FTCM models.

Ⅵ. Simulation

As an illustrative example, let us consider the two-tank system shown in Fig. 3(a). FCM for the two-tank system can be obtained as follows from the SDG shown in Fig. 3(b).

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

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

Fault 1 : Blockage of the upper pipeline

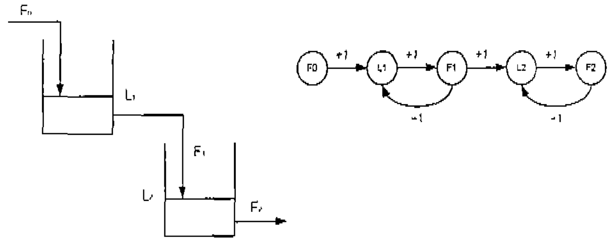

Fig. 3. The simplified process flow diagram of a two-tank system (a) and its signed directed graph (b).

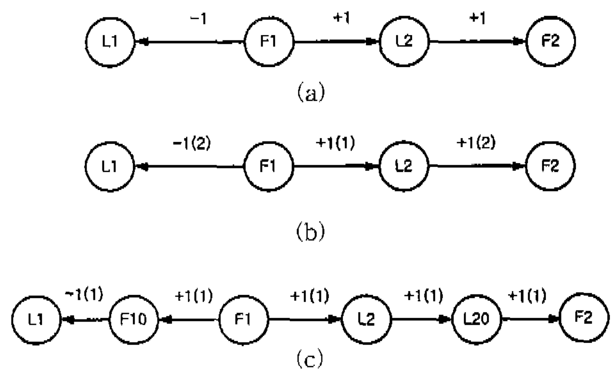

Fig. 4. Fault FCM model for upper pipeline blockage (a) fault FCM model considering the propagation delays (b) its FTCM representation by using value translation (c).

Fault 2 : Leakage of the upper tank

Fault 1 : Blockage of the lower pipeline

Fault 1 : Leakage of the lower tank

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

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

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

Among the four fault FCM models, we consider the first case(upper pipeline blockage). In this case, we can obtain the FCM representation graphically as in Fig. 4(a).

The initial pattern vector caused by the decrease in F_1 can be detected and represented as follows.

$$
\begin{array}{cccccc} & F_0 & L_1 & F_1 & L_2 & F_2 \\ W_0 = [& 0 & 0 & -1 & 0 & 0\ ] \end{array}
$$

If we successively applies this pattern to TAM recall process in (8), we obtain the following predicted pattern vectors.

$$
\begin{array}{r|ccccc}
 & F_0 & L_1 & F_1 & L_2 & F_2 \\
PW(0)= & [0 & 0 & -1 & 0 & 0] \\
PK(1)= & [0 & 1 & -1 & -1 & 0] \\
PK(2)= & [0 & 1 & -1 & -1 & -1] \\
PK(3)= & [0 & 1 & -1 & -1 & -1]
\end{array}
$$

As seen from the above sequence, PK(2) is a fixed point of the FCM dynamic system. Assume propagation delays in the fault FCM model have the relation $t_{32} = t_{45} = 2t_{34}$ as in Fig. 4(b), then the real observed pattern sequence will be as follows.

$$
\begin{array}{r|ccccc}
 & F_0 & L_1 & F_1 & L_2 & F_2 \\
W(0)= & [0 & 0 & -1 & 0 & 0] \\
W(1)= & [0 & 0 & -1 & -1 & 0] \\
W(2)= & [0 & 1 & -1 & -1 & 0] \\
W(3)= & [0 & 1 & -1 & -1 & -1]
\end{array}
$$

The predicted pattern sequence from TAM recall based on fault FCM model doesn't include W(1). In this case, two dummy nodes are necessary, one dummy node(F_{10}) between L_1 and F_1 and the other one(L_{20}) between L_2 and F_2 as in Fig. 4(c). The resultant fault FTCM model may be obtained as follows:

$$
FTCM_{fault_1} = \begin{array}{c|ccccccc|}
 & F_0 & L_1 & F_{10} & F_1 & L_2 & L_{20} & F_2 \\
\hline
F_0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
L_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
F_{10} & 0 & -1 & 0 & 0 & 0 & 0 & 0 \\
F_1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\
L_2 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
L_{20} & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
F_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{array}
$$

In the case of fault FTCM models, the sign of the extended branches can be easily assigned so that the product of signs of all edges in the extended path has the sign of the original one. The TAM recall based on fault FTCM model is exactly the same as in (8). Although the dummy nodes and branches should be considered in TAM recall, the value of dummy node cannot be obtained and its values are discarded for pattern match. To start the recall process, the initial observed pattern W(0) should be extended as PW(0). The resultant pattern sequences are as follows.

$$
\begin{array}{r|ccccccc}
 & F_0 & L_1 & F_{10} & F_1 & L_2 & L_{20} & F_2 \\
PW(0)= & [0 & 0 & 0 & -1 & 0 & 0 & 0] \\
PK(1)= & [0 & 0 & -1 & -1 & -1 & 0 & 0] \\
PK(2)= & [0 & 1 & -1 & -1 & -1 & -1 & 0] \\
PK(3)= & [0 & 1 & -1 & -1 & -1 & -1 & -1]
\end{array}
$$

The predicted fault pattern sequences are perfectly the same as the observed ones. Therefore, we can further utilize these predicted fault pattern sequences for temporal pattern matching scheme.

Ⅶ. Conclusion

In this work, an improved FCM-based fault diagnosis scheme utilizing the concept of FTCM is proposed. By introducing concept of FTCM into FCM-based diagnosis, problem pertaining to the propagation delays in FCM-based fault diagnosis can be easily solved. Especially, a method of translating the fault FCM into ones with one unit-time lag makes it possible to diagnose the fault for some discrete time t. The effectiveness of the proposed diagnostic scheme has successfully tested by two-tank system.

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