A Fuzzy Rule Based Approach for storing the Knowledge Acquired from Dynamical FCMs.

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Abstract **- Fuzzy Cognitive Maps (FCMs) have found many applications in social -financial -political problems. In this paper we propose a method of FCM operation, which can be used to represent and control any real system, including traditional electro-mechanical systems. In the proposed approach the FCM reaches its equilibrium point using direct feedback from the node values of the real system and the limitations imposed by the control objectives for the node values of the system. To avoid intensive interference of the updating mechanism with the real system, a technique is proposed which stores the previously encountered operational situations in a fuzzy if-then rule database. The proposed methodology is tested by simulating the operation of a hydro-electric plant.**

Index Terms - Fuzzy Cognitive Maps, Hebbian rule, State feedback, Weight Updating, Fuzzy Logic Rules.

I. INTRODUCTION

The scientific community was placed under the obligation of giving solutions to problems the settlement of which seemed rather difficult the years before. Fuzzy Cognitive Maps (FCM) can model dynamical complex systems that change with time following nonlinear laws [1]. FCMs use a symbolic representation for the description and modeling of the system. In order to illustrate different aspects in the behavior of the system, a fuzzy cognitive map is consisted of nodes with each node representing a characteristic of the system. These nodes interact with each other showing the dynamics of the system in study. An FCM integrates the accumulated experience and knowledge on the operation of the system, as a result of the method by which it is constructed, i.e., using human experts who know the operation of system and its behavior.

Fuzzy cognitive maps have already been used to model behavioral systems in many different scientific areas. For example, in political science [2], fuzzy cognitive maps were used to represent social scientific knowledge and describe decision-making methods [3], [4], [5]. Kosko enhanced the power of cognitive maps considering fuzzy values for their nodes and fuzzy degrees of interrelationships between nodes [6], [7]. After this pioneering work, fuzzy cognitive maps attracted the attention of scientists in many fields and they have been used in a variety of different scientific problems. Fuzzy cognitive maps have been used for planning and making decisions in the field of international relations and political developments [3] and to model the behavior and reactions of virtual worlds. FCMs have been proposed as a generic system for decision analysis [4], [8] and as coordinator of distributed cooperative agents. Some problems of electrical and mechanical engineering are also placed in the fuzzy part of science and they have been studied thoroughly enough the last years from a good many of scientists. A large number of different methods have occasionally been used in order to work out this kind of problems. As shown in this paper, the FCM approach can serve as a reliable approach for these problems too.

One open issue related to FCMs, is their operation in close cooperation with the real system they describe. This in turn implies that such an on-line interaction with the real system might require changes in the weight interconnections, which reflect the experts' knowledge about the node interdependence. This knowledge might not be entirely correct or perhaps, the system has undergone changes during its operation.

In this paper an FCM operation method is proposed, which is in close interaction with the system it represents. The FCM nodes are divided in control and reference nodes, where control nodes represent control variables of the system and reference nodes represent either variables with constant values or variables with desired (goal) values. In the proposed approach, the FCM reaches its equilibrium point using direct feedback from the node values of the real system and the limitations imposed by the reference nodes. The interconnections weights are on-line adjusted during this operation by using the Hebbian updating law, which however uses system feedback. Moreover, the updating procedure is further enhanced and accelerated by using information from previous equilibrium points of the system operation. This is achieved by dynamically building a database, which, for each encountered operational situation assigns a fuzzy if-then rule connecting the involved weight and node values. The range of the node and weight variables is dynamically partitioned to define appropriate membership functions. This way, the weight updating using system feedback gradually starts from values which are closer to the desired ones and therefore the procedure is significantly sped-up.

The paper is organized as follows: Section II gives a short description of FCMs and their way of operation. Section III introduces the proposed combined operation of the FCM and the real system and presents the relevant

Hebbian rule to update interconnections weights. Section IV presents the proposed approach for storing, in a fuzzy representation, previous operational information of the system and the speed-up of the updating procedure. The presentation of the new approach is built by using a simulation study of a hydro-electric power plant. The final conclusions are given in Section V.

II. Fuzzy Cognitive Maps Representation And Development

Fuzzy cognitive maps approach is a hybrid modeling methodology, exploiting characteristics of both fuzzy logic and neural networks theories and it may play an important role in the development of intelligent manufacturing systems. The utilization of existing knowledge and experience on the operation of complex systems is the core of this modeling approach. Experts develop fuzzy cognitive maps and they transform their knowledge in a dynamic cognitive map [9].

The graphical illustration of FCM is a signed directed graph with feedback, consisting of nodes and weighted interconnections. Nodes of the graph stand for the nodes that are used to describe the behavior of the system and they are connected by signed and weighted arcs representing the causal relationships that exist among nodes (Fig. 1). Each node represents a characteristic of the system. In general it stands for states, variables, events, actions, goals, values, trends of the system which is modeled as an FCM [12]. Each node is characterized by a number A_j, which represents its value and it results from the transformation of the real value of the system's variable, for which this node stands, in the interval [0, 1]. It must be mentioned that all the values in the graph are fuzzy, and so weights of the interconnections belong to the interval [-1, 1]. With the graphical representation of the behavioral model of the system, it becomes clear which node of the system influences other nodes and in which degree.

The most essential part in modeling a system using FCMs, is the development of the fuzzy cognitive map itself, the determination of the nodes that best describe the system, the direction and the grade of causality between nodes. The selection of the different factors of the system, which must be presented in the map, will be the result of a close-up on system's operation behavior as been acquired by experts. Causality is another important part in the FCM design, it indicates whether a change in one variable causes change in another, and it must include the possible hidden causality that it could exist between several nodes. The most important element in describing the system is the determination of which node influences which other and in what degree. There are three possible types of causal relationships among nodes that express the type of influence from one node to the others. The weight of the interconnection between node C_i and node C_j denoted by W_{ij}, could be positive ($W_{ij} > 0$) for positive causality or negative ($W_{ij} < 0$) for negative causality or there is no relationship between node C_i, and node C_j, thus $W_{ij} = 0$.

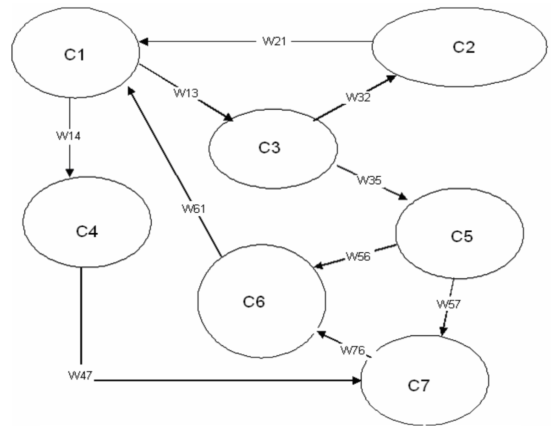


Fig. 1: A simple fuzzy cognitive map

The causal knowledge of the dynamic behavior of the system is stored in the structure of the map and in the interconnections that summarize the correlation between cause and effect. The value of each node is influenced by the values of the connected nodes with the corresponding causal weights and by its previous value. So, the value A_j for each node C_j is calculated by the following rule [12]:

$$A_j^s = f\left(\sum_{i=1, i \neq j}^{N} A_i^{s-1} W_{ij} + A_j^{s-1} \right) \quad (1)$$

where A_j^s, is the value of node C_j at step s, A_i^{s-1} is the value of node C_i, at step s-1, A_j^{s-1} is the value of node C_j at step s-1, and W_{ij} is the weight of the interconnection between C_i and C_j, and f is a squashing function.

Squashing functions:

1) $f = \tanh(x)$ maps the nodes values in [-1 , 1]

2) $f = \frac{1}{1+e^{-cx}}$ by using c=1 we convert the nodes values in [0 , 1]. It also called sigmoid function. The second function is the most common function which is used in FCM's.

III. Weight Updating Using System Feedback

In this section we will analyze the proposed method of updating the interconnections weights of FCM taking into account feedback node values from the real system. Using the updated weights the FCM reaches a new equilibrium point by means of equation (1). Some of the new node values can be applied as control values to the real system. One commonly used technique for updating weights in FCMs is the Hebbian updating rule [10], [1], [11]. In our approach the updating is made by using the conventional Hebbian rule, which however, uses measurements from the node values taken from the real system. This way the updating of the weights reflects real changes that have to be made in our knowledge about the system, which is represented by the interconnection weights. This situation is more apparent in cases where there exist steady value nodes, which, in the real system, are not affected by the values of the other nodes. In this case, if the FCM convergence equation (1) is left to operate with weight adjustments that do not take into account the steady node values fact, then the equilibrium point will give node values for the above mentioned nodes, which might be different than the steady values, which in turn implies an unrealistic point of operation for our system.

Let us, for example, analyze an FCM having one or more nodes with constant values. This means that no human action can intervene, in a mechanic way with this value. Suppose that in the FCM of Fig. 2 nodes C1 and C2 cannot change their values. The values of these nodes derive from the system that is examined. The table of interconnection weights for this system is:

$$W = \begin{bmatrix} 0 & 0 & W13 & W14 & 0 \\ 0 & 0 & W23 & 0 & W25 \\ 0 & 0 & 0 & W34 & 0 \\ 0 & 0 & W43 & 0 & 0 \\ 0 & 0 & W53 & 0 & 0 \end{bmatrix}$$

We see that columns 1 and 2 that concern nodes C1 and C2 are zero. When applying equation (1) for node value updating we have to consider the steady values of nodes C1 and C2 by using a companion adjusting equation. Thus, equation (1) is now replaced by the following two equations:

$$A_j^s = f\left(\sum_{i=1, i \neq j}^{N} A_i^{s-1} W_{ij} + A_j^{s-1} \right) \qquad (2)$$

And for the steady state nodes one has:

$$A_j^{s,FCM} = A_j^{system} \qquad (3)$$

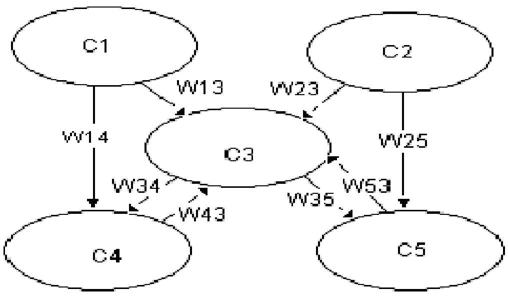


Fig. 2: FCM with steady state nodes

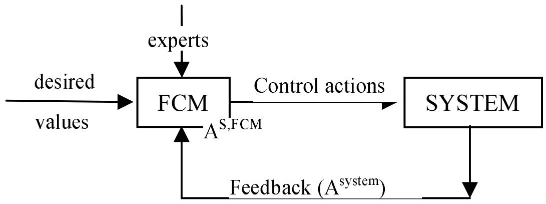


Fig. 3: Control structure

where A_j^{system} is the node's value, derived from the real system. These values are either measured on-line or are known beforehand as the steady nodes values of the above example. In order to drive the FCM in a realistic representation of the system and its control actions we have to update the interconnection weights using these measured node values from the real system. Based on the updated weights, equations (1) and (2) will produce a new set of node values which represent the control actions applied to the real system. The procedure, which is depicted in Fig. 3, is repetitively applied during the operation of the system. The weights that are non zero are renewed according to the Hebbian rule:

$$p = A_j^{system} - \frac{1}{1 + e^{-\left(\sum_{i=1, j \neq j}^{N} A_i^{s,FCM} W_{ij} + A_j^{s,FCM} \right)}} \qquad (4)$$

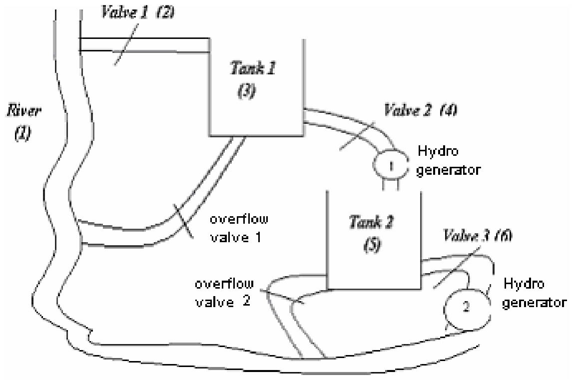
$$W_{ij}^k = W_{ij}^{k-1} + ap(1-p) A_i^{s,FCM} \qquad (5)$$

where k is the number of iteration and a is the learning rate (usually =0.1).

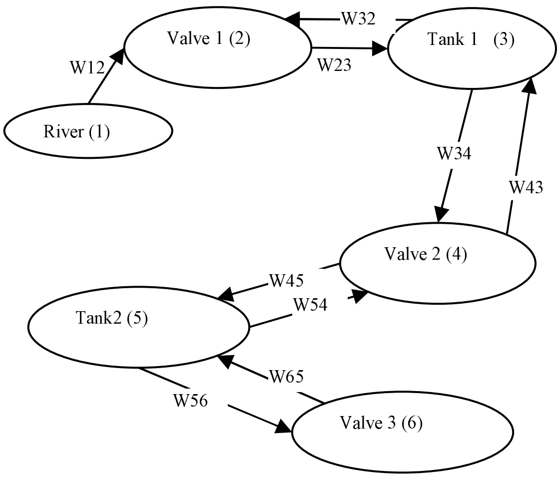
The procedure described in Fig. 3 uses repetitively equations (2), (3), (4) and (5) to provide with an FCM, which totally corresponds and cooperates with the real system. The control nodes of the system (nodes C3, C4 and C5 of Fig. 2) are now taking values which take into account the steady node values (C1 and C2) and the weight interconnections updated values.

IV. Fuzzy Representation Of Previous Operation Points

The procedure described in the previous section modifies our knowledge about the system by continuously modifying the weight interconnections and consequently the node values. During the repetitive updating operation the procedure uses feedback from the system variables. This means that in each iteration all the intermediate weight and node values, some of which are control values, are fed to the real system and its response is used to give the new updating direction.



(a)



(b)

Fig. 4: (a) Hydroelectric station, (b) A Fuzzy cognitive map representing the hydroelectric factory shown in (a)

It is obvious that this procedure continuously “annoys” the physical system, something that in many cases is undesirable. In the sequence we propose a methodology that alleviates this “annoyance” and speeds up the updating procedure.

To make the method clear, we choose a simple mechanical problem of a hydroelectric power station shown in Fig. 4(a). The FCM representation of the system is shown in Fig. 4 (b). We want to regulate the flow in the two Hydro-generators (1 and 2), in order to comply with possible power demands.

The system has one steady value node [River -reference node1], three control nodes [Valve 2 - node 4, Valve 3 - node 6 and Valve 1 – node 2] and two simple operation nodes [Tank 1 - node 3, Tank 2 - node 5]. One or more of nodes 2, 3, 4, 5 and 6 values have to be regulated so that hydro-generators 1 and 2 can receive the desired water flow values.

Based on experts knowledge regarding the mechanics of the system a representative weight matrix W is the following:

$$W_{imp} = \begin{bmatrix} 0 & -0.9539 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.7592 & 0 & 0 & 0 \\ 0 & 0.6457 & 0 & 0.0729 & 0 & 0 \\ 0 & 0 & -0.598 & 0 & 0.7999 & 0 \\ 0 & 0 & 0 & 0.3519 & 0 & 0.2959 \\ 0 & 0 & 0 & 0 & -0.4201 & 0 \end{bmatrix}$$

which, after applying equations (2) and (3), gives the following FCM equilibrium node values.

$$A = \begin{bmatrix} 0.6 & 0.5592 & 0.6498 & 0.7402 & 0.7362 & 0.7183 \end{bmatrix}$$

Suppose we want to drive nodes 3 and 5 to 0.652 and 0.7398 respectively. In this case we should adapt the weights of the FCM using repetitively equations (2) – (5). After 32 iterations we will find that the FCM accurately describes the operation of the real system. The final W matrix is:

$$W_{final} = \begin{bmatrix} 0 & -0.9539 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.7696 & 0 & 0 & 0 \\ 0 & 0.4148 & 0 & 0.0914 & 0 & 0 \\ 0 & 0 & -0.6138 & 0 & 0.8081 & 0 \\ 0 & 0 & 0 & 0.3818 & 0 & 0.3431 \\ 0 & 0 & 0 & 0 & -0.4121 & 0 \end{bmatrix}$$

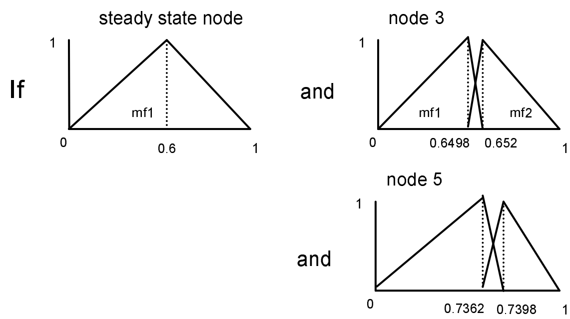
and A vector is:

$$A = \begin{bmatrix} 0.6 & 0.5655 & 0.652 & 0.7485 & 0.7398 & 0.7273 \end{bmatrix}$$

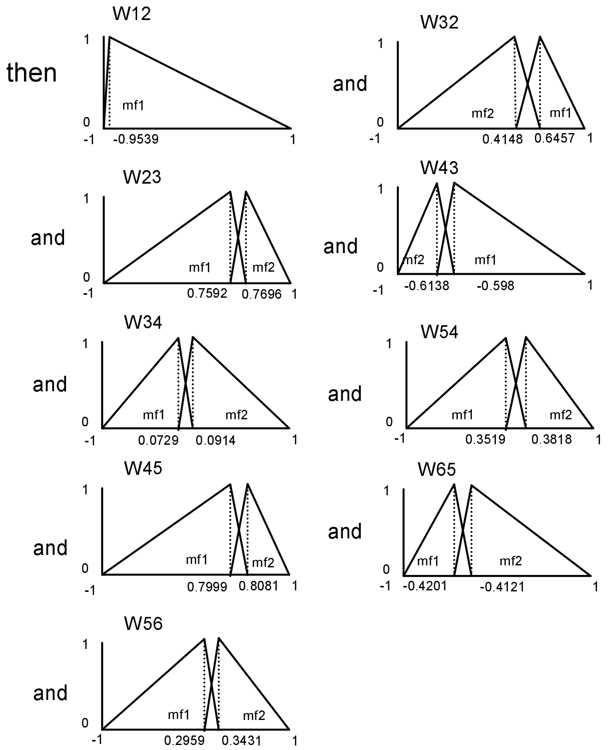
To avoid running again so many iterations to compute new node and weight values for other desired node values, which might be close to the ones encountered above we want to keep the weight and node information arisen from the above equilibrium points. To do that we are storing the node and weight dependencies in a fuzzy rule based database.

For example, the fuzzy rule database, which is obtained using the information from the two previous equilibrium points, is resolved as follows:

Left hand side (if part)



And right hand side (then part)



There are two rules related to the above two different equilibrium situations:

Rule 1

if node 1 is mf1(0.6) and node 3 is mf1(0.6498) and node 5 is mf1(0.7362)

then w12 is mf1 and w32 is mf1 and w23 is mf1 and w43 is mf1 and w34 is mf1 and w54 is mf1 and w45 is mf1 and w65 is mf1 and w56 is mf1

Rule 2

if node 1 is mf1(0.6) and node 3 is mf2(0.652) and node 5 is mf2(0.7398)

then w12 is mf1 and w32 is mf2 and w23 is mf2 and w43 is mf2 and w34 is mf2 and w54 is mf2 and w45 is mf2 and w65 is mf2 and w56 is mf2

The number and shape of the fuzzy membership functions of the variables of both sides of the rules are gradually modified as new desired equilibrium points appear to the system during its operation. To add a new triangular membership function in the fuzzy description of a variable, the new value of the variable must differ from one already encountered value more than a specified threshold. The threshold comes usually as a compromise between the maximum number of allowable rules and the detail in fuzzy representation of each variable.

Suppose now that we want to drive node 3 to 0.76 and node 5 to 0.766 by having the steady state node to 0.659. We run the above fuzzy rules using the Mamdani min implication and the Center of Area (COA) defuzzification method. Then with only these two rules we come to the following weight matrix values.

$$W = \begin{bmatrix} 0 & -0.2701 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.851 & 0 & 0 & 0 \\ 0 & 0.712 & 0 & 0.1021 & 0 & 0 \\ 0 & 0 & -0.634 & 0 & 0.8467 & 0 \\ 0 & 0 & 0 & 0.4198 & 0 & 0.3542 \\ 0 & 0 & 0 & 0 & -0.3671 & 0 \end{bmatrix}$$

$$A = \begin{bmatrix} 0.659 & 0.7436 & 0.7011 & 0.7592 & 0.7559 & 0.7308 \end{bmatrix}$$

In the sequel we run equations (2) – (5), which after only 8 iterations concludes to the FCM which accurately describes the operation of the real system. The final W matrix is:

$$W = \begin{bmatrix} 0 & -0.5674 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.9236 & 0 & 0 & 0 \\ 0 & 0.8834 & 0 & -0.0423 & 0 & 0 \\ 0 & 0 & -0.4120 & 0 & 0.9162 & 0 \\ 0 & 0 & 0 & 0.2455 & 0 & 0.3751 \\ 0 & 0 & 0 & 0 & -0.3042 & 0 \end{bmatrix}$$

and the equilibrium node values are

$$A = \begin{bmatrix} 0.659 & 0.7379 & 0.76 & 0.7023 & 0.7660 & 0.7355 \end{bmatrix}$$

Thus, we have a significant number of iteration reductions for reaching a new desired equilibrium point that is “close” to an already encountered equilibrium situation. To make the method operating sufficiently in a large range of operational situations the designer has either to teach the system in these situations off-line or to let the system gain this knowledge on line through its operation.

V. Conclusions

In this paper a new method for weight updating in FCMs using system feedback is proposed. So far, the existing approaches were using the simple method of weight updating without taking into account the feedback from the real system. The diversity of the proposed method lies in the fact that FCM reaches its equilibrium point using direct feedback from the node values of the real system and the limitations imposed by the reference nodes, which nodes represents either variables with constant values or variables with desired (goal) values. Moreover, a technique for storing knowledge from already encountered operational situations is proposed. This technique stores this information in the form of a number of fuzzy if-then rules. The fuzzy membership partition of the range of each variable and the fuzzy rules can be extracted in an on-line or off-line fashion. Combining the fuzzy representation database with the feedback dependent weight updating of the FCM results in a very efficient updating mechanism, which reaches the new desired equilibrium point in very few iterations.

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