An Approach for Online Weight Update Using Particle Swarm Optimization in Dynamic Fuzzy Cognitive Maps

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***Abstract*— Fuzzy cognitive maps (FCM) is a method to update a given initial vector to obtain the most stable state of a system, using a neighborhood of weights between these vectors and updating it over a series of iterations. FCMs are modeled with graphs. Neighbor weights between nodes are between -1 and 1. Nowadays it is used in business management, information technology, communication, health and medical decision making, engineering and computer vision. In this study, a dynamic FCM structure based on Particle Swarm Optimization (PSO) is given for determining node weights and online updating for modeling of dynamic systems with FCMs. Neighborhood weights in dynamic FCMs can be updated instantly and the system feedback is used for this update. In this work, updating the weights of the dynamic FCM is a PSO based approach that takes advantage of system feedback. In previous literature suggestions, dynamic FCM structure performs the weight updating process by using rule-based methods such as Hebbian. Metaheuristic methods are less complex and more efficient than rule-based methods in such optimization problems. In the developed PSO approach, the initialize vector state of the system, the weights between the vector nodes, and the desired steady state vector are taken into consideration. As a fitness function, the system has benefited from the convergence state to the desired steady state vector. As a stopping criterion for PSO, 100 * n number of iteration limits have been applied for the initial vector with n nodes. The proposed method has been tested for five different scenarios with different node counts.**

***Keywords*— Fuzzy Cognitive Map, Dynamic Map, Pso, Online Weight Update**

I. INTRODUCTION

Fuzzy cognitive maps are used for modelling complex systems. It was first introduced by Bart Kosko in 1986. The representation of FCMs is mainly based on the graph theory. The features affecting the system to be modelled are expressed as nodes on the fuzzy cognitive maps, while the relations between these systems are expressed as the neighbourhood weights between the nodes. This model first obtains an initial vector and the FCM is subjected to a series of iterations until the most stable or desired state of the system is achieved. Various methods are used to determine the weights while the system is modeled. Usually the relationship between the nodes is expressed linguistically or numerically by an expert group working in the field of the problem being addressed. Weights are determined by subjecting the data obtained from this expert group to a fuzzy membership function. Besides, meta-spatial optimization or artificial neural networks and learning-based methods are used to determine initial weights on FCMs. One FCM example is shown in Fig 1.

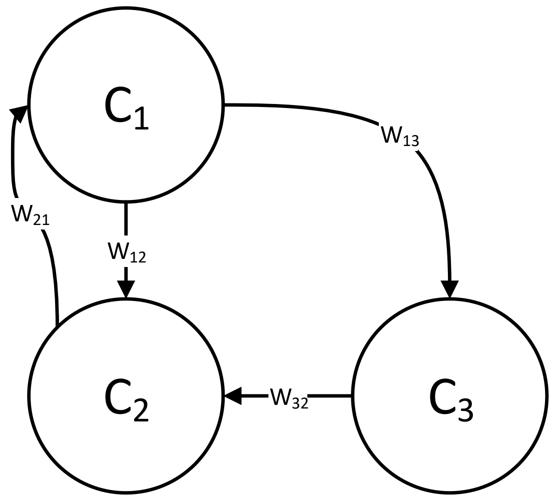

Fig. 1. An example of FCM [1].

Today, FCMs can be used in business management, information technology, communications, healthcare and medical decision making, engineering and computer vision. There are many solutions in the literature that utilize FCMs [1-24]. In one of these, Gozhyj Aleksandr has benefited from FCMs for modelling water quality [1]. In the study done, the properties that affect water quality firstly are expressed as nodes. Then weights and neighbourhoods of the nodes were determined. FCM was created and analysis of system characteristics was carried out. After the FCM was established, the end result water quality analysis was performed on the simulated data. In another study, Andrey Ivanov used FCM to simulate the use of wind energy by Finland until 2030 [2]. In the study conducted, the test was carried out by using the data obtained from different databases and academic studies as a reference. The multiple generated FCM models were finally combined under a single FCM model. The characteristics used in the FCM model are generally determined by the trade policies of Finland, energy policies, and the adequacy of different energy sources. The problem addressed in another study is that it is unclear how to respond to some reduced crop yields in a particular region [3]. One way of coming up from such uncertainties to work is to use scenarios as a way to discover future projections from existing targets and constraints. Expert opinions were used to determine the factors affecting productivity in the proposed method, and the adaptation of fertilizer applications was targeted in this way.

In this study, a dynamic complex system is modelled and operated through FCMs, and an online weight update method based on particle-lot optimization is given. In the literature, there are studies focusing on PSO-based methods for modelling dynamic systems with FCM and determining the weights of associations in FCMs. In one of them, Parsopoulos focuses on the determination of weights in FCMs using a PSO based method [4]. The main point of view in the work being done is that the FCM uses the PSO to reach the most stable desired situation. In the proposed method, FCM learning is achieved with a PSO based method by taking the initial state, weight values, desired weight ranges and desired steady state values of FCM. The block diagram of the proposed method is as shown in Fig 2.

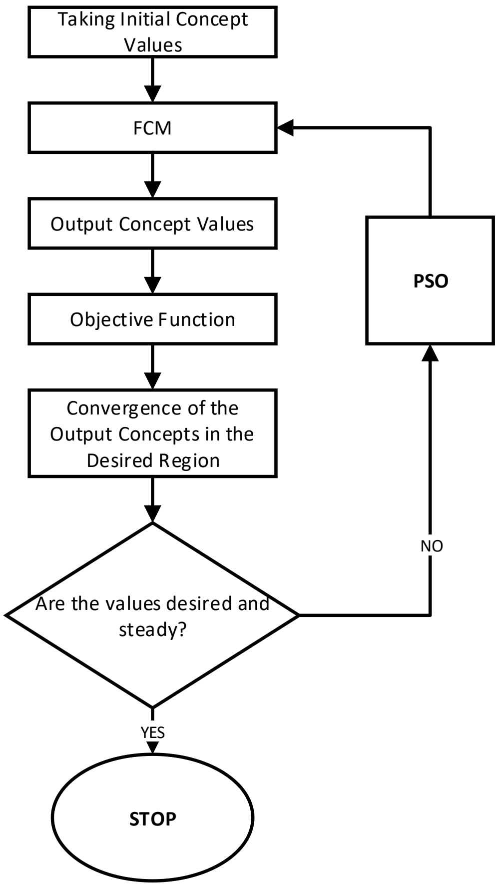

Fig. 2. Block diagram which belongs to literature work [4].

In addition to PSO, support vector machines, artificial neural networks and some classifier or buster methods have been used in studies focusing on other FCM weight learning. The main difference of this study from the studies focused on FCM in the literature is that it presents a generalized method to online weight updating process in order to obtain desired node values in each FCM iteration during modelling and operation of dynamic systems. The proposed method has been tested with different scenarios and very efficient results have been obtained.

II. PROPOSED METHOD

In this study, an online weight updating method is proposed that utilizes particle swarm optimization for modelling dynamic systems with FCM. When the other studies in the literature are examined, it is focused on weight learning for stabilizing the systems mostly modelled with FCM. The proposed method in this study allows weight updating in each iteration of the FCM, but it can also perform the weight update process in the desired state if the system wants to switch to the stable state. The block diagram of the proposed method is as shown in Fig 3.

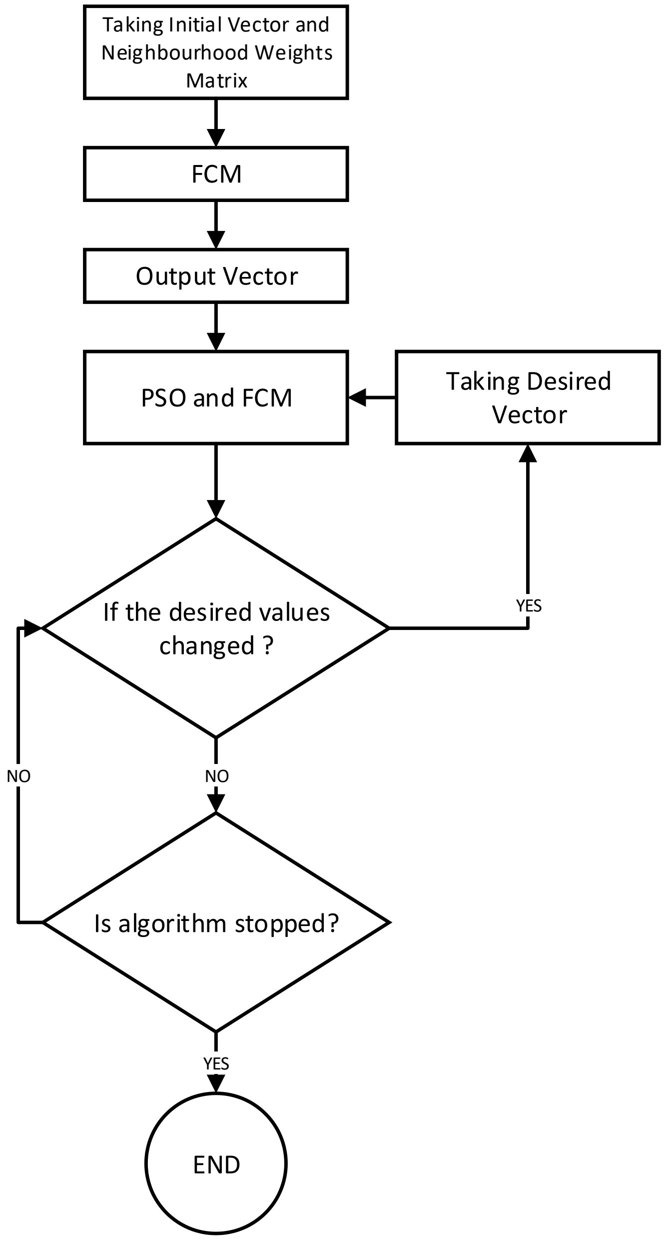

Fig. 3. Block diagram which belongs to proposed method in this study.

First, the initial vector and the initial weights, which contain the first node values of the FCM, are taken. Then the FCM is run once and the desired output vector is taken. Optimization is performed according to the desired output vector, neighbourhood weights are calculated, and new neighbourhood weights are again obtained by PSO to keep the output vector constant until new value input occurs. For better understanding of the proposed method, it is helpful to explain the concepts of FCM and PSO.

A. Fuzzy Cognitive Maps

In the FCM step of the proposed method, the FCM is operated once according to the incoming initial vector and neighbourhood weights. The operation of the FCM is done separately for each node relationship. The value of each node in the next iteration is calculated as follows.

$$C_i = \mathrm{sgn}(C_i + \sum_{j=1}^{n} Wij * Cj) \qquad (1)$$

The sgn function included in Equation 1 is the sigmoid threshold function. The equation expressing the sigmoid function is as follows.

$$1/(1+e^{-x}) \qquad (2)$$

B. Particle Swarm Optimization

Particle swarm optimization has been developed in the nature, inspired by the systematic method birds use to find feed. Today, PSO is used to solve many problems. The general steps of particle swarm optimization are given in Fig 4.

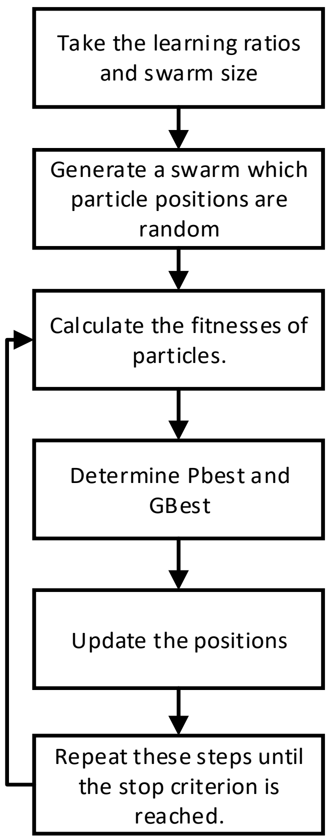

Fig. 4. Block diagram which belongs to proposed method in this study.

In the first step, it is determined how many pieces of crawler will be used during optimization. Then, the creation of the drag is completed by generating particles whose positions are composed of uniform random numbers. The fitness function used in this study is performed by operating the FCMs according to the weights expressed by each particle and determining the distance to the desired output vector. Pbest refers to the position in which a particle has the best fitness value according to all iterations so far. Gbest refers to the position where all particles have the best fitness value so far. The position update process is performed depending on the values of Gbest, Pbest, predetermined learning rates and random uniformly generated numbers. The equation that performs the update operation is as follows. In the above equation, x represents the particle position, v particle speed, axis number of the j position, number of iterations in the particle, c learning rate, and r is the random number generated.

$$v_j^{k+1} = wv_j^k + c_1 r_1 (Pbest_j - x_j^k) + c_2 r_2 (Gbest - x_j^k)$$

$$x_j^{k+1} = x_j^k + v_j^{k+1} \qquad (3)$$

The PSO stop criterion is used as the iteration limit of 100 * n to express the number of n nodes.

III. Experimental Results

The developed method in this study is done with the Java programming language. The output vector of the FCM for each particle is used as the fitness function of the PSO algorithm. For an FCM with n nodes as stopping criterion, the number of iterations is 100 * n. The reason of this is that the result obtained from the PSO is the result of convergence even if the iteration continues after the stopping criterion. The proposed method has been tested on FCMs with 3 different number of nodes. In the first scenario, the FCM has a 2-node initial vector in total. Therefore, the dimension of the matrix representing the neighbourhood weights is 2x2. In Table I, the initial values of the 2-node FCM, the values obtained as a result of an iteration operation, the desired FCM output vector from the PSO and the output generated by the PSO are given. Table II contains data for the 3-node FCM scenario. Table III contains data for the outputs of the PSO for the 4-node FCM.

TABLE I
Data belong to first scenario.

	First Node	Second Node
Desired Value	0.5	0.7
Initial Value	0.2	0.3
Output Value	0.5	0.7

TABLE II
Data belong to second scenario.

	First Node	Second Node	Third Node
Desired Value	0.6	0.7	0.8
Initial Value	0.3	0.4	0.5
Output Value	0.6	0.7	0.8

TABLE III
Data belong to third scenario.

	First Node	Second Node	Third Node	Fourth Node
Desired Value	0,6	0,7	0,7	0,5
Initial Value	0,2	0,3	0,4	0,5
Output Value	0,59	0,697	0,70	0,5

When the experimental data are analysed, it is found that the operated FCMs are very close to the desired result thanks to the online weight update with PSO. The positional distance obtained for the first scenario was calculated as 0, 0 for the second scenario and 0.0033 for the third scenario. The weights obtained are as follows.

TABLE IV
Calculated weights for first scenario.

0,212	-0,924
-0,375	0,35

TABLE V
Calculated weights for second scenario.

-0.18902563	-0.6161939	-0.1767356
0.11529532	0.5391339	0.1327322
-0.28045636	0.5641456	0.8724881

TABLE VI
Calculated weights for third scenario.

-0.3093005	-0.60621	-0.3846111	-0.32688555
-0.23184107	0.9672715	0.027072813	0.15627213
0.6152122	0.15815265	0.28956854	-0.36410236
0.52	0.29	0.67	0.15234

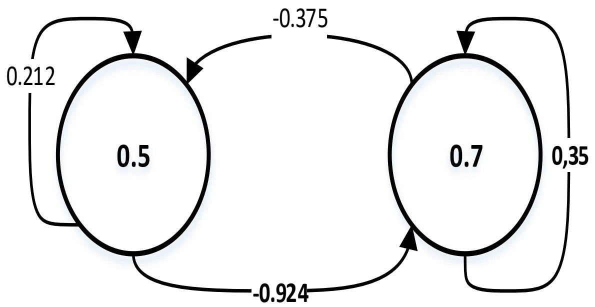

Fig5. FCM output which belongs to first scenario.

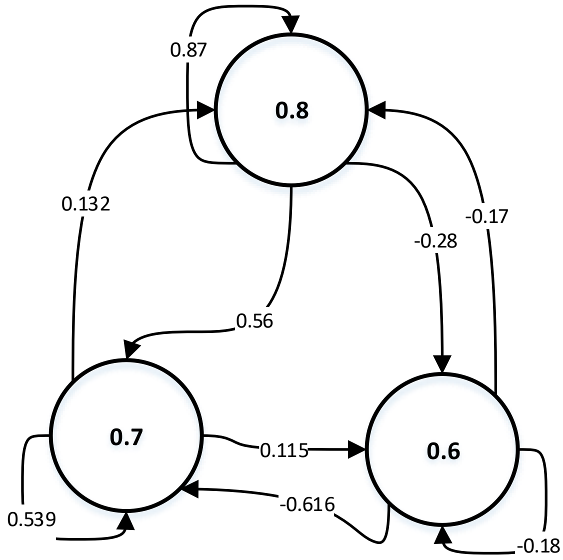

Fig. 6. FCM output which belongs to second scenario.

IV. Conclusion

In this study, a FCM structure which updates online weight with PSO is proposed for modelling dynamic systems. FCMs provide solutions to many problems in the literature. FCMs that provide solutions to a variety of inbound problems, such as business management, healthcare, engineering, computer vision, etc., often use the transition state as a stopping criterion. The method proposed in this study is to update the online weight with PSO to obtain the desired state or stable state. The efficiency of the proposed method with the experimental data has been proven. When the results of different scenarios were examined, it was observed that the PSO based weight update process gave successful results. The algorithm given in this study is two iterative structures of computer science(particle swarm optimization and FCM methods are suggestions of a solution presented in hybrid). And this causes the increasing of the algorithmic complexity. The applicability of the proposed solution on different problems is important, although this is not satisfactory in terms of algorithmic cost. Proposed method limitate the applicability on real-time problems because of algorithmic complexity. For this reason this method's application on system modelling, estimation etc. will be more efficient. Proposed method take the desired steady-state vector as a parameter and it outputs weights of FCM with a meta-heuristic optimization accordingly this. Different studies that focus on the development of the weight updating procedure with a particle-weighted method to capture the steady state and to introduce the desired state vector in a non-manual way with different computational intelligence based studies will also be developed at a later stage through the given method.

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