Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-29 (2016) 300–304

A new conception on the Fuzzy Cognitive Maps method

Eleni S. Vergini * **Petros P. Groumpos** **

* *Department of Electrical and Computer Engineering, University of Patras, Rion 26500, GREECE (e-mail: vergini@ece.upatras.gr)*
** *Department of Electrical and Computer Engineering, University of Patras, Rion 26500, GREECE (e-mail: groumpos@ece.upatras.gr)*

Abstract: Fuzzy Cognitive Maps, being a combination of Fuzzy Logic and Neural Networks, have been gaining researchers' interest on an international level. In recent years there has been an effort to evolve the method of Fuzzy Cognitive Maps and improve its response and effectiveness. Towards this direction various approaches and different learning algorithms have been used with very good results. This proves that Fuzzy Cognitive Maps method is very promising and worth of further investigation and development. Classical Fuzzy Cognitive Maps theory will be presented and a new conception will be put forward and implemented. The results will be analytically presented and the conclusions will leave space for more creative and evolving research.

Keywords: Fuzzy Cognitive Maps, Zero Energy Building

1. INTRODUCTION

During the last decades there has been an evolution in computer science and as a consequence many innovations have been made concerning Systems' Modelling and Control. Trying to get as close to human perception and reasoning, Fuzzy Cognitive Maps are a modelling method which has been under research during the last decades and they have been applied in modelling of various systems, giving very promising results.

Cognitive Maps were firstly introduced by R. Axelrod in 1976, as a formal way of representing social scientific knowledge and modeling decision in social and political systems. Since then, Cognitive Maps have been applied in a number of different scientific areas. In 1986, Kosko introduced a soft computing methodology as an extension of Cognitive Maps and named it Fuzzy Cognitive Maps (FCM). See Axelrod [1976] and Kosko [1986].

FCMs combine the reasoning of Fuzzy Logic and the system approach of Artificial Neural Networks (ANN). Learning Algorithms, being an important part in the training procedure of ANNs, were also applied on FCMs, improving their response. There is a variety of algorithms which were developed, some of them are based on the initial Hebbian Algorithm (Papageorgiou et al. [2003]) and some of them based on the Generic Algorithms and many others (Papageorgiou [2012]). Learning Algorithms usually use historical data in order to appropriately train the system and avoid the need of human intervention. In addition, they contribute to the achievement of dynamical system response, which is very important especially in the case of complex systems.

The aim of this paper is to propose a new equation based on FCMs theory. Section 2 includes two partitions. In the first subsection, the basic theory of FCMs is analytically presented, along with the mathematical equations and detailed information. On the other hand, in the second subsection a new equation is proposed, based on the FCM reasoning and background. The third section of the paper is dedicated to the presentation of a Zero Energy Building (ZEB) FCM model. This model will be used in sections 4 and 5, where the implementation of the ZEB FCM model will be analyzed in detail. The final section of this paper considers the conclusion of this implementation and the future research prospects.

2. FUZZY COGNITIVE MAPS

2.1 Classical Theory of Fuzzy Cognitive Maps

FCMs became popular because they are very simple and close to human reasoning. They are used for modelling dynamic and complex systems. These systems have many parameters and also they are difficult to model using a mathematical approach. For that reason, FCMs are considered to be appropriate to solve complex problems without using complex mathematics. On the other hand, they are based on experts' opinion and their human decision making approach of problems.

Combining the theory of both Neural Networks and Fuzzy Logic, FCMs use a graph to represent a given system as a collection of concepts and the interrelations between them. They are usually assorted as neuro-fuzzy systems and they are competent to incorporate and adapt human knowledge.

In a simple FCM graph, as it is shown in Fig.1, the system variables are defined by experts, and each one of them is considered to be a concept (C_1, C_2, etc). Concepts take values in the interval $[0, 1]$. The interconnection between two concepts is called weight and it is defined by taking a value in interval $[-1, +1]$.

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2016.11.083

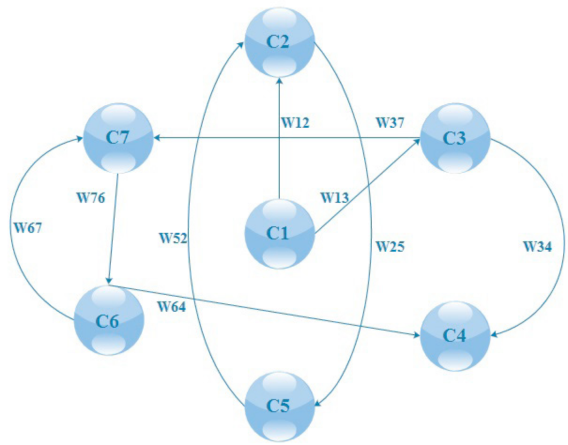

Fig. 1. A Simple FCM Graph

- If $w_{ji} < 0$ then there is a negative interrelation between concepts C_i and C_j. This means that an increase of the C_j value will cause a decrease of C_i value.
- If $w_{ji} > 0$ then there is a positive interrelation between concepts C_i and C_j. This means that an increase of the C_j value will cause an increase of C_i value.
- If $w_{ji} = 0$ then there is not any interrelation between concepts C_i and C_j. This means that their values are independent to each other.

The absolute value of each weight signifies the level of influence between the two concepts. Apart from a graph representation, a FCM can be determined by a square matrix, which is called "Weight Matrix". The weight between two concepts is set in their corresponding cell.

A group of experts can be asked to specify the variables and the concepts. Experts also define the interconnections among concepts using linguistic rules. Using these linguistic rules, which were suggested by experts, the weights' values are determined, using the defuzzification method of Center of Gravity (COG), taking a value which belongs to the interval [-1,+1]. The value, C_i, of each concept is influenced by the values of concepts-nodes (C_j) connected to it, and is updated in each iteration k according to Eq.1.

$$C_i{}^{(k+1)} = f(C_i{}^{(k)} + \sum_{j=1, j\neq i}^{n} (C_j{}^{(k)} w_{ji})) \quad (1)$$

where w_{ji} is the weight of the arc connecting concept C_j to concept C_i, and function f is the sigmoid function given by Eq.2

$$f(x) = \frac{1}{1 + \mathrm{e}^{-\lambda x}} \quad (2)$$

In Eq.2, $\lambda > 0$ is a parameter that determines the f function steepness in the area around zero.

In recent years, researchers have improved FCMs using various learning methods. The initial weight matrix, which is defined by experts, is updated using learning algorithms and finally it is applied on the system in order to calculate the final output value.

The main advantage of FCMs is the fact that they are a simple presentation of a real system, they are close to human reasoning and they can be applied on very complex systems, where mathematical models' application can be rather difficult. The use of experts' opinion and knowledge is another advantage for FCMs, since it ensures that the response of the model will be close to the response of the real system. The use of learning algorithms, using historical data, in order to train the FCM or in order to improve the experts' opinion has contributed to the development of automated or semi-automated models for FCM learning. See Stylios et al. [1997] and Groumpos [2010].

2.2 A new Conception

After the implementation of the classical FCM method on various models and without using the learning algorithms, it has been observed that for a FCM with determined and constant weight matrix the use of Eq.1 and Eq.2 lead to the same output value no matter what the initial concept values are. Starting from this observation, and looking for a solution to this problem, it was estimated that, apart from the initial concepts' values, the initial disturbances are necessary in order to calculate the system output. A different disturbance would force the system to reach a different equilibrium point because it has a different impact on the system response.

Taking the above reasoning as a basic idea, the classical FCM equation, Eq.1, and the weight values' explanation which was given in section 2.1 the new conception, which is suggested in this paper, was created. In section 2.1 it was mentioned that "If $w_{ji} > 0$ this means that an increase of the C_j value will cause an increase of C_i value." This means that in order to have a change in the C_i concept value, there should be a disturbance on the value of C_j, in other words there should be a DC_j. Considering this fact, Eq.3 is suggested to be used in order to calculate the new concept values.

$$C_i{}^{(k+1)} = C_i{}^{(k)} + \sum_{j=1, j\neq i}^{n} (w_{ji} DC_j{}^{(k)}) \quad (3)$$

where:

$$DC_j{}^{(k)} = C_j{}^{(k)} - C_j{}^{(k-1)} \quad (4)$$

Considering the fact that every system for k=0 starts from a specific steady state and the concepts have specific initial values which do not change, we reach the conclusion that:

$$DC_j{}^{(0)} = 0, \forall j \quad (5)$$

If there is not any disturbance to any of the concepts then DC_j remains 0 for all concepts and for every iteration k. This means that if the algorithm is applied there will be no change in the concept values no matter how many iterations are held.

On the other hand if there is a disturbance in a concept, for example in iteration k, then $DC_j^{(k)} \neq 0$ and this will affect the values of all the concepts $C_i^{(k+1)}$ which are interconnected to C_j.