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MODELING THE BUILDING ENERGY MANAGEMENT SYSTEM OF A BUILDING USING A REVISED APPROACH OF FUZZY COGNITIVE MAPS

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Abstract. Fuzzy Cognitive Maps (FCMs) are a very simple, useful and powerful tool for modeling and analyzing dynamic complex systems. FCMs can structure virtual worlds that dynamically change with time. Mathematical models of FCMs are reviewed and a number of problems which emerged with them are briefly analyzed. In order to address some of these drawbacks a revised approach is proposed. This approach is being used to analyze the behavior and control the Building Energy Management System of a building. Simulation results of the new method are presented and discussed.

Keywords: Building energy management system; energy efficiency; fuzzy cognitive maps.

INTRODUCTION

The energy consumed by buildings represents a large part of the world's total energy consumption with a total shareof 40%. This is the reason that energy efficiency of buildings becomes an issue of outmost importance. Many scientists have turned their attention to the development of new methods of taking advantage of renewable energy sources, as well as control the existing technologies, to achieve the aforementioned goal. These efforts have led to the appearance of a new research field; that of the Intelligent Buildings (IBs). Many definitions have been given to describe what an IB really is, in our research the more suitable definition is the one given be the European Intelligent Building Group (EIGB) which states that "intelligent is a building which offers its users the most effective environment and on the same time uses and manages its resources in a manner that ensures the reduction of the cost due to the use of equipment and facilities"[1]. Various methods have been used to control the operation of a building our research we focus on the methods of Fuzzy Logic and Fuzzy Cognitive Maps (FCMs). Fuzzy Cognitive Maps (FCMs) is a methodology for modeling complex systems which exploits the knowledge and experience of an experienced user. They are the evolution of the Cognitive Maps which were introduced by R. Axelrod in 1976 [2].

Fuzzy Cognitive Maps were computing methodology which gives users the ability to encounter problems in the same way the human mind does; using a conceptual procedure which can include ambiguous or fuzzy descriptions [3].

They therefore offer an economical , flexible , fast and versatile approach to a variety of problems (social, political, economic, environmental and mechanical) which are extremely complex and a purely mathematical approach would be time consuming, laborious and require wasting many resources. Kosko introduced FCMs as a method to represent the causal relationship between concepts- nodes. Their goal is to represent knowledge in a symbolic way and model the behavior of systems containing elements with complex relationships, which sometimes can be hidden or illegible. Fuzzy Cognitive Maps are a very promising modeling method that as stated above has been used in a large variety of systems with very good results. However, several problems concerning the extension of this method have emerged. For this reason, a revised approach of the method in modeling FCMS is needed. The aim of this paper is to propose a revised this approach and it is outlined as follows. In section 2 the Fuzzy Cognitive Method is being presented and the problems of the method are being analyzed. In section three a revised mathematical approach to solve these problems is being proposed. In section 4 the proposed methodology is being tested in an experiment which attempts to control the building energy management system of a building. Finally, in the fifth section conclusions are being presented and future research topics are being proposed.

EXISTING FUZZY COGNITIVE MAPS MODEL Fuzzy cognitive maps theory

Fuzzy Cognitive Maps (FCMs) came as a combination of the methods of Fuzzy Logic and Neural Networks. They constitute a computational method that can examine situations during which the human thinking process involves fuzzy or uncertain descriptions. An FCM presents a graphical representation used to describe the cause and effect relations between nodes, thus giving us the opportunity to describe the behavior of a system in a simple and symbolic way. To ensure the operation of the system, FCMs embody the accumulated knowledge and experience from experts who know how the system behaves in different circumstances. In other words, they recommend a modeling process consisting of an array of interconnected and interdependent nodes Ci (variables), as well as the relationships between them W (weights). Concepts take values in the interval [0, 1] and weights belong in the interval [-1, 1]. Fig.1 shows a representative diagram of a FCM [4].

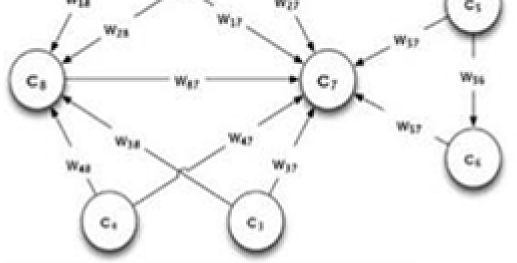

Fig. 1. Fuzzy Cognitive Map

The sign of each weight represents the type of influence between concepts. There are three types of interconnections between two concepts Ci and Cj:

wij>0, an increase or decrease in Ci causes the same result in concept Cj.

wij<0, an increase or decrease in Ci causes the opposite result in Cj.

wij=0, there is no interaction between concepts Ci and Cj.

The degree of influence between the two concepts is indicated by the absolute value of wij.

During the simulation, the value of each concept is calculated using the following rule:

$$A_i(k) = f\left(A_i(k-1) + \sum_{j=1, j\neq 1}^{n} A_j(k-1) w_{ji}\right). \quad (1)$$

Where k represents the iteration step, n is the number of concepts and f is the sigmoid function given by the following equation:

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

Where λ determines the steepness of function f.

The FCMs' concepts are given some initial values which are then changed depending on the weights; the way the concepts affect each other. The calculations stop when a steady state is achieved; the concepts' values become stable [1], [5-8].

As causal patterns change and experts update the causal relationships between concepts, the use of Non-Linear Hebbian Learning (NHL) procedure helps the FCM to modify its fuzzy causal web [9][10].

Due to the non-linear structure of the FCM the NHL can contribute to its training and consequently to the prediction and control of the Building Energy Management System function.

In this algorithm, the learning rule for FCMs integrates a learning rate parameter η, weight decay parameter γ, and the input/output concepts. The value of each concept changes through Eq. (1) whereas weight value is calculated using Eq. (3).

$$W_{ji}^{(k+1)} = \gamma W_{ji}^{k} + \eta A_i^{k} [A_j^{k} - sign(w_{ji}^{k})] W_{ji}^{k} A_i^{k}. \quad (3)$$

Through the NHL algorithm, the only weights that change are the non-zero ones, all the other weights of the weight matrix W_{ji} keep their initial zero value [11].

Inefficiencies of fuzzy cognitive maps model

As stated in the introduction the FCMs is a modeling methodology which is very promising when we need to model complex systems which are highly non-linear and involve fuzzy or uncertain situations. However, with the current modeling of the method various problems emerge. These drawbacks dictate the need to use a different approach concerning the FCMs method; while on the same time keeping the core of the method intact. These problems concern various steps of the method. In this subsection, we are going to list and analyze each one and on the next section we are going to propose a revised approach to solve them. But before we begin, we should state that even if they appear separate its one is connected to the other. The first drawback concerns the calculation method of the values of the concepts; (Eq.1). The calculation equation takes into consideration the change that each concept causes separately instead of the total change which is caused to the concept Ci. This results in a significant increase to the value of the concept that goes far beyond the interval [0,1].

This is the reason why the sigmoid function (Eq. 2) is needed; to suppress the result to the interval [0,1]. But due to the shape of the curve any concept value beyond 3 leads the sigmoid function to correspond it to the val-ue 1 which is greatly problematic as the final output is corresponded to the linguistic varia-ble "high" even if this is not always the expected or correct result. Secondly continuing the subject of the sigmoid function there is another drawback that leads to high output values. This is the fact that the center of the curve instead of being on the (0,0) point on the xy axis it is on the (0.5,0) point. This means that each concept's lowest value can be the 0.5. This problem combined with the first one makes it difficult to interpret the result even with the use on the experts' interpretation criterion (Eq. 4).

$$R(x) = \begin{cases} 0, & x < 0{,}5 \\ \dfrac{x - 0{,}5}{0{,}5}, & x > 0{,}5 \end{cases} .(4)$$

Continuing with the NHL learning method (Eq. 3), while running several simulations we have observed that due to the way weights are being calculated if the number of iterations of the algorithm is increased; to reach a steady state, the causality reverses and all the Wij be-come positive. This is a very serious drawback as it changes the causality between concepts and in several occasions instead of having a lower we are going to have a larger result which can cause serious stability issues to several systems. Finally, the last problem that demands our attention is the fact that some concepts are not being affected by others thus they should stay static through the whole iteration process. However due to the current sigmoid function and Eq.1 their value changes after the first iter-ation.

These problems dictated the need to have a revised approach concerning the modeling of Fuzzy Cognitive Maps.

A REVISED APPROACH

In this section of the paper a revised approach is being proposed to partly solve the above-mentioned problems. The changes that are being proposed try to address each problem separately but also in connection to the others.

New calculation equation

The first problem that we are going to address is the one of the calculation of the value of each concept. Until now in order to calculate the new value we simply summed the weighted values of all the concepts that affected the one in question (Eq.1). What we propose is to calculate a unified value to be added to the previous value of the concept. This value is going to represent the total variation caused from all the other concepts. The new equation proposed for this reason is:

$$A_i[k+1] = f\left(A_i[k] + \frac{\sum_{j=1, j\neq 1}^{n} A_j[k] w_{ji}}{\sum_{j=1, j\neq 1}^{n} w_{ji}}\right).(5)$$

As a result of this calculation the new value is almost always between the interval [0,1], a fact that makes the use of the sigmoid function more accurate.

Modifying the sigmoid function

Secondly concerning the sigmoid function, we are going to propose a modified form where we can adjust the various parameters (slope, upper, lower limit, symmetry with the y axis) to fit our needs. This function is described by the following equation [12]:

$$f(x) = m + \frac{M - m}{1 + e^{(-r(x - t_0))}} \quad . (6)$$

Where:

•m is the lower limit of the curve

- M is the upper limit of the curve
- r is the slope of the curve and
- to is the symmetry to the y axis

For the purpose of this paper we are going to use the following values:

- m=-1,
- M=1,
- r=1,
- to=0

We can see the sigmoid function of the curve to the following figure (Fig. 2).

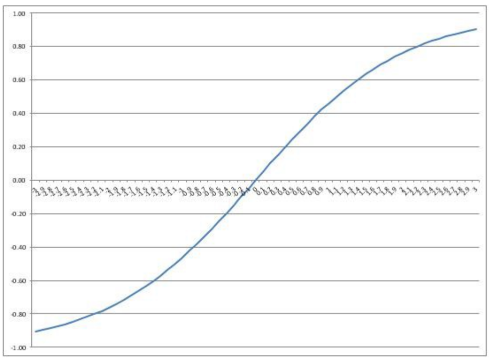

Fig. 2. Sigmoid Function

Using the aforementioned equation, we can also solve the last problem that we analyzed in the previous section of the paper; the constant concepts maintain their initial value.

The learning algorithm

In this subsection, we are going to propose an alternation of the NHL equation for the calculation of the weights. Our goal is to maintain the correct causality (as given by the experts) between the concepts regardless the number of the iterations that is needed to reach a steady state. For this purpose, we propose the following equation, which is the same as Eq. 3 but slightly modified.

$$W_{ji}^{(k+1)} = sign(W_{ji})^k[\gamma|W_{ji}^k| + \eta A_i^k[A_j^k - sign(w_{ji}^k)]W_{ji}^k A_i^k] \quad . (7)$$

By separating the sign of Wji and doing the calculation with the absolute value we achieve the correct causality without losing the accuracy of our results.

BUILDING ENERGY MANAGEMENT SYSTEM

The Building Management System (BEMS) is a system of outmost importance for the control of the building. As heating, cooling and domestic hot water production are three operations that consume excessive amounts of energy we designed a system to reduce it.

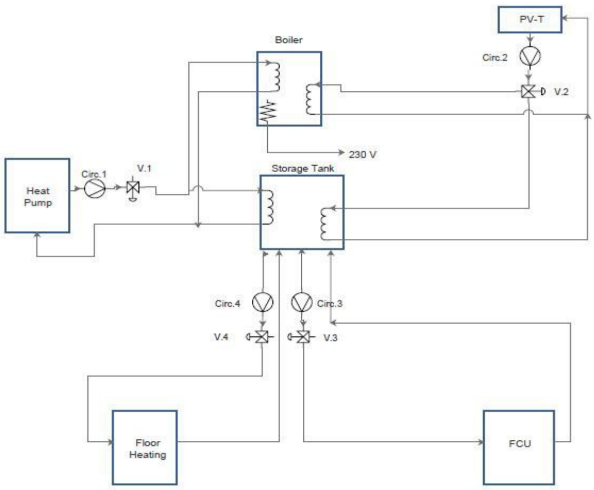

Fig. 3. Building Energy Management System

The system is shown in Fig. 3, and consists of:

A boiler for the domestic hot water storage.

A storage tank for the storage of water for the heating and cooling of the building.

A Photovoltaic Thermal Unit for the production of electricity and hot water.

A Heat Pump (air to water) for heating and air conditioning needs of the building.

A Floor Heating unit which can reduce the fuel needed by 30%.

A Fan Coil Unit (FCU) to cover the rest of the cooling and heating needs.

Four circulators and triode valves are used to distribute the water to the various parts of the automation.

The control algorithm will focus on these valves and circulators to achieve the maximum energy savings [13–16].

FUZZY COGNITIVE MAP DEVELOPMENT

In this part of the paper we are going to develop the Fuzzy Cognitive Map which can also be used to control the BEMS as it was described in section 3 of the paper.

Concept definition

In order to have an accurate comparison we used as concepts the inputs and outputs of the previous algorithm, properly adjusted to meet the requirements of this control method.

The concepts were divided into three categories; the input concepts, the medium output concepts and the final output concepts of the FCM.

The concepts as well as the category they belong to, are listed below Inputs:

C1: PV-T Temperature
C2: FCU Temperature
C3: Floor Heating Temperature
C4: DHW Demand
C5: Contamination Flag
States:
C6: Storage Tank Temperature
C7: Boiler Temperature
C8: Valve 1a
C9: Valve 1b
C10: Valve 2a
C11: Valve 2b
C12: Valve 3
C13: Valve 4
C14: Circulator 1
C15: Circulator 2
C16: Circulator 3
C17: Circulator 4
Outputs:
C18: Resistance Operation
C19: Heat Pump Operation

Concepts 1-4 and 6-7 take values from 1to 4 (low, medium low, medium high and high). Concepts 5, 14-19 take OFF-ON values. Concepts 12-13 take the value AC which is the position of the valve. Finally, since the valve position is a discrete value, valves 1 and 2 were divided to two separate concepts; the first having the one-way positions and the second having the two-way position.

Interconnections' specification

Continuing the interconnection weights between nodes will be defined. This process will be undertaken by experts who in cooperation with each other will decide the interconnection weights. As part of this work the interconnections between the nodes emerged from an extensive study of the building's simulation based on real weather data. The values positive or negative will vary between the following ones:

W (weak): Very weak interconnection between the nodes Ci, Cj.

M (medium): Medium interconnection between the nodes Ci, Cj

S (strong): Strong interconnection between the nodes Ci, Cj

VS (very strong): Very strong interconnection between the nodes Ci, Cj.

These values will then be defuzzified [17,18] and a corresponding numerical value will be assigned to each one of them.

In the following table, the weight matrix proposed by the experts is being presented.

Table 1. Weight Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19
C1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.98	0	0	0	-0.12
C2	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	-1	0	0	0
C3	0	-0.25	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	-1	0	0
C4	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0
C5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
C6	0	0	0	0	0	0	0	-0.9	-1	0.5	0	0	0	-1	-0.6	0	0	0	0
C7	0	0	0	0	0	0	0	0.63	0	-1	-1	0	0	-0.7	-1	0	0	0	0
C8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C9	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C11	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0
C13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
C16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C17	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0
C18	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0
C19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C20	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0

The Fuzzy Cognitive Map is presented in Fig. 4.

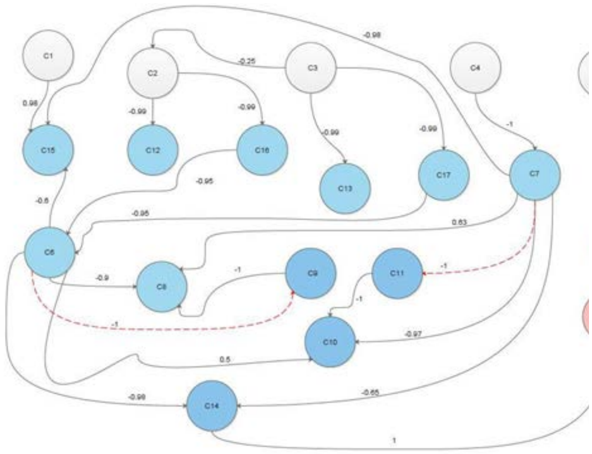

Fig. 4. Fuzzy Cognitive Maps for BEMS modeling

The red dashed lines represent the relationship between the boiler and storage tank temperature with the concepts regarding the common position of the valves and acts only when it is necessary to send water to both directions.

Results of the algorithm

To understand this process, we will give the following example.

Inputs:

C1=0.9

C2=0.25

C3=0.3

C4=0.2

C5=0

then the algorithm gives appropriate values to the concepts. The initial vector A is:

A initial= [0.9 0.25 0.3 0.2 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0]

After a few iterations, the system reaches equilibrium. So, the final vector A will occur after the repetitions and it will be:

A final:

[0.9 0.25 0.3 0.2 0 0.176 0.328 0.318 0.529 0.448 0.430 0.321

0.542 0.556 0.498 0.312 0.303 0 0.765]

i.e. the outputs will be OUT1 = 0 OUT2=0.765 and the way

the outputs reach the equilibrium point, which is shown in the figure below (Fig.5). These values can be directly defuzzified without using an interpretation criterion

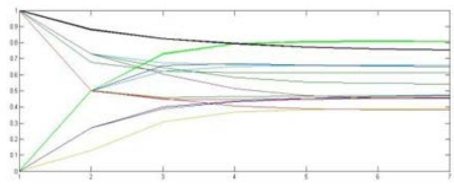

Fig. 5. System Output

In order to give a better view on the new meth-od we are going to compare its results with the ones from a simulation ran using the existing Fuzzy Cognitive Maps model. The results from the former simulation for the same initial val-ues are the following [13]:

A final

[0.659 0.612 0.659 0.659 0.659 0.385 0.457 0.441 0.659 0.379 0.659 0.474 0.46 0.452 0.650 0.474 0.460 0.807 0.749]

However, these values require the use of the interpretation criterion; Eq (4). So, the final output vector becomes:

A final

[0.318 0.225 0.318 0.318 0.318 0 0 0 0.318 0 0.318 0 0 0
0.315 0 0 0.614 0.499]

We can easily notice that with the proposed method the concepts whose values should re-main constant, as they are not being affected by any other weight, have the expected value whereas with the previous method they stabi-lize always at the value 0.318 regardless of their initial one. This causes the other values to change and differ from the expected ones. Es-pecially in the case of the operation of the air conditioning where it should operate at a medi-um velocity and the result of the previous method dictates that it should operate at a high one, thus consuming more energy and creating an uncomfortable environment for its users. Therefore, the revised proposed method is addressing this drawback of the previous FCM models.

Conclusions and future research

Summarizing this paper, it becomes obvious they need to further investigate and improve the Fuzzy Cognitive Maps method. Fuzzy Cognitive Maps is a control method that is very promising in the field of energy efficiency of buildings.

The experiments and simulations conducted above reveal the following conclusions:

The convenience offered by FCMs when we face complex problems, such as the control of a building automation which require the consideration of many parameters. The controller which was developed gives us much faster and accurate results on how to effectively use the building automation without wasting time in the mathematical modeling of the problem.

The FCM developed simplifies the study of energy saving.

The improvements proposed in this paper lead to a more accurate results of the method and can lead to further improvements.

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METADATA

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