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Modeling Complex Systems Using Fuzzy Cognitive Maps

Chrysostomos D. Stylios and Peter P. Groumpos

***Abstract*—This research deals with the soft computing methodology of fuzzy cognitive map (FCM). Here a mathematical description of FCM is presented and a new methodology based on fuzzy logic techniques for developing the FCM is examined. The capability and usefulness of FCM in modeling complex systems and the application of FCM to modeling and describing the behavior of a heat exchanger system is presented. The applicability of FCM to model the supervisor of complex systems is discussed and the FCM-supervisor for evaluating the performance of a system is constructed; simulation results are presented and discussed.**

***Index Terms*—Complex systems modeling, fuzzy cognitive maps, soft computing.**

I. Introduction

Modern technological systems are complex and they are usually comprised of a large number of interacting and coupling entities that are called subsystems and/or components. These systems have nonlinear behavior and cannot simply be derived from summation of analyzed individual component behavior. In the case of complex dynamical systems, conventional modeling and controlling methods have a limited contribution. The modeling of complex systems requires new methods that can utilize the existing knowledge and human experience. Furthermore these methods are equipped with sophisticated characteristics such as failure detection, optimization and identification qualities. In this research, the soft computing methodology of fuzzy cognitive map (FCM) has been improved and enhanced using a new construction algorithm, and is implemented for modeling complex systems.

Fuzzy cognitive map is an illustrative causative representation of the description and modeling of complex systems. FCM draws a causal representation, which intends to model the behavior of any system. FCM is an interactive structure of concepts, each of which interacts with the rest showing the dynamics and different aspects of the behavior of the system [1]. The human experience and knowledge on the operation of the complex system is embedded in the structure of FCM and the FCM developing methodology, i.e. using human experts that have observed and known the operation of the system and its behavior under different circumstances [2]. The FCM model of the whole system is illustrated by a graph showing the cause and effect along the concepts (Fig. 1).

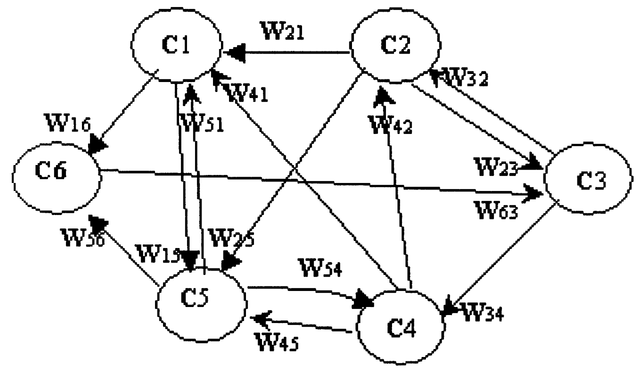

Fig. 1. Simple FCM scheme.

The objective of this research is to introduce a methodology for developing FCMs based on fuzzy logic theory, to investigate the advantages and potential use of FCM in modeling complex systems and to prove how appropriate FCMs are used to exploit the knowledge and experience of experts on the description and modeling of the operation of a complex plant. The development of FCM is based on using words to describe worlds, [3]. FCM represents knowledge and relates states, variables, events, inputs and outputs in a manner, which is analogous to that of human beings. This soft computing methodology could help humans to construct sophisticated systems, as it is generally accepted that the more symbolic and fuzzy representation is used to model a system the more sophisticated the system is.

This paper is organized as follows. Section II describes the representation and mathematical formulation of FCM, and the algorithm of a new methodology for developing FCMs is proposed. Section III describes the development of a FCM model for the heat exchanger system that is common in process industry. Section IV presents the features and potential use of FCM for modeling complex systems, and a two level hierarchical structure is proposed, where the supervisor is modeled as FCM, and the model of a FCM-supervisor which evaluates the performance of a system is developed. Finally, Section V concludes the paper.

II. Fuzzy Cognitive Maps

FCMs consist of nodes and weighted arcs, which are graphically illustrated as a signed weighted graph with feedback. Nodes of the graph stand for the concepts describing behavioral characteristics of the system. Signed weighted arcs represent the causal relationships that exist among concepts and interconnect them [4]. This graphic display shows clearly which concept influences which concept and what this degree of influence is [5].

A. FCM Description

Fig. 1 illustrates a simple FCM consisting of six concepts. Concepts represent conceptual characteristics of the system and weight W_{ij} represents the cause and effect influence of one concept on another. In general, concepts represent key-factors and characteristics of the modeled system and stand for inputs, outputs, variables, states, events, actions, goals, and trends of any system. It is mentioned that concepts correspond to features of the system that experts use to describe its operation in terms of linguistic expressions, such as the high temperature of water

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or the performance of a system. Concepts take fuzzy values that are represented by value A_i, which results from the transformation of the real value of the system's variable for which a concept stands for, in the interval [0,1]. The relationships between concepts are described using a degree of causality and not the usual binary logic. Experts describe this degree of influence using linguistic variables for every weight; so weight W_{ij} for any interconnection can range from -1 to 1.

In the FCM structure the degree of causal relationship between different factors-concepts of the FCM can have either positive or negative sign and values of weights express the degree of the causal relationship [6]. Linkages between concepts express the influence one concept on another. There are three possible types of interaction. Interaction can express

- either positive causality between two concepts $(W_{ij} > 0)$ when the increase on the value of the i_{th} concept causes an increase of the value of the j_{th} concept;
- negative causality $(W_{ij} < 0)$ when the increase on the value of the i_{th} concept causes a decrease of the value of the j_{th} concept;
- no relationship $(W_{ij} = 0)$ between the i_{th} concept and the j_{th} concept.

The calculation rule that was initially introduced to calculate the value of each concept is based only on the influence of the interconnected concepts [1], [7]

$$A_j^t = f\left(\sum_{\substack{i=1 \\ i\neq j}}^{n} A_i^{t-1} W_{ij}\right) \tag{1}$$

where A_j^t is the value of concept C_j at time step t, A_i^{t-1} is the value of concept C_i at time step $t-1$, and W_{ij} is the weight of the causal interconnection from concept i_{th} toward concept j_{th}.

A more general formulation is proposed here to calculate the values of concepts at each time step, for FCM

$$A_j^t = f\left(\mathrm{k}_1^{\mathrm{i}} \sum_{\substack{i=1 \\ i\neq j}}^{n} A_i^{t-1} W_{ij} + \mathrm{k}_2^{\mathrm{j}} A_j^{t-1}\right). \tag{2}$$

The coefficients k_1^i and k_2^j must satisfy the conditions $0 \leq k_1^i \leq 1$ and $0 \leq k_2^j \leq 1$. The selection of coefficient k_1^i and k_2^j is dependent on the nature and type of each concept and may differ from concept to concept. This means that experts who develop the FCM may suggest that a concept is highly dependent on the interconnected concepts. Therefore k_1^i will be very high, close to value one or will not be so dependent on the other concepts and thus k_1^i will be quite low, close to zero. Hence k_1^i has a different value for every i concept.

The coefficient k_2^j represents the proportion of the contribution of the previous value (past history) of the concept in the computation of the new value and which differs from concept to concept. The coefficient k_1^i expresses the influence of the interconnected concepts in the configuration of the new value of concept A_i. Here the two coefficients are introduced. Initially, however, Kosko [1], [8] introduced FCM and assumed that the previous value of each concept did not participate in the calculation of the new value of concept, thus $k_2^j = 0$ and the coefficient $k_1^i = 1$.

For this research, it is assumed that the influence of the interconnected concepts is high and thus coefficient $k_1^i = 1$ and experts are asked to suggest the value of coefficient k_2^j for every concept. Equation (3) is proposed that includes the previous value of each concept in the calculation rule, which results in smoother variation of the values of concepts after each recalculation of their value, as it will become apparent in the example in Section III. The value A_j^t for each concept C_i at every time step is calculated by the following equation:

$$A_j^t = f\left(\sum_{\substack{i=1 \\ i\neq j}}^{n} A_i^{t-1} W_{ij} + \mathrm{k}_2^{\mathrm{j}} A_j^{t-1}\right) \tag{3}$$

where, A_j^t is the value of concept C_j at time step t, A_j^{t-1} the value of concept C_j at time step $t-1$, A_i^{t-1} the value of concept C_i at time step $t-1$, and W_{ij} is the weight of the interconnection from concept C_i to concept C_j and f is a threshold function.

Generally, two kinds of threshold functions are used in the FCM framework. One is the unipolar sigmoid function, where $\lambda \succ 0$ determines the steepness of the continuous function f and squashes the content of the function in the interval [0,1]

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

Another threshold function that has been used and which transforms the content of the function is in the interval $[-1,1]$, i.e.,

$$f(x) = \tanh(x).$$

The selection of the threshold function depends on the method that is used to describe the concepts. More specifically there are two methods, which are used to describe them in terms of FCM. The first one introduces two opposite concepts to the same FCM i.e. a concept named "wrong decision" and another one named "right decision" that take values in the interval [0,1]. The second method accepts negative values for one concept i.e. there is a concept named "decision" that can take negative values to describe the wrong decision and positive values to describe the right decision. In the latter the values of concept belong to the interval $[-1,1]$.

The overall mathematical description of a FCM, which is comprised of n concepts can be considered with an $1 \times n$ state vector $\mathbf{A}$, which gathers the values of the n concepts and an $n \times n$ weight matrix $\mathbf{W}_0$, which gathers the values of weights W_{ij} between concept C_i and C_j and the diagonal is zero. Thus, (3) calculates the value for every concept and can be written in a more compact form that will calculate the value of all the concepts of FCM

$$\mathbf{A}^t = f\left(\mathbf{A}^{t-1}\mathbf{W}_0 + k_2^j \mathbf{A}^{t-1}\right). \tag{4}$$

Or, if we replace the diagonal elements of weight matrix $\mathbf{W}_0$ that are zero with the weights $W_{ii} = k_2^j$, there will be produced a weight matrix $\mathbf{W}$ and (4) will be transformed in (5) that calculates all the values of the n concepts of FCM at time step t

$$\mathbf{A}^t = f(\mathbf{A}^{t-1}\mathbf{W}). \tag{5}$$

Thus, (5) computes the new state vector $\mathbf{A}^t$ of FCM at time step t, which results from the multiplication of the previous, at time step $t-1$, state vector $\mathbf{A}^{t-1}$ by the weight matrix $\mathbf{W}$.

B. Developing Fuzzy Cognitive Maps

The method that is used to develop and construct the FCM has great importance for its potential to sufficiently model a system. The proposed method is depending on the group of experts who operate, monitor and supervise the system and develop the FCM model. The proposed methodology extracts the knowledge on the system from the experts and exploits their experience on the system's model and behavior.

In the first step of the methodology, the group of experts determines the number and kind of concepts that comprise the FCM. An expert from his/her experience knows the main factors that describe the behavior of the system; each of these factors is represented by one concept of the FCM. Experts know which elements-concepts of the system influence other elements; for the corresponding concepts they determine the negative or positive effect of one concept on the others, with a fuzzy degree of causation. In this way, an expert decodes his/her own knowledge on the behavioral model of the system and transforms his/her knowledge in a dynamic weighted graph, the FCM.

A methodology of developing a FCM based on fuzzy expressions to describe the interrelationship among concepts is proposed here. Experts are asked to describe the relationship between two concepts with a fuzzy rule describing the cause and effect and then they infer the degree of influence from one concept on another using linguistic notion [10]. With this method experts are forced to think about and describe the existing relationship between the concepts and so they justify their suggestion. Each expert, in fact, determines the influence of one concept on another as "negative" or "positive" and then evaluates the degree of influence using a linguistic variable, such as "strong influence," "medium influence," "weak influence" etc.

The proposed methodology is applied using the following algorithm. It is supposed that there are M experts who evaluate every interconnection and describe it with a fuzzy rule inferring a linguistic weight. According to the proposed algorithm, at least $M/3$ of the experts have to fully agree with their suggestions thus an average weight of the interconnection is calculated. Otherwise they are asked to reassign this particular weight. At the next step of the algorithm, the suggested linguistic weights for an interconnection may be aggregated using the well-known fuzzy logic method of SUM, an aggregated linguistic weight is produced, then the defuzzification method of center of gravity is applied and a numerical weight for the interconnection is calculated [11], [12]. If for one interconnection the M experts have suggested more than $2M/3$ weights, which do not belong to the same neighborhood, the aggregated weight does not express an overall suggestion. Thus, this is in contrast to the idea of aggregation of human knowledge and experience, which is behind FCM theory. The definition of neighborhood of weights is proposed here.

Definition 1. Neighborhood of Weights: A linguistic weight does not belong to a neighborhood when it is not partially overlapping with at least another linguistic weight proposed by another expert.

Here the credibility weight for every expert is introduced in order to increase the objectivity of the FCM developing method, accepting that initially all the experts are equally credible and have the same credibility weight, which is reduced by r% every time there is a wrong suggestion for an interconnection. Every expert that assigns a linguistic weight for an interconnection, which does not belong to the neighborhood of the proposed weights, is penalized, which means his/her credibility, is reduced by r%. The credibility of every expert is introduced in the calculation of the aggregated weight through the multiplication of the suggested linguistic weight by the corresponding credibility weight. After a good number of experiments were conducted, there was evidence that experts tend to make some wrong suggestions unintentionally. The relatively small reducing degree is suggested to be $r = 5\%$.

Algorithm for Developing Fuzzy Cognitive Maps

Step 1: For all the M experts, set credibility weight $b_k = 1$

Step 2: Each of the M experts is asked to suggest and describe each of the N concepts that comprise the FCM.

Step3: For all the ordered pair of concepts (C_i and C_j) each k_{th} of the M experts is asked to make the following statement:

WHEN the value of concept C_i {**increases**, **decreases**, **is stable**}**THIS** causes value of concept C_j to {**increase**, **decrease**, **nothing**} **THUS** the influence of concept C_i on concept C_j is *T(influence)*

Step 4: IF for one interconnection more than 2M/3 different linguistic weights are suggested
THEN
ask experts to reassign weights for this particular interconnection and go to step3
ELSE
IF the k_{th} expert has proposed for an interconnection a linguistic weight that does not belong to the neighborhood of weights
THEN
disregard this particular linguistic weight and penalize the expert who chose the "distant" weight and set him a new credibility weight $b_k = r b_k$

Step 5: Aggregate all the linguistic weights proposed for every interconnection using the SUM method where the membership function μ suggested by k_{th} expert is multiplied by the corresponding credibility weight b_k. Use the COG defuzzification method to calculate the numerical weight W_{ij} for every interconnection.

Step 6: IF there is an ordered concept pair not examined go to step 3
ELSE
construct the weight matrix $\mathbf{W}$ whose are the defuzified weights W_{ij}

END.

The causal interrelationships among concepts are declared using the variable *Influence* which is interpreted as a linguistic variable taking values in the universe $U = [-1, 1]$. Its term set *T(influence)* is suggested to comprise nine variables. Specifically using nine linguistic variables, an expert can describe in detail the influence of one concept on another and can discern between different degrees of influence. This is very difficult if the term set has greater (let's say 12 or 15) or less variables (let's say 3 or 6) for the description of the influence that would be either extremely detailed or very generic. Here are the nine variables: *T(influence)*={negatively very strong, negatively strong, medium, negatively weak, zero, positively weak, positively medium, positively strong and positively very strong}. The corresponding membership functions for these terms are shown in Fig. 2 and they are μ_{nvs}, μ_{ns}, μ_{nm}, μ_{nw}, μ_{z}, μ_{pw}, μ_{pm}, μ_{ps} and μ_{pvs}.

Fig. 3 illustrates an example where five experts describe the relationship between two concepts with five linguistic weights with the corresponding membership functions: μ_{nm}, μ_{pm}, μ_{ps}, μ_{ps} and μ_{ps}, as shown at the 'selected values' part of the figure. At the graphical part of the figure the three different membership functions μ_{nm}, μ_{pm}, μ_{ps} are illustrated along with the aggregated linguistic weight. In this case it is supposed that the five experts have the same credibility weight equal to 1. The five linguistic variables are aggregated using the SUM method and the result has magnitude 3 as shown in the Fig. 3. The aggregated weight could be defuzzified using the COG method and the crisp weight of 0.45 would be produced and assigned to this interconnection. However according to the algorithm (step 4, second if), the

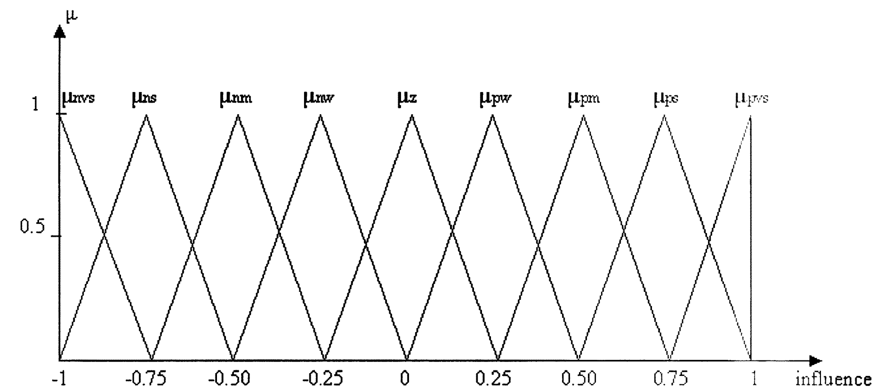

Fig. 2. Membership functions for the linguistic variable *influence*.

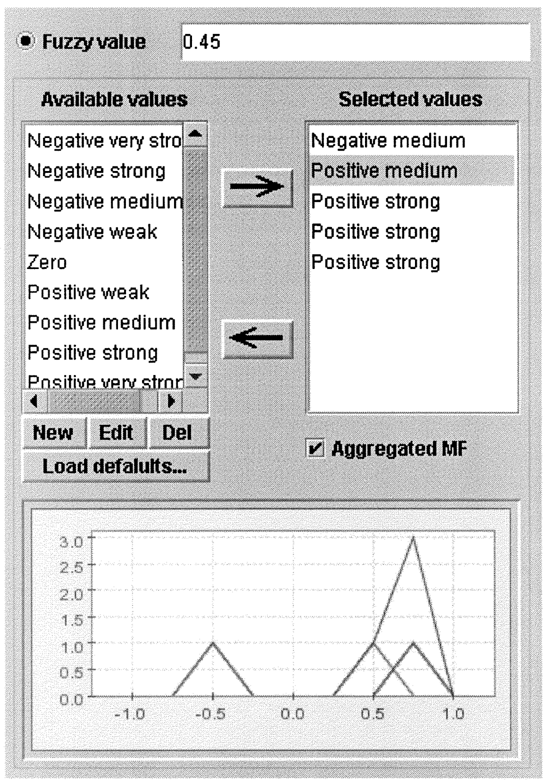

Fig. 3. Illustration of five linguistic weights suggested by experts and the aggregated weight.

proposed linguistic weights are checked in terms of their neighborhood. The linguistic weight with the membership function μ_{nm} is found not to belong to the neighborhood and thus it is not taken into consideration. Furthermore the corresponding expert who proposed this weight is penalized by reducing his/her credibility by $r\%$. Therefore, the remaining four proposed linguistic weights are aggregated and defuzzified and the numerical weight of 0,688 is produced, which will be the weight of this interconnection.

The proposed methodology has the advantage that experts do not have to assign numerical causality weights but they are asked to describe the relationship among concepts using the IF THEN rule and to infer the degree of causality. This approach is similar to methods for developing fuzzy rule based system but it requires much effort and experts have to put greater attention because of the nature of concepts [10]–[12]. Moreover the idea of credibility weights for experts is introduced.

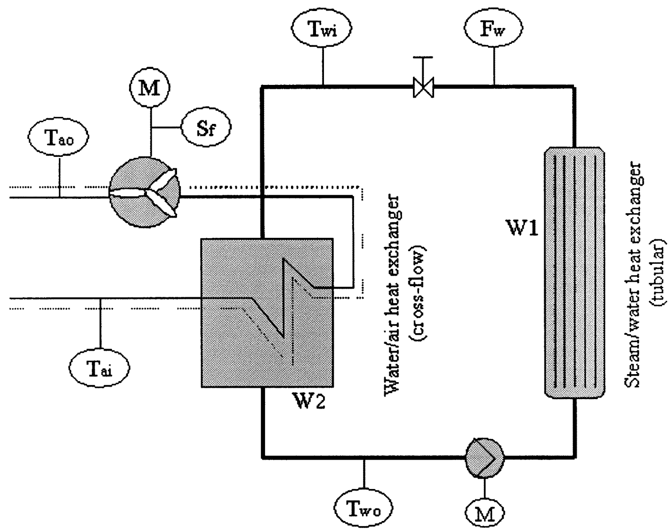

Fig. 4. Heat exchanger system description.

III. Heat Exchanger Fuzzy Cognitive Map Model

Heat exchanger is a standard part in the chemical and process industry [13]. Temperature control is still a major challenge as the heat exchanger is used over a wide range of operating conditions. The nonlinear behavior of the system depends strongly on the flow rates and on temperatures of the media. A cross-flow water/air heat exchanger is considered, which is subject to immeasurable or nonmodeled disturbances that require the use of knowledge based techniques. The requirement is the development of a behavioral model for the heat exchanger system, which will control the water outlet temperature by manipulating the flow rate of the air. This observation makes suitable the use of the soft computing techniques of FCM. The need to use FCM is motivated by the nature of the process under investigation where there is no analytic model or there is an inadequate one, but the human operator can manually control the process to a satisfactory degree. Thus, FCM can be used to model and control the heat exchanger process.

In most process industries the thermal plant comprises two heat exchangers, but our pilot plant that is under investigation and is depicted in Fig. 4, considers only the secondary circuit. The heat exchanger is comprised of: W1, which is a tubular steam/water heat exchanger, and W2, which is the cross-flow water/air exchanger under investigation. The water in the examining circuit is heated by means of W1. On the left side of the circuit, the water is cooled in the cross-flow water/air heat exchanger W2. Fan sucks in cold air from the environment (temperature T_{ai}). After passing the heat exchanger and the fan, the air is blown out back to the environment. The water temperature T_{wo} is controlled by manipulating the fan speed S_f. The control variable T_{wo} depends on the manipulated variable S_f and the measurable disturbances: inlet water temperature T_{wi}, air temperature T_{ai} and water flow rate F_w. In most plants, the water flow rate is usually regulated by a PI-controlled pneumatic valve, strongly influences the behavior of the heat exchanger W2 and it is a major challenge in designing a temperature controller for T_{wo} when the flow rates vary in a wide range [14], [15].

The operators of the heat exchanger gather experience that can be used to further build the model. The first step in constructing the FCM model of the heat exchanger is the determination of the concepts that comprise the FCM. Concepts will stand for the input and output variables of the process. In the previous paragraph the thermal plant was described and the concepts of the FCM were derived from this discussion. Four different experts following the algorithm presented in Section II developed the FCM model that is comprised of five concepts.

Concept1: The fan speed S_f, which is the manipulated variable.
Concept2: The water flow rate F_w.
Concept3: The water inlet temperature T_{wi}.
Concept4: The air inlet temperature T_{ai}. It is the environmental temperature that cannot be manipulated as it depends on weather and season.
Concept5: The water outlet temperature T_{wo}, which is the output of the model.

When the experts have described the concepts of the FCM model for the heat exchanger, the causal interconnections between concepts have to be determined. Experts are asked to describe the relation between concepts according to the third step of the proposed algorithm and to infer a linguistic value for each linkage.

The connections between concepts are

Linkage1: It connects concept1 (fan speed S_f) with concept5 (water outlet temperature T_{wo}). When value of S_f increases the value of T_{wo} decreases.
Linkage2: It connects concept2 (flow rate F_w) with concept5 (water outlet temperature T_{wo}). When value of F_w increases the value of T_{wo} increases.
Linkage3: It connects concept2 (flow rate F_w) with concept1 (fan speed S_f). When value of F_w increases the value of S_f increases.
Linkage4: It connects concept3 (water inlet temperature T_{wi}) with concept5 (water outlet temperature T_{wo}). When value of T_{wi} increases the value of T_{wo} increases.
Linkage5: It connects concept3 (water inlet temperature T_{wi}) with concept1 (fan speed S_f). When value of T_{wi} increases the value of S_f increases.
Linkage6: It connects concept3 (water inlet temperature T_{wi}) with concept2 (flow rate F_w). When value of T_{wi} increases the value of F_w decreases.
Linkage7: It connects concept4 (air inlet temperature T_{ai}) with concept5 (water outlet temperature T_{wo}). When value of T_{ai} increases the value of T_{wo} increases.
Linkage8: It connects concept4 (air inlet temperature T_{ai}) with concept1 (fan speed S_f). When value of T_{ai} increases the value of S_f decreases.
Linkage9: It connects concept5 (water outlet temperature T_{wo}) with concept2 (flow rate F_w). When value of T_{wo} increases the value of F_w decreases.
Linkage10: It connects concept5 (water outlet temperature T_{wo}) with concept1 (fan speed S_f). When value of T_{wo} increases the value of S_f increases.

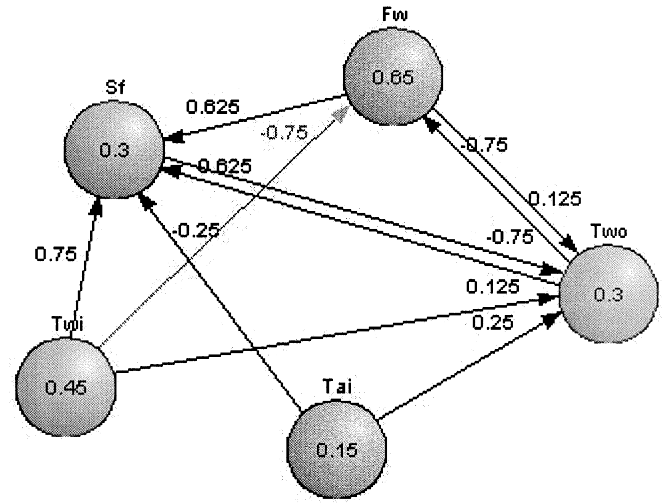

Fig. 5. FCM model of the heat exchanger.

Fig. 5 depicts the FCM that experts developed to describe, model and control the heat exchanger system. The FCM model for the heat exchanger is in accordance with the models and experiments described in [13]–[15]. This FCM was developed according to the algorithm applied in Section II-B and the following weight matrix was produced

$$\mathbf{W} = \begin{bmatrix} 0, & 0.625 & 0.75 & -0.25 & 0.625 \\ 0, & 0 & -0.75 & 0 & -0.75 \\ 0, & 0 & 0 & 0 & 0 \\ 0, & 0 & 0 & 0 & 0 \\ -0.75, & 0.125 & 0.125 & -0.75 & 0 \end{bmatrix}.$$

The values of concepts correspond to real measurements that have been transformed in the interval [0,1]. A transformation interface with the corresponding mechanism is needed, which will transform the measures of the system to their representative values of concepts in the FCM model and vice versa. The initial measurements of the heat exchanger system have been transformed to concept values and the initial vector of FCM is formed

$$\mathbf{A}_0 = [0.3 \quad 0.65 \quad 0.45 \quad 0.15 \quad 0.3].$$

In the illustration of the FCM in Fig. 5 the initial value of each concept and the interconnections with their weights are shown. For these initial values of concepts, FCM starts to simulate the behavior of the process. At each running step of the FCM, the value of concepts is calculated according to (4). For the FCM area, a running step is defined as the time step during which the values of the concepts are calculated. The value of each concept is defined by taking all the causal linkage weights pointing to this concept and multiplying each weight by the value of the concept that causes the linkage, and adding the last value of each concept. Then, the sigmoid function with $\lambda \succ 0$ is applied and thus the result belongs to the range [0,1].

The FCM model for the heat exchanger with the $\mathbf{A}_0$ initial vector values simulates the behavior of the system, and the values of concepts for five steps are depicted in Fig. 6. Table I shows the values of concepts for 5 simulation steps. As it can be seen, the values of FCM concepts do not change after four steps. Evaluating these simulation results we see that the value of fan speed S_f has increased, the value of flow rate F_w has decreased and after the third step, the water outlet temperature T_{wo} is reduced under the value of 0.40 that is within the accepted limits. When the FCM reaches an equilibrium region, new values of

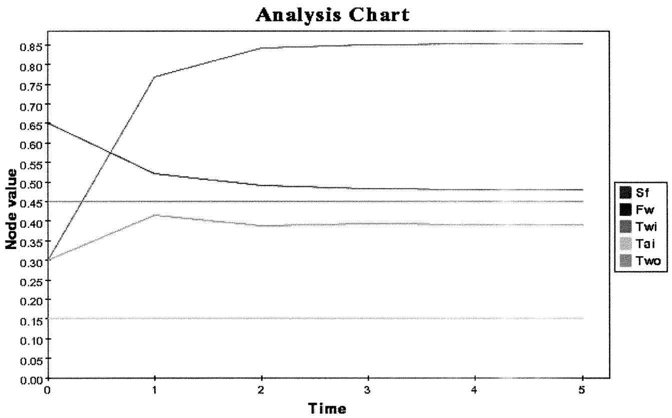

Fig. 6. Variation of values of concepts for FCM model of the five simulation steps.

TABLE I
VALUES OF CONCEPTS FOR THE FCM MODEL OF HEAT EXCHANGER FOR 5 SIMULATION STEPS

Step	Sf	Fw	Twi	Tai	Two
0	0,3	0,65	0,45	0,15	0,3
1	0,767	0,5218	0,45	0,15	0,413
2	0,840	0,4898	0,45	0,15	0,386
3	0,849	0,4818	0,45	0,15	0,392
4	0,851	0,4798	0,45	0,15	0,391
5	0,851	0,4793	0,45	0,15	0,391

input concepts are transformed to the corresponding real values and vice versa. In this example, when FCM reaches an equilibrium region, the new values of input concepts C1 (fan speed S_f) and C2 (flow rate F_w) are transmitted to the real system and set the corresponding fan speed S_f at 85,1% and reducing the flow rate F_w at 47.9%. Then, measurements of the water inlet temperature T_{wi}, the air inlet temperature T_{ai} and the water outlet temperature T_{wo} are transmitted to FCM. Finally the FCM-model will receive the new measurements from the heat exchanger, it will interact, it will reach an equilibrium region and it will transmit the values of concepts to the heat exchanger and this iterative procedure continues.

IV. FUZZY COGNITIVE MAP SUPERVISOR MODEL OF COMPLEX SYSTEMS

Complex processes are characterized by high dimension, comprised of subsystems that are strongly interconnected and mutually dependent. For such systems soft computing modeling techniques are proposed to address uncertainty issues [16]. A large number of complex processes are not well understood and their operation is "tuned" by experience rather than through the application of pure mathematic principles [17], [18]. Capturing and utilizing the expert's knowledge effectively and efficiently, promises to improve complex system models [19], [20]. Usually operators of the system observe multiple data simultaneously and they make decisions based on their experience and empirical knowledge [21].

The best-known way to manage complexity and model complex systems is the use of hierarchical approaches to modeling, design and operation [22]. An elegant approach is the supervision of complex systems with two-level hierarchical structure, such as the hierarchical structure, which is proposed and shown in Fig. 7. The implementation of FCM for modeling the supervisor of the whole system seems to be a promising methodology. In the lower level of the hierarchical structure will be the complex plant, which has been decomposed in subsystems and for each subsystem the corresponding local model has been constructed along with its conventional controller. These controllers (PID controller, local

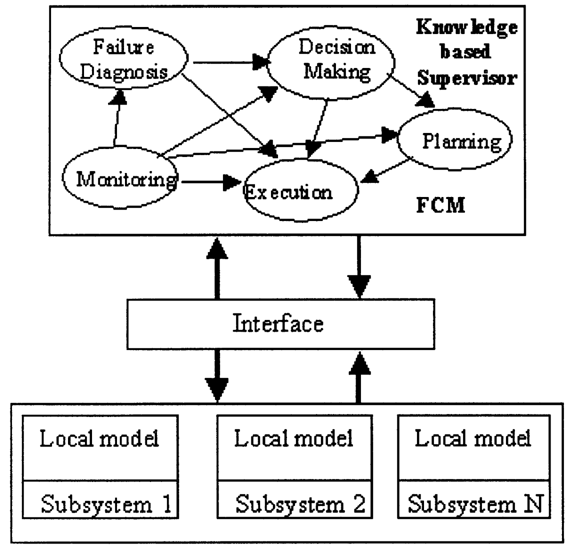

Fig. 7. Generic hierarchical modeling structure for complex systems.

LQG optimization techniques etc) perform the usual tasks. The supervisor-FCM is an augmented model of the complex system, which represents the relationships among the subsystems and their models. The supervisor-FCM monitors and organizes all the subsystems in order to accomplish a task, to help the operator make decisions, to plan strategically and to detect and analyze failures. The role of the FCM is to extend the range of application of a conventional controller by using a more abstract representation of the process, general control knowledge and adaptation heuristics, and to enhance the performance of the whole complex system.

The supervisor-FCM model can be expanded to include advanced features, such as fault diagnosis and effect analysis [23], or planning and decision making characteristics. Some FCM concepts could stand for device failure modes, their effects and causes, subsystem's normal or irregular operation, the functionality of the system, the system mission, and the ultimate function of the system. A very interesting quality of using the supervisor-FCM for complex systems is its ability to redesign the system, which can help the designer in estimating what will happen if some parameters of the system are altered. Another useful characteristic of the supervisor-FCM is its efficiency in examining what will happen if a scenario is running, and what will the consequences be for the whole process if a state of the system changes [24].

The usefulness of the FCM approach to modeling the supervisor of hierarchical systems will be shown by developing a part of the supervisor for the heat exchanger problem. The FCM-supervisor models the overall performance of the heat exchanger and the influence of failures and maintenance on the system's performance. Four experts have developed the FCM-supervisor, which is shown in Fig. 8, using the algorithm proposed in Section II. They decided what are the most important aspects that influence the "exchanger performance," so FCM is built around the main concept C1, which represents the "Exchanger Performance." Then, experts determined the factors of the heat exchanger system that influence this concept, thus concept C1 is dependent on the following concepts:

Concept C2: "Failures on fan system;"
Concept C3: "Failures on the water flow control system;"
Concept C4: "Other malfunctions of subsystems;"
Concept C5: "Maintenance of subsystems;"

Subsequently, experts described the relationship between concepts and determined the influence from one concept to another using the

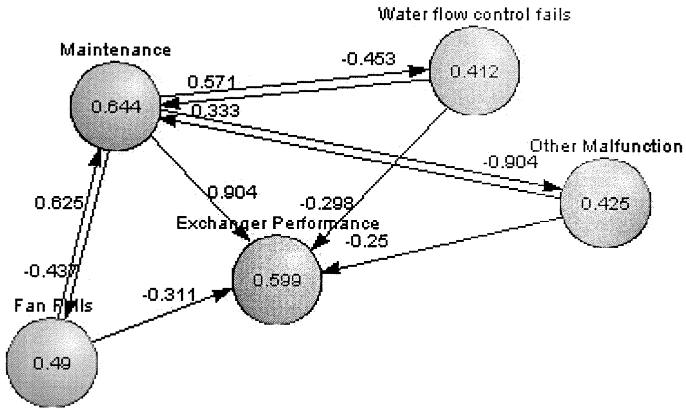

Fig. 8. FCM-supervisor model describing heat exchanger performance.

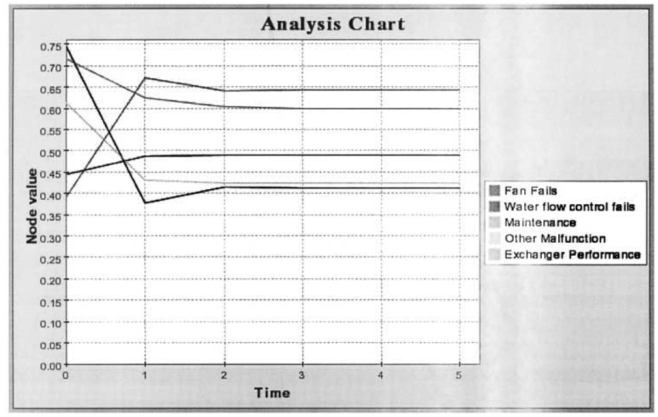

Fig. 9. The variation of values of FCM-supervisor concepts for 5 simulation steps.

TABLE II
VARIATION OF CONCEPTS VALUES OF FCM-SUPERVISOR

Step	Exchanger Performance	Fan Fails	Water flow control fails	Other Malfunction	Maintenance
0	0,715	0,446	0,743	0,614	0,39
1	0,62438	0,487166	0,377046	0,430126	0,671892
2	0,604287	0,489912	0,415368	0,424906	0,640817
3	0,599781	0,490095	0,411298	0,424758	0,644307
4	0,598768	0,490108	0,41173	0,424754	0,643915
5	0,59854	0,490108	0,411684	0,424754	0,643959

algorithm of Section II-B. Using this method they created the weight matrix of the FCM-supervisor. Experts have a strategy on their mind how the FCM concepts influence each other and to which degree. When the value of Concept 2 "failures on fan system" is increased, this causes the value of concept C1 "exchanger performance" to decrease and at the same time to require the increase of the "maintenance of subsystems" that is represented by concept C5. On the other hand, the increase of "maintenance" reduces the appearance of "failures on fan system," that is, concept C2. This is the cogitative behind the experts who developed the FCM-supervisor.

Moreover, experts were asked to suggest the coefficient k_2^j for each concept that represents the proportion of the contribution of the previous value (past history) of the concept itself in the computation of the new value; and these coefficients are in the diagonal of the weight matrix

$$\mathbf{W} = \begin{bmatrix} 0.936, & -0.311 & -0.298 & -0.25 & 0.904 \\ 0, & 0.267 & 0 & 0 & -0.437 \\ 0, & 0 & -0.438 & 0 & -0.453 \\ 0, & 0 & 0 & 0.116 & -0.904 \\ 0, & 0.625 & 0.571 & 0.333 & -0.489 \end{bmatrix}.$$

The initial state vector $\mathbf{A}_0$ of FCM-supervisor is the following $\mathbf{A}_0 = [0.715\ 0.446\ 0.743\ 0.614\ 0.39]$. The FCM-supervisor with this initial state vector and the weight matrix starts to simulate and models the behavior of the FCM-supervisor. The results of the simulation using (5) for the values of concepts of FCM-supervisor for 5 steps are presented in Table II and shown on Fig. 9. Examining the FCM-supervisor it is concluded that the initial high value of the "exchanger performance" is reduced and the initial low value of "maintenance" increases in order to compensate the high values of concepts "failures on fan system" and "failures on the water flow control system." Finally the FCM-supervisor reaches an equilibrium region of concepts values and stops to interact; if the values outlined by this region are accepted that means the value of "exchanger performance" is greater than the minimum acceptance level $(EP > 0.55)$; then the overall performance is accepted, otherwise the designer has to redesign the system and to develop a new infrastructure that will have better "exchanger performance" and/or more efficient "maintenance" that will eliminate failures appearance in the heat exchanger system.

Here only a part of the FCM-supervisor has been developed to illustrate the role of the supervisor and it is obvious that the actual FCM-supervisor has to include many other concepts, representing different variables and factors from different subsystems; to accomplish general operations and playing different scenarios.

V. SUMMARY

The soft computing technique of FCM for modeling and analyzing complex systems has been presented in this research paper. A calculation rule and a new algorithm has been proposed for developing FCMs using a method to extract knowledge and experience from experts who monitor, supervise and operate a complex system. One of the most important steps during the development of FCM model is the determination of the concepts by experts, which best describe the system and the assignment of the direction and grade of causality among concepts. The use of FCM to model the process industry problem of heat exchanger was illustrated, this example revealed how a FCM is constructed, how concepts are chosen and how values are assigned to the interconnections between concepts. Subsequently, the constructed FCM model was used to model and control the heat exchanger, run simulations and the results obtained were presented. A two-level hierarchical structure was also proposed to handle modeling of complex systems, where the supervisor is modeled as a FCM. The FCM modeling approach is symbolic, presenting abstract knowledge and is based on human expert experience and knowledge. FCM models the behavior of a complex system and offers an opportunity to produce new knowledge based system applications, addressing the need to handle uncertainties and inaccuracies associated with real problems. The obtained simulation results for both examples are satisfactory and promise to advance further the modeling and controlling of complex systems using soft computing methodologies, namely FCM.

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