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Fuzzy Cognitive Map Approach to Process Control Systems

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Abstract

A new approach to describe and control complex systems is proposed which is based on Fuzzy Cognitive Map (FCM) Theory. In this paper the description and the mathematical model of Fuzzy Cognitive Maps are examined and a new equation for calculation of Fuzzy Cognitive Maps (FCM) values is suggested. A new methodology for constructing and developing Fuzzy Cognitive Maps that exploits experts who use fuzzy rules to explain the cause and effect among concepts is described. The application of FCMs in a process control problem is investigated indicating the effectiveness of FCMs. A two-level structure for Supervisory Control of the process is proposed, where the supervisor is modeled as an FCM and is used for failure detection and decision analysis; some interesting points for further research are included. There is an increasing demand for more autonomous and intelligent systems, and the application of FCMs in the field of control and systems may contribute in the development of such systems.

Keywords: Fuzzy Cognitive Map, Control Systems, Supervisory Control.

1. Introduction

It is widely recognized that conventional methods in control systems have significantly contributed to the research and solution of many control problems, but their contribution on the solution of increasingly complex dynamical systems has started to show some practical difficulties. It has became quite clear that the requirements in control and even more in supervisory control cannot be met only with the existing conventional control theory. Thus, it is necessary to investigate and use new methods that will exploit past experience, will have learning capabilities, and will be equipped with failure detection and identification characteristics. In other words, soft computing becomes an important alternative to conventional control. One such new theory for control, as well as for modeling systems, which will contribute to the effort for more intelligent control methods, is the Fuzzy Cognitive Map (FCM) Theory, which is proposed in this paper.

Fuzzy Cognitive Map (FCM) Theory uses a symbolic representation for the description and modeling of systems. It utilizes concepts to illustrate different aspects in the behavior of the system and these concepts interact with each other showing the dynamics of the system. A Fuzzy Cognitive Map (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 that know the operation of system and its behavior in different circumstances. Due to the dynamic nature of FCMs this can be exploited to represent and perform the control of a system.

A political scientist R. Axelrod [1)] first introduced cognitive maps for representing social scientific knowledge and describing the methods that are used for decision making in social and political systems. Then B. Kosko [6,7)] enhanced the power of cognitive maps considering fuzzy values for the concepts of the cognitive map and fuzzy degrees of interrelationships between concepts. 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. New kinds of Fuzzy Cognitive Maps have been proposed such as the extended FCM [5)] and the Neural Cognitive Maps [9)]. Fuzzy Cognitive Maps have been used for planning and making decisions in the field of international relations and political developments [17)] and they have been proposed as a generic system for decision analysis [20)] and for distributed cooperative agents [21)]. Fuzzy Cognitive Maps also have been used to analyze electrical circuits [14)], and to structure Virtual worlds [2)]. In the control related themes, FCMs have been used to model and support plant control [4)], to represent Failure Models and Effects Analysis for a system model [11,12)], and to model the supervisor of control systems [15,16)]. It is obvious that there is high interest in the use of FCM in a wide range of different fields.

In this paper the objective is to define and construct Fuzzy Cognitive Maps for process control systems and discuss their use for modeling complex systems. In section 2 the general description of FCMs is presented and a new calculation rule is proposed. Section 3 describes a new soft computing methodology for constructing and developing Fuzzy Cognitive Maps. In section 4 the implementation of an FCM to control a chemical process is proposed and some new results are described. Then in section 5 a two-level structure of FCMs that will be used to perform supervisory control with advanced characteristics is developed, and the failure part of a supervisor-FCM is constructed. Finally, section 6 concludes the paper and gives some future research directions.

2. Fuzzy Cognitive Maps

A Fuzzy Cognitive Map (FCM) could be regarded as a combination of Fuzzy Logic and Neural Networks. In a graphical illustration a FCM seems to be a signed weighted graph with feedback, consisting of nodes and weighted arcs. Nodes of the graph stand for the concepts that are used to describe the behavior of the system. Concepts are connected by signed and weighted arcs representing the causal relationships that exist between the concepts (Figure 1). Each concept represents a characteristic of the system; in general it stands for events, actions, goals, values, trends of the system that is modeled as an FCM. Each concept is characterized by a number A_i that represents its value and results from the transformation of the real value of the system's variable, for which this concept stands, in the interval [0,1]. It must be mentioned that all the values in the graph are fuzzy, so weights of the arcs are in the interval [-1,1]. Observing this graphical representation, it becomes clear which concept influences other concepts through the interconnections between concepts. This representation permits easily updating in the structure of the graph, such as the adding or deleting of an interconnection or a concept.

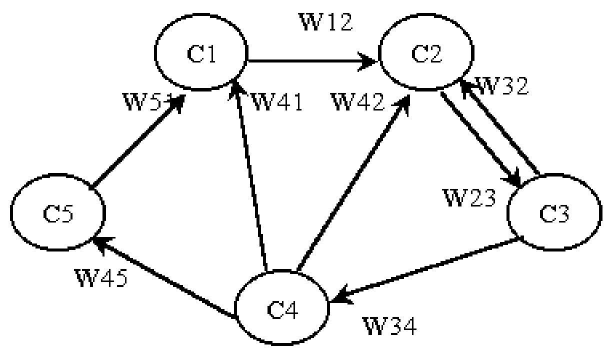

Figure 1. A simple Fuzzy Cognitive Map

Between concepts, there are three possible types of causal relationships, which express the type of influence of one concept to the others. The weight, denoted by W_{ij}, of the arc between concept C_i and concept C_j, could be positive, $(W_{ij} \succ 0)$ which means that an increase in the value of concept C_i leads to the increase of the value of concept C_j, and a decrease in the value of concept C_i leads to the decrease of the value of concept C_j. Or there is negative causality $(W_{ij} \prec 0)$ which means that an increase in the value of concept C_i leads to the decrease of the value of concept C_j and vice versa. When, there is no relationship between concept C_i and concept C_j, then $W_{ij} = 0$.

The value of each concept is influenced by the values of the connected concepts with the corresponding weights. A new calculation rule is proposed, which takes into consideration the last value of each concept. So the value A_i for each concept C_i is calculated by the following rule:

$$A_i^t = f(\sum_{\substack{j=1 \\ j \neq i}}^{n} A_j^{t-1} W_{ji} + cA_i^{t-1}) \tag{1}$$

Where A_i^t is the value of concept C_i at time t, A_j^{t-1} is the value of concept C_j at time $t-1$, A_i^{t-1} is the value of concept C_i at time $t-1$, and W_{ji} is the weight of the interconnection between C_j and C_i, and f is a threshold function. In this computational method a nonnegative parameter c is used that represents the fraction of the previous value of each concept which is added to the summed multiplication and so, the new value of each concept is calculated. This parameter can be in the range $0{,}01 \leq \text{c} \leq 1$. The choice of this parameter influences the number of steps that the FCM needs to reach an equilibrium point. The optimal choice for this parameter is around 0.1 where values of concepts converge faster than in the case where $c=1$ or $c=0.01$ where more simulation steps are needed to reach an equilibrium point.

Another more compact, mathematical model for Fuzzy Cognitive Maps, consists of a $1\times n$ state vector $\mathbf{A}$ which includes the values of the n concepts and an $n\times n$ weight matrix $\mathbf{W}$ which gathers the weights W_{ij} of the interconnections among the n concepts of the FCM. The matrix $\mathbf{W}$ has n rows and n columns where n equals the total number of distinct concepts of the FCM and the matrix diagonal is zero since it is assumed that no concept causes itself.

$$\mathbf{A}_t = f(\mathbf{A}_{t-1}\mathbf{W} + c\,\mathbf{A}_{t-1}) \qquad (2)$$

So the multiplication of the previous state vector $\mathbf{A}_{t-1}$ at time $t-1$ with the weight matrix $\mathbf{W}$ and the addition of the previous state vector $\mathbf{A}_{t-1}$ computes the new state vector $\mathbf{A}_t$. The new vector shows the effect that the change in the value of one concept has in the whole Fuzzy Cognitive Map. Equation (2) also includes the previous value of each concept, and so the FCM possesses memory capabilities and there is a smooth change after each new interaction among the concepts of the Fuzzy Cognitive Map.

3. Methodology for constructing Fuzzy Cognitive Maps

A Fuzzy Cognitive Map is a type of network, which is built by experts, using an interactive procedure of knowledge acquisition. An expert defines the main concepts that represent the model of the system, for this purpose, his knowledge and experience on the operation of the system are exploited. At first, the expert determines the concepts that best describe the system. A concept can be a characteristic of the system, a state or a variable or input or an output of the system. He knows which factors are crucial for the modeling of the system and he represents each one by a concept. Moreover, he has observed which elements of the system influence other elements; and for the corresponding concepts he determines the negative, positive or zero effect of one concept on the others. He gives a fuzzy value for each interconnection, since it is assumed that there is a fuzzy degree of causality between concepts.

In order to have better results in the development of the FCM, a group of experts is used, and the methodology is more objective as the experience and knowledge of the group of experts is exploited. All experts are polled together and they determine the relevant factors, the main characteristics of the system and thus the concepts, which should be contained in the Fuzzy Cognitive Map. Then, they determine the structure and the interconnections of the network using fuzzy conditional statements.

In this paper a new methodology for developing Fuzzy Cognitive Maps is proposed. It is based on Fuzzy Logic reasoning. Experts are asked to describe the relationships among concepts and they use IF-THEN rules to justify the cause and effect relationship among concepts and infer a linguistic weight for each interconnection.

The fuzzy rule of the form if-then describes the relationship between two concepts which appears as the weight of the interconnection. A fuzzy rule of the following form is assumed, where A, B, C are linguistic variables:

*IF an **A** change occurs in the value of concept C_i THEN a **B** change is caused in the value of concept* C_j. Thus, influence of *concept C_i to concept C_j is **C***

Every expert proposes a linguistic rule for every interconnection; the inference of the rule will be a linguistic value for the relationship between the two concepts. So the causal relationship will be described by a fuzzy rule, which gives the grade of causality between concepts and so the corresponding weight is inferred. Thus, everyone of the group of experts suggests for each interconnection a linguistic weight and the set of weights of each interconnection are integrated and a defuzzification method is used to produce a numerical weight for the interconnection. In fuzzy logic literature many methods for defuzzification have been proposed, such as the popular method of Center of Area, which is used here and the produced numerical weight will belong to the interval [-1,1].

As an example, the case where four experts describe the relationship among two concepts will be examined. Experts describe the relationship among concepts using the following fuzzy rules with linguistic variables.

1st expert:

IF a *very small change* occurs in value of concept C_i THEN *a large change* in value of concept C_j is caused.

Inference: The influence of C_i to C_j is *positively very high* and so value of W_{ij} is *positively very high*

2nd expert:

IF a *small change* occurs in value of concept C_i THEN a *large change* in value of concept C_j is caused.

Inference: The influence of C_i to C_j is *positively high* and so value of W_{ij} is *positively high*

3rd expert:

IF a *very small change* occurs in value of concept C_i THEN a *very large change* in value of concept C_j is caused.

Inference: The influence of C_i to C_j is *positively very much high* and so value of W_{ij} is *positively very much high*

4th expert:

IF a *small change* occurs in value of concept C_i THEN a *very large change* in value of concept C_j is caused.

Inference: The influence of C_i to C_j is *positively very high* and so value of W_{ij} is *positively very high*

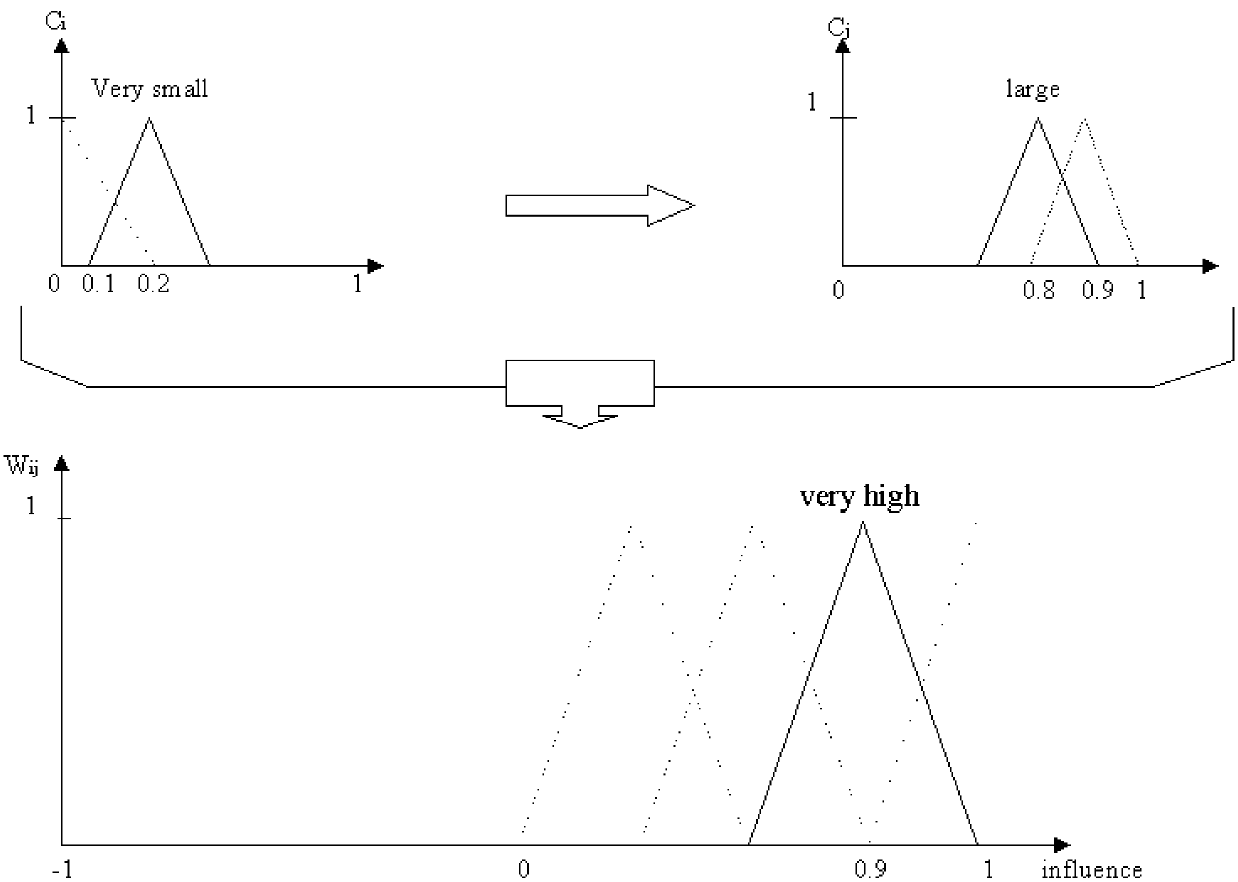

Figure 2. The 1st expert suggestion fuzzy rule for an interconnection.

Thus, these four fuzzy rules for the interconnection between C_i and C_j will be combined, the four linguistic variables for weight W_{ij} will pass through the defuzzifier, and the result will be a crisp number. For this example, it was supposed that well-known triangular membership functions stand for the weight as presented in figure 2. The defuzzifier method of Center of area was used and the result of the defuzzifier was $W_{ij} = 0.87$.

In this way, each expert describes the operation of Fuzzy Cognitive Map by an ensemble of fuzzy rules. Then, rules that concern one interconnection are evaluated in parallel using fuzzy reasoning, and the results of the rules are combined and defuzzified. The result will be a crisp number that will represent the weight of each interconnection. This construction methodology is straightforward to operators of the system; they determine the influence of one factor of the system to another using simple rules. This is very similar to the way in which humans relate states, variables, and events and store them in their mind as a causal network of causes and effects. The proposed methodology for developing Fuzzy Cognitive Maps exploits the experience and knowledge of a group of experts who use fuzzy rules to describe the behavior of the system. This is considered an objective methodology, which does not require experimental data for the values of concepts, as other methods do [13] especially for the kind of problems that FCMs are used usually, such as modeling of complex systems. Figure 2 depicts this new approach in constructing the Fuzzy Cognitive Map structure.

Up to now a new methodology for developing Fuzzy Cognitive Maps was presented, where experts involved in the construction of an FCM determine concepts and causality among them. Sometimes, this construction approach may lead to a distorted model of the system, since it is possible that experts have not considered the appropriate factors of the system and they may have assigned wrong causality weights among concepts of Fuzzy Cognitive Maps. But, the best performance of Fuzzy Cognitive Maps can be obtained by combining them with Neural Network characteristics and integrating their benefits. More specifically, neural learning techniques are utilized to train the Fuzzy Cognitive Map and determine the appropriate weights of the interconnections among concepts. The result will be a hybrid neuro-fuzzy system. Unsupervised learning laws have been proposed for the training of FCM, where the gradient of each weight is calculated by the application of general rule:

$$w'_{ij} = g(w_{ij}, A_i, A_j, A'_i, A'_j) \tag{3}$$

The Differential Hebbian learning law can be used as it has been proposed [8], in order to train the FCM, which means adjusting the weights of the interconnections between concepts, as if they were synapses in a neural network. The development of the appropriate learning algorithms for training Fuzzy Cognitive Maps needs more investigation and it will be the result of future research.

4. Implementation of FCMs in a Process Control Problem

In this section the modeling and control of a practical example will be examined. As it has become clear, the most important component in developing an FCM is the determination of the concepts that best describe the system and the direction and grade of causality among concepts. These aspects will be illustrated through this example.

The considered system has been used as an example to examine three different hybrid systems modeling methods [3] and here the applicability of Fuzzy Cognitive Maps in this process control problem will be examined. The system consists of two tanks depicted in figure 3. Each tank has an inlet valve and an outlet valve. The outlet valve of the first tank is the inlet valve of the second.

The control objective of the system is to keep the amount of liquid, in both tanks, between some limits, an upper $H_{\max}$ and a low limit $H_{\min}$. Another objective is to keep the temperature of the liquid in both tanks between a maximum value $T_{\max}$ and a minimum value $T_{\min}$. The desired target is keeping these variables in the range of values:

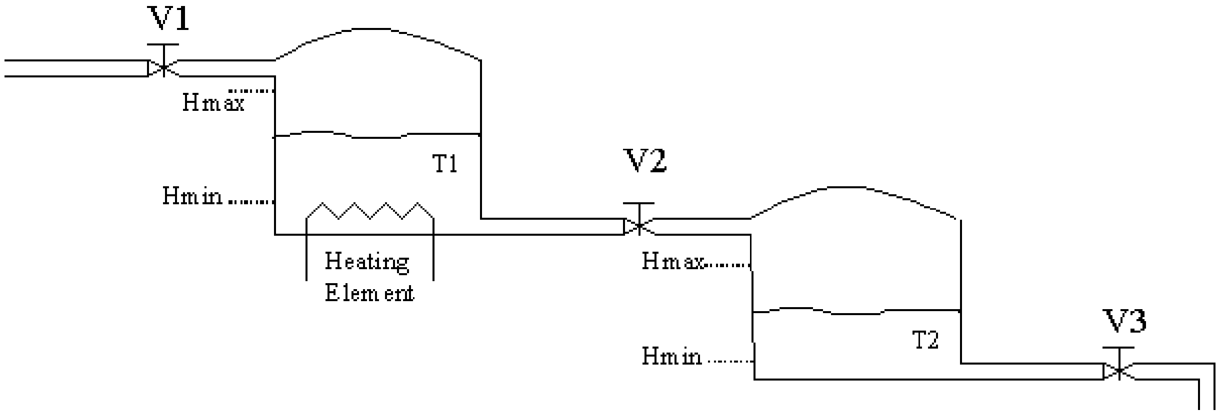

Figure 3. Example of a process system to be controlled

$$
\begin{aligned}
H^1_{\min} &\le H^1 \le H^1_{\max} \\
H^2_{\min} &\le H^2 \le H^2_{\max} \\
T^1_{\min} &\le T^1 \le T^1_{\max} \\
T^2_{\min} &\le T^2 \le T^2_{\max}
\end{aligned} \tag{4}
$$

The temperature of the liquid in tank1 is increased through the operation of a heating element. The temperature of the liquid in tank2 is measured with a thermometer, and controlled by a control system, so that when the temperature of liquid2 decreases, valve2 opens, so hot liquid comes into tank2.

An FCM will be constructed which will model and control the whole system. In order to determine the concepts of the FCM that describe the system, the variables of the system (such as the level of the liquid in each tank and/or the temperature) must be taken into account. Then, concepts are assigned for the system's elements that affect the variables (for example the state of the valves) of the system.

For this plant a Fuzzy Cognitive Map with eight concepts is developed, which gives a good description of the system and can be used to control the plant:

Concept1 The amount of liquid which tank1 contains. This amount is dependent on valve1 and valve2.

Concept2 The amount of liquid in tank2. This amount is dependent on valve2 and valve3.

Concept3 The state of the valve1. The valve is open, closed, or partially open.

Concept4 The state of the valve2. The valve is open, closed, or partially open.

Concept5 The state of the valve3. The valve is open, closed, or partially open.

Concept6 The temperature of the liquid in tank1.

Concept7 The temperature of the liquid in tank2.

Concept8 Describes the operation of the heating element which increases the temperature of the liquid in tank1.

These concepts must be connected with each other. First, the concepts that will be connected to each concept must be decided. Then, the sign of the connection is decided, and then the weight of each connection is determined.

The connections between concepts are:

Event1 It connects concept1 with concept3. It relates the amount of the liquid in tank1 with the operation of the valve1. When the height of the liquid in the tank is low, it is necessary to increase the amount of incoming liquid in the tank1 and so valve1 is opening.

Event2 It relates concept1 with concept4; when the height of the liquid in tank1 is high, the opening of valve2 (concept4) reduces the amount of liquid in tank1.

Event3 It connects concept2 with concept4; when the height of the liquid in tank2 is low, the opening of valve2 (concept4) increases the amount of liquid that comes into tank2.

Event4 It relates concept2 with concept5; when the height of the liquid in tank2 is high, the opening of valve3 (concept5) helps in keeping the amount of the liquid below an upper limit.

Event5 It connects concept3 (valve1) with concept1 (tank1); any change in valve1 influences the amount of liquid in tank1.

Event6 The value of concept4 (valve2) causes the decrease or not of the value of concept1 (tank1).

Event7 The value of concept4 (valve2) causes the increase or not of the amount of liquid in tank2 (concept2).

Event8 It relates concept5 (valve3) with concept2 (tank2), the value of concept5 causes the decrease or not of the amount of the liquid in tank2.

Event9 It connects concept6 (temperature in tank1) with concept8 (the operation of the heating element).When the temperature in tank1 is low, it causes the opening of the heating element.

Event10 It connects concept8 with concept6; the value of concept8 (operation of the heating element) increases the value of concept6 (temperature in tank1).

Event11 It connects concept6 with concept3 (valve1); when the temperature in tank1 reaches an upper limit, the opening of valve1 causes liquid of low temperature to enter tank1.

Event12 It relates concept7 (temperature in tank2) with concept4 (valve2); when the temperature in tank2 is below a limit, valve2 should open, thus allowing new hot liquid to enter tank2 from tank1.

Event13 It shows the effect of concept4 (valve2) on concept7 (the temperature in tank2); when valve2 (concept4) is open, hot liquid comes into tank2 and the temperature in tank2 (concept7) is increased.

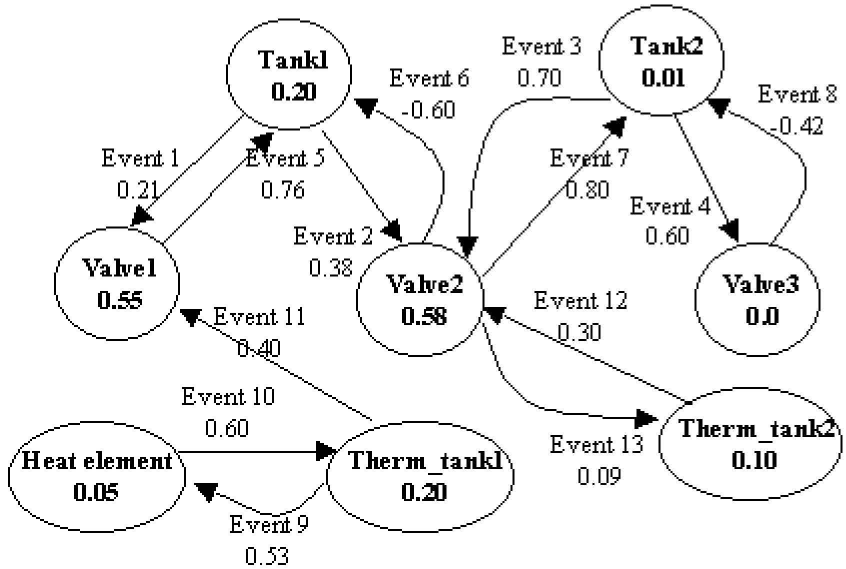

Figure 4. The initial FCM, with the first values for the concepts

In assigning weights to the interconnections, the experience of a group of experts is utilized. These experts use the methodology described in section 3 to determine the cause and effect relationship among concepts. As an example, the experts describe the influence of valve1 (concept3) on the amount of liquid in tank1 (concept1) using a set of fuzzy rules from which it is inferred that there is positive influence, which is transformed in the weight 0.76 (event 5). Each event (connection between concepts) has a weight, which ranges between [-1,1] and the group of experts determined it. Each concept has a value, which ranges in the interval [0,1] and it is obtained after thresholding the real value of the concept. It is apparent that an interface is needed which will transform the real measures of the system to their representative values in the FCM and vice versa

The mathematical and graphical model of the Fuzzy Cognitive Map that describes the system makes apparent how the designer of the model can easily add or remove connections. Moreover, a concept can be added or removed, in order to analyze the performance of the system from a different perspective and to improve the system's description, without a reconstruction of the whole model. For example, another concept, that could be added later, is a concept that will represent the desirable output for valve3.

Figure 4 shows the FCM that is used to describe and control the system, with the initial value of each concept and the interconnections between concepts. The values of concepts correspond to the real measurements of the physical magnitude. At each simulation step of the FCM, the value of each concept is defined by the result of taking all the causal weights pointing into this concept and multiplying each weight by the value of the concept that causes the event, according to equation (1). For this example in the calculation rule, it is assumed that $c = 0.1$ and the sigmoid function $f(x)=\frac{1}{1+e^{-x}}$ is applied on the result of calculation, which is transformed in the interval between 0.00 and 1.00.

Table I. The values of FCM concepts for 10 simulation steps.

Step	Tank1	Tank2	Valve1	Valve2	Valve3	Heat_element	Therm_tank1	Therm_tank2
1	0.2000	0.0100	0.5500	0.5800	0	0.2000	0.1000	0.0500
2	0.5225	0.6142	0.5441	0.5426	0.5015	0.5125	0.5155	0.5277
3	0.5350	0.5707	0.5912	0.6979	0.6032	0.5909	0.5251	0.5804
4	0.5210	0.5895	0.6006	0.6964	0.5994	0.6004	0.5288	0.5918
5	0.5227	0.5901	0.6010	0.6982	0.6020	0.6023	0.5289	0.5932
6	0.5225	0.5902	0.6013	0.6985	0.6021	0.6026	0.5289	0.5935
7	0.5225	0.5902	0.6013	0.6985	0.6021	0.6026	0.5289	0.5936
8	0.5225	0.5902	0.6013	0.6985	0.6021	0.6026	0.5289	0.5936
9	0.5225	0.5902	0.6013	0.6985	0.6021	0.6026	0.5289	0.5936
10	0.5225	0.5902	0.6013	0.6985	0.6021	0.6026	0.5289	0.5936

The simulation step of the FCM is defined as the period during which the values of the all concepts are calculated and change. It must be mentioned that each simulation step holds for a time unit. Table I represents the value of each concept for 10 simulation steps.

The weights of the interconnections are considered fixed, and the FCM runs for the initial values. Figure 5 depicts the surface that the variation of the values of 8 concepts for 10 simulation steps plot. By examining figure 5 it can be seen that the Fuzzy Cognitive Map is driven to an equilibrium point after six simulation steps. When the FCM is in this equilibrium point, if a disturbance occurs in the real system and causes a change in the value of one or more concepts, the FCM will interact for a limited number of steps and it will reach again another fixed point.

In this problem it has been assumed that there is no time relationship in the changes of the concepts values: when the value of one concept changes, in the same time unit the values of the rest concepts change according to their influence of the first. This is referred to as a simulation step. But in a realistic system, effects take place in different time units. For this example, a change in concept6 (the temperature of the liquid in tank1) will lead almost immediately to a change on the state of the heat element (concept8). But a change in the state of the valve1 takes some time to have full effect on the amount of liquid in the tank1. Thus, time tags corresponding to each effect should be introduced. However, the methodology proposed by Park and Kim in [10)] could be used to account time units for each effect from concept to concept.

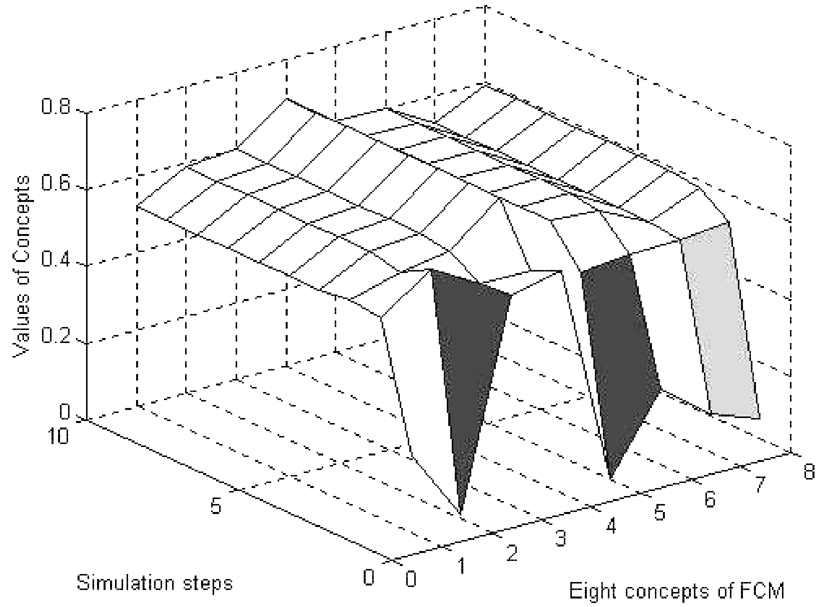

Figure 5. The surface of values of 8 concepts for 10 simulation steps.

5. Supervisory Control for the process control problem

Modern systems become more complex and highly sophisticated, they are characterized by highly nonlinear dynamics that couple a variety of physical phenomena in the temporal and spatial domains. For such systems intelligent fuzzy logic based techniques and object modeling are proposed to address uncertainty issues and provide flexible platforms [18)]. It is not surprising, therefore, that much of these processes are not well understood and their operation is "tuned" by experience rather than through the application of scientific principles. Capturing and utilizing the expert's knowledge, effectively and efficiently, promises to improve plant operational conditions [19)]. Usually operators of the system observe multiple data simultaneously and they make tough decisions based on their experience and empirical knowledge.

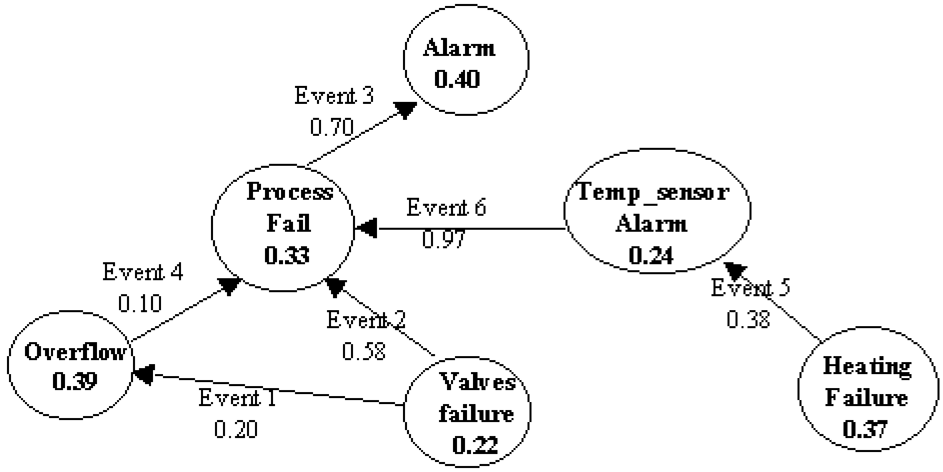

Figure 6. Supervisory Fuzzy Cognitive Map for failure modes.

A Fuzzy Cognitive Map, constructed by exploiting the experience of the system's operators can replicate this approach. This FCM lies in the upper level and serves as a supervisor. It consists of concepts that may represent the irregular operation of some elements of the system, failure mode variables, failure effects variables, failure cause variables, severity of the effect or design variables, planning schemes, etc.

For the previously presented process example, the FCM-supervisor will describe the failure states of the valves, possible failures in control valve opening, the flow rate of the liquid, the possible malfunction in the heating element, leaks in the tanks or other alarm schemes. First of all, it is necessary to select the main concepts of the FCM that will stand for complex and frequently observable faults; others will represent measures and plain failures. Interconnections among concepts will show existing interactions. All are determined empirically by carefully investigating the faults that have occurred during past operation of the system. A drawing of this map is depicted in figure 6. Here, concepts for failure of heating element, failure of valves, conditions of overflow and temperature sensor alarm are used to determine process failures. Moreover, this FCM will include concepts for the determination of a specific operation of the system. As an example, in a similar chemical process, different amounts of liquid in the output at different times could be needed, according to the required density of the liquid. The outputs of the supervisor FCM are signals to indicate potential problem in the end product. This is only the failure detection and identification portion of the supervisor, which will give the appropriate commands to the process controller in the lower level.

In the previous section a model for a process control problem has been proposed. This model could be enhanced if a two-level structure model is considered (Figure 7). In the lower level of the structure lies an FCM that was previously constructed in order to control the process and it will reflect the model of the process during normal operation conditions. In the upper level, there is the supervisor FCM of figure 6 which is used for failure modes, effects analysis and it has been completed with a black box which stands for the decision analysis part of the Fuzzy Cognitive Map. The decision making part of the FCM evaluates alarm signals, process failure signals and other inputs, and sends control signals to the FCM on the lower level which influences the process.

The two FCMs will interact with each other and there will be an amount of information that must pass from one FCM to the other. So, the interface consists of two parts: one will pass information from the FCM in the lower level to the FCM in the upper level, and the other interface will pass information in the opposite direction. This two-part interface is necessary because changes on two or more concepts in the FCM of the lower level could mean change in one or more concepts in the upper level and so information must be interpreted and transmitted to the corresponding concepts on the higher level FCM. The other part of the interface will receive information from the FCM on the upper level and will transmit it to the lower level influencing the corresponding concepts. Generally, two or more concepts of the one FCM pass through the interface and influence one or more concepts in the other FCM.

As an example, the values of concepts "tank1" and "tank2" at the FCM on the lower level determine the value of concept "overflow" at the FCM on the upper level, using the following reasoning:

IF *Tank1* is low (<30%) OR *Tank2* is low (<30%) THEN *Overflow* is low

IF *Tank1* is medium (30%< or <60%) OR *Tank2* is medium (30%< or <60%) THEN *Overflow* is low

IF *Tank1* is high (>60%) OR *Tank2* is high (>60%) THEN *Overflow* is high

But the value of concept "valves_failure" on the second Fuzzy Cognitive Map is determined through the measurement of special sensors.

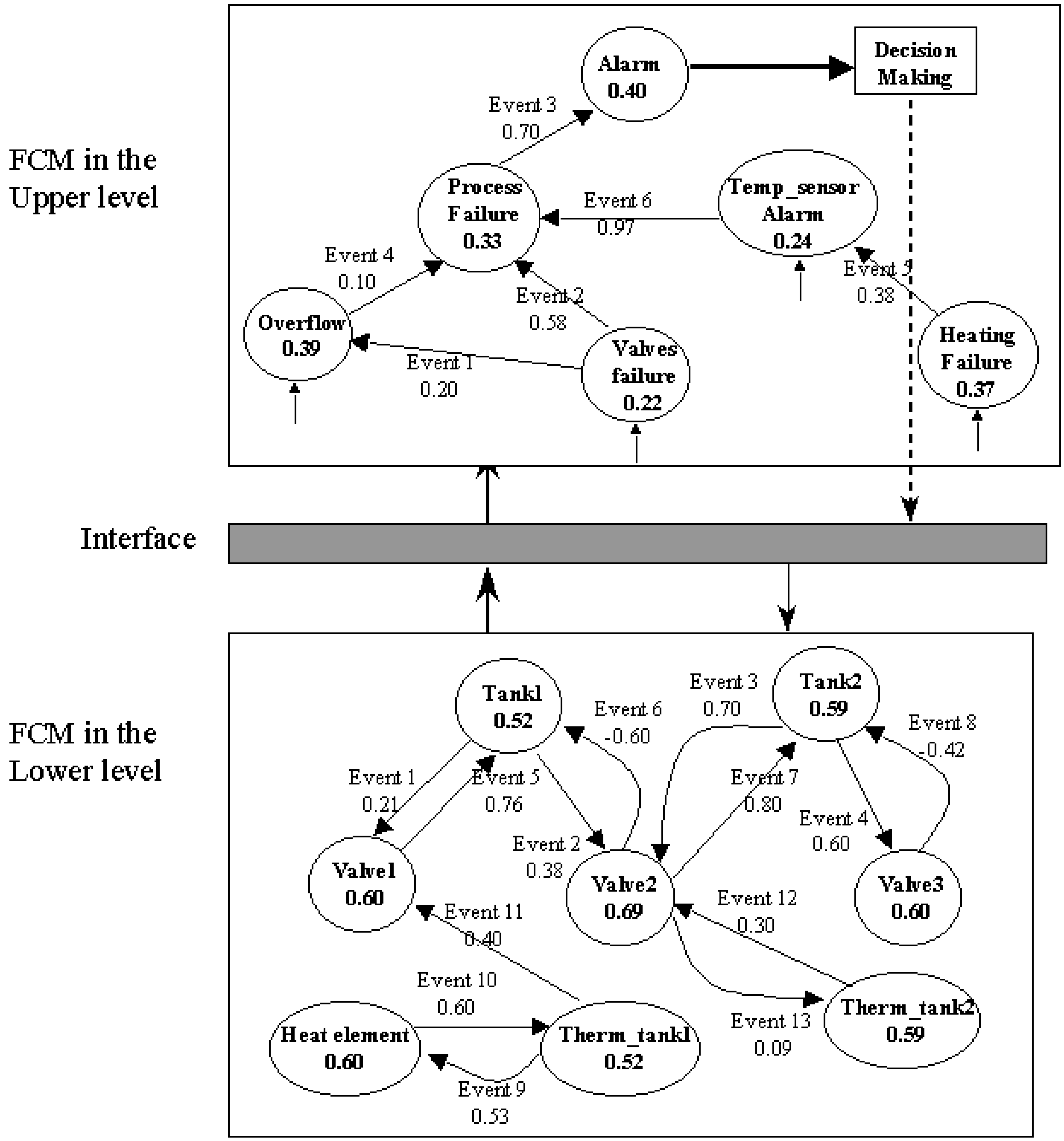

Figure 7. The two-level structure controller with FCM on each level.

In the failure diagnosis part of supervisory FCM there are two concepts 'alarm' and 'process_failure' that indicate the possibility of failure in the process. The operator of the system can evaluate their values and take some actions, or when the decision part of supervisor will be constructed, values of these two concepts will be evaluated from this FCM part. A more complete structure for the Fuzzy Cognitive Map that acts as the supervisor of the entire system and lies in the upper level, is the subject of future research work. This FCM will include failure schemes for malfunction of the actuators, failures of the flow sensors, complicated failures of flow rate with overflow of the tanks.

The cooperation of two-level FCMs seems to be alluring and lead to more sophisticated systems. Moreover, it gives the stimulus to investigate another approach, where in the lower level there is a more conventional controller, like a Neural Network, and the supervisor in the upper level is a FCM.

6. Summary

Fuzzy Cognitive Map Theory, a new soft computing approach to describe the behavior of complex systems and control them, which best utilizes existing experience in the operation of the system, has been examined. The proposed methodology for constructing and developing Fuzzy Cognitive Maps exploits experts who use fuzzy rules to explain the cause and effect among concepts. For complex systems it is extremely difficult to depict the entire system by a precise mathematical model. Thus, it is more attractive and useful to represent it in a graphical way showing the causal relationships between states-concepts. Since this symbolic method of representation and control of a system is easily adaptable and relies on human expert experience and knowledge, it can be considered intelligent.

The implementation of this method in a process control problem was presented and its simplicity in describing the system's operation was shown. The prospect to expand the proposed methodology in more advanced control schemes has been discussed, by adding a second FCM in a higher level which will be used for failure analysis, prediction, decision analysis and planning.

Fuzzy Cognitive Maps seem to be a useful method in describing the dynamics and controlling of complex systems, by exploiting the knowledge on the operation of the system, which will help the designer of a system in decision analysis and strategic planning. Fuzzy Cognitive Maps are an appealing tool in the description of the supervisor of complex control systems, and can be complemented with other techniques and to lead to more effective control systems.

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