Paper:

Fuzzy Cognitive Map Approach to Process Control Systems

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We propose an approach to describe and control complex systems based on fuzzy cognitive map (FCM). A mathematical model of FCMs and a calculation method are described as well as a methodology for constructing and developing them that exploits experts who use fuzzy rules to explain cause and effect among concepts. We apply FCMs in a process control problem and demonstrate their effectiveness. We propose a two-level structure for supervisory control of the process, where the supervisor is modeled as an FCM used for failure detection and decision analysis. There is increasing demand for more autonomous, intelligent systems, and the application of FCMs in control and systems may contribute in developing such systems.

Keywords: Fuzzy cognitive map, Control systems, Supervisory control, Soft computing

1. Introduction

Conventional control has significantly contributed to the solution of many control problems, but its contribution to solutions of increasingly complex dynamical systems has practical difficulties. Requirements in control and in supervisory control cannot be met with existing conventional control theory and new methods are required that exploit past experience, can learn, and provide failure detection and identification. Soft computing thus becomes an important alternative to conventional control. Fuzzy cognitive map (FCM) usage for control and modeling systems is expected to contribute much to the effort to create more intelligent control systems.

FCM describes and models a system symbolically, using concepts to illustrate different aspects of system behavior that interact, showing system dynamics. A FCM integrates experience and knowledge on system operation due to how it is constructed, i.e., using human experts that know system operation and its behavior in different circumstances. Due to their dynamic nature, FCMs are exploited to represent and conduct system control.

Political scientist R. Axelrod[1] introduced cognitive maps for representing social scientific knowledge and describing methods used for decision making in social and political systems. B. Kosko[6,7] enhanced cognitive maps considering fuzzy values for concepts of the cognitive map and fuzzy degrees of interrelationships between concepts. After this pioneering work, FCMs attracted the attention of scientists in many fields and have been used in different scientific problems. New FCMs have been proposed such as the extended FCM[5] and the neural cognitive maps[9]. FCMs have been used for planning and making decisions in international relations and political developments[17] and have been proposed for generic decision analysis[20] and distributed cooperative agents[21]. FCMs have been used to analyze electrical circuits[14] and to construct virtual worlds[2]. In control themes, FCMs have been used to model and support plant control[4], represent failure models and effects analysis for a system model[11~12], and to model the control system supervisor[15~16]. The objective of this paper is to define and construct FCMs models for describing complex systems. Section 2 describes FCMs and proposes a calculation rule. Section 3 proposes a soft computing methodology for constructing and developing FCMs. Section 4 implements FCM to model and control a chemical process. Section 5 suggest the use of two-level FCMs to conduct supervisory control and discusses the failure part of a supervisor-FCM. Section 6 gives conclusions and prospects.

2. FCMs

The FCM is regarded as a combination of fuzzy logic and neural networks. Graphically, the FCM seems to be a signed weighted graph with feedback, consisting of nodes and weighted arcs. Nodes stand for concepts describing system behavior and are connected by signed and weighted arcs representing causal relationships between concepts (**Figure 1**). Each concept represents a system characteristic, generally events, actions, goals, values, and trends of the system modeled as an FCM. Each concept is characterized by a

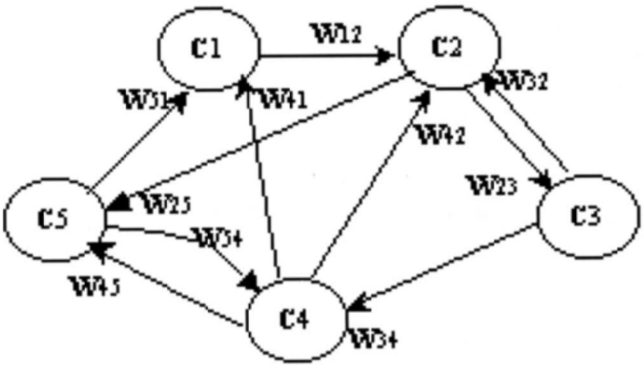

Fig. 1. A simple Fuzzy Cognitive Map

number A_i representing its value and results from transformation of the real system variable, for which this concept stands, in the interval [0,1]. All values in the graph are fuzzy, so weights of arcs are in the interval [-1,1]. This graphical representation makes clear which concept influences other concepts showing interconnections between concepts and permitting updating of the graph, such as adding or deleting an interconnection or a concept.

Between concepts, there are three possible types of causal relationships expressing the type of influence of a concept to the others. This causal relationship is expressed by the weight, denoted by W_{ij} for the arc from concept C_i towards concept C_j. It can be positive, ($W_{ij} \succ 0$) meaning that an increase in the value of concept C_i leads to an increase in the value of concept C_j, and a decrease in the value of concept C_i leads a decrease in the value of concept C_j. There may be negative causality ($W_{ij} \prec 0$) meaning that an increase in the value of concept C_i leads to a decrease in value of concept C_j and vice versa. When no relationship exists between concept C_i and concept C_j, then $W_{ij} = 0$.

The value of each concept is influenced by values of connected concepts with the corresponding weights. A new calculation rule is proposed, it considers part of the last value of each concept, value A_i for each concept C_i is calculated by the following rule:

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

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

A more compact mathematical model for FCM consists of a $1 \times n$ state vector A including values of n concepts and $n \times n$ weight matrix W gathering weights W_{ij} of interconnections among n FCM concepts. Matrix W has n rows and n columns where n equals the total number of distinct FCM concepts and the matrix diagonal is zero since it is assumed that no concept causes itself.

$$A_t = f(A_{t-1}W + cA_{t-1}) \quad \ldots \ldots \ldots \ldots (2)$$

Multiplication of previous state vector A_{t-1} at time t-l with weight matrix W and addition of previous state vector A_{t-1} computes a new state vector A_t. The new vector shows the effect of the change in the value of one concept on the whole FCM. Equation (2) includes the previous value of each concept, so the FCM possesses memory and there is a smooth change after each new interaction among FCM concepts.

3. Constructing FCMs

A FCM is a type of network built by experts using interactive knowledge acquisition. An expert defines main concepts representing the system model, based on his knowledge and experience in system operation. The expert determines concepts that best describe the system. A concept is a system characteristic, state, variable, input, or output. The expert knows which factors are crucial for modeling the system and represents a concept for each. The expert has observed which system elements influence other elements and, for corresponding concepts, determines the negative, positive, or no effect of a concept on others using a fuzzy value for each interconnection, since it is assumed that there is a fuzzy degree of causation between concepts.

To have better results in FCM development, a group of experts is used and the development methodology becomes more objective as the experience of a group of experts is exploited. All experts are polled together and determine relevant factors, main system characteristics, and thus concepts that should compose the FCM. They determine the structure and interconnections of the network using fuzzy conditional statements.

We propose a methodology for developing FCMs based on fuzzy logic. Experts are asked to describe relationships among concepts and use IF-THEN rules to justify the cause and effect relationship among concepts and infer a linguistic weight for each interconnection.

The fuzzy rule with the form if-then describes the relationship between two concepts appeared 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 value of concept C_i THEN B change is caused in value of concept C_j

Inter: The 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 is a linguistic value for the relationship between the two concepts. So the causal relationship is described with a fuzzy rule, which gives the grade of causality between concepts so the corresponding weight is inferred. Thus, every one of the group of experts suggests for each interconnection a linguistic weight and the set of weights of each interconnection are integrated and defuzzification is used to produce a numerical weight for the interconnection. In fuzzy logic literature, many methods for defuzzification have proposed such as Center of Area, used here, and the produced numerical weight belongs to the interval [-1,1].

As an example, the case where 4 experts describe the

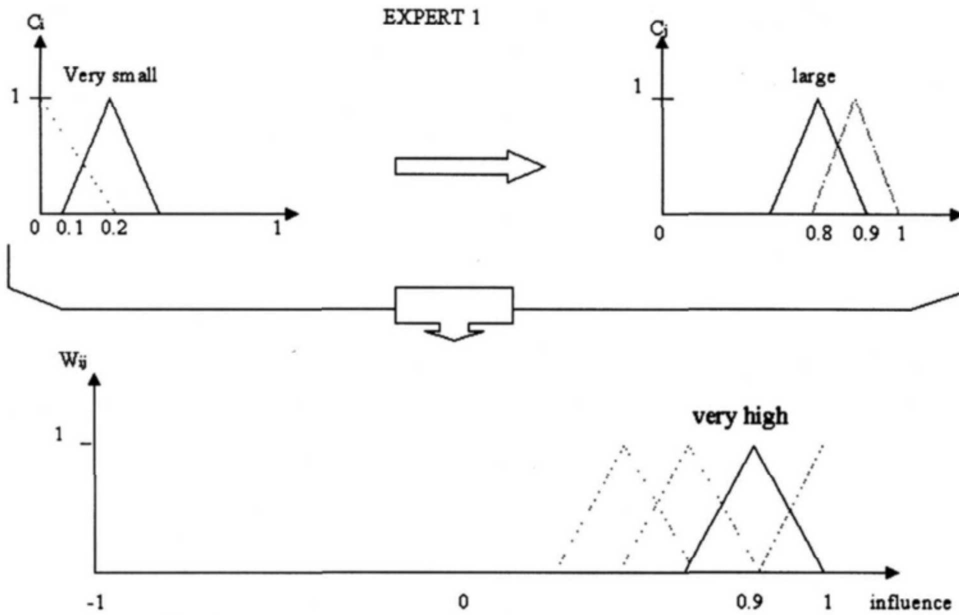

Fig. 2. The 1st expert suggestion fuzzy rule for an interconnection.

relationship among two concepts is 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.

Infer: The influence of C_i to C_j is *positively very high* 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.

Infer: The influence of C_i to C_j is *positively high* 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.

Infer: The influence of C_i to C_j is *positively very much high* 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.

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

These 4 fuzzy rules for the interconnection between C_i and C_j are combined, the 4 linguistic variables for weight W_{ij} will pass though the defuzzifier, and the result is a crisp number. For this example, it was supposed that well known triangular membership functions stand for the weight (**Figure 2**) and the defuzzifier Center of Area was used and the result of the defuzzifier was $W_{ij} = 0.87$.

Each expert thus describes FCM operation by an ensemble of fuzzy rules. Rules that concern each interconnection are evaluated in parallel using fuzzy reasoning and results of rules are combined and defuzzified and the result is a crisp number representing the weight of each interconnection. This construction methodology is very comprehensive to system operators, who determine the influence of one factor of the system to another using simple reasoning 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 methodology that we propose for developing FCMs exploits the experience and knowledge of a group of experts who use fuzzy rules to describe system behavior. This is an objective and does not require experimental data for values of concepts, as other methods do[13] especially for problems that usually use FCMs such as modeling of complex systems.

Experts involved in the construction of FCM determine concepts and causality among them. Sometimes this approach may yield a distorted model, since it is possible that experts have not considered appropriate factors and may have assigned inappropriate causality weights among FCM concepts. The best conductance of FCMs is obtained by combining them with neural network characteristics and integrating their advantages. More specifically, neural learning techniques are used to train the FCM and determine appropriate weights of interconnections among concepts. The result is a hybrid neurofuzzy system. Unsupervised learning methods have been proposed for FCM training, where the gradient of each weight is calculated by the application of general rules:

$$w_{ij}' = g\,(w_{ij}, A_i, A_j, A_i', A_j') \quad \ldots\ldots\ldots\ldots \quad (3)$$

Differential Hebbian learning law is used as proposed[8] to train the FCM, meaning adjusting weights of interconnections between concepts, as if they were synapses in a neural network. The development of appropriate learning algorithms for training FCMs needs more study and is the subject of future research.

4. Implementation of FCM in a Process Control Problem

As is clear, the most important component in developing an FCM is the determination of concepts that best describe the system and the direction and grade of causality among concepts. These aspects are represented in the example below.

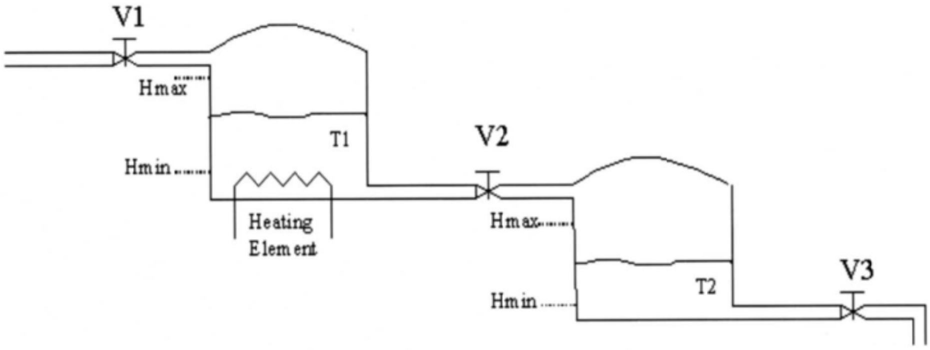

Fig. 3. Example of a process system to be controlled

The system was used as an example to examine 3 different hybrid modeling methods[3] and the applicability of FCM is such process control systems is examined. The system consists of 2 tanks (**Figure 3**). Each tank has inlet and outlet valves. The outlet valve of the first tank is the inlet valve of the second.

The control objective 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 liquid in both tanks between maximum value $T_{\max}$ and minimum value $T_{\min}$. The desired target is keeping these variables in the range of values:

$$\begin{array}{l} H^1_{\min} \le H^1 \le H^1_{\max} \\ H^2_{\min} \le H^2 \le H^2_{\max} \\ T^1_{\min} \le T^1 \le T^1_{\max} \\ T^2_{\min} \le T^2 \le T^2_{\max} \end{array} \qquad (4)$$

The temperature of liquid in tank 1 is increased through operation of a heating element. The temperature of liquid in tank 2 is measured with a thermometer and controlled so that when the temperature of liquid 2 decreases, valve 2 opens, so hot liquid enters tank 2.

An FCM is constructed to model and control the system. To determine FCM concepts that describe the system, system variables must be taken into account, such as the level of liquid in each tank and/or the temperature. Concepts are assigned for the system's elements that affect system variables such as the state of valves.

For this plant, an FCM is developed with 8 concepts, which describes the system well and controls the plant:

Concept 1 The amount of liquid tank 1 contains. This is dependent on valves 1 and 2.

Concept 2 The amount of liquid in tank 2. This is dependent on valves 2 and 3.

Concept 3 The state of valve 1. The valve is open, closed, or partially open.

Concept 4 The state of valve 2. The valve is open, closed, or partially open.

Concept 5 The state of valve 3. The valve is open, closed, or partially open.

Concept 6 The temperature of liquid in tank 1.

Concept 7 The temperature of liquid in tank 2.

Concept 8 Describes operation of the heating element increasing the temperature of liquid in tank 1.

These concepts must be connected. First for each concept it must be decided to which other concepts it is connected to. The sign of the connection is decided, then the weight of each connection is determined.

Connections between concepts are:

Event 1 Connects concept 1 with concept 3. It relates the amount of liquid in tank 1 with operation of valve 1. When the height of liquid in the tank is low, it is needed to increase the amount of incoming liquid in tank 1 so valve 1 is opening.

Event 2 Relates concept 1 with concept 4 concept 4;when the height of liquid in tank 1 is high, opening of valve 2 (concept 4) reduces the amount of liquid in tank 1.

Event 3 Connects concept 2 with concept 4; when the height of liquid in tank 2 is low, opening of valve 2 (concept 4) increases the amount of liquid that enters tank 2.

Event 4 Relates concept 2 with concept S; when the height of liquid in tank 2 is high, opening of valve 3 (concept S) helps in keeping the amount of liquid below an upper limit.

Event 5 Connects concept 3 (valve 1) with concept 1 (tank 1); any change in valve 1 influences the amount of liquid in tank 1.

Event 6 The value of concept 4 (valve 2) causes the decrease or not of the value of concept 1 (tank 1).

Event 7 The value of concept 4 (valve 2) causes the increase or not of the amount of liquid in tank 2 (concept 2).

Event 8 Relates concept S (valve 3) with concept 2 (tank 2), the value of concept S causes the decrease or not of the amount of liquid in tank 2.

Event 9 Connects concept 6 (temperature in tank 1) with concept 8 (operation of the heating element). When the temperature in tank 1 is low, it causes the opening of the heating element.

Event 10 Connects concept 8 with concept 6; the value of concept 8 (operation of the heating element) increases the value of concept 6 (temperature in tank 1).

Event 11 Connects concept 6 with concept 3 (valve 1); when the temperature in tank 1 reaches an upper limit, opening of valve 1 causes liquid of low temperature to enter tank 1.

Event 12 Relates concept 7 (temperature in tank 2) with concept 4 (valve 2); when the temperature in tank 2 is below a limit, valve 2 should opened so new hot liquid enters tank 2 from tank 1.

Event 13 Shows the effect of concept 4 (valve 2) on concept 7 (the temperature in tank 2); when valve 2 (concept 4) is open then hot liquid enters tank 2 and the temperature in tank 2 (concept 7) is increased.

In assigning weights to interconnections, the experience

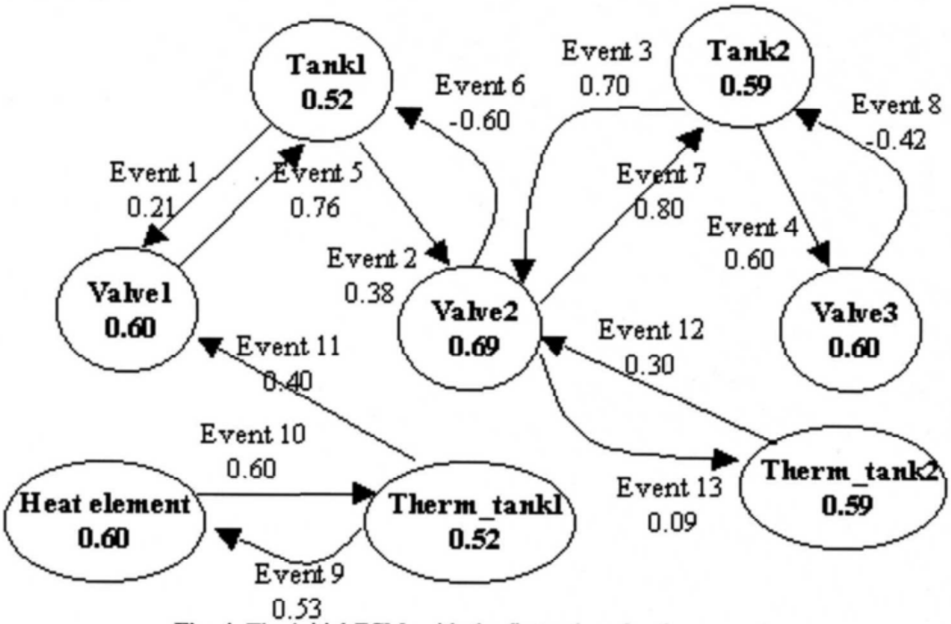

Fig. 4. The initial FCM, with the first values for the concepts

Table 1. The values of FCM concepts for 10 simulation steps.

Step	Tank 1	Tank 2	Valve 1	Valve 2	Valve 3	Heat_element	Therm_tank 1	Therm_tank 2
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

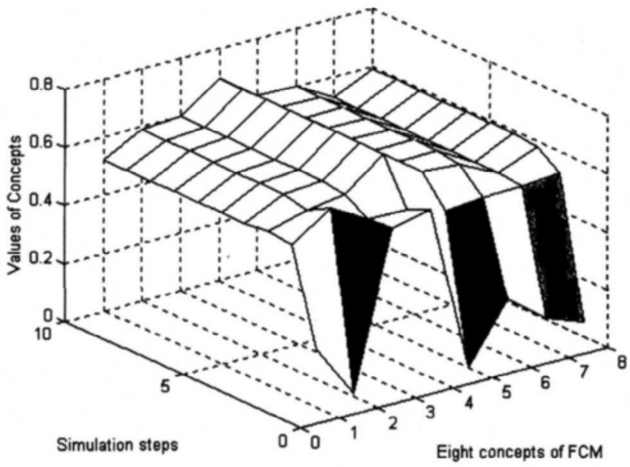

Fig. 5. The surface of values of 8 concepts for 10 simulation steps.

of a group of experts is used who use the methodology in section 3 to determine the cause and effect relationship among concepts. As an example, experts describe the influence of valve 1 (concept 3) on the amount of liquid in tank 1 (concept 1) using a set of fuzzy rules from which it is inferred that there is positive influence, transformed in weight 0.76 (event 5). Each event (connection between concepts) has a weight, which ranges between [-1,1] and was determined by a group of experts. Each concept has a value, which ranges in the interval [0,1] and is obtained after thresholding the real value of the concept. An interface is needed to transform real measures of the system to representative values in the FCM and vice versa.

The mathematical and graphical model of the FCM that describes the system makes apparent how the designer of the model can easily add or remove connections. A concept is added or removed to analyze system operation from a different perspective and to improve the system's description, without reconstruction of the whole model. For example, another concept that could be added later is one representing desirable output for valve 3.

Figure 4 shows the FCM used to describe and control the system, with the initial value of each concept and inter-

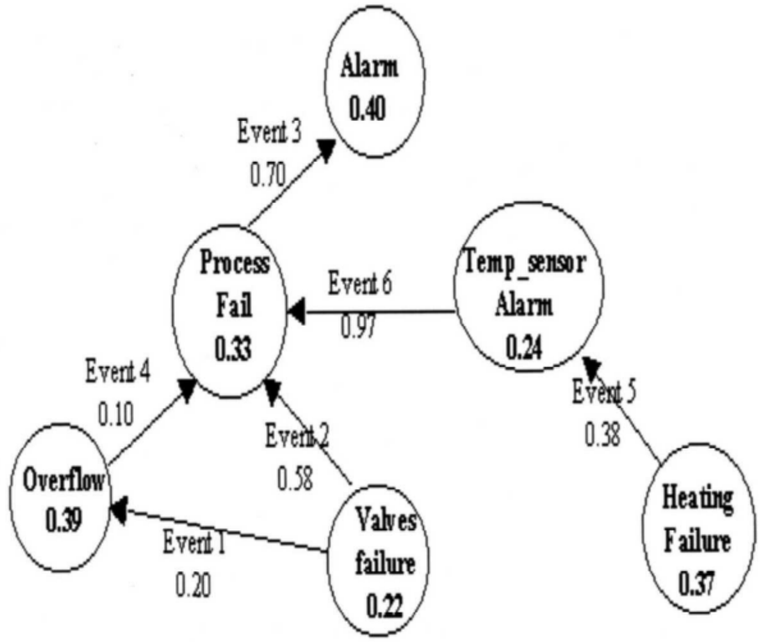

Fig. 6. Supervisory Fuzzy Cognitive Map for failer modes.

connections between concepts. The values of concepts correspond to real measurements of physical magnitude. At each simulation step of the FCM, the value of each concept is defined by the result of taking all causal weights pointing into this concept and multiplying each weight by the value of the concept that causes the event based on equation (1). It is assumed that c=0.1 and sigmoid function $f(x) = \dfrac{1}{1 + e^{-x}}$ is applied on calculation result, transformed in the interval between 0.00 and 1.00.

As the simulation step of the FCM is defined, the period during which values of all concepts are calculated and change. Each simulation step holds for a time unit. **Table 1** shows values of concepts for 10 simulation steps.

Weights of interconnections are considered fixed, and the FCM runs for initial values. **Figure 5** depicts the surface of the variation of values of 8 concepts for 10 simulation steps. **Figure 5** shows that the FCM is driven to equilibrium after 6 simulation steps. When the FCM is at equilibrium, if a disturbance occurs in the real system, which will cause the change in the value of one or more concepts, the FCM will interact for a limited number of steps and will reach again equilibrium.

Here, we assumed that there is no time relationship in changes of concept values, when the value of one concept changes, in the same time unit values of the of the rest concepts change based on their influence of the first. This is referred to as a simulation step. In a realistic system, effects take place in different unit times. For example, in **Figure 3** a change in concept 6 (the temperature of liquid in tank 1) will lead almost immediately to a change on the state of the heat element (concept 8) but a change in the state of valve 1 takes some time to have full effect in the amount of liquid in tank 1. Thus, time tags are introduced corresponding to each effect, but then problems would appear on estimating different time units for each effect but could follow the methodology proposed by Park and Kim[10].

5. Supervisory Control for Process Control Problem

In complex systems, it is difficult to represent states and variables of the process that are good indicators of faults, and more elaborate models are necessary. As systems become complex and sophisticated, they are characterized by highly nonlinear dynamics coupling a variety of physical phenomena in temporal and spatial domains. For such systems, intelligent fuzzy logic based techniques and object modeling were proposed to address uncertainty issues and provide flexible platforms[18]. These processes are thus not well understood and their operation is "tuned" by experience rather than through mathematical scientific principles. Capturing and using expert knowledge effectively and efficiently promises to improve plant operation[19]. System operators observe multiple data simultaneously and make tough decisions based on experience and empirical knowledge.

This is replicated by an FCM constructed by exploiting the experience of system operators. This FCM lies in the upper level and serves as a supervisor. It consists of concepts that may represent irregular operation of some system elements, failure mode variables, failure effect variables, failure cause variables, severity of the effect or design variables, planning schemes, etc.

For the previous example, the FCM-supervisor describes failure states of valves, possible failures in control valve opening, the flow rate of liquid, possible malfunction in the heating element, leaks in tanks, and other alarm schemes. We must select FCM concepts that will stand for complex and frequently observable faults; others will represent measures and plain failures and interconnections among concepts will show existing interactions. All are determined empirically by carefully investigating faults in the past (**Figure 6**). Concepts for failure of heating element, failure of valves, conditions of overflow and temperature sensor alarm are used to determine process failures. This FCM includes con-

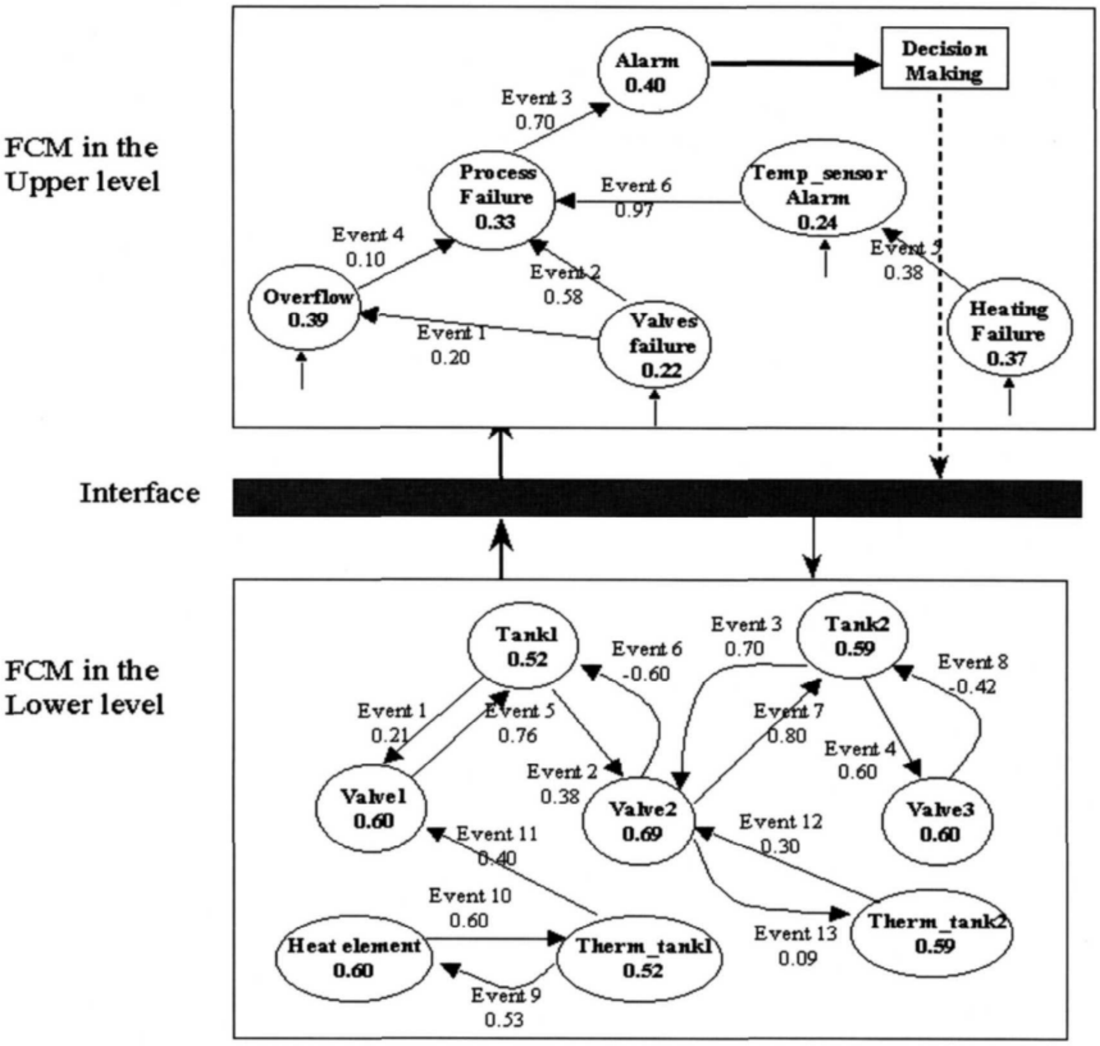

Fig. 7. The two-level structure controller with FCM on each level.

cepts for determining specific system operation. In a similar chemical process, different amounts of liquid in the output at different times could be needed, based on the requisite density of liquid. The outputs of the supervisor FCM are signals to indicate potential problems in the end product. This is only the failure detection and identification of the supervisor, which gives appropriate commands to the process controller in the lower level.

In the previous section, a model for a process control problem was proposed, and could be enhanced if a two-level structure model is considered (**Figure 7**). In the lower level of the structure, there is the FCM previously constructed to control the process and reflect the model of the process during normal operation. In the upper level, the supervisor FCM (**Figure 6**) used for failure modes, effects analysis, and completed with a black box for decision analysis of the FCM. The decision maker of the FCM evaluates alarm signals, process fail signals and inputs, and sends control signals to the lower FCM influencing the process.

The two FCMs interact and information must pass from one to the other. The interface consists of two parts: one passes information from the FCM in the lower level to the FCM in the upper level and the other vice versa. This two-part interface is necessary because changes on one or more concepts in the lower FCM could mean change in a concept in the upper level and the corresponding procedure, when information descends from the upper FCM towards the lower level. Generally, two or more FCM concepts on the lower level pass through the interface and influence one concept in the upper FCM, and an analogous interface exists for the inverse transmission of information.

As an example values of concepts "tank 1" and "tank 2" at the lower FCM determine the value of concept "overflow" at the upper FCM, using the following reasoning:

IF *Tank 1* is *low* (<30%) OR *Tank 2* is *low* (<30%) THEN *Overflow* is *low*

IF *Tank 1* is *medium* (30% or <60%) OR *Tank 2* is *medium* (30% or <60%) THEN *Overflow* is low

IF *Tank 1* is *high* (>60%) OR *Tank 2* is *high* (>60%) THEN *Overflow* is high

But the value of concept "valves_fail" on the second FCM is determined through the measurement of special sensors.

The failure diagnosis of the supervisory FCM is constructed where there are two concepts 'alarm' and 'process_fail' that indicate the possibility for failure in the process. The decision maker part of supervisor evaluates values of these two concepts and take action. A more complete structure for the FCM that acts as the supervisor of the entire system lies in the upper level, it is subject of future work. This FCM will include failure schemes for malfunction of actuators, failures of flow sensors, and complicated failures of flow rate with overflow of tanks.

The cooperation of the two FCMs is alluring and could lend itself to more sophisticated systems. It is suggesting another approach, where the lower level has a more conventional controller such as a neural network, and the upper supervisor is an FCM.

6. Summary

FCM theory, a soft computing approach to describe the behavior of complex systems and control them, best uses existing experience in system operation. The proposed methodology for constructing and developing FCMs exploits experts who use fuzzy rules to explain 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 useful to graph it, showing causal relationships between states-concepts. Since this symbolic representation and control is easily adaptable and relies on human expert experience and knowledge, it is considered intelligent.

The implementation in a process control problem is presented and its simplicity in describing the system's operation shown. The prospect for it to be expanded in more advanced control schemes was discussed by adding a second FCM in a higher level for failure analysis, prediction, decision analysis, and planning.

FCMs seem useful in describing dynamics and control of complex systems, by exploiting knowledge on system operation, which will help the designer of a system in decision analysis and strategic planning. FCMs are useful in describing the supervisor of complex control systems complemented with other techniques and will lead to more effective control systems.

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