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Fuzzy Cognitive Maps: a model for intelligent supervisory control systems

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Abstract

Fuzzy Cognitive Maps (FCMs) is a new approach in modelling the behaviour and operation of complex systems. FCMs are proposed to be used in the modelling of control systems and particularly in the modelling of the upper part or supervisor of a hierarchical control system. The description and the formulation of FCM are examined, moreover a process control problem is presented and its model and control is investigated using FCMs. Then the implementation of FCM in the modelling of the supervisor of a control system is discussed and it becomes apparent how efficient FCMs are in expressing qualitative information and knowledge about the process structure. Finally, some interesting points for further research are presented and discussed.

Keywords: Fuzzy Cognitive Map; Supervisory control; Intelligent systems

1. Introduction

In the past years, conventional methods were used, successfully, to model and control systems but their contribution is limited in the representation, analysis and solution of complex systems. In such systems, the inspection of their operation, especially from the upper level, depends on human leadership. Generally, there is a great demand for the development of autonomous complex systems that can be achieved taking advantage of human like reasoning and description of systems. Human reasoning process for any procedure includes uncertain descriptions and can have subtle variations in relation to time and space; for such situations Fuzzy Cognitive Maps (FCMs) seem to be capable to deal with.

FCM is a combination of Fuzzy Logic and Neural Networks; it combines the heuristic and common sense rules of Fuzzy Logic with the learning heuristics of the Neural Networks. They were introduced recently by Kosko [1,2], who enhanced cognitive maps with fuzzy reasoning, that had been previously used in the field of socio-economic and political sciences to analyse social decision-making problems [3]. Kosko considered fuzzy values in the variables of cognitive maps and utilised them in order to represent causal reasoning. The use of FCMs for many applications in different scientific fields was proposed. FCM had been employed to analyse extend graph theoretic behaviour [4], to make decision analysis and co-operate distributed agents [5,6], were used as structures for automating human problem solving skills [7] and as behavioural models of virtual worlds [8]. FCMs were also used to model and

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support plant control systems of a water system [9,10]. FCMs were proposed as system models for Failure Modes and Effects Analysis in process industry (i.e., the oil refinery) [11,12] and they were used for strategic planning and analysing the business behaviour of a car industry [13]. Authors of this paper proposed the use of FCM from a different standpoint, as a model of the Supervisor in complex control systems [14,15]; the investigation concerns hierarchical intelligent systems which incorporate knowledge and are capable of learning relational structures and evidential reasoning.

The organisation of this paper is as follows. Section 2 describes briefly the formulation and development of FCMs and in Section 3 the different uses of FCMs in control aspects are summarised. Section 4 presents a generic model that control directly a process; the development of a controller for a process problem is described in detail and this FCM is used to control the process. Section 5 discusses the implementation of FCMs in Supervisory Control problems. Finally, Section 6 concludes the paper and gives some possible future research directions.

2. Fuzzy Cognitive Maps

The graphical illustration of FCM is a signed directed graph with feedback, which is consisted of nodes and weighted arcs. Nodes of the graph stand for the concepts that are used to describe the behaviour of the system and they are connected by signed and weighted interconnections representing the causal relationships that exist between the concepts (Fig. 1). It must be mentioned that all the values in the graph are fuzzy, so concepts takes values in the range between [0,1] and the weights of the interconnections belong to the interval $[-1,1]$. From simple observation of the graphical representation of FCM, it becomes clear, which concept influences which other concepts, showing the interconnections among concepts and it permits thoughts and suggestions for the reconstruction of the graph, as the adding or deleting of an interconnection or a concept. In conclusion, FCMs are fuzzy-graph structure, which allow systematic causal propagation, in particular forward and backward chaining.

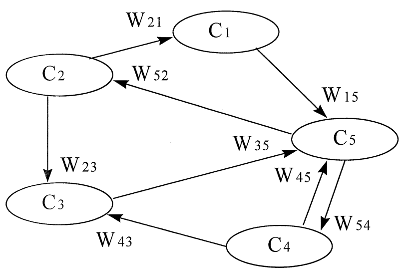

Fig. 1. Graphical drawing of a Fuzzy Cognitive Map with concepts and weighted interconnections.

Behind the graphical representation of an FCM there is a mathematical formulation which describes the FCM. Values of concepts are fuzzy and arise from the transformation of the real values of the corresponding variables for each concept; and there are fuzzy values for the weights of the interconnections among concepts. Then, FCM is free to interact, at every step of interaction every concept has a new value that is calculated according to the following equation:

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

Namely, A_i^t is the value of concept C_i at step t, A_j^{t-1} is the value of concept C_j at step t-1, and W_{ji} is the weight of the interconnection from concept C_j to concept C_i and f is a threshold function that squashes the result of the multiplication in the interval [0,1].

Building an FCM model of a process or plant depends on human experts who have knowledge on the operation of the system [14]. One expert or operator of the system is asked to describe the behaviour and model of the system. According to his experience, he develops an FCM, he determines the concepts, which stand for the different aspects that influence the process, the paths of system's malfunction; generally concepts stand for states, variables, events, actions, goals, values, trends of the system. The expert has observed the grade with which each variable of the system influences others and so, he determines the negative, positive or nilpotent effect of one concept on the others, with a fuzzy degree of causation.

This approach is dependent on the reliability and knowledge of each one expert. It is possible to exploit the knowledge of a group of experts who have experience on the operation or modelling of the system. Firstly, all the experts are polled together in order to determine the relevant factors that should be present in the map. Then, experts are individually asked to express the relationship among these factors. In this way, a collection of individual FCMs is created which must be combined into a collective map. If it is considered that there are experts of varying credibility then their contribution is multiplied with a nonnegative 'credibility' weight before combining it with other expert's opinions. And if there is an expert who is extremely knowledgeable about certain factors or parts of the system and not others, it can be used different credibility weights on different links. On the other hand, it is still an open question if the contribution of all experts should be considered equally or for some of them, it is necessary to penalise their contribution with a negative credibility weight.

3. The use of FCM in control

After the presentation of FCMs, their illustration and their methodology with which they are constructed; their application is examined in control aspects. There are two distinct uses of a knowledgeable based model like the FCM in the upper level of a process [16]. One, when FCM is used for direct control and FCM influences directly the process, as it is depicted in Fig. 2.

In this case, FCM is replacing completely the conventional control element and it performs every function that a conventional controller could implement. It is similar to the closed loop control approach because FCM is depended directly on the real behaviour of the process. Such an application of FCM will be presented in Section 4 where a process problem will be examined and an FCM will be constructed in order to control the process.

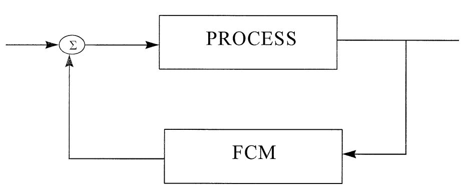

Fig. 2. Structure of FCM for Direct Control.

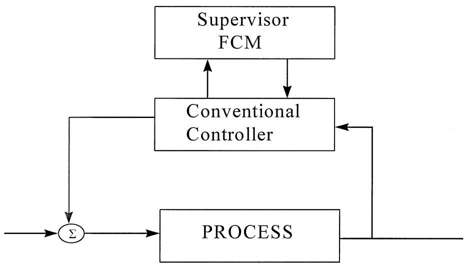

Fig. 3. Structure of a Supervisor Control using an FCM.

Another important use of FCM is for supervisory control of a conventional control element, thus complementing rather than replacing a conventional controller. The scheme of this structure is depicted in Fig. 3. In this case, the role of FCM is to extend the range of application of a conventional controller by using more abstract representation of process, general control knowledge and adaptation heuristics and enhance the performance of the overall system. Thus, FCM may replicate some of the knowledge and skills of the control engineer and it is built by using a combination of the knowledge representation techniques as causal models, production rules and object hierarchies.

At the conventional controller level or at the process itself may exist more than one controllers for different parts of the process and only local information is available to each controller who communicates with the supervisor at the higher level. The role of the supervisor is to elaborate information of the controllers and to allocate actions to controllers taking into account their effect on the global system. Supervisor indicates undesired or unpermitted process states and takes actions such as fail safe or reconfiguration schemes. Supervisory FCM is used to perform more demanding procedure as failure detection, diagnose abnormalities, decision making, planning tasks and intervene when a certain task or state is reached and take control in abnormal or hazardous situations. A human supervisor of the controlled process usually performs these tasks.

4. An FCM system for direct control of a process

The first type of application of FCM is considered for the direct control of a process or a complex plant. Then the controlled system can be described in detail as the multilevel model that is illustrated on Fig. 4, where in the upper layer a storage of the existing knowledge of the system's operation is lying. This knowledge is represented by an FCM, which models the operation, and best describes the behaviour of the process in the lower level and an expert, as previously presented, constructs it. If the nature of the process under control is such that appropriate analytic models do not exist or are inadequate, but human operation at the process can manually control the process to a satisfactory degree, then the need to use an abstract methodology as FCMs is motivated.

The function of the whole model of the system can be described from the lower level to the upper one. In the lower level sensors measure some defined variables of the process and these measurements must pass to the higher level where information of the process is organised and categorised. After that, available information on process is clustering and grouping, because some measured variables could cause changes in the value of one or more concepts of the FCM, then the organised information can easily transformed in FCM mode which passes into the FCM on the upper level. The FCM on the upper level is accompanied by a box, which symbolises the knowledgeable expert who developed the FCM, and another one box, which represents FCM training procedure. FCMs have been described as the combination of Neural Networks and Fuzzy Logic. Thus, learning techniques and algorithms can be borrowed from Neural Networks theory and can be utilised in order to train FCM and adjust the weights of its interconnections.

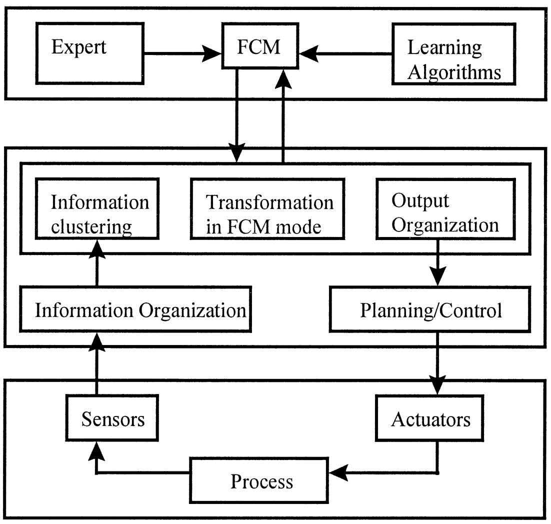

Fig. 4. A generic model of the controlled process using FCM for direct control.

The procedure of the operation of the generic model of Fig. 4 has as follows. Firstly, the FCM is initialised, each concept takes an initial value that best represents the current state according to the expert's opinion and the weights of the FCM have been determined during the training period. The input information from the process level causes change in the value of one or more concepts of the FCM. Then, concepts of the FCM interact each other until an equilibrium point is reached, in this case the value of some concepts have changed and this information must pass to the lower level and influence the process so the reverse procedure is followed. Values of some concepts are transformed in physical magnitudes in a similar to the defuzzification procedure that is implemented in fuzzy control systems. The information which descend from the FCM represent real values for some variables of the system so it must be organised, filtered in some way and it will posted to the Planning/Control part. The Control part will determine the control actions that must be applied to the process and some variables of the process will be influenced by the control signals that planning and control part is sending.

The above has briefly described how this generic model works. However sometimes, if FCM is not appropriate developed or not well trained, values of the concepts of the FCM may lead the FCM into a limit cycle where values of all concepts will periodically change, and in this case an external human influence and interaction are needed.

This was the description of a generic model for direct control using FCM. Now the modelling of a practical process problem will be examined. The most important component in defining an FCM is the determination of the concepts that best describe the system and the direction and grade of causality between concepts. These aspects will be represented through an example taken from a process control problem. The system consists of two tanks depicted in Fig. 5. 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 objective of the control system is first to keep the height of liquid, in both tanks, between some limits, an upper H_{max} and a low limit H_{min}, and second, the temperature of the liquid in both tanks must be kept between a maximum value T_{max} and a minimum value T_{min}. The temperature of the liquid in tank 1 is regulated through a heating element. The temperature of the liquid in the tank 2 is measured through a thermometer; when the temperature of the liquid 2 decreases, valve 2 needs opening, so hot liquid comes into tank 2 from tank 1. The control objective is to keep values of these variables in the following range of values:

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

For this system an FCM is to be constructed. Variables and states of the system, such as the height of the liquid in each tank or the temperature, will be the concepts of an FCM, which describes the system. Then concepts are assigned for the system's elements that affect the variables such as the state of the valves. For this simple system, eight concepts are proposed as a first attempt and they give a good model of the system. Later on, any other concept can be added, which could help the overall view and control of the system:

Concept1: The height of the liquid in tank 1. The height of liquid is dependent on state of valve 1 and valve 2.
Concept2: The height of the liquid in tank 2. The height of liquid is related to valve 2 and valve 3.
Concept3: The state of the valve 1. The valve is open, closed or partially open.
Concept4: The state of the valve 2. The valve is open, closed or partially open.
Concept5: The state of the valve 3. The valve is open, closed or partially open.
Concept6: The temperature of the liquid in tank 1.
Concept7: The temperature of the liquid in tank 2.
Concept8: Describes the operation of the heating element, which has different levels of operation and which increases the temperature of the liquid in tank 1.

These concepts must be connected with each other. First it must be decided for each concept to which another concept is connected. Then the sign of the connection is decided, and then the weight of each connection is determined. For this procedure the human experience on the system's operation is used.

The connections between concepts are:

Event1: Connects concept 1 with concept 3. It relates the amount of the liquid in tank 1 with the operation of the valve 1. When the height of the liquid in the tank is low, opening of valve 1 increases the amount of incoming liquid;
Event2: Relates concept 1 with concept 4; when the height of the liquid in tank 1 is high, opening

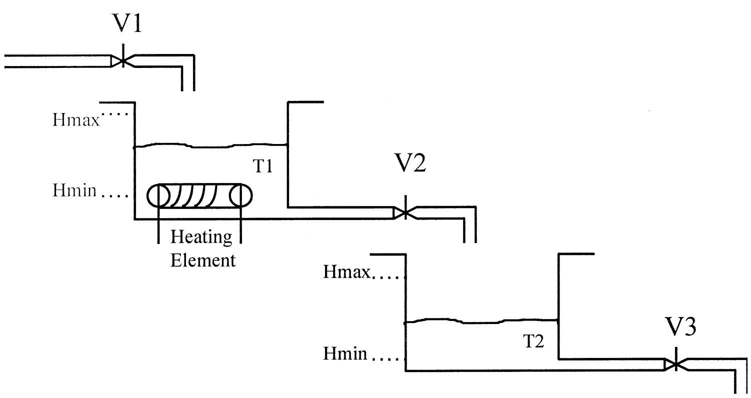

Fig. 5. Example of a process system to be controlled.

of valve 2 (concept 4) reduces the amount of liquid in tank 1;
Event3: Connects concept 2 with concept 4; when the height of the liquid in tank 2 is low, opening of valve 2 (concept 4) increases the amount of liquid in tank 2;
Event4: Relates concept 2 with concept 5; when the height of the liquid in tank 2 is high, opening of valve 3 (concept 5) reduces the height of liquid in tank 2;
Event5: Connects concept 3 (valve 1) with concept 1 (tank 1); any change in valve 1 influences the amount of liquid in tank 1;
Event6: The value of concept 4 (valve 2) causes the decrease or not of the value of concept 1 (tank 1);
Event7: The value of concept 4 (valve 2) causes the increase or not of the amount of liquid in tank 2 (concept 2);
Event8: Relates concept 5 (valve 3) with concept 2 (tank 2), the value of concept 5 causes the decrease or not of the amount of the liquid in tank 2;
Event9: Connects concept 6 (temperature in tank 1) with the concept 8 (the operation of the heating element). When the temperature in tank1 is low, it causes the opening of the heating element;
Event10: Connects concept 8 with concept6; the value of concept 8 (operation of the heating element) increases the value of concept 6 (temperature in tank 1);
Event11: Connects concept 6 with concept 3 (valve 1); when the temperature in tank1 reaches an upper limit, opening of valve 1 empties liquid of low temperature in tank 1;
Event12: Relates concept 7 (temperature in tank 2) with concept 4 (valve 2); when the temperature in tank 2 is below a limit, opening of valve 2 causes hot liquid to pass from tank 1 to tank 2;
Event13: Shows the effect of concept 4 (valve 2) on concept 7 (the temperature in tank 2); when the valve 2 (concept 4) is open then hot liquid comes into tank 2 and the temperature in tank 2 (concept 7) is increased.

Interconnections among concepts can easily be changed and some new can be added or others can be removed if the human operator decides so, in order to have a better model of the system. Moreover, a concept can be added or removed if this improves the system's description. For example, another concept, that could be added later, is a concept, which will include the desirable output of the valve3.

Each concept of the FCM takes a value which ranges in the interval [0,1] and it is obtained after thresholding the real measurement of the variable or state which each concept represent. As an example, only 20% of the tank contains liquid, so the concept 1 at Fig. 6 which represent the height of liquid in tank takes the value 0.2. Using a similar methodology other concepts take values. The values of the events (interconnections between concepts) are determined more arbitrary. Each connection is charac-

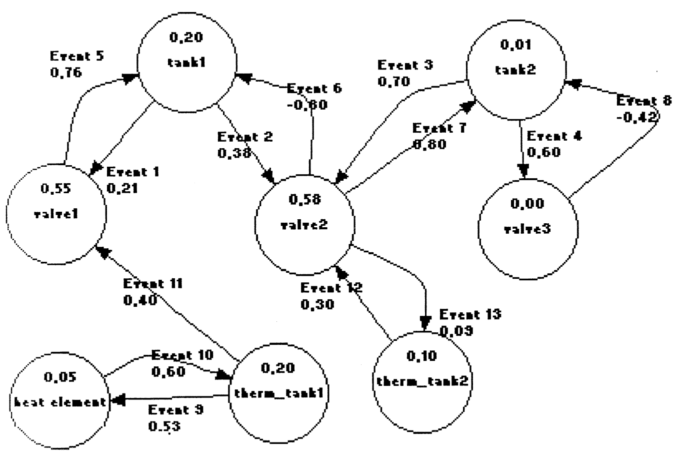

Fig. 6. The initial FCM, with the first values for the concepts.

Table 1
The values of concepts at each step of FCM interaction

Steps	Tank 1	Tank 2	Valve 1	Valve 2	Valve 3	Heat element	Therm _tank 1	Therm _tank 2
1	0.20	0.01	0.55	0.58	0.00	0.05	0.20	0.10
2	0.49	0.61	0.53	0.53	0.50	0.53	0.51	0.51
3	0.50	0.55	0.58	0.68	0.59	0.57	0.58	0.51
4	0.47	0.57	0.58	0.67	0.58	0.58	0.58	0.52
5	0.48	0.57	0.58	0.68	0.59	0.58	0.59	0.52
6	0.48	0.57	0.58	0.68	0.59	0.58	0.59	0.52

terised by a weight that ranges between $[-1,1]$, which is decided by the human expert who developed the FCM and determined the positive or negative causality, between two concepts and its degree. So he determined that the state of the valve 1 (concept 3) influences positively with a degree 0.76 (Event 5) the amount of liquid in tank 1 (concept 1). These weights among concepts were adjusted and changed during the training period of the FCM. Generally, it should be mentioned that the transformation from the real values of the physical measurements to the values of the concepts, needs more investigation and it must take into consideration the actual mechanism with which real values are transformed in FCM mode and vice versa.

Fig. 6 shows the FCM that was constructed to model and control the process, with the initial value of each concept and the weighted interconnections between concepts. The values of concepts correspond to the real measurements of the physical process. The values of the events (weights) have been determined after observation of the changes in the real experimental system and after training the FCM using the Differential Hebbian learning method [2].

A running step of the FCM is defined to be the time unit during which the values of the concepts are calculated and change according to Eq. (1). At each running step of the FCM, the values of each concept is defined by the result of taking all the causal event weights pointing into this concept and multiplying each weight by the value of the concept that causes the event. Then the sigmoid function is applied to the result of the calculations and it is transformed to the interval between 0.00 and 1.00.

The weights of the interconnections are considered fixed after the training period and FCM interacts for the initial values. It can be seen that after only five running steps, FCM reaches a stable state. In Table 1, the values of concepts for six steps are depicted. After this equilibrium point, if a disturbance occurs in the real system, which will cause change in the value of one or more concepts, FCM will interact for a limited number of cycles, perhaps another five or six cycles and it will reach again another equilibrium point (Fig. 7).

In this approach to the process control problem, it was assumed that values of concepts change simultaneously, in the same time unit for every concept, which is referred to as a running step. But, in a realistic system, effects take place in different unit times. For example, in Fig. 6 a change in concept6 (the temperature of the liquid in tank1) will lead almost immediately to a change to the state of the heat element (concept8). However a change in the state of the valve1 will take some time to have full effect in the amount of liquid in the tank 1. Thus, time lags would be introduced corresponding to time duration of each effect, but there could be a difficulty in estimating time lags for each effect. They could be estimated following the methodology proposed in Ref. [17].

In this section, the usage of FCM for direct control of a process was presented. This methodology could be enhanced in the future if it is considered an analogous to the Ramadge–Wohnam [18] approach where the process is modelled as state transition structure, in which some transitions are labelled as controllable (those that can be disabled by external intervention) and uncontrollable (those

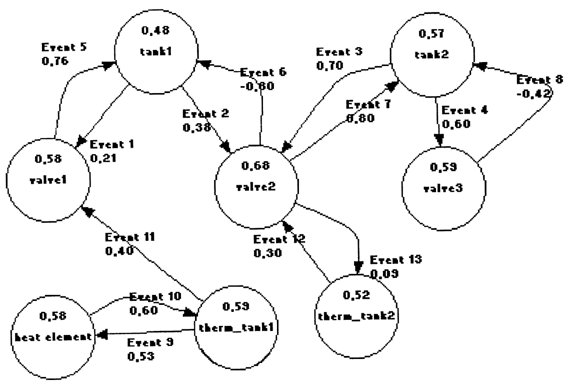

Fig. 7. The FCM after five running cycles.

cannot be prevented from occurring). Similarly, some concepts of the FCM can be considered as controllable when the change of their values can influence the real process, control it and drive a value to a desired point. Some concepts of FCM can be characterised as uncontrollable when they represent states of the process in which it is impossible to interfere and change their real value. In this process example the temperature of tank 2 is uncontrollable, as there is no direct control action which can influence this magnitude; but the state of any valve is controllable.

5. FCM as supervisor of control system

Supervisory Control systems have been described as systems that can perform some of the tasks that human operator successfully performs in supervising systems. Human operators do not operate a process by resolving mathematical equations but they integrate all the process information, either complete or incomplete, with the knowledge about the process to infer solutions for engineering problems [19]. Such an approach should be able a supervisory system to handle and express the qualitative information and have knowledge about the process structure. Supervisory control is composed of various types of reasoning related to different aspects of knowledge about a process. An appropriate model for supervision has to be built independently, rather than aiming at specific control tasks, so that it can involve all the necessary knowledge and furthermore this model should represent both qualitative and quantitative information.

Supervisory control is highly dependent on the experience of the process operators, something that is reflected in the methodology with which FCM is constructed. FCM is a model for representing and decoding the expert's knowledge and experience. This approach is based on the fact that there may be many physical properties of the process that are not part of the analytical model which is used in conventional approach to design the controller; they may result from the complexity of the process or from lack of understanding of the physics involved. On the other hand, experienced process operators may have developed a number of heuristic control rules, which allow them to control such a process in a satisfactory manner. The proposed technique of FCM can be used to model the heuristic control laws and perform more demanding tasks. FCM employs a symbolic qualitative model which allows one expert to explicitly represent and reason with the available heuristic knowledge which supports high level reasoning and creates more flexible control systems.

The structure of the Supervisory Control System has been described in Section 3 and it has been illustrated in Fig. 3. In this model, a conventional controller is used to perform the usual control tasks and regulate the process. On the upper level of the hierarchy, there is an FCM, which stands for the supervisor of the system. This FCM is activated if an abnormal behaviour occurs during the process and tries to bring the behaviour back into the acceptable operation region or some emergency measure sequences could be performed. The Supervisor FCM can be used to model device failure modes, effects and causes analysis [11], decision analysis and strategic planning [13]. When the process is regarded as abnormal, operators will identify the possible reasons and decide how to correct the abnormal behaviour through analysing the interactions between process components. Similarly, an FCM could be used for supervisor control, which can be consisted of concepts that stand for the irregular operation of some elements of the system, for failure mode variables, for failure effects variables, for failure cause variables, severity of the effect and design variables. The construction of FCM can be based on the operator's heuristic knowledge about alarms, faults, what is their cause, and when they happen. Moreover, this FCM will include concepts for description and determination of a specific operation of the system or other qualitative preferences for the planning and scheduling of the process.

In Section 4, the usage of an FCM has been presented for the direct control of a process. It can be considered that above this FCM there is another level with the supervisor of the whole system modelled as an FCM. This co-operation of two-level FCMs seems to be challenging and it could lend itself to more sophisticated systems. The two FCMs will interact with each other and there would be an amount of information that must pass from the one FCM to the other. Thus two interfaces are needed, one will pass information from the FCM in the lower level to the FCM in the upper level and another one interface in the opposite direction. The two interfaces are necessary because changes on two or more concepts in the FCM on the lower level could mean change in one concept in the upper level and the corresponding procedure, when information descends from the FCM on the upper level towards the lower level.

Symbolic representation and processing of the supervisor of a hierarchical system using FCM or any other similar approach will undoubtedly play an important role in the construction of Intelligent Control Systems. The objective is the development of a hierarchical intelligent system, which will combine the features of primary controllers such as stability, controllability and features of human operators such as flexibility and learning capabilities. The proposed modelling with FCM, based on the human knowledge and experience of the system, and inspired by the parallelism, that humans use to store knowledge and make decisions, seems to be a sophisticated control strategy which will lend to a higher degree of autonomous systems.

6. Summary

For large and complex systems that are common in the process industry, it is extremely difficult to describe the entire system by a precise mathematical model. Thus, it is more attractive and useful to represent it, in a graphical abstract way showing the causal relationships between states-concepts. This symbolic method of modelling and control of a system is easily adaptable and relies on expert experience and follows the general rule of ''decreasing precision and increasing intelligence'' [20].

The implementation of an FCM controller for a process control problem has been presented. Through this example, it has been shown how FCMs describe in a simple way the system's behaviour and control the process. The prospect to expand the control capabilities of the system, by adding a second FCM on a higher level which will perform supervision tasks such as failure analysis, decision analysis and planning, has then been discussed. Fuzzy Cognitive Map seems to be a useful modelling method, which can be used to control complex systems. This method is appropriate for systems not fully mathematically described, however these systems are working well under human supervision and intervention. There are plenty of such systems in the chemical process industries, the cement industry and the oil industry.

Future research may examine the description and construction of FCM in the supervisory level, appropriate learning algorithms for FCMs, and control related aspects such as the stability and controllability of FCMs. FCM appear to be an appealing tool in the description of the supervisor of complex control systems. Its combination with other methods may lead to the next generation of control industrial systems.

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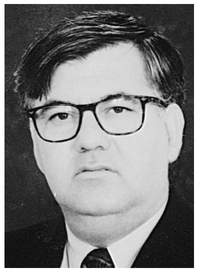

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