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The challenge of modelling supervisory systems using fuzzy cognitive maps

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This paper examines fuzzy cognitive map (FCM) theory and its use in supervisory control systems. An FCM is a graph used to depict cause and effect between concepts that stand for the states and variables of the system. An FCM represents the whole system in a symbolic manner, just as humans have stored the operation of the system in their brains, thus it is possible to help man's intention for more intelligent and autonomous systems. FCM representation, construction and a mathematical model are examined; a generic system is proposed and the implementation of FCM in a process control problem is illustrated and a model for supervisors of manufacturing systems is discussed. Although an FCM seems to be a simple model of system behaviour, it appears to be a powerful and effective tool describing the behaviour of a system and representing the accumulated knowledge of a system.

Keywords: Supervisory control systems, fuzzy cognitive map

1. Introduction

The challenge of using FCMs to model the upper part or supervisor of a process or plant is investigated. A brief discussion will denote the growing interest of scientists in the application of FCMs, then the structure and the construction of an FCM will be examined: it will be described as a generic system in which the supervisor is modelled as the FCM, and the ability of FCM to control a simple practical process will be shown. Finally, the implementation of FCMs as a model of the supervisor of a manufacturing system is proposed.

FCM theory developed recently (Kosko, 1986) as an expansion of cognitive maps that had been employed to represent social scientific knowledge (Axelrod, 1976), to make decision analysis (Zhang *et al.*, 1989) and to analyse extend graph–theoretic behaviour (Zhang and Chen, 1988). FCMs have been used for planning and making decisions in the fields of international relations, in modelling political developments and social systems (Taber, 1991, 1994) in administrative science, in management science, in operations research and organizational behaviour (Craiger and Coovert, 1994; Craiger *et al.*, 1996). Styblinski and Meyer (1991) have used FCMs to analyse electrical circuits, and Dickerson and Kosko (1994) have used FCMs to structure virtual worlds. From a different point of view, FCMs have been used by Gotoh *et al.* (1989) to model plant control and we have proposed the application (Stylios *et al.*, 1997) of FCMs in the modelling of supervisors.

The purpose of this paper is to represent the construction of a knowledge-based supervisory control system with a FCM. In this FCM, the knowledge and experience that the human operator has gathered on the operation of a complex plant will be depicted. FCMs lie in some sense between fuzzy logic (efficient in representing heuristic, common-sense rules) and neural networks (efficient at learning heuristics from data). This may increase the intelligence of the system; as the more intelligent a system becomes, the more symbolic and fuzzy representation is used.

2. Fuzzy cognitive maps

An FCM is a methodology for representing the behaviour of models and it is a combination of fuzzy logic and neural networks (Kosko, 1986, 1992). An FCM describes the behaviour of a system in terms of 'concepts' and effects among concepts. An FCM (Fig. 1) is a fuzzy signed directed graph with feedback, where nodes of the graph represent concepts or elements that comprise the model and are connected by signed and weighted arcs representing the causal relationships that exist among concepts. An FCM is a fuzzy-graph structure that exhibits desirable properties, has the ability to specify any model of any

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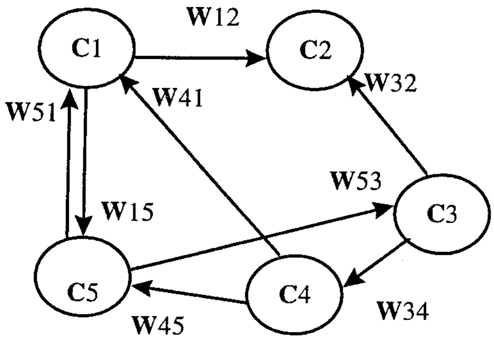

Fig. 1. A fuzzy cognitive map.

complexity, shows linear or non-linear relations and allows causal propagation, in particular forward and backward chaining.

Each node-concept represents one of the key-factors of the described system; in general it stands for states, variables, events, actions, goals and trends of the system. Each concept is characterized by a number, A_i, that represents its value and it results from the transformation of the real value of the system's variable, for which, this concept stands, in the interval [0, −1]. For the real system, relationships among its characteristics are considered in order to describe its behaviour; how and which factor influences others? It must be mentioned that all values in the graph are fuzzy, so weights of the arcs take values in the interval [−1, 1]. Thus, there are three possible types of causal relationship between concept C_i and concept C_j according to the sign of the arc:

(1) $W_{ij} > 0$ indicates positive causality between concept C_i and concept C_j – this means that an increase in the value of concept C_i leads to an increase of the value of concept C_j and vice versa;

(2) $W_{ij} < 0$ indicates negative causality between concept C_i and concept C_j – this means that an increase in the value of concept C_i leads to a decrease of the value of concept C_j and a decrease of the value of concept C_i leads to an increase of the value of concept C_j; and

(3) $W_{ij} = 0$ indicates no relationship between concept C_i and C_j.

The strength of W_{ij} indicates how strongly concept C_i influences concept C_j. The sign of W_{ij} indicates whether the relationship between concepts C_i and C_j is direct or inverse. The direction of causality indicates whether concept C_i causes concept C_j, or vice versa. These three parameters have to be considered when assigning a value to W_{ij}.

An FCM is not only graphically described, but mathematically, using vectors and matrices. It uses an $1 \times n$ state vector $\boldsymbol{A}$, which gathers the values of each one of the n concepts and an $n \times n$ edge matrix, $\boldsymbol{F}$. Each element, e_{ij} of the matrix, $\boldsymbol{F}$, represents the value of the relationship, W_{ij}, between concept C_i and C_j. The matrix $\boldsymbol{F}$ has n rows and n columns, where n equals the total number of distinct concepts used by experts to construct the FCM and the matrix diagonal is zero because it is assumed that no concept can cause itself.

The value A_i for each concept C_i is calculated by the following rule:

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

A_i is the value of concept C_i at time $t + 1$, A_j is the value of concept C_j at time, t, and W_{ji} is the weight arc from C_j to C_i and f is a threshold function that transforms the result of the multiplication in the interval [0, 1] where concepts take values.

A more general and compact mathematical model for FCMs is presented by the following equation:

$$\boldsymbol{A}_{\text{new}} = \boldsymbol{A}_{\text{old}} \times \boldsymbol{F} \tag{2}$$

So, Equation 2 computes the new state vector, $\boldsymbol{A}$, that results from the multiplication of the old, at time, t, state vector $\boldsymbol{A}$, by the edge matrix, $\boldsymbol{F}$. The new state vector holds the new values of the concepts after interaction among concepts of the map. The interaction was caused by a change in the value of one or more concepts.

Values of each one of the concepts of the FCM belong in the range [0, 1] based upon expert opinion for the current state, and then the concepts are free to interact. In each step of the interaction the new state vector, $\boldsymbol{A}$, is computed according to Equation 2; and this interaction, after a number of steps, would lend FCMs in:

(1) a fixed equilibrium point;
(2) a limited cycle; and
(3) chaotic behaviour.

An FCM represents the human knowledge on the operation of the system, so in order to build a map one expert is asked to draw an FCM according to his/her experience. With this procedure, concepts are determined; one expert knows the factors that influence the behaviour of the system, each one of these factors is represented by a concept on the FCM. Moreover, the expert has observed which elements of the system influence the other elements; for corresponding concepts the expert determines the negative or positive effect of one concept on the others, with a fuzzy degree of causation.

It is possible to exploit the experience of a group of operators and experts on the operational behaviour of the system. First of all, experts are pooled and they determine the relevant factors that should be present on the map as concepts. Then, experts are individually asked to express the relationships that exist among these concepts–factors. In this manner, a collection of individual FCMs is constructed and it must be combined into one collective map. If it is considered that some of the experts are more or less knowledgeable about the operation of the system, different credibility factors must be applied for each expert. So, there are experts with varying credibility, whose maps are multiplied by a non-negative 'credibility' weight, b_i, before combining them with other experts' constructions. If there is an expert who is extremely knowledgeable about certain parts of the system and not others, or someone else who does not have a very good knowledge on some parts of the system, different credibility weights have to be posed on different links of the FCM. Thus, the construction of a consummate FCM demands the determination of the credibility weights: the matrix, $\boldsymbol{F}$, of the whole FCM is constructed by adding the matrices $\boldsymbol{F}_i$, of various FCMs:

$$\boldsymbol{F} = \sum_{1}^{N} b_i \boldsymbol{F}_i \tag{3}$$

where $\boldsymbol{F}$ is the whole FCM, b_i is the credibility weight for the ith expert and $\boldsymbol{F}_i$ is the weight matrix of the FCM of ith expert, and N is the number of experts.

An FCM is able to manage and model systems of unlimited complexity with an unlimited number of concepts and with feedback causal relations among concepts. It avoids many of the knowledge-extraction problems that are usually posed by rule-based systems and it is efficient in modelling, managing and controlling any complex system.

3. The generic system

From the previous discussion, the FCM will be used as the process model in the upper level of a process. So a generic model is proposed, which is depicted in Fig. 2, that can be used for any technological process or complex system.

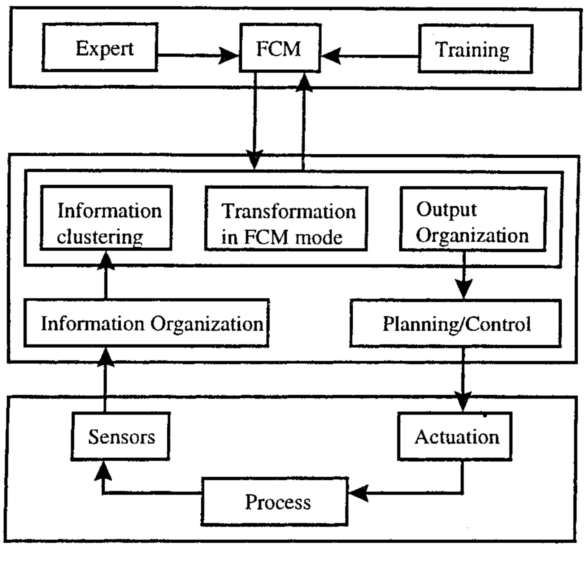

Fig. 2. A general model of the plant.

The proposed model consists of three levels:

(1) the lower level – this is the physical system of complementary devices that measure the variables of the process and can actuate the process;

(2) the middle level – this constitutes the interface between the physical process and the supervisor;

(3) the upper level – is the supervisor of the system, i.e. the FCM.

The FCM in Fig. 2 is constructed by the method described in the previous section. An expert who knows the operation of the process, draws an FCM, and determines the concepts and the relationships among them that reflect the operation of the process. So this FCM will contain some human knowledge of the modelling, behaviour and operation of the complex lower-level system and this is depicted in the upper level by the expert item that influences the FCM. After primitive construction, the FCM can be refined using training methods, based on unsupervised neural networks and learning algorithms (Kosko, 1986, 1992), i.e. the Hebbian learning algorithm. During the learning period, the weights of the interconnections will be adjusted according to existing measurements and data on the operation of the system, and then a more integrated FCM, will have been constructed.

After the construction and training of the supervisor, the FCM concepts take their initial values and the operation of the system starts. In the lower level, sensors measure the variables of the process and this information passes to the middle level; at this stage, the information is organized, clustered and transformed into FCM terms; then, it passes into the FCM, which lies in the upper level. This new information causes changes in the values of one or more concepts, then the FCM concepts interact and an equilibrium point is reached. So, there are new values to concepts, which means new values for some variables of the system. The new values must pass to the process level and so, in the middle level of the interface the reverse procedure is followed; values of concept are transformed in suitable output information, are categorized, cause control signals and influence the process through the actuators.

4. Practical process control problem

In this section, a well known problem from the process industry is utilized to show how an FCM is constructed, concepts are chosen and values are assigned to the interconnections between concepts. This FCM will be used to control the process, and for this example it is not equipped with the advanced characteristics that a supervisor has.

The process considered (Fig. 3) consists of one tank and three valves that influence the amount of liquid in the tank. Valves 1 and 2 empty two different kinds of liquid into the tank; during mixing of the two liquids a chemical reaction takes place in the tank. In the tank there is an instrument

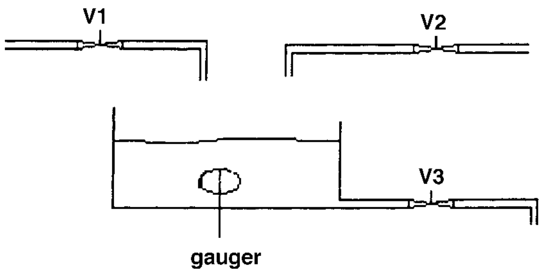

Fig. 3. The illustration of a simple process.

that measures the specific gravity of the liquid that is produced during the mixing: when the measured specific gravity lies in a specified range between $G_{\max}$ and $G_{\min}$, then a liquid of desired chemical composition is produced in the tank. Moreover, a limit is placed on the height of the liquid in the tank, which cannot exceed an upper limit, $H_{\max}$, and a lower limit, $H_{\min}$. So, the control target has to keep these variables in the middle of their range of values:

$$\begin{aligned} G_{\min} \leq G \leq G_{\max} \\ H_{\min} \leq H \leq H_{\max} \end{aligned} \tag{4}$$

In order to construct an FCM that will model and control this simple system, the concepts of the map must be determined. The concepts represent the variables and states of the plant as it is at the height of the liquid in the tank, or the state of the valve. So a primitive FCM will have five concepts and later any new concept that will help our view and control of the system can be added:

(1) Concept 1 – the amount of the liquid that Tank 1 contains is dependent on the operational state of Valves 1, 2 and 3;
(2) Concept 2 – the state of Valve 1 (it is closed, open or partially opened);
(3) Concept 3 – the state of Valve 2 (it is closed, open or partially opened);
(4) Concept 4 – the state of Valve 3 (it is closed, open or partially opened); and
(5) Concept 5 – the reading on the specific gravity instrument.

After having selected the concepts that can represent the model of the system and its operational behaviour, the interconnections between concepts must be decided. At first, it is decided for each concept to which another concept is connected. Then, the sign and weight of each connection is determined. This procedure is done by a specialist who has experience of the system's operation; or for better results, FCMs could be trained with an unsupervised method.

The connections between concepts are:

- Event 1 – connects Concept 2 (Valve 1) with Concept 1 (Valve 1 causes the increase, or not, of the amount of liquid in the tank, i.e. Concept 1);
- Event 2 – relates Concept 3 (Valve 2) with Concept 1 (it relates the state of Valve 2 with the amount of liquid in the tank;
- Event 3 – connects Concept 4 (Valve 3) with Concept 1 (the state of Valve 3 causes the decrease, or not, of the amount of liquid in the tank;
- Event 4 – relates Concept 1 with Concept 2 (when the height of the liquid in the tank is high, Valve 1, i.e. Concept 2, needs closing and so the amount of incoming liquid into the tank is reduced);
- Event 5 – connects Concept 1 (tank) with Concept 3 (when the height of the liquid in the tank is high, the closing of Valve 2, i.e. Concept 3, reduces the amount of incoming liquid);
- Event 6 – connects Concept 5 (the specific gravity) with Concept 4 (Valve 3) (when the specific gravity of the liquid in the tank takes a value, Valve 3 is opened and the liquid produced continues to another process);
- Event 7 – shows the effect of Concept 1 (tank) on Concept 5 (specific gravity), when the amount of liquid in the tank is varied, this influences the value of the specific gravity of the liquid; and
- Event 8 – relates Concept 5 (specific gravity) with Concept 2 (Valve 1), when the specific gravity is very low then Valve 1 (Concept 2) is opened and liquid from this source comes into the tank.

It is obvious that the FCM permits the addition or removal of any concept if this improves the system's description and, furthermore, the addition or removal of any connection between the concepts that describe the system. This is a very useful ability that will help the designer of a system to evaluate the influence of a process on some of the characteristics of a system.

Figure 4 shows the FCM that is used to describe and control this simple system, the initial value of each concept,

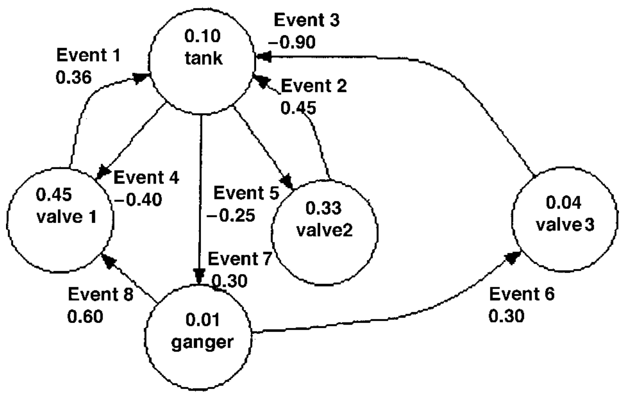

Fig. 4. The initial FCM, with the first values for the concepts.

the interconnections and the weights between concepts. The values of the concepts correspond with the real measurements of physical magnitude. The values of each event (connection between concepts) have been arbitrarily determined after observation of the changes in the real experimental system, by the specialist who designed the map.

Each concept has a value that ranges between [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. It should be mentioned that the transformation from the real values of the physical measurements to the values of the concepts, needs investigation and must take into consideration the actual mechanisms depicted in the FCM.

At each running step of the FCM, the values of the concepts are calculated according to Equation 1. The value of each concept is defined by 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 used and so the result is in the range [0, 1].

The weights of the interconnections are considered fixed and then the FCM interacts for the first initial values. Figure 5 shows the FCM after six running cycles; it must be mentioned that each running cycle holds for a time unit. It can be seen that after only four running cycles, the FCM reaches a fixed point. In Table 1 the value of each concept for the first five cycles is represented.

5. Supervisor of manufacturing systems modelled as an FCM

Manufacturing systems are complex systems for which it is impractical and impossible to construct a realistic mathematical model. For such systems, the human operator offers supervisory intelligent control through the use of an imprecise and robust control methodology. The FCM is a

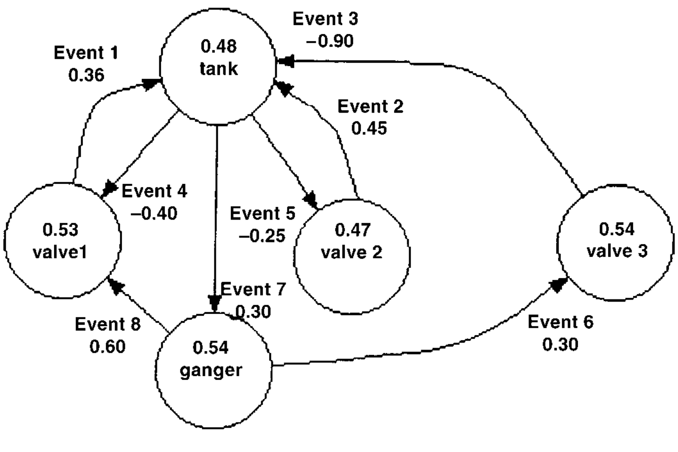

Fig. 5. The FCM after six running cycles.

Table 1. The values of FCM concepts for the first six running cycles

	Tank	*Gauger*	*Valve* 1	*Valve* 2	*Valve* 3
1	0,10	0,01	0,45	0,39	0,04
2	0,57	0,51	0,49	0,49	0,50
3	0,49	0,54	0,52	0,46	0.54
4	0,48	0,54	0,53	0,47	0,54
5	0,48	0,54	0,53	0,47	0,54
6	0,48	0,54	0,53	0,47	0,54

symbolic representation for the description and modelling of complex systems, describing different aspects in the behaviour of complex systems in terms of concepts; interaction among concepts shows the dynamics of a system.

For the modelling of a manufacturing control system, a two-level approach is proposed in order to achieve a more sophisticated manufacturing system. On the lower level conventional control methodologies are used, and in the upper level lies an ‘intelligent supervisor’ that attempts to emulate a human control capacity using an FCM.

Figure 6 depicts the two-level hierarchy that is used to model a general manufacturing system. Each machine-process on the lower level has its own local controller that performs usual control actions. The supervisor is used for more generic purposes: to organize all the machines in order to accomplish a task, to help the operator make decisions, to plan strategically and to detect and analyse failure.

The control problem that is illustrated in the previous section can be improved if this two-level structure is considered. In the lower level of the structure will lie the FCM that has just been constructed, which will play the role of a conventional controller and will reflect the process model during normal operational conditions. In the upper level, a supervisory FCM will include advanced features such as fault diagnosis, effect and cause analyses (Pelaez and Bowles, 1995, 1996), prediction capabilities, decision analysis, and strategic planning. The FCM will consist 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 effects, design variables. The construction of a map will be based on the operator’s heuristic knowledge about alarms, faults, what are their causes, and when will 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 this FCM, analysis can be implemented of the data coming from the lower level, which will represent vital components of the plant, detecting features that reflect the operational state of the plant. To draw this FCM, the integration of several expert opinions will be needed in order to achieve its diagnosis and predictive task, which is extremely difficult.

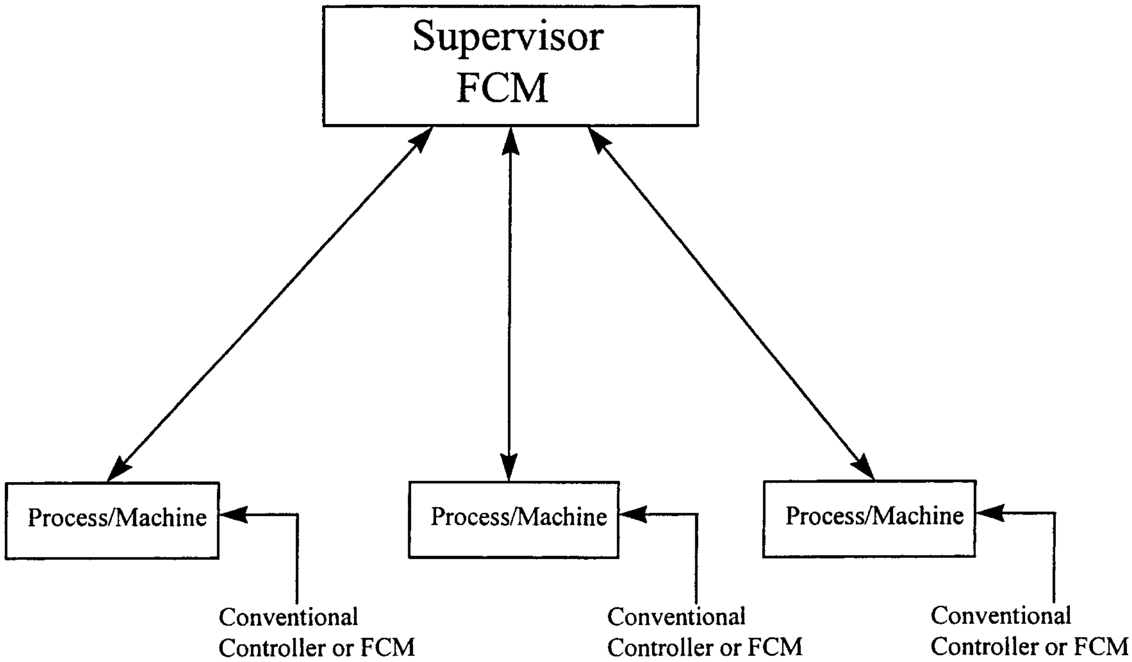

Fig. 6. A two-level structure approach.

The most important use of an FCM is for supervisory control of a conventional control element, thus complementing rather than replacing a conventional controller. In this case, the role of the FCM is to extend the range of application of a conventional controller by using a more abstract representation of the process, general control knowledge and adaptational heuristics, and to enhance the performance of the whole system. Thus, the FCM may replicate some of the knowledge and skills of the control engineer and it is built using a combination of knowledge representation techniques as causal models, production rules and object hierarchies and it is used to perform more demanding procedures such as failure detection, decision making and planning (tasks usually performed by a human supervisor of the controlled process).

6. Conclusions

In this paper a new methodology, an FCM, for modelling the supervisor of a complex control system has been presented. The paper has examined the presentation and construction of an FCM and a generic system has been proposed for modelling complex systems. An FCM has been implemented in a simple process control problem that makes apparent the qualities and characteristics of the method. It has been observed how simply an FCM describes a system's behaviour and its flexibility in any change of the system. A more integrated approach, i.e. a two-level structure, where the FCM in the upper level is used for more sophisticated supervisory control of manufacturing systems, has been proposed.

An FCM provides accessible modelling of a system's operation and it best exploits man's knowledge on the operation and behaviour of the system. For complex systems it is not easy, sometimes it is impossible, to construct a precise mathematical model and it is more useful to model it, in a symbolic manner, which may lend to more efficient autonomous and intelligent systems. After this presentation, an FCM seems to be a prospective method in the description of the supervisor of complex control systems, which can be teamed up with other methods and will lead to next-generation manufacturing systems.

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