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A Soft Computing Approach for Modelling the Supervisor of Manufacturing Systems

C. D. STYLIOS and P. P. GROUMPOS
Laboratory for Automation and Robotics, Department of Electrical and Computer Engineering, University of Patras, Rion 26500, Greece; e-mail: stylios@ee.upatras.gr

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Abstract. The development of a novel soft computing approach to model the supervisor of manufacturing systems is described, it is named Fuzzy Cognitive Maps (FCMs) and it is used to model the behaviour of complex systems. Fuzzy cognitive maps combine characteristics of both fuzzy logic and neural networks. The description and the construction of fuzzy cognitive maps are examined, a new methodology for developing fuzzy cognitive maps is proposed here and as an example the fuzzy cognitive map for a simple plant is developed. A hierarchical two-level structure for supervision of manufacturing systems is presented, where the supervisor is modelled as a fuzzy cognitive map. The fuzzy cognitive map model for the failure diagnosis part of the supervisor for a simple chemical process is constructed.

Key words: supervisory manufacturing systems, fuzzy cognitive maps, soft computing.

1. Introduction

In modern manufacturing systems, the representation and processing of information has become one of the most critical factors of production and is the key for the efficient operation of highly automated plants. Manufacturing systems are systems with a great potential to implement new ideas and methods, which will enhance their performance. A promising domain is the utilisation of intelligent techniques and the development of intelligent manufacturing systems. An intelligent manufacturing system should utilise effectively all the company resources, especially the insights and experience of front-line operators and experts, in order to achieve continuous improvements in productivity. The use of many concepts from discipline areas such as information theory, neural networks and fuzzy logic has been proposed to model and control systems that would create hybrid intelligent systems [13].

During the last decades manufacturing systems have utilised the advantages of computer and automation technology and have made many advances. The requirements for more advanced manufacturing systems, which are characterised by high autonomy and intelligence, have led engineers to investigate and invent new techniques that integrate and combine known advanced methodologies and which will be the core of sophisticated manufacturing systems. The development of these systems requires new techniques for modelling and controlling systems other than the existing conventional theories. Thus, we propose the investigation and utilisation of new methods that exploit past experience, have learning capabilities, are supplied with failure detection and identification characteristics and can handle with imprecision and uncertainty.

A technique that has some of the previously described features is Fuzzy Cognitive Maps (FCMs). FCMs can model dynamical complex systems that change with time following nonlinear laws. FCMs use a symbolic representation for the description and modelling of the system. A fuzzy cognitive map is consisted of concepts in order to illustrate different aspects in the behaviour of the system, with each concept representing a characteristic of the system, and these concepts interact with each other showing the dynamics of the system. An 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 behaviour.

Fuzzy cognitive maps have already been used to model behavioural systems in many different scientific areas. For example, in political science [1] fuzzy cognitive maps were used to represent social scientific knowledge and describe decision-making methods. Kosko enhanced the power of cognitive maps considering fuzzy values for their concepts and fuzzy degrees of interrelationships between concepts [8, 9]. 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. Fuzzy cognitive maps have been used for planning and making decisions in the field of international relations and political developments [20] and to model the behaviour and reactions of virtual worlds [3]. FCMs have been proposed as a generic system for decision analysis [23] and as coordinator of distributed co-operative agents [24]. Fuzzy cognitive maps have been used to model and control a dynamic plant [6], to represent failure models and effects analysis for a system model [15], and to model the supervisor of control systems [18, 19]. It is obvious that there is high interest in the use of FCMs in a wide range of different scientific fields, but there still remains to see an extensive use of FCMs on process and manufacturing problems, which are nonlinear systems requiring such methods.

Generally, the application of soft computing methodologies, such as FCMs, in the field of manufacturing systems may contribute in the development of more autonomous and intelligent manufacturing systems. In this paper, fuzzy cognitive maps are proposed to model the supervisor of a hierarchical two level system. Using this symbolic abstract methodology to model the supervisor, the principle of “decreasing precision and increasing intelligence” is followed [16].

The organisation of this paper is as follows. Section 2 presents the challenge of using soft computing methodologies in manufacturing systems. In Section 3 fuzzy cognitive maps representation and construction are examined and a new methodology for developing FCMs is proposed. In Section 4 a simple fuzzy cognitive map for a simple chemical plant is developed. Section 5 discusses a two level structure for supervisory systems, where the supervisor is modelled as a fuzzy cognitive map and the failure diagnosis part of the supervisor-FCM is developed for a chemical process. Finally, Section 6 concludes the paper and gives some possible future research directions.

2. Soft Computing Methodologies for Manufacturing Systems

As manufacturing facilities become more complex and highly sophisticated, the quality of the production phase has become more critical. Manufacturing of such typical products as aircraft, automobiles, appliances, and medical equipment, involves a large number of complex processes most of which are characterised by highly nonlinear dynamics that couple a variety of physical phenomena in the temporal and spatial domains. It is not surprising, therefore, that these processes are not well understood and their operation is "tuned" by experience rather than through the application of scientific principles [22]. Capturing and utilising the expert's knowledge, effectively and efficiently, promises to improve plant operational conditions.

Fuzzy cognitive maps are based on fuzzy logic and neural networks. Many industrial processes are not controlled by conventional techniques in an efficient and cost effective way and it has been claimed that fuzzy logic can deal successfully with such processes, which are usually multi-variable, inherently nonlinear and time-varying in nature. In addition, fuzzy logic can also deal with ill-defined systems of unknown dynamics, as they do not require a priori mathematical model of the plant implementation. One of the main advantages of applying fuzzy logic control is its development along linguistic lines. The fuzzy controller consists of a set of linguistic conditional statements or rules, which can be easily developed from common sense or from engineering judgement [4].

Neural networks have the ability to learn from input-output functions, and so, they provide simpler solutions to complex control problems. Furthermore, neurons are nonlinear elements, and hence, neural networks are basically nonlinear systems, which can be used to learn and solve nonlinear control problems for which traditional and conventional control methods do not always have an optimal solution [11]. Novel methodologies based on fuzzy logic techniques and neural network theory are utilised to extract model of systems and represent human knowledge.

The synergistic and complementary use of fuzzy logic and neuro-computing has initiated the development of soft computing methodologies. These soft computing methodologies have been investigated and proposed in order to be utilised in the description and modelling of complex systems. Fuzzy cognitive maps belong to this category. Neuro-fuzzy systems have been proposed as advanced techniques in the modelling and control of real world problems that are usually imprecisely defined and require human intervention [7]. Neuro-fuzzy systems have the ability to incorporate human knowledge and to adapt their knowledge base via optimisation techniques.

3. Fuzzy Cognitive Maps Representation and Development

Fuzzy cognitive maps approach is a hybrid modelling methodology, exploiting characteristics of both fuzzy logic and neural networks theories and it may play an important role in the development of intelligent manufacturing systems. The utilisation of existing knowledge and experience on the operation of complex systems is the core of the proposed modelling approach. Experts develop fuzzy cognitive maps and they transform their knowledge in a dynamic cognitive map.

The graphical illustration of FCM is a signed directed graph with feedback, consisting of nodes and weighted interconnections. 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 arcs representing the causal relationships that exist among concepts (Figure 1). Each concept represents a characteristic of the system; in general it stands for states, variables, events, actions, goals, values, trends of the system which is modelled as an FCM. Each concept is characterised by a number A_i, which 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 $[0, 1]$. It must be mentioned that all the values in the graph are fuzzy, and so weights of the interconnections belong to the interval $[-1, 1]$. With the graphical representation of the behavioural model of the system, it becomes clear which concept of the system influences other concepts and in which degree. This representation permits the easy update of the construction of the graph, such as the adding or deleting of an interconnection or a concept.

The most essential part is the development of fuzzy cognitive maps, the determination of the concepts that best describe the system, the direction and the grade of causality between concepts. The selection of the different factors of the system, which must be presented in the map, will be the result of a close-up on system's operation behaviour as been acquired by experts. Causality is another important part in the FCM design; it indicates whether a change in one variable causes change in another, and it must include the possible hidden causality that it could exist between several concepts. The most important element in describing

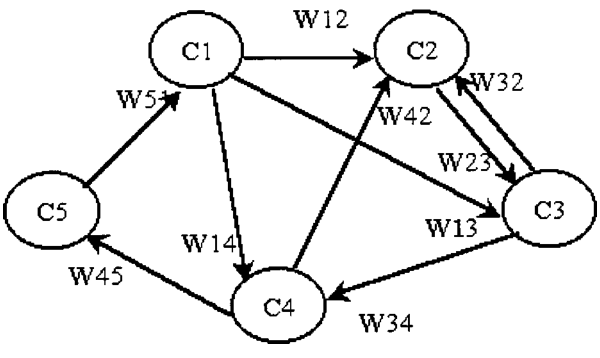

Figure 1. A simple fuzzy cognitive map.

the system is the determination of which concept influences which other and with which degree. There are three possible types of causal relationships among concepts that express the type of influence from one concept to the others. The weight of the interconnection between concept C_i and concept C_j, denoted by W_{ij}, could be positive ($W_{ij} > 0$) for positive causality or there is negative causality ($W_{ij} < 0$) or there is no relationship between concept C_i and concept C_j, thus $W_{ij} = 0$. The causal knowledge of the dynamic behaviour of the system is stored in the structure of the map and in the interconnections that summarise the correlation between cause and effect.

The value of each concept is influenced by the values of the connected concepts with the corresponding causal weights and by its previous value. So the value A_j for each concept C_j is calculated by the following rule:

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

where A_j^s is the value of concept C_j at step s, A_i^{s-1} is the value of concept C_i at step $s-1$, A_j^{s-1} is the value of concept C_j at step $s-1$, and W_{ij} is the weight of the interconnection between C_i and C_j, and f is a threshold function. Threshold functions squeeze the result of multiplication in the interval $[0, 1]$. Equation (1) includes the previous value of each concept, and so the FCM possesses memory capabilities and there is a smooth change after each simulation step.

The development and design of the appropriate fuzzy cognitive map for the description of a system requires the contribution of human knowledge. The experts develop fuzzy cognitive maps using an interactive procedure of presenting their knowledge on the operation and behaviour of the system. The procedure described here is a new approach that differs from other proposed methods for constructing FCMs [17]. We assume that the experts and operators of the system know the behaviour of the system and that they have developed a mental model of the system in their mind; this model can be easily transformed in a fuzzy cognitive map, which is a conceptual model. Experts are asked to determine the concepts that best describe the model of the system, since they know which factors are the key principles and functions of the system operation and behaviour, and they introduce a concept for each one. Experts have observed the operation and behaviour of the system during its operation, since they are the operators and supervisors of the system, who control it using their experience and knowledge. They have stored in their mind the correlation among different characteristics, states, variables and events of the system and in this way they have encoded the dynamics of the system using fuzzy rules.

The procedure for constructing fuzzy cognitive maps is as follows: experts define the main concepts that represent the model of the system, they describe the structure and the interconnections of the network using fuzzy conditional statements. Experts use IF–THEN rules in order to describe the causal relationship among concepts, and based on these rules FCM is structured and the weighted interconnections are determined.

The fuzzy if-then rule, that experts use to describe the relationship among concepts and thus to develop the fuzzy cognitive map, assumes the following form, where ***A*** and ***B*** are linguistic variables:

*IF value of concept C_i is **A** THEN value of concept C_j is **B**.*

The set of linguistic variables for each concept takes the following values with the corresponding membership functions:

Value of concept C_i is very very low with membership function μ_{vvl}.
Value of concept C_i is very low with membership function μ_{vl}.
Value of concept C_i is low with membership function μ_l.
Value of concept C_i is less than medium with membership function μ_{lm}.
Value of concept C_i is medium with membership function μ_m.
Value of concept C_i is greater than medium with membership function μ_{gm}.
Value of concept C_i is high with membership function μ_h.
Value of concept C_i is very high with membership function μ_{vh}.
Value of concept C_i is very very high with membership function μ_{vvh}.

A group of experts are polled together and they are asked to describe the relationships among concepts of fuzzy cognitive map using a linguistic fuzzy rule and every expert proposes a fuzzy rule for each interconnection. In this way, experts describe the causal interrelation between two concepts of the fuzzy cognitive map by an ensemble of linguistic rules, and a database of linguistic rules is created, these rules are combined and create the final overall rule. The overall rule describes the causal relationship between the value of concept C_i and concept C_j, thus the weight between concept C_i and concept C_j can be inferred from the rule.

The calculation of the overall rule for each interconnection is based on the fuzzy inference Tsukamoto model [21] and the overall output is taken as the weighted average of each rule's output. This method aggregates each rule's output and the overall rule will be an input–output function, which will have as input the value of concept C_i and output the value of concept C_j. The produced input–output function g_{ij} describes the causal relation between concept C_i and concept C_j and it represents the weight w_{ij}, thus this methodology does not require the determination of a crisp value for the weight of each interconnection. With the use of the causal function the calculation rule for fuzzy cognitive maps of Equation (1) becomes:

$$A_j^s = f\left(\sum_{i=1\, i\neq j}^{n} g_{ij}\left(A_i^{s-1}\right) + A_j^{s-1}\right). \tag{2}$$

This development methodology is very comprehensive to operators of the system because they describe the influence that one factor of the system has on another using simple rules. This is very similar to the way with which humans relate states, variables, events and store them in their mind as a picture of causes and effects among elements of the system. Moreover, the proposed methodology asks experts to describe the relation between two concepts using a linguistic rule and experts do not have to infer about the interrelationship itself and the corresponding weight, this approach is more objective method than other proposed methodologies for constructing FCMs.

As an example, the case of three experts, who describe the relation between concept C_i and C_j will be examined. Experts propose the following rules:

*1st Expert: IF value of concept C_i is **Very very low** THEN value of concept C_j is **Very very low***

*2nd Expert: IF value of concept C_i is **Very low** THEN value of concept C_j is **Low***

*3rd Expert: IF value of concept C_i is **Low** THEN value of concept C_j is **Very very high***

Figure 2 illustrates the procedure for development the input output function g_{ij}, which represent the causal relationship from concept C_i towards concept C_j. These three rules are combined with the proposed Tsukamoto reasoning method and so the overall rule is produced (Figure 2(d)), which describes the relationship between these two concepts.

This procedure is followed to determine all the weighted interconnection of a fuzzy cognitive map. The next step in developing a FCM is the training of the map: unsupervised learning algorithms proposed in Neural Network theory [7], such as the Hebbian learning rule is used to train the fuzzy cognitive map and adjust the causal functions-weights of the interconnections among concepts according to the concepts' variation [10]. The result will be a trained fuzzy cognitive map, and so a hybrid neuro-fuzzy model of the system will have been developed.

4. Developing Fuzzy Cognitive Maps for a Plant

At the plant floor there is the common technical information system of the process control, which consists of the computerised and the technical management systems that are shared between the production and management teams [12]. This information could be unified and used to construct a fuzzy cognitive map, which will represent a conceptual, organisational and operational model of the system [2]. Knowledge on manufacturing plants includes the layout of the plant, the expected behaviour of some parts of the plant, an aggregation of attributes or quality variables that are important. This information is captured using a fuzzy cognitive map structure as been defined above. The expert relates a process or a succession of processes to a concept, or a concept stands for a specific production procedure.

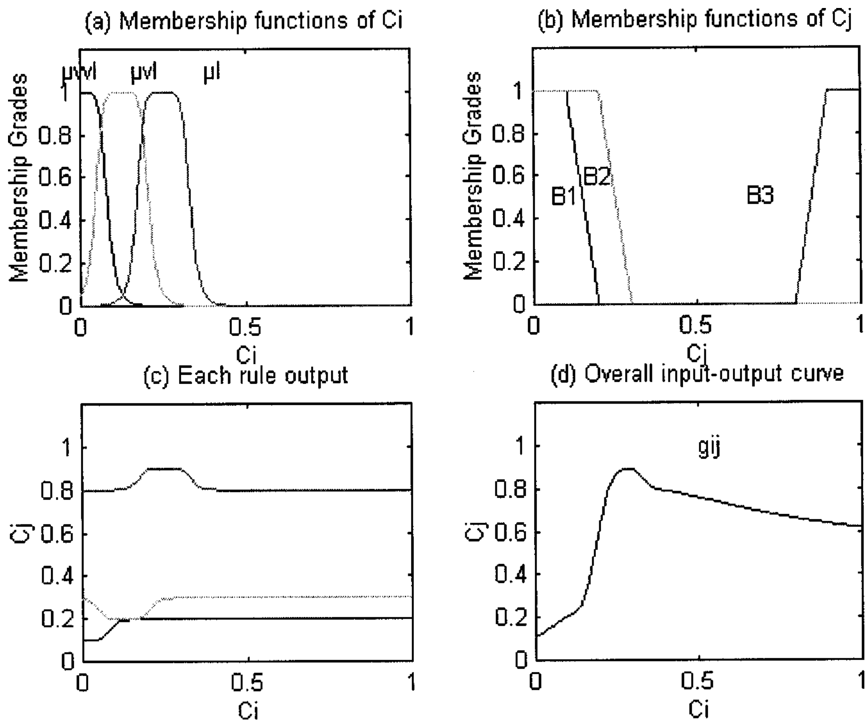

Figure 2. (a) Membership functions for concept C_i; (b) membership functions for concepts C_j; (c) each rule's output curve; (d) overall input–output curve describing the causal relationship of concept C_i towards concept C_j.

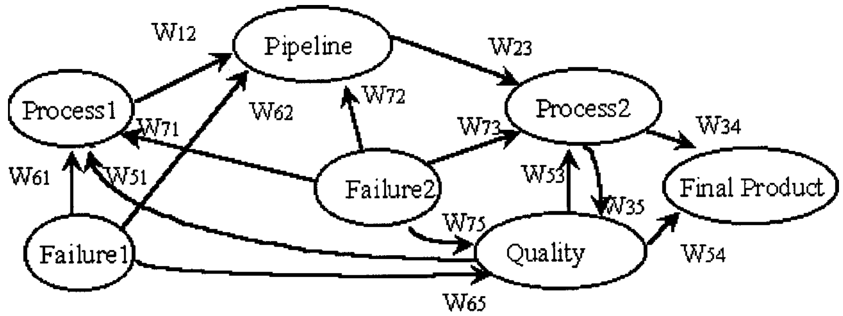

Figure 3. Fuzzy cognitive map for a simple chemical plant.

A chemical plant is consisted of two processes, which take place in two subplants, and the product of Process 1 is input to the Process 2 through a pipeline that connects the two subplants. Conventional controllers are used to control these two processes and human operators supervise the whole system. A fuzzy cognitive map that will model human supervision at the chemical plant is developed and it is illustrated in Figure 3. It consists of seven concepts that represent general characteristics of the plant and is developed by a group of experts who supervise the process and know the operation of the system:

Concept 1: the state of Process 1;
Concept 2: it represents the state of Pipeline which connects the two processes;
Concept 3: the state of the Process 2;
Concept 4: the Final Product of the two chemical processes;
Concept 5: the quality of the Final Product;
Concept 6: the appearance of Failure 1, mostly related to Process 1;
Concept 7: the appearance of Failure 2, mostly related to Process 2.

The group of operators-experts of the system associate qualitatively the main characteristics of the plant, which are presented as concepts, according to the existing causal relationships among them. Experts describe relationships among concepts using the following reasoning. Process 1 influences positively the concept of Pipeline. Pipeline influences positively the state of Process 2, and Process 2 influences positively the Final Product and the concept for the quality of the final Product. The state of the quality influences positively Process 1, Process 2 and Final Product. When Failure 1 appears, it influences negatively Process 1, and consequently the state of Pipeline which is depending on Process 1, and the Quality of the Final product is influenced negatively. When, Failure 2 happens, it has negative effect on Process 2 and influences negatively the operation of Process 1 and Pipeline, as they are pre-processors of Process 2. Failure 2 influences negatively the quality of the final product.

After the initial drawing of the fuzzy cognitive map, the selection of concepts and the description of the causal relationships among them, the methodology proposed in Section 3 is used and weights are assigned to every causal relationship among concepts. When the fuzzy cognitive map has been constructed, it is used to describe the quality of the final product and the influence of failures in the final product, simulating this mode of operation of the system. In each step of the simulation, values of concepts change according to the equation (2) and the fuzzy cognitive map simulates the behaviour of the real system. Values of concepts stand for some variables and states of the system, and so their corresponding concept values represent values of variables in the real system with some concepts taking their values as inputs from the real system.

The fuzzy cognitive map that has just been developed performs quite simple supervisor tasks but in real-life complex industrial systems, operators and experts of the system observe multiple subsystems and data simultaneously and make tough decisions based on their experience and empirical knowledge. In trying to replicate all these actions, the need for a supervisor of the whole process comes up, and this supervisor has to have advanced attributes, such as monitoring, failure diagnosis, planning and decision making. For this purpose, a two-level supervisor of the system is proposed, which consists of two fuzzy cognitive maps (Figure 4).

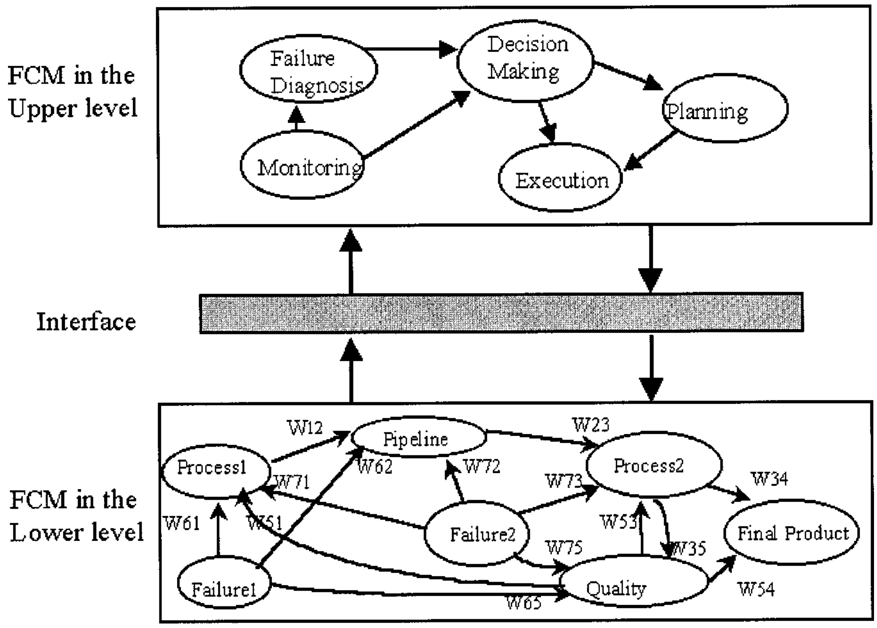

Figure 4. The two-level supervisor structure with FCM on each level.

The previously constructed FCM lies on the lower level and another augmented fuzzy cognitive map is lying on the upper level and each one of its concepts is actually an FCM itself, so we have the decision making FCM, the planning FCM, the monitoring FCM and the execution FCM. The decision-making FCM evaluates alarm signals, processes fail signals and other inputs from the lower level, and the execution level sends to the lower level FCM control signals that influence the process.

5. A Two-Level Supervisory Structure for Manufacturing Systems

The fuzzy cognitive maps methodology is proposed for the to development of an abstract model of the operation and behaviour of manufacturing systems that experts, who are controlling the process manually and successfully construct. The primary attention is focused on the human behaviour and experience, rather than to the controlled process. This distinctive feature makes fuzzy cognitive maps applicable and attractive for dealing with the supervised problem where the process on the lower level is so complex that it is impossible or too expensive to derive a mathematical model; but the process is supervised and controlled satisfactorily by human operators.

In this section the structure proposed in Section 4 is expanded; it is supposed that the plant is sufficiently controlled by local controllers, and the two level structure of Figure 5 is proposed with the supervisor on the second level. Here, the supervisor is modelled as a fuzzy cognitive map and it includes parts for monitor-

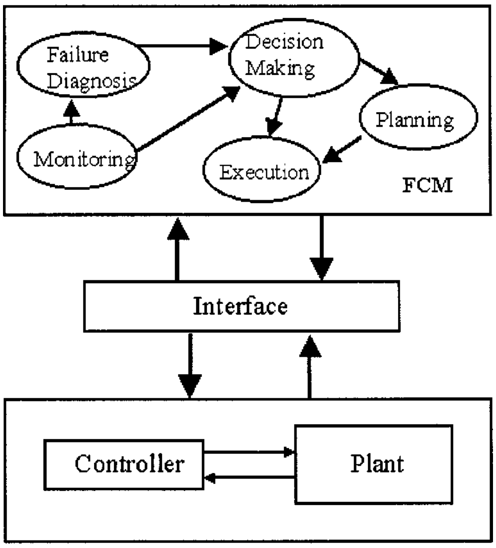

Figure 5. The general two-level structure controller.

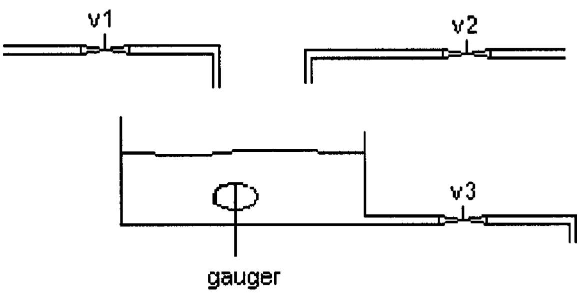

Figure 6. A simple chemical process example.

ing, failure diagnosis, decision making, planning, and should give the appropriate commands to the process controller in the lower level. The plant on the lower level has its own local controller that performs usual control actions. The supervisor is used for more generic purposes: to organise the overall plant in order to accomplish various tasks, to help the operator make decisions, to plan strategically the control actions and to detect and analyse failures. The main idea of the hierarchical two-level structure for complex systems is widely acceptable [5] and now it is proposed modelling the supervisor with an abstract soft computing methodology, which emulate, human supervision actions. This approach for modelling the supervisor is based on knowledge models rather than on state equations or input–output approach, which have been developed in the area of large-scale systems, thus it is different to other known supervisory architectures as they use completely different principles.

In the two-level structure, there is an interaction between the two levels and there will be an amount of information that must pass from the one level to the

Table I. Concepts for the tank levelling system

Concept	Description
C1	Water level overflow
C2	leaks through valve
C3	Valve 1 not fully closed
C4	Valve 2 not fully closed
C5	Valve 3 not fully closed
C6	Valve 1 fails closed
C7	Valve 2 fails closed
C8	Valve 3 fails closed
C9	Valve 1 fails open
C10	Valve 2 fails open
C11	Valve 3 fails open

other. So, the interface consists of two parts: one part will pass information from the controller in the lower level to the fuzzy cognitive map in the upper level, and the other part will transform and transmit information in the opposite direction.

As an example, a part of the supervisor for a chemical process problem, (examined by Stylios and Groumpos [18]) is constructed. The considered system consists of one tank and three valves that influence the amount of liquid in the tank; Figure 6 shows an illustration of the system. Valve 1 and valve 2 empty two different liquids into the tank; during the mixing of the two liquids a chemical reaction takes place in the tank, and new liquid is produced. The specific gravity of the liquid in the tank is an indicator of whether the desired liquid has been produced, which continues to the next process through valve 3. The Specific gravity of the produced liquid is measured with a specific gravity instrument.

For this process example, the two-level structure of Figure 5 is suggested. The control objectives are to keep the height in the produced liquid in the tank between a low level H_{min} and a high level H_{max} and to open valve 3 when the desired liquid – which has specific gravity between G_{min} and G_{max} – is produced in the tank. These control objectives are accomplished by the local controller in the lower level of the structure. In this structure, the failure diagnosis part of the supervisor will be constructed, as a fuzzy cognitive map, and this FCM interacts with the others FCMs for monitoring and decision making. The process of building the failure fuzzy cognitive map will include the identification of potentially relevant variables that will be selected as concepts of FCM [14]. For this purpose, existing lists of potential device failure modes, failure effects, cause effects and historical data on the likelihood of a failure occurrence are used by the experts to define the set of concepts and assign weight interconnections among concepts. Table I lists eleven

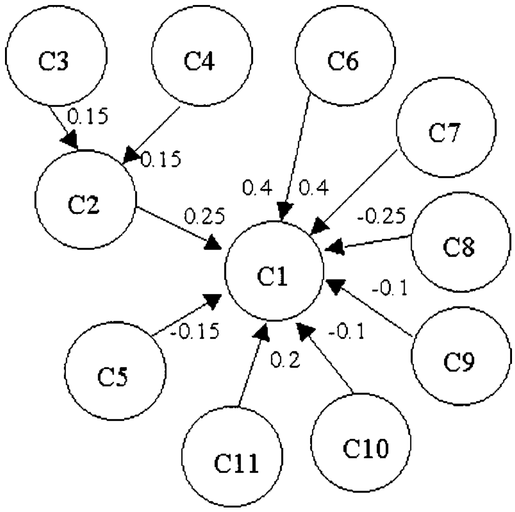

Figure 7. The failure diagnosis part of FCM supervisor.

concepts, which constitute the failure modes and effects analysis part of the fuzzy cognitive map. For the concepts of Table I, experts using fuzzy reasoning have described the causal relationships among concepts, with the proposed methodology of Section 3. Then, the crisp weights for each interconnection have been produced and the fuzzy cognitive map of Figure 7 is constructed.

In this section, a two-level structure for supervisory systems was presented, where the supervisor is modelled as a fuzzy cognitive map, and a part of this FCM was constructed for a specific process example. The whole supervisor will be developed in the future and will stand by the human operator and have the ability to replace many of his actions.

6. Summary

In this paper, a novel approach for modelling the supervisor of complex manufacturing systems have been examined which best utilises existing experience and knowledge in the operation of the system. A novel methodology for constructing fuzzy cognitive maps was presented and the development of a supervisor fuzzy cognitive map for a plant example was described. Also, a two level structure for supervisory systems was proposed. Experts or operators who manually and successfully control the process construct the supervisor-fuzzy cognitive map. This methodology gives more attention to human experience, rather than to the process being controlled. The role of the FCMs is to extend the range of application of a conventional controller by using a more abstract representation of the process, general control knowledge and adaptation heuristics and to enhance the performance of the whole system.

A complete structure for the fuzzy cognitive map that stand as the supervisor of the entire system and it is lying on the upper level is the subject of our future research work. In this FCM, the structure of the decision making, planning and execution part will have been developed and the mechanism, with which the lower level is influenced, will have been described. Future research may examine the application of FCMs in real life systems and investigate aspects such as the stability, controllability and the state space of the model.

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