PERGAMON

Chaos, Solitons and Fractals 11 (2000) 329–336

CHAOS
SOLITONS & FRACTALS

www.elsevier.nl/locate/chaos

Modelling supervisory control systems using fuzzy cognitive maps

Peter P. Groumpos *, Chrysostomos D. Stylios

Department of Electrical and Computer Engineering, Laboratory for Automation and Robotics, University of Patras, Rion 26500, Greece

Abstract

Modelling complex systems and their supervisior has attracted the high interest of many scientists and engineers. There has been a need for highly sophisticated Autonomous Intelligent Systems. A very promising methodology to model the Supervisor of a plant is the use of Fuzzy Cognitive Maps (FCM). FCM are a combination of Fuzzy Logic and Neural Networks. A new mathematical model for FCMs is proposed and its representation is examined in this paper. FCM construction is presented through the development of the model for a simple control process problem. Then, issues for the application of FCM as the model of the supervisor of a complex system are addressed and a hierarchical two-level structure is proposed.

1. Introduction

The requirements of next generation modelling and control systems, which will be characterised by high autonomy and intelligence, have led engineers to search and invent new techniques that will be used as the core of these systems. Fuzzy Cognitive Maps (FCM) is a new symbolic method for modelling and controlling a system which relies on expert experience and follows the principle of "decreasing precision and increasing intelligence" [12], therefore, this very promising methodology can be the medium to model and construct Intelligent Supervisory Control Systems.

FCM can model dynamical systems, which change with time following non-linear laws [7,8]. In FCM context, the representation of these systems is not mathematical but symbolic. FCM consist of nodes and interconnections among nodes that compose the model of a dynamic system. Nodes of the map stand for the states, variables, events, values, goals and trends of the dynamic system. Among nodes, which represent characteristics of the system, there are causal links that represent the cause and effect from one factor of the system to the others.

FCMs have already been used to model complex dynamic systems, characterised by hard non-linearities. FCMs have been used to model the behaviour and reactions of virtual worlds, representing their simple needs as survival threat, searching for food, etc. [3,4]. A similar usage has been realised for the modelling of social systems, where anything that affects one sector will affect other sectors as well, as social systems are feedback systems characterised by fuzzy degrees of causation they have sufficiently been modelled by FCMs [17]. Another use of FCM is to model dynamic systems with chaotic characteristics, such as social and psychological processes and the organisational behaviour including the ability to model simultaneously both mediator and moderator relations [1,2]. FCMs have been used for planning and making decisions in the fields of international relations, in modelling political developments [16]. From a different point of view,

* Corresponding author. Tel.: +30-61-997295; fax: +30-61-997309.
E-mail address: groumpos@ee.upatras.gr (P.P. Groumpos)

PII: S 0 9 6 0 - 0 7 7 9 (9 8) 0 0 3 0 3 - 8

FCMs have been used to control a plant [6], to model the supervisor of distributed systems [14] and to develop system models for Failure Models and Effects Analysis [11].

In Section 2, the representation, construction and a new proposing mathematical model of FCM will be examined. Section 3 demonstrates the use of FCM to model and control a simple process problem. In Section 4, the use of FCM for the modelling of the supervisor of complex systems is proposed. In Section 5 aspects of FCM convergence are examined and then some future directions and conclusions are given in Section 6.

2. Fuzzy cognitive maps

FCMs are fuzzy signed graphs with feedback. They consist of nodes-concepts C_i and the interconnections e_{ij} between concept C_i and concept C_j. A FCM models a dynamic complex system as a collection of concepts and causal relations between concepts. A simple illustrative picture of a FCM is depicted in Fig. 1, for five possible nodes-concepts.

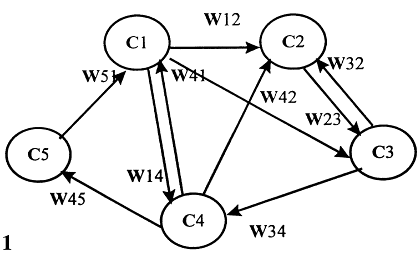
Interconnections e_{ij} between concepts are characterised by a weight w_{ij}, which describes the kind and grade of causality between two concepts. Weights take fuzzy values in the interval [−1, 1]. The sign of the weight indicates positive causality $w_{ij} \succ 0$ between concept C_i and concept C_j, which means that an increase of the value of concept C_i will cause an increase in the value of concept C_j and a decrease of the value of concept C_i will cause a decrease in the value of concept C_j. When there is negative causality between two concepts, then $w_{ij} \prec 0$; the increase in the first concept means the decrease in the value of the second concept and the decrease of concept C_i causes the increase in value of C_j. When there is no relationship between concepts, then $w_{ij} = 0$. The strength of the weight w_{ij} indicates the degree of influence between concept C_i and concept C_j.

The value of each concept is calculated by the computation of the influence of other concepts to the specific concept, by applying the calculation rule of Eq. (1):

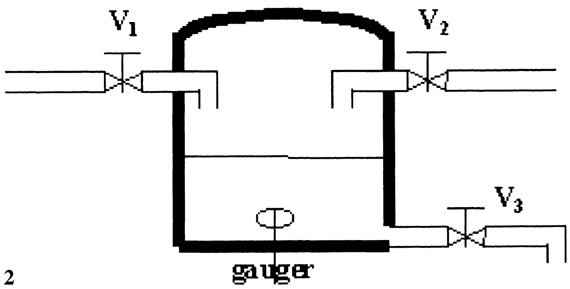
$$A_i(s) = f\left(\sum_{\substack{j=1 \\ j\neq i}}^{n} A_j(s-1)w_{ji}\right), \tag{1}$$

where $A_i(s)$ is the value of concept C_i at step s, $A_j(s-1)$ is the value of concept C_j at step $s-1$, w_{ji} is the weight of the interconnection between concept C_j and concept C_i and f is a threshold function, which will convert the result into the fuzzy interval [0, 1] or [−1, 1], where concepts can take values. Sigmoid function and hyperbolic tangent function are two popular functions, which are used in FCM calculations, for the two corresponding intervals.

The mathematical description of FCM consists of a $n \times 1$ vector $\boldsymbol{A}$ which gathers the values of n concepts, and an $n \times n$ matrix $\boldsymbol{W} = [w_{ij}]_{1 \leqslant i,j \leqslant n}$ which represents the matrix of the causal edge weights for the FCM, where the dimension of the matrices is equal to the number n of the distinct concepts that are



1



2

Fig. 1. Graphical representation of a simple FCM.

Fig. 2. The illustration of the simple process.

presented on the map. So the new state vector $\boldsymbol{A}$ at step s of simulation is calculated according to the equation:

$$\boldsymbol{A}_s = f\left(\boldsymbol{W}^{\mathrm{T}}\boldsymbol{A}_{s-1}\right). \tag{2}$$

The calculation rule of FCM can be improved if the previous value of each concept is taken into consideration. FCM will have memory capabilities and so the values of concepts will have a slight variance after each simulation step. Here, in order to take into account these observations, a new mathematical formulation is presented for the first time. Namely, we propose the following equation:

$$A_i(s) = f\left[k_1\sum_{\substack{j=1\\ j\neq i}}^{n} A_j(s-1)w_{ji} + k_2 A_i(s-1)\right], \tag{3}$$

where $A_i(s)$ is the value of concept C_i at step s, $A_i(s-1)$ the value of concept C_i at step $s-1$, $A_j(s-1)$ the value of concept C_j at step $s-1$, and w_{ji} the weight of the interconnection from C_j to C_i, and f a threshold function, like the sigmoid function. The parameter k_2 represents the proportion of the contribution of the previous value of the concept in the computation of the new value and the k_1 expresses the influence from the interconnected concepts in the configuration of the new value of concept A_i. For the two parameters k_1 and k_2, it is,

$$0 \leqslant k_1, k_2 \leqslant 1. \tag{4}$$

Using Eq. (3), a more general and compact mathematical model for FCM is proposed by the following equation:

$$\boldsymbol{A}_s = f\left[k_1(\boldsymbol{W}^{\mathrm{T}}\boldsymbol{A}_{s-1}) + k_2\boldsymbol{A}_{s-1}\right]. \tag{5}$$

Therefore, Eq. (5) computes the new state vector $\boldsymbol{A}_s$, which results from the multiplication of the previous, at step $s-1$, state vector $\boldsymbol{A}_{s-1}$ by the edge matrix $\boldsymbol{W}^{\mathrm{T}}$ and the adding of a fraction of the values of concepts at step $s-1$. The new state vector holds the new values of the concepts after the interaction among concepts of the map. The interaction was caused by the change in the value of one or more concepts.

It is proposed for the values of two parameters to vary during the training period of the FCM, starting with a high value for parameter k_2, near or equal to 1, and a low value for parameter k_1 near to zero, and then to converge to equal values. Generally, the values of two parameters are dependent on specific FCM for each particular system and the selection of the values of two parameters needs more investigation.

It must be mentioned that the role of experts is very critical in the designing and construction of FCM. Experts, who have knowledge on the operation and model of the system, determine the concepts and interconnections of the map [14]. At this point the Neural Network nature of FCM can been exploited and learning algorithms are utilised in order to train FCM. Unsupervised learning are proposed to train the weights of FCM [9]. During the training period, the weights of the map change with a first-order learning law that is based on the correlation or differential Hebbian learning law:

$$w'_{ij} = -w_{ij} + A'_i A'_j. \tag{6}$$

So $A'_i A'_j \succ 0$ if values of concepts C_i and C_j move in the same direction, and $A'_i A'_j \prec 0$ if values of concepts C_i and C_j move in opposite directions, therefore, concepts which tend to be positive or negative at the same time will have strong positive weights, while those that tend to be opposite will have strong negative weights.

3. A process control problem

In this Section, an example is presenting the utilisation of FCM in modelling and controlling a well-known process problem. This example will reveal how a FCM is constructed, how concepts are chosen, how values are assigned to the interconnections between concepts and then, the constructed FCM is used to control the process.

The considered system is part of a chemical process and it consists of one tank and three valves that influence the amount of liquid in the tank, Fig. 2 shows an illustration of the system. Valve1 and valve2 empty two different kinds of liquids into the tank, and during the mixing of the two liquids some chemical reactions take place in the tank. Inside the tank there is a sensor that measures the specific gravity of the new liquid, which is produced into the tank, as result of the mixing of the two liquids. When the value of the specific gravity lies in the range ($G_{\max}$) and ($G_{\min}$), this means that the desired liquid has been produced in the tank. Moreover, there is a limit of the height of liquid in the tank, which cannot exceed an upper limit ($H_{\max}$) and a lower limit ($H_{\min}$). So, the control target is to keep these variables in the range of values:

$$\begin{aligned} G_{\min} &\leqslant G \leqslant G_{\max}, \\ H_{\min} &\leqslant H \leqslant H_{\max}. \end{aligned} \tag{7}$$

The construction of a FCM, which will control this simple system, includes the selection of main characteristics of the system that will be represented as concepts of the map. Concepts will stand for the variables and states of the system as for example, the height of liquid in the tank or the state of the valves. A FCM, which consists of five concepts is constructed:

Concept1	The amount of liquid that the tank_1 contains. This amount is dependent on the operational state of valve1, valve2 and valve3.
Concept2	The state of valve1. Valve may be closed, open or partially opened.
Concept3	The state of valve2. Valve may be closed, open or partially opened.
Concept4	The state of valve3. Valve may be closed, open or partially opened.
Concept5	The reading on the instrument of specific gravity.

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, with which other concept, it will be connected and the sign of each interconnection. Then, weights for connection are determined, an expert or a group of experts describe the influence of one concept to another using a linguistic variable, like great influence, medium influence, little influence, which is transformed in numerical value. The connections between concepts represent the influence of one concept to the other. So event1 connects concept2 (valve1) with concept1 because valve1 causes the increase or not of the amount of liquid in the tank (concept1), the other casual events have been determined in a similar reasoning. Three operators-observers of the system have assigned linguist variables to events (connections between concepts), which are transformed in numerical weights using a defuzzification method [5] and so the weight matrix $\boldsymbol{W}$ is constructed:

$$\boldsymbol{W} = \begin{bmatrix} 0 & -0.4 & -0.25 & 0 & 0.3 \\ 0.36 & 0 & 0 & 0 & 0 \\ 0.45 & 0 & 0 & 0 & 0 \\ -0.9 & 0 & 0 & 0 & 0 \\ 0 & 0.6 & 0 & 0.3 & 0 \end{bmatrix}.$$

Table 1
The values of FCM concepts for eight simulation steps

Step	Tank	Valve1	Valve2	Valve3	Specific gravity
1	0.1000	0.4500	0.3900	0.0400	0.0100
2	0.5748	0.4915	0.4938	0.5007	0.5075
3	0.4871	0.5186	0.4641	0.5380	0.5430
4	0.4779	0.5327	0.4696	0.5406	0.5365
5	0.4791	0.5326	0.4702	0.5401	0.5358
6	0.4793	0.5324	0.4701	0.5401	0.5359
7	0.4793	0.5324	0.4701	0.5401	0.5359
8	0.4793	0.5324	0.4701	0.5401	0.5359

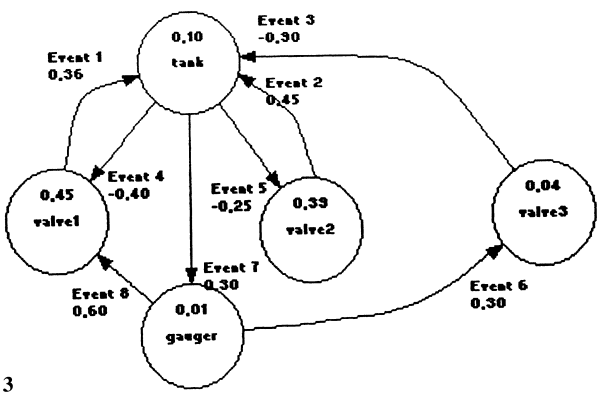
Fig. 3 shows the FCM, which is used to describe the behaviour and control this simple system, the initial value of each concept, the interconnections and the weights between concepts can be seen. The values of concepts correspond to the real measurements of a physical magnitude. Each concept has a value, which ranges between [0, 1] and it is obtained by transforming 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 more investigation.

At each simulation step of the FCM, the value of concepts is calculated according to Eq. (1). The value 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 used and so the result is in the range [0, 1]. The FCM interacts for the initial values of concepts. In Table 1 the values of concepts for eight simulation steps are represented, it can be seen that after only six simulation steps, the FCM reaches a fixed equilibrium point. It must be mentioned that the duration of each simulation step is one time unit. The complete example with simulation results is presented in [15].

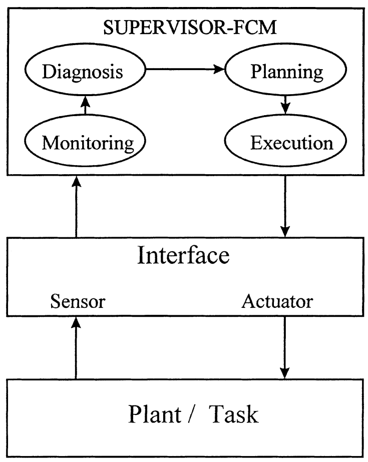
4. The use of fuzzy cognitive maps in the modelling of the supervisor

For complex systems, the construction of a realistic, accurate mathematical model is impractical and sometimes impossible. For such systems a human operator offers Supervisory Intelligent Control through the use of an imprecise model, operators of the system observe multiple data simultaneously and they make tough decisions based on their experience and empirical knowledge. To cope with complex objectives, an autonomous system requires integration of symbolic and numerical data, qualitative and quantitative information reasoning and computation. Furthermore, the problem of suitable performance criteria is still an open question.

For such systems and the above associated problems, the FCM model is a very promising good solution in order to model and implement supervisor tasks. This model describes different aspects of the behaviour of a complex system in terms of concepts, which stand for features of the system, and interrelations among concepts showing the dynamics of the system. Supervisor is modelled as an FCM and it will perform planning and scheduling of available resources to achieve a set of goals, deciding the strategies and procedures in various situations, deciding what an abnormal situation is and what actions would be appropriate. The supervisor will monitor the task, will make adjustments, will diagnose apparent abnormalities or failure, taking control when an abnormal situation occurs and will have learning capabilities to utilise



3



4

Fig. 3. The initial FCM, with values for concepts and interconnections.

Fig. 4. The Hierarchical Supervisory Model of a plant.

past experience in order to improve process knowledge [13]. The FCM can be used to model the operation and diagnosis schemes of the task representing states, goals, commands of the system, normal and abnormal operation.

A hierarchical two level structure is proposed to model complex systems, this structural approach is going to develop a more sophisticated model. The proposed hierarchical model of the system is depicted in Fig. 4. On the lower level, conventional control methodologies are used to deal with the predetermined control actions, reflecting the model and control of the systems during normal operation conditions. On the upper level there is an Intelligent Supervisor, which performs the described tasks and attempts to emulate such a human control capacity using a FCM. This FCM includes concepts for decision making, planning and it will give the appropriate commands to the process controller in the lower level, evaluate alarm signals, process fail signals and other inputs and send control signals to the lower level, which influence the process. In the two level structure, there is interaction between the two levels and there will be an amount of information that must pass from one level to the other. So, the interface consisted of two parts, one will pass information from the controller in the lower level to the FCM in the upper level and the other part will transform and transmit information in the opposite direction. This interface combines, interprets filters information from the lower level and then, this information is transformed and transmitted to the supervisor-upper level and vice versa.

FCM on the upper level will consist of concepts that may represent the irregular operation of some elements of the system, failure mode variables, failure effects variables, failure cause variables, severity of the effect or design variables. In this example, the FCM could describe the failure states of the valves, possible malfunction in the specific gravity instrument, leaks in tank and other alarm schemes. Moreover, this FCM will include concepts for determination of a specific operation of the system. In this FCM, analysis of the data coming from the lower level can be implemented, which will represent vital components of the plant detecting features that reflect the operational state of the plant. As an example, in a similar chemical process, as the one represented in Section 3, it could need different amounts of liquid in the output at different times, according to the requisite density of the liquid. In case of a catastrophic alarm or other emergency signal, the failure analysis FCM must act directly to the shop floor level, and for this case a separate mechanism is needed. Another part of the upper level FCM can be used for decision making, FCM are well suited for dealing with this kind of problem and many other knowledge oriented problems.

FCM is a symbolic method, which can increase the effectiveness, autonomy and intelligence of systems. FCM can easily describe the system's behaviour and handle with flexibility any change of the system and it has the capability to expand the control of the system, by equipping the FCM in a higher supervisory level with failure analysis, prediction and planning qualities. The goal of a supervisory system is very abstract

5

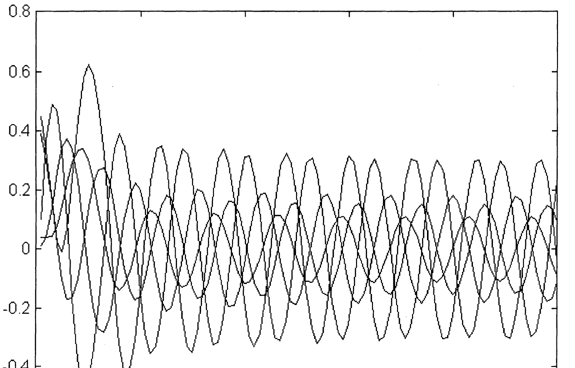


Fig. 5. The variation of values of five concepts for 100 simulation steps.

and application dependent, but the general goal is to ensure safe and optimal operation of the process plant.

5. Fuzzy cognitive map convergence

FCM can be used to model the operation and behaviour of any dynamic complex system. When FCM has been developed, it interacts and recalculates values of the concepts using Eq. (1) or (3) that are used to calculate the values of concepts at each step of simulation. Threshold function plays an important role in the simulation of the behaviour of the system, and FCM converge depends on the selection of the threshold function. When threshold function is not applied in Eq. (1) or (3), the state vector will contain real numbers and the behaviour of the FCM will be heavily dependent on the initial values of concepts.

As an example the FCM, which was constructed in Section 3, will be examined. At this simulation example, calculation rule of Eq. (3) is used, assuming that $k_1 = 1$ and $k_2 = 0.9$ and the threshold function $f(x) = \tanh(x)$ is applied. It must be mentioned that the hyperbolic tangent function gives values of concepts in the range $[-1, 1]$. Simulation starts with the same initial values and results of simulation are depicted in Fig. 5, where variation of values of five concepts have been drawn for 100 simulation steps. Examining Fig. 5, the inferred conclusion is that FCM is driven to a limited cycle after 25 steps, which is repeated almost every 18 simulation steps.

FCM can be used to model non-linear systems with chaotic behaviour, an example of using FCMs for modelling chaotic behaviour is presented in [10]. Two examples of FCM convergence to a fixed point and a limited cycle has been presented in Section 3 and Section 5 respectively, generally, FCM are models of dynamic systems and their simulation can lead to,
1. A fixed equilibrium point,
2. A limited cycle,
3. Chaotic behaviour.

6. Future research – conclusions

Future research must examine the description and construction of FCM in the supervisor level, the learning laws for the training of an FCM, and a map construction that will be human independent. Other issues that have to be addressed, in order to exploit thoroughly the role of an FCM as supervisor, are the state space of the system, the controllability and the asymptotic stability of the system. FCMs have many characteristics which make them suitable for use in Failure Mode and Effects Analysis, which is critical for development of Intelligent Systems. However, they must be examined in conjunction with other methods.

FCM seems to be a useful method in modelling and controlling complex systems, which will help the designer of a system in decision analysis and strategic planning. FCM appear to be an appealing tool in the description of the supervisor of hierarchical and distributed systems, which teamed up with other methods will lead to the next generation control systems. The supervisor-FCM is constructed directly from experts or operators who are manually and successfully controlling the process, exploiting their knowledge on system's model and behaviour. This methodology gives more attention to the human's experience, rather than to the process being controlled. The FCM model includes representations of subsystems normal and irregular operation and it is supplied with useful qualities for strategic planning, decision making, failure diagnosis and prediction. This distinctive feature makes FCM 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 satisfactory by human operators.

The representation and the mathematical formulation of a FCM utilising past values of concepts have been examined. The implementation of the FCM method in a process control problem has been presented and the simplicity with which it describes the system's behaviour was shown. It is proposed to use FCM to model the Supervisor of a plant. Finally, FCM convergence is presented and some thoughts for future directions in this new and very exciting area have been presented.

References

[1] J.P. Craiger, M.D. Coovert, Modeling dynamic social and psychological processes with fuzzy cognitive maps, Proceedings of the IEEE International Conference on Fuzzy Systems, 1994, pp. 1873–1877.
[2] J.P. Craiger, D.F. Goodman, R.J. Weiss, A.B. Butler, Modeling organizational behavior with fuzzy cognitive maps, Int. J. Computational Intelligence and Organizations 1 (1996) 120–123.
[3] J.A. Dickerson, B. Kosko, Fuzzy virtual worlds, AI Expert (1994) 25–31.
[4] J.A. Dickerson, B. Kosko, Virtual worlds as fuzzy dynamical systems, in: B. Sheu (Ed.), Technology for Multimedia, IEEE Press, New York, 1996.
[5] D. Driankov, H. Hellendoorn, M. Reinfrank, An introduction to fuzzy control, Springer, New York, 1996.
[6] K. Gotoh, J. Murakami, T. Yamaguchi, Y. Yamanaka, Application of fuzzy cognitive maps to supporting for plant control, Proceedings of the SICE Joint Symposium of 15th Syst. Symposium and 10th Knowledge Engineering Symposium, 1989, pp. 99–104.
[7] B. Kosko, Fuzzy cognitive maps, International Journal of Man-Machine Studies 24 (1986) 65–75.
[8] B. Kosko, Neural Networks and Fuzzy Systems, Prentice-Hall, Upper Saddle River, NJ, 1992.
[9] B. Kosko, Fuzzy Engineering, Prentice-Hall, Upper Saddle River, NJ, 1997.
[10] F.M. McNeil, E. Thro, Fuzzy logic: A practical approach, AP Professional, San Diego, 1994.
[11] C.E. Pelaez, J.B. Bowles, Using fuzzy cognitive maps as a system model for failure models and effects analysis, Information Sciences 88 (1996) 177–199.
[12] G. Saridis, Analytic formulation of the principle of increasing precision with decreasing intelligence for intelligent machines, Automatica 25 (3) (1989) 46–467.
[13] T.B. Sheridan, Supervisory control, in: G. Salvendy (Ed.), Handbook of Human Factors, Wiley, New York, 1987, pp. 1243–1268.
[14] C.D. Stylios, V.C. Georgopoulos, P.P. Groumpos, Introducing the theory of fuzzy cognitive maps in distributed systems, Proceedings of the 12th IEEE International Symposium on Intelligent Control, Istanbul, Turkey, 1997, pp. 55–60.
[15] C.D. Stylios, P.P. Groumpos, The challenge of modelling supervisory systems using fuzzy cognitive maps, Journal of Intelligent Manufacturing 9 (4) (1998) 339–345.
[16] R. Taber, Knowledge processing with fuzzy cognitive maps, Expert Systems with Applications 2 (1) (1991) 83–87.
[17] R. Taber, Fuzzy cognitive maps model social systems, AI Expert 9 (1994) 18–23.