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FUZZY COGNITIVE MAPS AND LARGE SCALE COMPLEX SYSTEMS

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Abstract: Most of the technological systems are characterized by complexity, coupled relationships with feedback and a demanding procedure to develop their models. This paper presents the Soft Computing technique of Fuzzy Cognitive Maps that are knowledge-based methodologies suitable to describe and model complex systems and handle with available information from an abstract point of view. Fuzzy cognitive Maps develop behavioral model of the system exploiting the experience and knowledge of experts. Fuzzy Cognitive Maps applicability in modeling complex systems is presented and a general hierarchical structure is proposed to model any complex system. Within the hierarchical structure, Fuzzy Cognitive Map models the coordinator of the system and develops an abstract conceptual model of the complex system. *Copyright © 2002 IFAC*

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1. INTRODUCTION

Technological systems all around the world are characterized by complexity and large scale. These complex systems have usually high non-linear dynamics, with many variables and states strongly interrelated, with feedback cycles of influence. Conventional modelling and control methods are adequate to model small or medium, mathematically well defined systems but they have not been successful to model large and complex systems. Thus, there is a need for the investigation of new modelling methods that will integrate and combine known advanced modelling methodologies as well as new innovative ideas which will take into consideration various requirements for the large complex systems and especially high autonomy and intelligence.

For complex systems, modelling is the basis for effective knowledge representation. On the other hand the requirements for modelling and controlling of large complex systems cannot be met only using conventional methodologies and theories. This brings up the necessity to investigate and use new methods that will exploit human experience and knowledge, will have self learning capabilities, will be supplied with failure detection and identification characteristics and can handle imprecision, uncertainty and complexity, which mainly characterize real large complex systems and the world (Driankov *et al.,* 1996; Medsker, 1995). A very promising research area is the synergism of discipline theories: such as Fuzzy Logic, Neural Networks, Probabilistic Reasoning and Knowledge Based Systems, known as Soft Computing Techniques and take advantage of their strong points and develop new models for Complex Systems. Soft Computing techniques have many advantages in modelling complex systems and processes.

This paper focuses on the use of Fuzzy Cognitive Maps to model large complex systems. The issues and problems of modelling large complex systems are discussed. It presents a general overview of Fuzzy Cognitive Maps. A decomposition approach is also proposed where a hierarchical structure is described with a Fuzzy Cognitive Map for the Supervisor.

2. MODELING LARGE COMPLEX SYSTEMS WITH SOFT COMPUTING

The majority of modern man-made systems are complex and highly sophisticated, they are characterized by highly nonlinear dynamics that couple a variety of physical phenomena. It is not surprising, therefore, that much of these processes are not well understood and their operation is "tuned" by experience rather than through the application of scientific principles. For such systems, intelligent soft computing based techniques are proposed to address uncertainty issues and provide flexible platforms. Capturing and utilizing the expert's knowledge, effectively and efficiently, promises to improve complex systems operational conditions. Usually human experts supervise complex systems observing multiple data simultaneously and they make tough decisions based on their experience and empirical knowledge (Jamshidi, 1983). Complex systems operate in changeable and unknown environment, as the factors that influence the system and determine their behaviour cannot be easily determined (Drouin *et al.,* 1991). Especially, when environmental conditions change, system has to adapt and the input-output characteristics of the system have to be altered (Mitchell and Sundstrom, 1997).

Complex systems could be characterized as infrastructures with interdependencies. They are compromised from a huge number of interacting entities. Such infrastructures affect many areas of daily life such as electric power, telecommunications, natural gas and petroleum production and distribution, transportation, water supply, banking and finance, agriculture and other fundamental systems and services (Rinaldi, *et al.* 2001).

Among entities consisting complex systems there are linkages of different degree, other linkages are loose and other tight. Complex systems with their interdependent entities have a wide range of spatial, temporal, operational and organizational characteristics. The interdependencies create an infrastructure topology characterized by interactions and feedback mechanisms that determine the behaviour of the large complex system.

It should be clearly stated here that we have not considered modelling large complex systems using known conventional methods (decentralized, multilevel, holonic agent, distributed etc) because this is outside the scope of this paper. There are so many books and papers been written in the last 15-30 years that it would be impossible to even try to touch it in this paper. The IFAC TC on LSS is holding a very interesting a very interesting symposium every three years and the interested scientist could review the recent proceedings of these symposiums (Filip *et al.* 2001; Koussoulas and Groumpos, 1998; Roberts, 1995).

3. FUZZY COGNITIVE MAPS

Fuzzy Cognitive Map (FCM) is a soft computing modeling technique used for causal knowledge acquisition and supporting causal knowledge reasoning process. FCMs permit the necessary cycles for knowledge expression within their feedback framework of systems. FCMs originated as a combination of ideas and methods from fuzzy logic and neural networks theories and have been introduced by Kosko (Kosko, 1986). Neuro-fuzzy systems have been proposed as advanced techniques for modeling and controlling real world problems that are complex, usually imprecisely defined and require human intervention. Neuro-fuzzy systems have the ability to incorporate human knowledge and to adapt their knowledge base via optimization techniques. They can play an important role in the conception, description and modelling complex systems (Lin and Lee, 1996).

Causal and cognitive maps have been used to describe decision-based systems (Axelrod, 1976). Fuzzy Cognitive Maps were supplied with fuzzy logic theory enhancing Cognitive Maps ability to present and model qualitatively dynamic systems (Kosko, 1986). Cognitive Maps have been used to make decision analysis and cooperate distributing agents (Zhang *et al.,* 1992). Many researchers have been attracted by the FCM potential to model causal flow between concepts (Dickerson and Kosko, 1994) and they have proposed new FCM models and new methods for developing FCM have been proposed (Craiger *et al.*, 1996; Stylios and Groumpos, 2000). Fuzzy values considered in cognitive maps and FCMs were used to represent causal reasoning and inference (Miao andn Liu, 2000). FCMs have proposed to represent complex social systems where relationship between social forces demands feedback (Taber, 1991, 1994). Fuzzy Cognitive Map used to model and support plant control systems and perform Failure Modes and Effects Analysis in the process industry (Pelaez and Bowles, 1996). Another investigation concerns hierarchical systems, where supervisor incorporates knowledge and is capable of learning relational structures and evidential reasoning and modeling the Supervisor of control systems (Stylios and Groumpos, 1999).

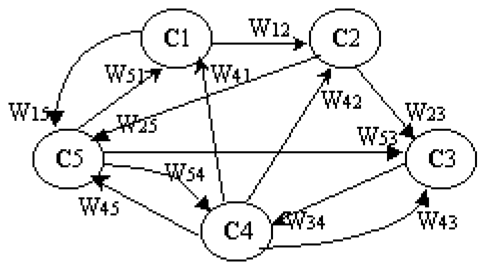

Fig. 1. The Fuzzy Cognitive Map model

A FCM illustrates the whole system by a graph showing the effect and the cause along concepts. FCM is a simple way to describe the system' s model and behavior in a symbolic manner, exploiting the accumulated knowledge of the system. A 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 behavior in different circumstances. Moreover, FCM utilizes learning techniques, which have implemented in Neural Network Theory, in order to train FCM and choose appropriate weights for its interconnections.

Nodes of the Fuzzy Cognitive Map stand for the concepts that are used to describe the behavior of the system and they are connected by signed and weighted arcs representing the causal relationships that exist between the concepts (Figure 1). It must be mentioned that all the values in the graph are fuzzy, so concepts take values in the range between [0,1] and the weights of the arcs are in the interval [-1,1]. Observing this graphical representation, it becomes clear which concept influences other concepts showing the interconnections between concepts and it permits updating in the construction of the graph, such as the adding or deleting of an interconnection or a concept.

A Fuzzy Cognitive Map consists of nodes-concepts and arcs between concepts. Each concept represents a characteristic of the system; in general it stands for events, actions, goals, values, trends of the system that is modeled as an FCM. 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 [-1,1].

Between concepts, there are three possible types of causal relationships, that express the type of influence from one concept to the others. The weights of the arcs between concept C_i and concept C_j could be positive $(W_{ij} \succ 0)$ which means that an increase in the value of concept C_i leads to the increase of the value of concept C_j, and a decrease in the value of concept C_i leads to the decrease of the value of concept C_j. Or there is negative causality $(W_{ij} \prec 0)$ which means that an increase in the value of concept C_i leads to the decrease of the value of concept C_j and vice versa.

Experts design and develop the fuzzy graph structure of the system, consisting of concepts-nodes that represent the key principles-factors-functions of the system operation and behaviour. Fuzzy Cognitive Maps describes the perception of experts about the system. Then, experts determine the structure and the interconnections of the network using fuzzy conditional statements. Experts concern to describe whether the states of one concept influence the state of another. Cause and effect relations among concepts are the basis of expectations and it is important in every system trying to model and replicate brain like intelligence. Experts use linguistic variables in order to describe the relationship among concept, and then all the linguistic variables are combined and so the weights of the causal interconnections among concepts are concluded. The simplest FCMs act as asymmetrical networks of threshold or continuous concepts and converge to an equilibrium point or limit cycles. At this level, they differ from Neural Networks in the way they are developed as they are based on extracting knowledge from experts. FCMs have non-linear structure of their concepts and differ in their global feedback dynamics.

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

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

Namely, A_i is the value of concept C_i at time t, A_i^{t-1} the value of concept C_i at time $t-1$, A_j^{t-1} the value of concept C_j at time $t-1$, and the weight W_{ji} of the interconnection from concept C_j to concept C_i and f is a threshold function.

The unipolar sigmoid function is the most used threshold function, (Lin and Lee, 1996) where $\lambda \succ 0$ determines the steepness of the continuous function f. The sigmoid function ensures that the calculated value of each concept will belong to the interval [0,1].

$$f(x)= \frac{1}{1 + e^{-\lambda x}} \tag{2}$$

A more general and compact mathematical model for Fuzzy Cognitive Map is presented by the following equation:

$$\mathbf{A}^t = f(\mathbf{A}^{t-1} \circ \mathbf{W} + \mathbf{A}^{t-1}) \tag{3}$$

So, equation (3) computes the new state vector $\mathbf{A}^t$, at time t that results from the multiplication of the previous one, at time $t-1$, state vector $\mathbf{A}^{t-1}$ by the weight matrix $\mathbf{W}$. The new state vector holds the new values of the concepts after the interaction among concepts of the Fuzzy Cognitive Map. The interaction is caused by the change in the value of one or more concepts.

FCMs can be applied to problems that there is lack of quantitative information on how different variables interact. Another case is when the direction of causality is at least partially known and can be articulated by an expert. Another case is when there are links between concepts from different domains with arrows of causality. All these features are shared by the problem of modelling complex systems.

4. FUZZY COGNITIVE MAPS MODELLING COMPLEX SYSTEMS

The common approach of decomposing a large complex system into subsystems is an old well known technique which has been used extensively on conventional methods (Mesarovic *et al.*, 1970; Siljak, 1979). Therefore it is also appropriate to follow the same direction on applying or using FCM to model large complex systemsBut this decomposition is not easily applicable when subsystems have common elements that prohibit the simplified approach of sum up the individual components behaviour. With our proposed perspective for the modelling and analysis of large complex systems; each component of the infrastructure constitutes a part of the intricate web that forms the overall infrastructure. Thus there is a challenge of decomposing large complex systems where human experience has a major role.

The general case where multiple infrastructures are connected as "systems of systems" is considered. A Fuzzy Cognitive Map models every one subsystem and the large complex system is modelled with the interacting Fuzzy Cognitive Maps. FCMs communicate with one another as they operate in an environment, receiving inputs from other FCMs and send outputs to them. The linkage between two FCMs has the meaning that one state-concept of one FCM influences or is correlated to the state-concept of the other. This distributed multi-FCM is shown in figure 2. FCMs are connected at multiple points through a wide variety of mechanisms, representing by bi-directional relationship existing between states of any pair of FCMs, that is, FCM_k depends on FCM_l through some links, and probably FCM_l depends on FCM_k through other links. There are multiple connections among FCMs such as feedback and feed forward paths, and intricate and branching topologies. The connections create an intricate web, depending on the weights that characterize the linkages. Interdependencies among FCMs increase the overall complexity of the "system to systems".

Figure 2 illustrates an augmented Distributed Fuzzy Cognitive Map, which aggregates five FCM models for the five subsystems of the complex system. Among the subsystems and so among the FCM models there are interdependencies that are illustrated as interconnections between concepts belonging to different FCMs, where each FCM can be easily modelled (Stylios and Groumpos, 2000).

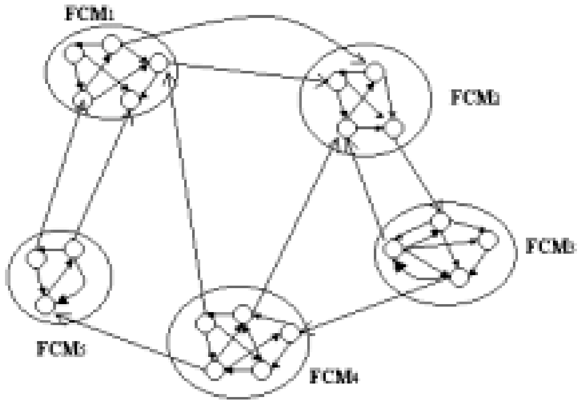

Fig. 2 The Distributed multi-FCM model

For complex systems the characteristics of the linkages among components could be the degree of coupling (tightness or looseness), the coupling order and the linearity or complexity of the interactions. Tight or loose coupling refers to FCMs that are highly dependent or less dependent on one another, and it representing by a corresponding weight. Depending on the nature of the infrastructure and their dependencies changes in Concept C^i of FCM_k could drive changes in Concept C^j of FCM_j.. The coupling order indicates whether two FCMs are directly connected to one another or indirectly coupled through one or more intervening FCMs. For example FCM_l is linked to FCM_m, which in turn is linked to FCM_k, but *l* is not directly linked to *k*.

Components of the infrastructure are influenced by past experiences and the other components, interacting with one other. This is illustrated by the equation 3 that calculates the new values for concepts of every one FCM.

A hierarchical structure is suggested where the Augmented FCM is used to model the supervisor (Fig. 3). The augmented FCM supervisor is consisted of concepts representing each one of the FCM modelling every component and some other concepts representing issues for emergent behaviour, some components failure and etc. The Augmented FCM is used to play some scenarios for the large complex system with the interdependencies. The supervisor FCM is an augmented model of the complex system and it represents the relationships among the subsystems and their models. On the lower level there local conventional and no conventional models for every one component of the large scale complex system.

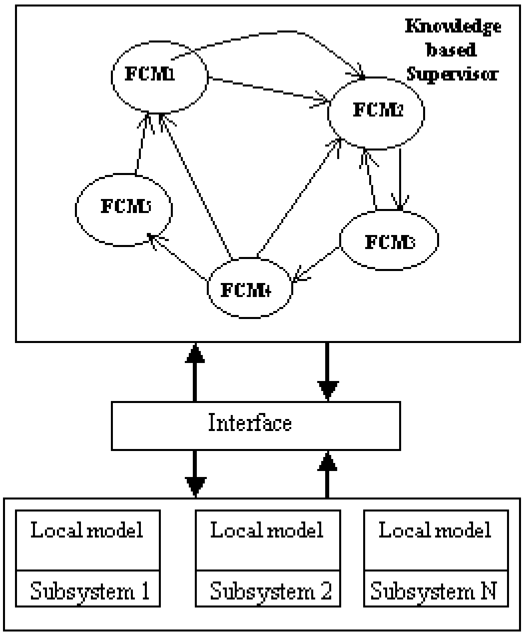

Fig. 3. The hierarchical structure for complex systems

The supervisor is used for more generic purposes; to organize all the subsystems in order to accomplish a task, to make decisions, to planning strategically and to detect and analyse failure. This supervisor will give priority to different subsystem-model each taking into consideration some factors and will determine the degree with which every subsystem-model is active every time and participate in the whole complex system. The main supervisory FCM task is the co-coordinating of the whole plant. This FCM extend the range of application of the complex system using a more abstract representation, general knowledge and adaptation heuristics and to enhance the performance of the whole system.

FCMs are built using a combination of the knowledge representation techniques as causal models, production rules and object hierarchies and it is used to perform more demanding procedure as failure detection, decision making, planning, tasks usually performed by a human supervisor of the controlled process. This structure has been used for real processes with very interested results (Stylios *et al.*1999). These results show clearly the useful of the proposed FCM hierarchical model.

5. CONCLUSIONS

Human experts play a key role in the modelling and control large complex systems. Capturing the heuristic knowledge of experts, representing, modelling and exploiting it using FCMs may provide the foundation of new directions in modelling complex systems. The increasing in the complexity and sophistication of complex systems requires the implementation of new soft computing techniques to develop intelligent systems. The soft computing modelling methodology of Fuzzy Cognitive Maps, which have been presented in this paper, has many opportunities for design and representation of new models for interdependent large complex systems. Taking advantage of this unique opportunity is the main issue that needs to be addressed.

FCM can represent complex causal relationships as is developed directly from experts who have knowledge on the behaviour of the system. Features of Fuzzy Cognitive Maps make them applicable and attractive for dealing with the supervised problem where the system on the lower level is complex but it may be supervised satisfactory by human experts. Human experts using imprecise and control methodology monitors and controls complex systems. Required characteristics of complex systems are the possession of human-like expertise within a specific domain, adaptation themselves and learning to do better in changing environments. Therefore, in closing, Fuzzy Cognitive Maps is a useful symbolic representation for the description and modelling of complex systems, describing different aspects in the behaviour of complex systems in terms of concepts; and interactions among concepts show the dynamics of a system.

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