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Using fuzzy cognitive maps to achieve intelligence in manufacturing systems

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Abstract

In order to develop the next generation sophisticated Flexible Manufacturing Systems a number of challenges and issues of Intelligent Manufacturing Systems need to be addressed by the scientific community. This paper presents an overview of new promising domains, such as fuzzy logic, neural networks, that could be utilized to achieve human intention for more advanced manufacturing systems; Fuzzy Cognitive Map, a new methodology, is proposed to model the supervisor of manufacturing systems.

1. INTRODUCTION

In the recent years, manufacturing systems have utilized the advantages of digital computers and automation technology and they have made a great advance. New rapidly emerging technologies provide designers with increasing flexibility and a wide range of choices in almost all aspects of system analysis and design, including hardware, software and material. The availability of these tools on the one side and the flourishing of new theories such as Fuzzy Logic, Neural Networks, Genetic Algorithms, Hybrid Systems on the other, motivate engineers to utilize them in order to create the next generation Intelligent and Flexible Manufacturing Systems.

Manufacturing Systems are existing and well working systems for many years but there is always a potential to implement new ideas and methods which will enhance their performance. A promising domain is the utilization of intelligent techniques and the development of Intelligent Manufacturing Systems. The Intelligent Manufacturing System will utilize effectively all the company resources, especially the insights and experience of front-line operators and experts, in order to achieve continuous improvements in productivity. Capturing and utilizing the expert's knowledge, effectively and efficiently, promises to improve plant operational conditions [1].

Many industrial processes have a difficulty to be controlled accurately 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 judgment [2].

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 have not always an optimal solution [3]. Thus, some novel proposed methodology, to extract model and represent human knowledge, is based on fuzzy logic techniques and neural network theory.

Conventional methods are used in modeling manufacturing systems but their contribution to the solution of the increasingly complex manufacturing systems will be limited, in such systems their operation, usually, depends on human leadership. Human reasoning process for any procedure includes uncertain descriptions and can have subtle variations in relation to time and space; in such situations Fuzzy Cognitive Map seem to be enable to deal with.

In this paper, Fuzzy Cognitive Map Theory (FCM) is proposed to be used in the modeling and control of the upper part of a manufacturing system, which have inherent a hierarchical structure. The description and the methodology that this theory suggests, are examined, moreover the application of Fuzzy Cognitive Maps to model a manufacturing system will be investigated. It will become apparent how useful FCMs can be and some interesting points for further research will be concluded.

2. NEURAL NETWORKS-FUZZY SYSTEMS AND FUZZY COGNITIVE MAPS

Fuzzy logic control systems have supplanted conventional technologies in many scientific applications and engineering systems. One major feature of fuzzy logic is its ability to express the amount of ambiguity in human thinking and subjectivity in a comparatively undistorted manner. Fuzzy logic is used to model continuous processes that are not easily broken down into discrete segments, processes without a mathematical model, or too complex processes, or processes with high levels of noise, uncertainty and involvement of human interaction [4].

Neural Networks are a new generation of information processing systems that have important characteristics and properties. They are able to learn arbitrary, non-linear input-output mapping directly from training data, they have the ability to generalize to situations that are different from the collected data, they can optimize their behavior by adjusting their connection weights and they are characterized by fault tolerance [5].

Fuzzy logic and neural networks are complementary technologies in the design of intelligent systems. Neuro-fuzzy systems aim at solving real world decision making problems, modeling and control problems [6]. These problems are usually imprecisely defined and require human intervention. Thus, neuro-fuzzy systems with their ability to incorporate human knowledge and to adapt their knowledge base via new optimization techniques, are likely to play an increasingly important roles in the conception and design of hybrid intelligent systems [7].

Fuzzy systems and Neural Networks are both numerical model-free estimators and dynamical systems. They share the ability to improve the intelligence of systems working in uncertain, imprecise and noisy environment. The synergism of the two systems, in one sophisticated model can be utilized in the modeling of the supervisor of Manufacturing Systems, improving its efficiency and lend to advanced Intelligent Manufacturing Systems.

Fuzzy Cognitive Maps are defined as a combination of Fuzzy Logic and Neural Networks [8]. FCMs create models that emulate human reasoning and decision making process using fuzzy causal relations. FCM is a methodology to capture the operator's knowledge, represent it and model it in terms of a neuro-fuzzy construction. FCMs are used to create models as collections of concepts and the various causal relations that exist among concepts. It is a qualitative model of the dynamic operation and behavior of the system.

FCMs are fuzzy-graph structures which are used to model the knowledge base of the examined system; they are causal networks storing domain knowledge in the nodes and edges of a network. FCMs have attracted the attention of scientists and have been used in a variety of different scientific problems. Recently Fuzzy Cognitive Maps are proposed to model a plant [9] [10], to structure Virtual worlds [11] and they are used for Failure Modes and Effects Analysis [12]. Fuzzy Cognitive Maps have been used to make decision analysis [13] and to strategically plan [14] and to represent the Hyperknowledge in strategy formation process [15]. Authors of this paper have proposed [16] the use of Fuzzy Cognitive Map from a different standpoint, as the model of the Supervisor in complex systems; the investigation concerns hierarchical intelligent systems which incorporate knowledge and are capable of learning relational structures and evidential reasoning.

When an expert or operator is asked to draw a model of a system, he describes the operation and behavior of the system using abstract concepts and causal interactions among concepts (Figure 1). The human operator who controls a plant can perform the appropriate control actions having in his mind the mental model of the system. A mental model is an internal representation employed to encode, predict, evaluate, and communicate the consequences of perceived and intended changes to the operator's current state within its dynamic environment. He has understand the causal relationships of the temporal sequence of events and states in the plant and can conceptualize its behavior. He uses a concept to represent a state, a variable, a measurement or a characteristic of the plant; and the interaction among concepts describe the operation and behavior of the physical plant. The causal knowledge is stored on the interconnections among concepts that summarizes instances of the correlation between cause and effect. An FCM consists of concepts and weighted interconnections among concepts that represent the fuzzy degree of causation with which each concept influence others.

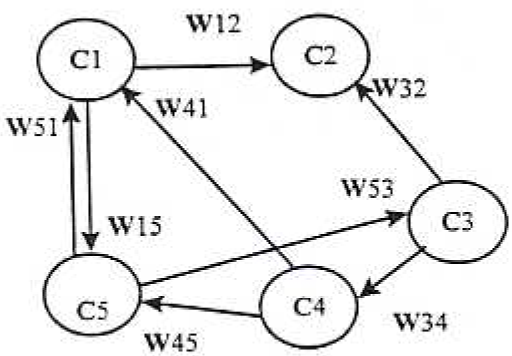

Figure1. A Fuzzy Cognitive Map

Each node-concept represents one of the key-factors of the modeled system and in general it stands for states, variables, events, actions, goals, values, trends of the system. Each concept represents a characteristic of the system; it is characterized by a number A_i that represents its value which results from the transformation of the real value of the system's variable, for which this concept stands. Nodes of the graph 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. It must be mentioned that all the values in the graph are fuzzy, so concepts takes values in the range between [0,1] and the weights in the range [-1,1]. With this graphical representation it becomes clear, which concept influences other concept showing the interconnections between concepts and it permits thoughts in the construction of the graph, as the adding or deleting of an interconnection or a concept.

Beyond the graphical representation of the FCM there is the need for a mathematical model. It is consisted of an nxn weight matrix, which includes the values of the interconnections between the n concepts of the FCM; and a vector 1xn which gather the values of the n concepts. The value of each one concept is influenced by the values of the connected concepts with the multiplication of corresponding weights and by its previous value. So the value A_i for each concept C_i is calculated by the following rule :

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

where 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, A_i^{old} is the value of concept C_i at time t, and W_{ji} is the weight of the interconnection between C_j and C_i, and f is a threshold function, like the unipolar transfer function:

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

Building the FCM model depends on human experts who have knowledge on the operation of the system, one expert, according to his experience, draws a FCM, he determines the concepts, which best describe the operation of the process, the paths of system's malfunction. Then, he determines the negative or positive effect of one concept on the others, with a fuzzy degree of causation. It is possible to exploit the existence of a group of experts who have experience on the operation or modeling of the system.

Beyond the interpretation of human experience on the operation of the plant using FCM, there is another important characteristic of this model. Fuzzy Cognitive Maps have the capability of learning. Learning is a key attribute of an intelligent system, it is used to address difficulties, resulting from nonlinear behavior, poorly modeled plant dynamics, complex objective functions and constrains. FCMs can be considered as a type of Neural Networks and learning methodologies can be used to adjust the weights among concepts and train the FCM [17].

3. SUPERVISOR OF MANUFACTURING SYSTEMS MODELLED AS FCM

The complex problems, that there are in Manufacturing Systems, require the development of intelligent systems that combine knowledge, techniques and methodologies from various sources. These intelligent systems are supposed to possess human-like expertise within a specific domain, adapt themselves and learn to do better in changing environments, and explain how they make decisions or take actions.

Manufacturing Systems are complex systems for which it is impractical and impossible to construct an exact mathematical model describing by differential equations. For such systems, the human operator offers Supervisory Intelligent Control through the use of an imprecise and robust control methodology. The FCM is a symbolic representation for the description and modeling of complex systems, describing different aspects in the behavior of complex systems in terms of concepts; and interaction among concepts shows the dynamics of a system.

The traditional control theory is based on the construction of mathematical models for controlled process. The proposed FCM methodology tries to establish the controller directly from experts or operators who are controlling the process manually and successfully. The primary attention is paid to the human's behavior and experience, rather than to the process being controlled. 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.

For the modeling of a manufacturing control system, a two level approach has been 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 such a human control capacity using an FCM [18].

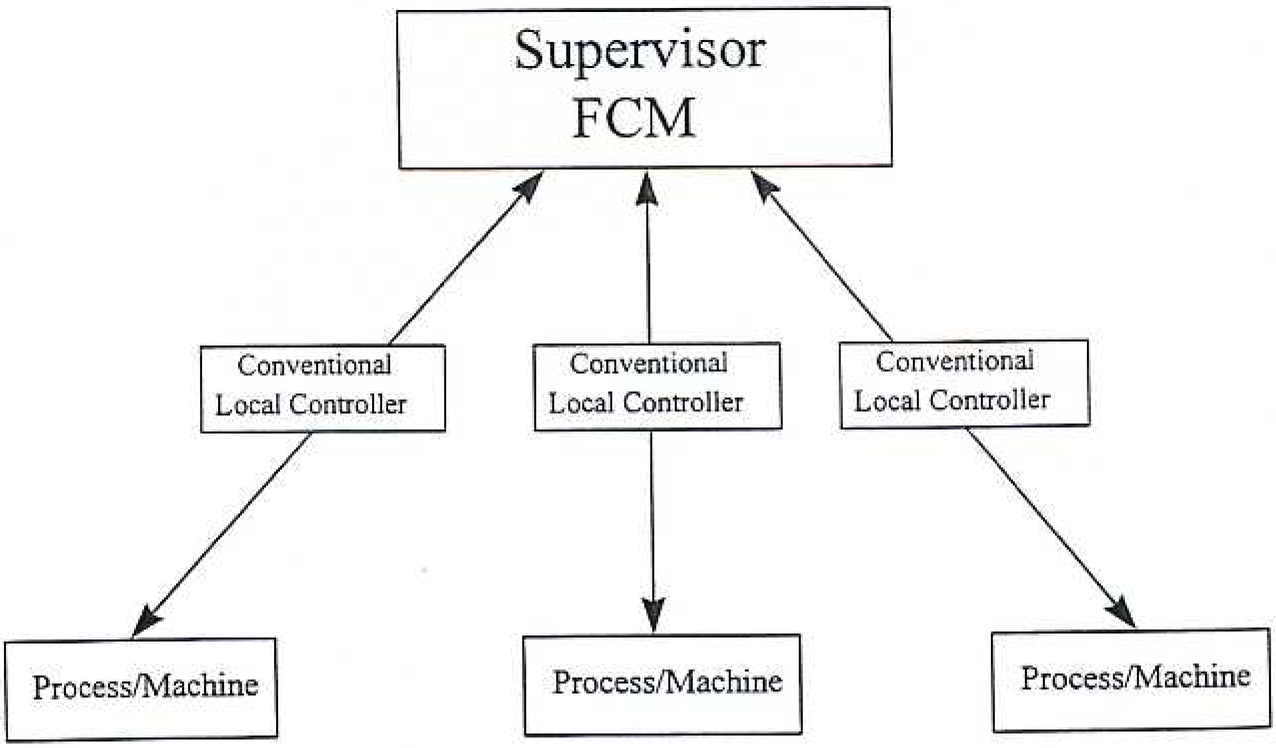

Figure 2. A two-level structure approach

Figure 2 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 planning strategically and to detect and analyze failure.

In the lower level of the structure lies the conventional controller which 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 [19] 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 they happen. Moreover, this FCM will include concepts for description and determination of a specific peration 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.

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 adaptation 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 procedure such as failure detection, decision making, and planning, tasks usually performed by a human supervisor of the controlled process.

4. FUZZY COGNITIVE MAP MODEL FOR MANUFACTURING SYSTEMS

Knowledge on manufacturing plants includes the layout of the plant, the expected behavior 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, that exploits human operator's experience and knowledge. The expert knows the operation of the system and has it stored in his memory in terms of concepts. He relates a process or a succession of processes to a concept, or a concept stand for a specific production procedure. An example using an FCM for a simple chemical process is depicted in figure 3.

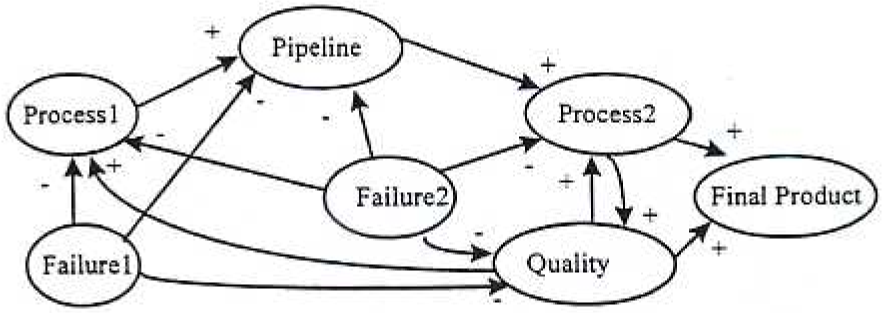

Figure 3. Fuzzy Cognitive Map of a chemical procedure.

The most essential part on such a mathematical graphical representation is the drawing of a FCM, the determination of concepts that best describe the system, the direction and the grade of causality between concepts. So, the selection of the different factors of the system, that must be presented in the map, it must be the result of a close-up on system's model and operation behavior. 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.

As it was said the Fuzzy Cognitive Map of Figure 3 models a simple chemical process. It consists of seven concepts and it is developed by a human operator who supervises the process:

Concept 1: the state of Process 1;
Concept 2 : it represents the 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 operator of the system has associated the concepts according to their causal relationship that are depicted on the figure 3 with the signed arcs among concepts. So the Process 1 influences positively the concept of Pipeline. Pipeline influences positively the state of Process 2 and Process 2 influence positively the Final Product and the concept for the Quality of the final Product. The state of the Quality influence positively the Process 1, Process 2 and Final Product. When Failure 1 has appeared, this influences negatively the Process 1, and consequently the state of Pipeline which is depending on the Process 1 and the quality of the final product is influenced negatively. When, Failure 2 happens this has negative effect on Process 2 and influence negatively the operation of Process 1 and Pipeline as they are preprocessors of the Process 2. Failure 2 influence negatively the concept which represent the Quality of the final product.

This is the first attempt to construct the model of the plant, during which it was decided what are the concepts of the model and what are the causal connections among them It should be noted that the cause effect relationship among elements of the model may be defined otherwise by another human expert.

After the initial drawing of the Fuzzy Cognitive Map, weights must be assigned to every causal relationship among concepts. Weights belong to the interval [-1,1] or alternatively it could be used words weights like *little* or *more* or less and each node-concept take a fuzzy value in the interval [0,1].

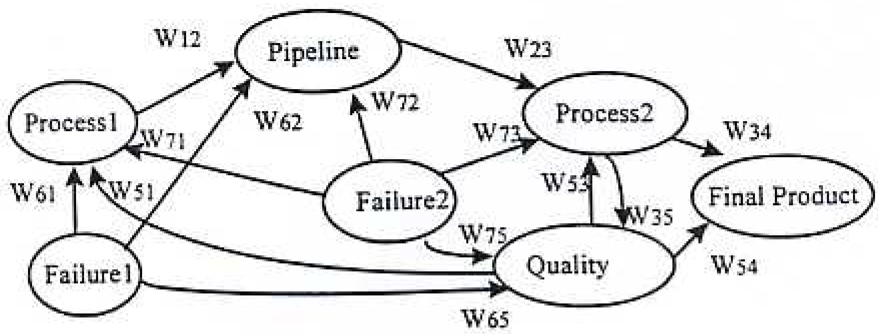

Figure 4. Fuzzy Cognitive Map with weights.

When the FCM has been constructed, it can be used to model the behavior and simulate the operation of the system. In each step of the simulation the values of concepts change according to the equation 1. This interaction among concepts continues until:

i) A fixed equilibrium is reached, after a number of interactions, values of concepts don't change;
ii) A limited cycle is reached, values of concepts change periodically; and
iii) Chaotic behavior is exhibited, values of concepts change continuously.

The idea of Fuzzy Cognitive Map learning is borrowed from Neural Networks theory. The weights of the causal edges change as if they were synapses in a neural network. There are used well knowing learning rules as the Hebbian learning rule. The learning rule, the choosing and training of the weights will determine the stability of FCM. Kosko [20] have proposed to check the stability for a simple FCM, the additive model, in terms of the eigenvalues of the weight connection matrix. The stability of Fuzzy Cognitive Map needs further investigation which is subject of future research work.

5. FUTURE RESEARCH AND DIRECTIONS

The new technologies that have been reviewed and presented in this paper offer tremendous opportunities for design and implementation of new generation of control systems that could not been possible to implement before. Taking advantage of this unique opportunity is the main issue that needs to be addressed. The real question is what methodologies might be developed to take advantage of existing and future technologies.

The increasing in the complexity and sophistication of large scale manufacturing systems requires the implementation of new intelligent strategies. Human expert has a key role in the supervision of manufacturing systems. Capturing the heuristic knowledge of experts, representing, modeling and exploiting it using FCMs may provide the foundation of new directions in intelligent manufacturing systems. There are many issues that have to be addressed such as the stability of FCMs, the necessary transformation mechanism from the real values to the concepts values and vice versa, the determination of appropriate weight connection matrix, the interface that there is between the two level of control hierarchy and a description of the human-FCM interface, and the time dependence in modeling FCM need to be further investigated.

Closing, for complex systems is extremely difficult to describe the entire system by a precise mathematical model. Thus, it is more attractive and useful to represent it, in graphical way showing the causal relationships between states-concepts. Since this symbolic method of modeling and control of a system is easily adaptable and relies on expert experience it can be considered intelligent. Fuzzy Cognitive Maps seem to be a useful method in modeling and can be used to model manufacturing systems which will help the designer of a system in decision analysis and strategic planning. Fuzzy Cognitive Maps appear to be an appealing tool in the description of the supervisor of manufacturing systems, which teamed up with other methods will lead to the next generation Manufacturing Systems.

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