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A CRITICAL OVERVIEW OF MODELLING METHODS AND DECISION SUPPORT SYSTEMS FOR COMPLEX DYNAMIC SYSTEMS

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Abstract: Nowadays, practical dynamic systems have become more and more complex. The challenging issues of modelling and controlling complex dynamic systems (CDS) are carefully considered and properly addressed. All characteristics that constitute CDS are discussed in many details. A short but useful historical overview of decision support systems (DSS) is given. The need for new conceptual and advanced models for addressing the challenging issues of CDS is provided. Fuzzy Cognitive Maps (FCMs) as a new modelling approach is briefly described. Two illustrative examples are provided along with some very promising and useful research results. Some drawbacks of the FCM approach are provided and analyzed. Finally interesting conclusions and future research directions are provided.
Keywords: Modelling, Complex dynamic systems, Decision support systems, Fuzzy logic, Fuzzy Cognitive Maps

1. INTRODUCTION

In this paper the mathematical modelling and in parallel making decisions for today's complex dynamic systems (CDS) is carefully, critically and wisely reviewed. The concept of complex dynamic systems arises in many scientific fields and technological areas. Examples of these systems are: energy networks, energy storage and distribution, hybrid power systems with different renewable energy sources, robotics, health, artificial intelligence systems, gene regulation and health delivery, safety and security systems, telecommunications, transportation networks, environmental systems, swarm of software agent, traffic patterns, ecosystems, biological systems, social and economic systems, and many other scientific areas can be considered to fall into the realm of complex dynamical systems. Such systems are often concurrent and distributed, because they have to react to various kinds of events, signals, and conditions. They may be characterized by a system with uncertainties, time delays, stochastic perturbations, hybrid dynamics, distributed dynamics and a large number of algebraic loops. The science of complex dynamical systems is a multidisciplinary field aiming at understanding the complex real world that surrounds us.

Complex dynamic systems contain a large number of mutually interacting entities (components, agents, processes, etc.) whose aggregate activity is nonlinear, not derivable from the summations of the activity of individual entities, and typically exhibit hierarchical self-organization. Another important characteristic of complex systems is that they are in some sense purposive. The description of complex dynamic systems requires the notion of purpose, since the systems are generally purposive. This means that the dynamics of the system has a definable objective or function. Complex systems are more often understood as dynamical systems with complex and unpredictable behavior. Multidimensional systems, nonlinear systems or systems with chaotic behavior, adaptive systems, modern control systems, and also the systems, which dynamics depend on, or determined by human being(s), are the formal examples of complex systems [15] ,[19], [20]. Thus complex dynamic systems is a rather broad research filed, whose researches are motivated by a variety of practical engineering systems or social, economic, and ecological concerns. Today modeling, control, and optimisation are major research issues for complex dynamic systems.

Furthermore in all dynamic processes and on our everyday activities decisions must be made. One of the challenges of accepting the "operation" of any complex dynamic system is the ability to make Decisions so the system runs efficiently and cost effectively. However making Decisions concerning complex systems often strains our cognitive capabilities. Uncertainty and related concepts such as risk and ambiguity are prominent in the research and accompanied literature on Decision-Making. Uncertainty is a term used in subtly different ways in a number of scientific fields, including statistics, economics, finance, physics, psychology, engineering, medicine, energy, environment, biology, sociology, philosophy, insurance, geology, military systems and Information and Communication Technologies (ICT). It applies to making "decisions=predictions" of future events, to physical measurements already made and/or computer generated data based on human made "systems". This prominence is well deserved. Ubiquitous in realistic settings, uncertainty constitutes a major obstacle to effective Decision Making Process (DMP).

Therefore the conceptual modeling and in parallel making decisions for today's complex dynamic systems is an exceptional challenge that goes beyond the classical modelling and controlling techniques. That is a challenge that this paper is going to address. In section 2 some challenging issues in modeling and control of CDS are reviewed, while in section 3 a short overview of Decision Support Systems (DSS) is presented. In section 4 the basics of Fuzzy Cognitive Maps are defined and in section 5 two specific examples using FCMs are studied and analyzed. Section 6 provides some drawbacks of the classical FCM approach while section 7 gives new research directions along with some interesting conclusions.

2. CHALLENGING ISSUES IN MODELLING AND CONTROLLING COMPLEX DYNAMIC SYSTEMS

Modeling is a fundamental work which is always a starting point for control, optimisation, and implementation of complex dynamic systems (CDS). Complex dynamical systems present problems both in mathematical modelling and philosophical foundations. The study of complex dynamical systems represents a new approach to science that investigates how relationships between parts give rise to the collective behaviors of a system and how the system interacts and forms relationships with its environment. Thus modeling complex dynamic systems is indeed a real chalenge. It is not so straightforward since complex dynamic systems comprise of collections of (heterogeneous) entities (molecules, cells, genes, fish, plants, people, electrical substations, planets, etc.). These entities can 'compute' (have I/O, state). Entities interact with other entities and their environment which usually is having a lot of uncertainties. Interactions among subsystems are localized and self-organizing and most of the times are nonlinear, dynamic, and possibly chaotic.

In connection with modeling and control complexity, complex dynamic systems have specific characteristics, among which are: uniqueness, weak structuredness of knowledge about the system, the composite nature of system, heterogeneity of elements composing the system, the ambiguity of factors affecting the system, multivariation of system behavior and high dimensionality of the system. In addition collective dynamics of a CDS give rise to 'Emergent Evolution Properties' (EEP) at higher scales in space and/or time among some which are: cooperation such as swarming, intelligence, consciousness, genetic regulation – homeostasis, development, disease, cascading failures in electrical grid, invasiveness in plants, hurricanes and self-repairing materials. Under such conditions, the key problem of complex dynamic systems and control theory consists in the development of methods of qualitative analysis of the dynamics and behavior of such systems and in the construction of efficient control algorithms for their efficient operation. In a general case, the purpose of control is to bring the system to a point of its phase space which corresponds to maximal or minimal value of the chosen efficiency criterion. There are many and different modelling approaches and methods for the classical physical and/or human made systems. Many of these can be found in main textbooks such as in [7], [14], [23]. The classical methods are: ordinary differential equations, input-output models, transformations, time-domain analysis, frequency-domain analysis, feedback systems, state space, non-linear systems, graphical representation of systems, control and optimization methods, Kalman-Filters, continuous vs. discrete methods, discretization of continuous systems, signal-flow graph methods, adaptive control, robust control, intelligent control and various other methods.

However today's' technologies for building such models for CDS with the characteristics that have (and will) been outlined are not only sufficient but even practical. As was said qualitative description of most of the parameters of complex dynamic systems results inevitably in fuzziness, complexity and uncertainty. One of the challenges of accepting the "operation" of any complex dynamic system is the

ability to make Decisions so the system runs efficiently and cost effectively. New conceptual and innovative approaches are needed.
Another one of the main and actual problems in the theory of complex dynamical systems and control sciences is a solution of "ill-posed, weakly- and poorly-structured and weakly-formalizable complex problems" associated with complex technical, organizational, social, economic, cognitive and many other objects, and with the perspectives of their evolution. Since the analysis and efficient control of CDS are impossible without a formal model of the system, technologies for building models of complex dynamical systems are absolutely necessary to be used.
Therefore the modeling and analysis of complex dynamic systems in the presence of principally non-formalizable problems and not probable of having strict mathematical formulation of the system, on environments that decisions are semi-structured or unstructured, knowledge-base systems (KBS) needs to be readdressed. All above characteristics must be taken into consideration. Construction of models of CDS must be based on the use of experts and their extensive knowledge about the system. This knowledge should be wisely used. However qualitative description of most of the parameters of complex dynamic systems results inevitably in fuzziness, complexity and uncertainty. All these unfortunately complicate the problem of formal modeling the CDS and it supports the fact that complex dynamical systems are usually difficult to model, analyze, design, and optimally controlled. Thus there is the need for seeking new advanced conceptual modelling methods. Such a new approach is the Fuzzy Cognitive Maps (FCM) [10], [13] which are presented below, in section 4.

3. DECISION SUPPORT SYSTEMS: A SHORT OVERVIEW

In the late 1960s, a new type of information system became practical-model-oriented DSS or Management Decision Systems (MDS). Two DSS pioneers, Peter Keen and Charles Stabell, claim the concept of decision support evolved from "the theoretical studies of organizational decision making done at the Carnegie Institute of Technology during the late 1950s and early '60s and the technical work on interactive computer systems, mainly carried out at the Massachusetts Institute of Technology in the 1960s. Prior to 1965, it was very expensive to build large-scale information systems. At about this time, the development of the IBM System 360 and other more powerful mainframe systems made it more practical and cost-effective to develop Management Information Systems (MIS) in large companies. MIS focused on providing managers with structured, periodic reports. The goal of the first management information systems (MIS) was to make information in transaction processing systems available to management for decision-making purposes. Unfortunately, few MIS were successful [1]. Perhaps the major factor in their failure was that the IT professionals of the time misunderstood the nature of managerial work. The systems they developed tended to be large and inflexible and while the reports generated from managers' MIS were typically several dozen pages thick, unfortunately, they held little useful management information [18]. The term "Decision Support Systems" first appeared in [8], although Andrew McCosh attributes the birth date of the field to 1965, when Michael Scott Morton's PhD topic, "Using a computer to support the decision-making of a manager" was accepted by the Harvard Business School. Gorry and Scott Morton constructed a framework for improving management information systems using Anthony's categories of managerial activity [8] and Simon's taxonomy of decision types Simon, Gorry and Scott Morton conceived DSS as systems that support any managerial activity in decisions that are semi- structured or unstructured. Keen and Scott Morton [12] later narrowed the definition, or scope of practice, to semi-structured managerial decisions; a scope that survives to this day. The managerial nature of DSS was axiomatic in Gorry and Scott Morton [8], and this was reinforced in the field's four seminal books: Scott Morton [24], McCosh and Scott Morton [17] and Sprague and Carlson [25].
Much of the early work on DSS was highly experimental. The aim of early DSS developers was to create an environment in which the human decision maker and the IT-based system worked together in an interactive fashion to solve problems; the human dealing with the complex unstructured parts of the problem, the information system providing assistance by automating the structured elements of the decision situation. The emphasis of this process was not to provide the user with a polished application program that efficiently solved the target problem. In fact, the problems addressed are by definition impossible, or inappropriate, for an IT-based system to solve completely. Rather, the purpose of the development of a DSS is an attempt to improve the effectiveness of the decision maker. In a real sense, DSS is a philosophy of information systems development and use and not a technology.
According to Sprague and Watson [26], around 1970 business journals started to publish articles on management decision systems, strategic planning systems and decision support systems. For example,

Scott Morton and colleagues published a number of decision support articles in 1968. In 1969, Ferguson and Jones discussed a computer aided decision system in the journal Management Science. In 1971, Michael S. Scott Morton's ground breaking book *Management Decision Systems: Computer-Based Support for Decision Making* [24] was published. In 1966-67 Scott Morton had studied how computers and analytical models could help managers make a key decision. He conducted an experiment in which managers actually used a Management Decision System (MDS). T.P. Gerrity, Jr. focused on DSS design issues in [9]. His system was designed to support investment managers in their daily administration of a clients' stock portfolio. DSS for portfolio management have become very sophisticated since Gerrity began his research. In 1974, Gordon Davis, a Professor at the University of Minnesota, published his influential text on *Management Information Systems*. He defined a Management Information System as "an integrated, man/machine system for providing information to support the operations, management, and decision-making functions in an organization".

For obvious reasons and for better understanding this paper, it is appropriate at this point to briefly comment on the meaning of the word intelligence as generic term. The precise definition of "intelligence" has been eluding mankind for thousands of years. However the true nature of intelligence has been debated more intensely than ever over the last century. As the science of psychology has developed one of the biggest questions it had to answer concerned the nature of Intelligence. Some of the definitions that have been given for intelligence have been the ability to adjust to one's environment. Of course by such a definition even a person who is generally considered to be dull can be regarded as being intelligent if he can take care of himself. Other definition is such as having the tendency to analyze things around you. However it can be argued that such behavior can lead to over-analyzing things and not reacting to one's environment and dealing with it in an "intelligent manner". All these have lead scientists and engineers to develop a challenging scientific area that of Intelligent Systems (IS). The area of broadly perceived as IS has emerged, in its present form, just after World War II, and was initially limited to some theoretical attempts to emulate human reasoning, notably by using tool from formal logic. The advent of digital computers has clearly played a decisive role by making it possible to solve difficult problems. In the mid-1950 the term artificial intelligence was coined. The early research efforts in this area, heavily based on symbolic computations alone, though have had some successes, have not been able to solve many problems in which numerical calculations have been needed, and new, more constructive approaches have emerged, notably computational intelligence which have been based on various tools and techniques, both related to symbolic and numerical calculations. This modern direction has produced many relevant theoretical results and practical applications in what may be termed Intelligent Systems (IS).

It is quite natural that a field, like that of intelligent systems, which is both scientifically challenging and has such tremendous impact on so many areas of human activity at the level of an individual, small social groups and entire societies, has triggered attempts to discuss basic topics and challenges involved at scientific gatherings of various kinds, from small and informal seminars, through specialized workshops and conferences to large world congresses.

More recently, this issue has been addressed by disciplines such as psychology, philosophy, biology and by artificial intelligence (AI); note that AI is defined to be the study of mental faculties through the use of computational models. Again no consensus has emerged as yet of what constitutes intelligence. Intelligence is also considered as a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings—"catching on", "making sense" of things, or "figuring out" what to do. Thus Fuzzy Logic and Fuzzy Cognitive Maps have emerged as serious scientific developments the last 25-30 years in modeling and controlling Complex Dynamic Systems (CDS). It is now time to see how FCM can be used "intelligently" to address challenging problems and issues in modelling and controlling CDS.

4. BASICS OF FUZZY COGNITIVE MAPS (FCM)

Fuzzy Cognitive Maps came as a combination of the methods of fuzzy logic and neural networks and were first introduced by Kosko [13] only 30 years ago. It is a very new method with less than 30 years of been used for modelling CDS with all the characteristics of such systems. A detailed presentation of FCM is provided in [11]. They constitute a computational method that is able to examine situations during which the human thinking process involves fuzzy or uncertain descriptions. An FCM presents a graphical representation used to describe the cause and effect relations between nodes, thus giving us the opportunity to describe the behavior of a system in a simple and symbolic way. In order to ensure the operation of the system, FCMs embody the accumulated knowledge and experience from experts who know how the system behaves in different circumstances. This knowledge is extracted using linguistic variables which then are transformed to numeric values using a defuzzification method. In other words, they recommend a modeling process consisting of an array of interconnected and interdependent nodes Ci (variables), as well as the relationships between them w (weights). Concepts take values in the interval [0, 1] and weights belong in the interval [-1, 1]. Figure 1 shows a representative diagram of a FCM.

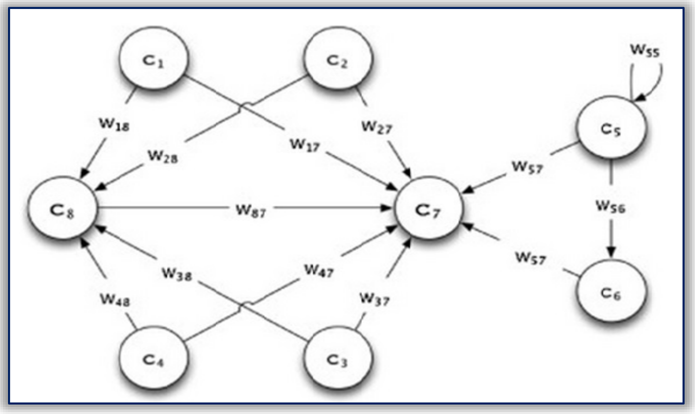

Figure 1. Fuzzy Cognitive Map

The full procedure of the development of a FCM follows the steps below:

- Step 1: Experts select the number and the kind of concepts C_i that constitute the Fuzzy Cognitive Map
- Step 2: Each expert defines the relationship between the concepts
- Step 3: They define the kind and the value of the relationship between the two nodes
- Step 4: Experts describe the existing relationship firstly as “negative” or “positive” and secondly, as a degree of influence using a linguistic variable, such as “low”, “medium”, “high” etc.

The sign of each weight represents the type of influence between concepts. There are three types of interconnections between two concepts C_i and C_j:

- $w_{ij}>0$, an increase or decrease in C_i causes the same result in concept C_j.
- $w_{ij}<0$, an increase or decrease in C_i causes the opposite result in C_j.
- $w_{ij}=0$, there is no interaction between concepts C_i and C_j.

The degree of influence between the two concepts is indicated by the absolute value of w_{ij}. During the simulation the value of each concept is calculated using the following rule:

$$A_i(k) = f\Big(k_1 A_i(k-1) + k_2 \sum_{\substack{j=1 \\ j\neq i}}^{n} A_j(k-1)\, w_{ji}\Big) \tag{1}$$

where n is the number of concepts, $A_i(k+1)$ is the value of the concept C_i at the iteration step k+1, $A_j(k)$ is the value of the concept C_j at the iteration step k, w_{ji} is the weight of interconnection from concept C_j to concept C_i and f is the sigmoid function. “k_1” expresses the influence of the interconnected concepts on the configuration of the new value of the concept A_i and “k_2” represents the proportion of the contribution of the previous value of the concept in computing the new value.

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

Where λ>0 determines the steepness of function f. The FCM’s concepts are given some initial values which are then changed depending on the weights; the way the concepts affect each other. The calculations stop when a steady state is achieved, the concepts’ values become stable. A more comprehensive mathematical presentation of FCMs with application to real problems with very useful results is provided in [10], [11], [22].

Fuzzy Cognitive Maps overcome some of their convergence problems with learning algorithms. The main ideas stem from neural networks. Unsupervised methods such as Hebbian techniques are the most common used. More specifically Nonlinear Hebbian learning has been used to optimize efficiency of control problems [21] and medical diagnosing problems [4] with encouraging results.

In this learning algorithm the nodes are triggered simultaneously and interact in the same iteration step with their values to be updated through this process of interaction. The algorithm which modifies the initial weights defined by experts is described by the following relationship:

$$w_{ij}^{(k)} = g\cdot w_{ij}^{(k-1)} + h\cdot A_j^{(k-1)}\cdot\left(A_i^{(k-1)} - \mathrm{sgn}(w_{ij})\cdot w_{ij}^{(k-1)}\cdot A_j^{(k-1)}\right) \tag{3}$$

where the coefficient h is a very small positive scalar factor called learning parameter, and the coefficient g called weight reduction parameter.

Weights w_{ij} are updated for each iteration step and they are used in equation (1) in order to compute the new values of concepts. Two stopping criteria terminate the procedure. The first one concerns the minimization of function F_1 which is the sum of the square differences between each Desired Output Concept i (DOC_i) and a target value T_i. T_i is defined as the mean value of the range of $DOC_i=[T_i^{min}, T_i^{max}]$.

$$F_1 = \sqrt{\sum_{i=1}^{m}(DOC_i - T_i)^2} \quad (4)$$

$$T_i = \frac{T_i^{\min} + T_i^{\max}}{2} \quad (5)$$

The second criterion is the minimization of the variation of two subsequent values of Desired Output Concepts:

$$F_2 = \left|DOC_i^{(k+1)} - DOC_i^{(k)}\right| \quad (6)$$

When the termination conditions are met the new final weight matrix w_{ij} with the DOCs are returned.

5. TWO ILLUSTRATIVE EXAMPLES USING FUZZY COGNITIVE MAPS

» Example 1: Stability of an enterprise in a Crisis Period

With a simple example of Decision Making for the Stability of an Enterprise in a Crisis Period using FCMs authors show that the new approach of FCMs in modelling CDS is very promising. In the current FCM model there is only one decision concept (output), i.e. the stability of an enterprise in a crisis period is studied: concept_8. The factor concepts are considered as measurements (via special statistic research) that determine how each measurement-concept will function in this model and they are: C1: sales, C2: turnover, C3: expenditures, C4: debts & loans, C5: research & innovation, C6: investments, C7: market share, C9: present capital, while C8: stability of enterprise is the output of the system.

Figure 2 shows a simple FCM model for the enterprise system. At this point it should be noted that in economic systems there is no causality but correlation between the defined factor-concepts of this problem. Experts noted that the acceptable-desired region for the final value of concept C8 is:

$$0.70 \le C_8^{(\text{final})} \le 0.95 \quad (7)$$

If $C_8^{(\text{final})}$ is inside this region then the enterprise is out of danger and the economic crisis period does not put at risk the stability and the smooth function of the enterprise. Weights in table 1 are determined after defuzzifying (with COA method) the fuzzy values that were given by the experts (mostly economists).

In addition, the degree of occurrence of each input-concept factor is denoted with qualitative degrees of high, medium, and low. Respectively for the output concept C8 the qualitative degrees are very low, low, medium, high and very high. The initial values of the outputs were set equal to zero.

Table 1. Weights between concepts for Enterprise System

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0	0.6	0	-0.4	0.2	0.3	0.6	0.8	0
C2	0	0	0	-0.2	0.2	0.5	0.1	0.3	0
C3	0	0	0	0.4	-0.5	-0.4	0	-0.6	-0.5
C4	0	0	-0.4	0	-0.7	-0.8	0	-0.7	-0.4
C5	0.2	0.3	0	0	0	0.5	0.3	0.2	-0.2
C6	0.3	0.2	0.6	0.5	-0.3	0	0.3	0.3	-0.4
C7	0.4	0.3	0	-0.2	0	0	0	0.4	0.5
C8	0	0	0	0	0	0	0	0	0
C9	0	0	0	-0.3	0.2	0.4	0	0.2	0

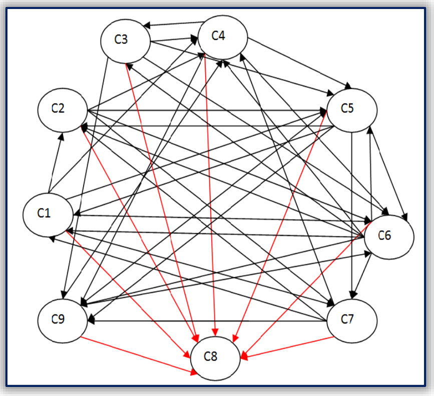

Figure 2. A conceptual FCM model for Stability of the Enterprise

Table 2. Initial factor-concepts

Factor-concepts	Case 1
C1	H
C2	M
C3	L
C4	L
C5	M
C6	L
C7	L
C9	M

Table 3. Final decision-concepts

Decision-concepts	Case 1
C8 (Stability of the Enterprise)	0.8391

The iterative procedure is being terminated when the values of C_i concepts has no difference between the latest three iterations. Considering λ=1 for the unipolar sigmoid function and after 11 iteration steps the FCM reaches an equilibrium point.

Authors considered as initial values for the concepts the followings:

$$A^{(0)} = [0.8867\ 0.4667\ 0.0967\ 0.0967\ 0.4667\ 0.0967\ 0.0967\ 0.65\ 0.4667] \qquad (8)$$

It is observed that in the latest three iterations there is no difference between the values of concepts C_i. So after 11 iteration steps, the FCM reaches an equilibrium point where the values do not change any more from their previous ones, that is:

$$A^{(11)} = [0.8140\ 0.8708\ 0.7145\ 0.6121\ 0.4743\ 0.7462\ 0.8581\ 0.8391\ 0.4779] \qquad (9)$$

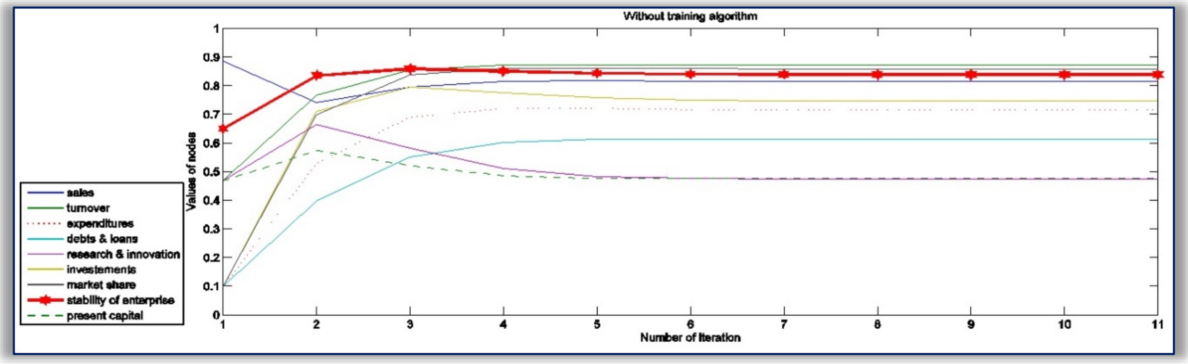

Figure 3. Subsequent values of concepts till convergence

Since the final value of $C_8^{(final)}$ is inside the acceptable region, defined by the experts, then there is great certainty that the enterprise can survive the crisis period.

» **Example 2: A health problem**

The second example of Decision Making concerns a more complicated model of clinical diagnosis of meniscus injury. Patient's symptoms and mechanisms of injury (the way with which damage happens to skin, muscles, organs and bones) compose the possibility of meniscus injury. This FCM model is based on Anninou et al. conference paper [2]. The possible symptoms and mechanisms of injury are presented in tables 4 and 5. The weights extracted by experts and show the interconnections between them are illustrated in Figure 4.

Table 4. Symptoms

Symptoms	Expanded Description
C1: Clicking	Do you feel a clicking sensation or hear a clicking noise when you move your knee?
C2: Catching	Do you feel that sometimes something is caught in your knee that momentarily prevents movement?
C3: Giving way / weakness	Do you sometimes feel that your knee will give out and not support your weight?
C4: Localized pain	Is your knee pain centered to one spot on the knee that you can point to with your finger?
C5: Episodic pain	Do you have pain that comes and goes with specific movements and activities?
C6: Pain with activity	Do you experience pain that is caused by specific activities?
C7: Pain with pivoting/twisting	Do you feel pain when you pivot or twist your knee?
C8: Change in quality/pattern of pain	Have you had a change in type, location, or frequency of your pain?
C9: Locking	Do you feel that your knee sometimes gets stuck temporarily so that you can't move it further?
C10: Acute swelling	Did your knee get swollen immediately or in 2 hours after injury?
C11: Subacute swelling	Did your knee get swollen gradually after the injury up to the next day?
C12: Weight bearing	Was it possible for you to stand up and walk after injury?
C13: Continued in athletic activity	Did you continue to your activity after the injury?

Table 5. Mechanisms of Injury

M1	Hyperextension + valgus
M2	Hyperextension + varus
M3	Hyperflexion
M4	Pure valgus
M5	Pure varus
M6	Rotational injury
M7	Weight bearing of the knee during injury?
M8	Foot / leg blocked during the injury?

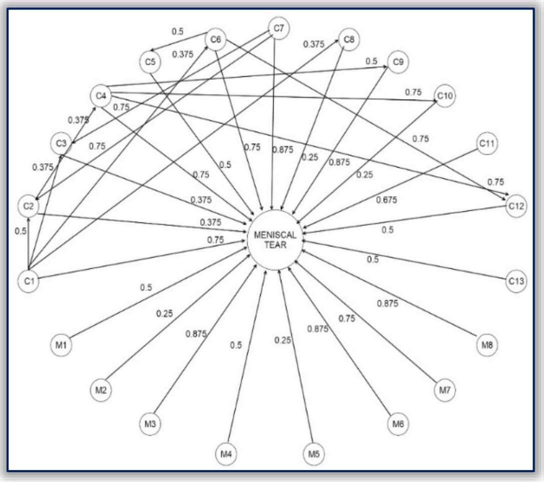

Figure 4. FCM Model for Meniscal Tear

Table 6. Data Collected By 11 Patients

Patients	Mechanisms of Injury	Symptoms
1	M3,M7	C1, C4, C6, C7, C11
2	M6,M7,M8	C1,C2,C4,C6,C7,C11
3	-	C1,C3,C4,C6,C7,C11
4	M7,M8	C1,C4,C6,C7,C11
5	-	C1,C2,C4,C6,C7,C11
6	M6,M7,M8	C2,C4,C7,C11,C12,C13
7	-	C1,C2,C3,C4,C7,C11
8	-	C2,C4,C6,C7,C11,C12,C13
9	M6,M7,M8	C1,C2,C4,C5,C6,C7,C11
10	M4	C1,C3,C4,C5,C11
11	M6,M7,M8	C1,C2,C4,C7,C11

The number of patients was eleven, with ages ranging from 18 to 54, and they arrived at General University Hospital of Patras. History and physical examination were performed and physicians collected the following initial characteristics as in Table 6.

According to equation (1), the subsequent values till convergence for the 1st patient in Figure 5 shows that the output is 0.93, so patient suffers from meniscus injury.

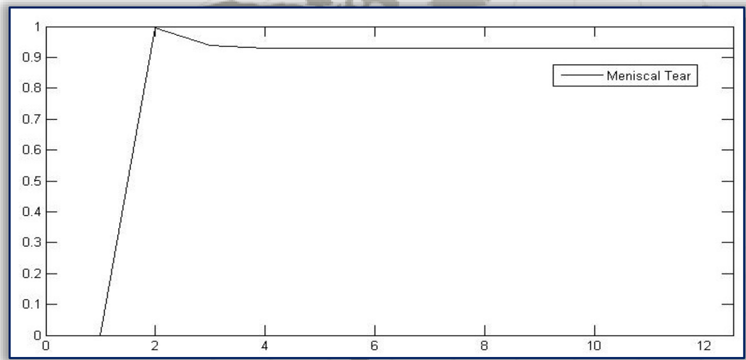

Figure 5. Subsequent values of Meniscal Tear till convergence

Table 7. Overall Results

Patients	Meniscal Tear
1	High
2	High
3	High
4	High
5	High
6	High
7	High
8	High
9	High
10	Medium
11	High

The nature of medical problems and decisions does not require a precise numeric interpretation of the output between 0 and 1, but an ambiguous description that directly determines whether the patient is healthy, something which can be achieved by fuzzy rules. In order to explain this final number of output, the entire bandwidth spectrum of the output value is used. The exact match was defined by the experts as follows:

- $0 < \text{low} < 0.4$
- $0.41 < \text{medium} < 0.79$
- $0.8 < \text{high} < 1$

Authors use the following fuzzy rules defined by physicians-experts to explain each output:

- IF Meniscal Tear is Low THEN the patient does not suffer from meniscal tear
- IF Meniscal Tear is Medium patient needs further examination and clinical tests.
- IF Meniscal Tear is High THEN the patient suffers from meniscal tear.

The final outputs for the rest patients according to the above fuzzy rules are in Table 7.

6. SOME DRAWBACKS OF CLASSIC FCM APPROACH

Since 1986 there have been many efforts for the evolution of classic theory approach of FCM, depending on the specific problem. Learning algorithms tried to fix the convergence problems. Hebbian learning methods (Active and Nonlinear Hebbian Learning) were the predominant ones, considering the initial weight matrix renewal to improve the equilibrium points [4], [22]. Nevertheless, they do not go into the depth of learning principles [27] and the initial system structure described by experts has been changed. The main problem stems from the existing idea of a single calculation rule for all the concepts. Firstly, all concepts are treated in the same way. That causes a big issue in which initial values should be defined for the output on advance. This makes the tool difficult to use because a final unknown diagnosis is the one requested, and the procedure of random definition of the output values complicate the method and affects the entire process. In addition, changes in the values of concepts affect the system in a way that is difficult to be predicted and could not be imported in real time into the model to be tested. Also, there is a high degree of difficulty to adjust each different problem to this existing model. Another important aspect is the analysis of the evolution of the resulting networks through time [5]. In addition, FCMs have stability problem regarding real world systems [6]. These reasons are enough to examine the possibility of a new, more comprehensive and flexible model.

Authors have proposed a new calculation rule comprised by two equations in order to offer more controllability to the model concepts. Concepts are separated to three categories: fuzzy states, inputs and outputs. The two equations extracted from the classic FCM are the followings:

$$x(k+1) = f[Ax(k) + Bu(k)] \tag{10}$$

$$y(k) = f[Cx(k) + Du(k)] \tag{11}$$

where $x(k) \in R^n$ is a state vector, $u(k) \in R^r$ is an exogenous known input vector, $y(k) \in R^m$ is the output vector and f is an activation function. The new model was implemented for first time in diagnosing meniscus injury in IFAC World Congress 2017 [3] with very encouraging results.

7. CONCLUSIONS AND FUTURE RESEARCH

In this paper one of the most difficult and challenging problem in modelling, analyzing and controlling complex dynamic systems (CDS) has been seriously addressed. The analysis and efficient control of CDS are impossible without a formal model of the system. However today's' technologies for building such models for CDS are not sufficient. Qualitative description of most of the parameters of complex dynamic systems results inevitably in fuzziness, complexity and uncertainty. One of the challenges of accepting the "operation" of any complex dynamic system is the ability to make Decisions so the system runs efficiently and cost effectively. New conceptual and innovative approaches are needed. It is absolutely necessary to accept that Knowledge is the one and only one that can lead us in developing such models. And this knowledge must come from more than one expert who has extensive experience in observing and working on today's CDS. Decisions must be made by new Decision Making Support Systems (DMSS) which utilize new advanced and intelligent systems. Such a new approach is proposed to be using Fuzzy Cognitive Maps (FCMs). FCMs offer the opportunity to produce new knowledge based on systems applications, addressing the need to handle uncertainties, fuzziness and inaccuracies associated with real CDS's problems. The illustrative examples been provided in this plenary paper and the obtained results are promising for future research efforts in this exciting field of research.

Challenging future research directions include: new models of FCMs for CDS using learning methods; describe in a more formal way equations (10) and (11) in which concepts are concepts are separated to three categories: fuzzy states, inputs and outputs; develop new DMSS using intelligent systems and advanced neural network theories; develop mathematical models using new advance FCMs for different applications and using a number of experts; develop new software tools for various CDS by modelling them with new FCM models equations (10) and (11); perform extensive simulations with new models and generate new knowledge.

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