FUZZY COGNITIVE MAPS MODELING AND SIMULATION

Evangelia Bourgani[a], Chrysostomos D. Stylios[a], George Manis[b] and Voula C. Georgopoulos[c]

[a]Dept. of Informatics Engineering, TEI of Epirus, Artas, Greece
[b]Dept. of Computer Science & Engineering, University of Ioannina, Ioannina, Greece
[c]School of Health and Welfare Professions, TEI of Western Greece, Patras, Greece

[a] eborgani@gmail.com; stylios@teiep.gr, [b] manis@cs.uoi.gr , [c] voula@teipat.gr

ABSTRACT
Fuzzy Cognitive Maps (FCMs) is a soft computing technique that has been used to model and simulate various and completely different applications from different areas. The FCM modeling approach is symbolic, presenting abstract knowledge and is based on human expert experience and knowledge. This study examines and compares the FCM models as they have been used for various applications.

Keywords: Fuzzy Cognitive maps, modeling

1. INTRODUCTION
Fuzzy Cognitive Maps (FCMs) originated from the combination of Fuzzy Logic and Neural Networks. An FCM models the behavior of a system in terms of interacting concepts; each concept represents an entity, a state, a variable, or a characteristic of the system (Kosko 1986). FCM models are easily understandable as they are similar to the human reasoning procedure, but they require experts' knowledge and contribution during the designing procedure. FCMs constitute a modeling and simulation tool to analyze decision making process for complex systems.

The result of modeling any process depends on the available data, description, information, knowledge and the suggested modeling approach. The fact that FCMs are based on knowledge of experts, which is affected by their experience and background, makes FCMs subjective and potentially vulnerable to possible errors and conflicts. Apart from that, not every possible condition may have been included during the construction of the model, which makes it insufficient. Thus, the results depend on the quality of data that are used to create the model.

FCM modeling creates an abstract representation of a real world system. The modeling and simulation process is simplified, while many assumptions about the system are made, the system's essential relationships are retained and unnecessary detail is omitted. FCMs are able to model and simulate systems in a wide variety of application areas, because of their capability to handle complexity with much and/or even incomplete or conflicting information.

FCMs have been used in many fields, solving a variety of different problems, including social and political sciences, medicine, business and management, engineering, environment and agriculture, information systems and technology, education. Each application has various concepts corresponding to the problem which is under investigation. The large number of concepts makes the system more accurate and completed. However, the less complex a system is the more comprehensible and readable it is. The need for better handling the increased complexity of some applications led to enhance FCMs with learning methods, use of levels and/or separation of the initial complex problem into multiple FCMs and use a supervisor to control the system or use other methods synergistically.

In this work, we describe modeling in various areas, which are completely different from each other, with respect to the concepts and the application requirements. It does not include all the applications, but some of the innovative and useful applications performed by FCMs are described.

2. OVERVIEW OF THE FCM MODEL
FCM is an illustrative causative representation for the description and modeling of any system. It is illustrated as a causal graphical representation consisting of interrelated concepts. FCMs are fuzzy signed directed graphs permitting feedback, where the weighted edge *wij* from causal concept *Ci* to affected concept *Cj* describes the amount by which the first concept influences the latter, as is illustrated in Fig. 1. The values in the graph are fuzzy, so the concepts take values in the range [0,1] and the weights of the arcs are in the interval [–1,1].The value A_i of the concept $C_i$expresses the degree of its corresponding physical value. At each simulation step, the value A_i of a concept C_i is calculated by computing the influence of other concepts C_j's on the specific concept C_i following the calculation rule:

$$A_i^{k+1} = f(A_i^k + \sum_{\substack{j \neq i \\ j=1}}^{N} A_j^k w_{ji}) \quad (1)$$

where A_i^{t+1} is the value of concept Ci at simulation step t+1, A_j^k the value of the interconnected concept Cj at simulation step k, w_{ji} is the weight of the interconnection between concept Cj and Ci, and f is a sigmoid threshold function:

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

where λ>0 is a parameter that determines its steepness.

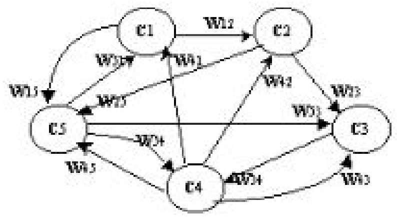

Figure 1: The fuzzy cognitive map model

3. BASIC FCM MODEL

The basic FCM model as described above uses abstract concepts and through the updating equation (1) changes the value of concepts until equilibrium state is reached. Observing the graphical representation (Fig.1), it is clear which concept influences other concepts and it can show the interconnections between concepts.

Concepts can originate from literature, experts and/or non-experts constructing the FCM model for each circumstance that is under investigation. The basic FCM uses the equation (1) for updating their values. Basic FCMs have been enhanced with learning methods or combined with other methods synergistically in order to overcome problems. The results can be linguistic values, which make the use of FCMs more comprehensible and easier to be analyzed and explained.

FCMs use fuzzy logic; hence they can incorporate vagueness and qualitative knowledge and also feedback processes. They can be used to simulate the changes of a system and can also address 'what if' questions. Regarding modeling, FCMs can combine aspects of qualitative methods with the advantages of quantitative methods. FCMs allow dynamically simulating and testing the influence of various scenarios and have been used to reach a decision or to evaluate a procedure or examine management scenarios on system components. Modeling with FCMs is a simple and transparent way for representing and useful to describe any system in many fields such as engineering, medicine, business and so on. Besides, FCM models can be highly accurate. However, the more complex a system is, the more accurate it is, but complexity decreases the comprehensibility of the system.

The basic FCM model has been used in many applications in various fields and for different purposes. The simulation gave generally satisfactory results. However, each model has its own drawbacks with respect to the field that is used.

For example, in **business and management**,FCMs have been used to model and simulate the information systems strategic planning process (SISP) (Kardaras and Karakostas 1999). For this application, FCMs are used as a means that can combine business and IT perspectives. The concepts of this model are extracted from SISP literature (i.e. case studies and theoretical frameworks) and from relevant practical experiences while the interrelationships are determined by planners using linguistic fuzzy weights. Using the proposed model, planners can develop scenarios and assess alternative ways of applying IT in order to improve organizational performance. It is a dynamic and flexible simulation tool that can handle changes in factors and conflicting assumptions. Planners can simulate different scenarios and when conflict issues are resolved the proposed strategy can be adopted.

In another application FCMs have been used to model third-Part Logistics providers (3PLs) (Huang, et al. 2010), where the concepts were obtained from field visits to selected 3PLs, interviews with experts and literature. This model relies on human reasoning in order to determine the initial concepts and weight values. The output values of the concepts are used to examine scenarios of the company's survivability. In reality, without FCM model's simulation, these features would need many days observation. Thus, this is a useful tool for quick and comprehensive exploration. However, this model uses few concepts and can give an indication of the company's evolution without sudden and unexpected changes. Since concept development is based on three different sources there is a need to include a credibility parameter from each source.

In **education**, basic FCM models have been used to evaluate the teaching-learning process (Laureano-Cruces, Ramírez-Rodríguez and Terán-Gilmore 2004). The proposed model is a reactive environment and it is based on a multi-nodal perspective, a holistic and complete approach (knowledge, abilities, attitudes, values). FCM allow a faster control of the different states of such environments. The cognitive components derive from the expert and the learner. Factors come from the literature, the expert and the learner. This model gives as output different didactic actions according to the event that provoke a condition and the tutor can choose the posed chain of actions or one of them. It is able to include expert's knowledge avoiding the symbolic representation of behavioral reasoning based on rules. Plachebo et.al. used FCM to engineering educational assessment (Pacheco, Carlson and Martins-Pacheco 2004). The need for combining several interrelated aspects makes FCM an efficient method, by means of constant feedback and re-assessment. The proposed tool was used for student assessment. The concepts used for this model were found in students of engineering courses. By activating a concept, positively and negatively, the simulation will give the concepts that are affected, which can be interpreted. The proposed model can be applied to any course, a group of courses, a whole college program an educational department, or to other processes that need to model uncertainty or linguistic imprecision. This is a dynamic model that the user can activate the relative concepts and analyze the outcome. The proposed model is highly based on human intervention.

Another application in education field that FCMs have been used is for modeling educational software adoption, which used in UK secondary schools (Hossain and Brooks 2008). The FCM approach let identifying and modeling both qualitative and quantitative factors and their complex causal relationships in the context of educational software adoption. They used empirically-based FCM, modeling factors in the adoption of educational software in schools. This model can provide information for educational software adoption in schools and can be used as a guide both for educational decision makers and for software developers to which direction they should focus their efforts. This is a model that uses the concept of credibility, assigning different values (weights) in the corresponding parameter, which make it more realistic, while in other applications credibility does not taken under consideration. However, the simulation of FCM by activating a factor may lead to contradictory outcomes, which declares the need for a more dynamic model. Besides, this model is applied using few schools from an area (which means similar characteristics) and as a result the outcome cannot be regarded as general.

For **environmental** issues, FCMs have been used in order to incorporate both experts' and local people's knowledge (Özesmi and Özesmi 2004). FCM's have been used because they are easy to build and can give qualitative results. Experts' knowledge does not require in every field but can be constructed based on simple observations by anybody including indigenous or local people. This is a basic difference to the other applications that are based on experts' opinions and experience. FCMs can analyze the stakeholder's approaches, which are in varying degree of sophistication, requiring in average a low in-depth academic investigation. They do not make quantitative predictions but they can show what will happen under given circumstances, by simulating the system. Hobbs et. al. used FCM to define management objectives for the Lake Erie ecosystem (Hobbs, et al. 2002). Using concepts from many experts and/or organizations, communication among experts with public understanding of ecosystem, the limits and possibilities of management is achieved. However, FCM analysis for defining management objectives gives some guidelines, but the information is insufficient for choosing one single ecosystem objective. This approach should be used complementary with other studies.

In the **technology** domain, FCMs have been used for identifying, classifying and evaluating indicators which related to the success of IT projects. FCM method used to illustrate the applicability and success of a new IT project, the Mobile Payment System(MPS) related to mobile telecommunications (Rodriguez-Repiso, Setchi and Salmeron 2007). Concepts derived from interviews that had the expertise to judge the success (Critical Success Factors, CSF) of an IT project. The initial matrix is converting to another matrix until the final one will obtain the relationships of causality between CSFs. Human factor needs constantly during the process and for analyzing and explaining the final matrix as it may contain misleading data. However, the opinion of an expert may lead to erroneous results, too.

Another application in the technology domain is the use of FCM in telecommunication (Li, et al. 2009). FCMs have been applied for distributed peer-to-peer (P2P) networks, in order to ensure the efficient and successful file sharing. FCMs used for team-centric peer selection and analyzed for improving the network performance. The approach used was compared with the traditional process (min number of hops). FCMs were constructed for candidate and intermediate peers. The concepts have been collected from the literature for the intermediate peer, while some of them were selected by the parameter collecting module for constructing the candidate FCM. With the FCM several important parameters can be considered so the best candidate peer is selected. However, the success of this method is highly dependable on the candidate peer selection. The results showed that FCM approach gives better results compared to the tradition min-hop selection. The output is real positive numbers corresponding to transfer rate and transfer time.

Basic FCM model has been used to simulate circumstances in almost every field. Because of its capability to combine and take into consideration various concepts, without direct relation, it has become a tool in every field. However, the basic FCM model face a number problems which some of them overcame using other methods. These are examples of the basic FCM model on which others are developed. Some applications, such as medical, modeled on more complex FCM structures discussed later on. For the other areas basic FCM models are highly applicable.

4. ENHANCING FCM MODELS USING LEARNING METHODS

The construction of FCMs is based on experts, which make FCM modeling subjective. This is one of the basic weaknesses; another one is the potential convergence to undesired steady states. Learning procedures constitute means to increase the efficiency and robustness of FCMs by updating the weight matrix so as to avoid convergence to undesired steady states, while other are used to make FCM models more automatic for decreasing human factor to the overall process.

The initial basic models of FCMs have been enhanced with learning methods. Each learning method influences the weight matrix with aim to optimize the result. Each leaning method exploits different sources such as historical data. Some learning methods require much human intervention some other less, determined by the under investigation field.

The desired steady state is characterized by values of an FCM's output concepts that are accepted by the experts. Thus, in order to overcome the weaknesses, FCMs have been combined with various learning methods, such as Non Linear Hebbian (NHL), Active Hebbian Learning (AHL), Genetic Algorithms (GAs), Particle Swarm Intelligence (PSO), Differential Evolution (DE). Models based on FCMs, using unsupervised learning methods, that is NHL and AHL, are semi-automated meaning that they require initial human intervention. In order to have more automated models, genetic algorithms (GAs) have been used. More recently, algorithms from the fields of Swarm Intelligence and Evolutionary Computations have been used to train FCM based on historical data, reducing even more the human intervention. They take into consideration all the initial knowledge suggested by human experts and not only the initial elements of the weight matrix. Each of the learning methods contributes and enhances the FCM model attributing additional characteristics such as making them more transparent and readable or less expert dependent.

The advantage of NHL is that it updates only those weights that experts determined, that is, the non-zero weights. The weight values of FCM are updated synchronously. The AHL algorithm adapts all the weights of the FCM model using an acyclic fragment approach for concepts (asynchronous activation and interaction among concepts based on the initial experts' knowledge). The AHL algorithm increases the FCMs' effectiveness, flexibility and robustness, and creates advanced FCMs with dynamic behavior and great modeling abilities where new features can easily be introduced, added or deleted allowing a model to continuously evolve. However, these learning methods require human intervention before the learning process starts. The Hebbian algorithm provides a small change to the weights in the direction of reducing prediction errors. On the contrary, genetic algorithm is a repetitive weight trial and error method that iterates the process of trying a new weight matrix until the prediction error is minimized. GAs are fully automatic in contrast to NHL and AHL methods and do not require input from a domain expert, thus leading to more objective models.

Many applications enhanced their results using learning methods to model their tool. In **medicine** FCM-NHL has been used to model the process to make a decision for the final dose of radiation (Papageorgiou, Stylios and Groumpos 2003). The principle of this model is that all the concepts in FCM model trigger synchronously at each iteration step and only those weights that experts determined are updated. Initial concepts and weight values are determined by experts. The final value should fulfill the requirements: deliver the highest volume of beam to tumor and keep the dose level at the minimum for health tissues and critical organs. This is a complex procedure that many factors should be taken under consideration. The simulation of this tool gave satisfactory results. This model was also used in another application for tumor grading with high accuracy (Papageorgiou, Spyridonos, et al. 2003). It is also a versatile modeling and grading tool, offering a degree of transparency, so the experts have some insight to the system behavior. AHL has been used for classification problems in medical applications, giving better results compared to FCM-NHL, under the same conditions. For tumor grading, better results are owed to the fact that the AHL algorithm can determine new FCM causal links between all the concepts in order to increase classification capabilities of the FCM. In this way the AHL algorithm increases the FCMs' effectiveness, flexibility and robustness, and creates advanced FCMs with dynamic behavior and great modeling abilities. Both the AHL and NHL algorithms are problem-dependent and they use the initial weight matrix. However, both processes are independent of the initial values of concepts and the system's output concepts manage to converge to the desired equilibrium points with appropriate learning parameters.

An extension of GAs is the Real Coded Genetic Algorithm used for prediction in medical cases. The RCGA performs linear transformation for each variable of the solution to decode it to the desired interval. Its main advantages are ability to be used with highly dimensional and continuous domains, and richer spectrum of evolution operators that can be applied during the search process. It has been used for long-term prediction of the patient state after a period of time following a suggested therapy plan for the individual patient. Specifically, FCM-RCGA has been used for prediction of prostate cancer (Froelich, et al. 2012). The simulation had real number output, which is the estimated prediction error, giving promising results. In another application, PSO & DE have been used to optimize the weight matrix of an FCM. The combination of these two algorithms used in radiation therapy to give a more reliable decision for the final dose. This fully automatic model (uses historical data) has been used in the hierarchical structure to optimize the weight matrix of the supervisor-FCM model.

In **business**, the improvement of FCM combined with GA has been used to evaluate forward-backward analysis of Radio Frequency Identification (RFID) supply chain (Kim, et al. 2008). This application tries to mine bidirectional cause-effect knowledge from the state of data. The input of the FCM is obtained by a linguistic method and uses GA to adjust the weight matrix, while the output estimates the fuzzification error between the real and predicted cause-effect. The simulation gave large errors, which is justified by the randomly selected initialization.

In **agricultural**, FCMs (enhancing with NHL) has been used for crop yield prediction (Papageorgiou, Markinos and Gemptos 2009) making a decision for the yield (if it is low or high). Experts determined the concepts and the threshold value to evaluate the procedure. Besides, it has been simulated using NHL algorithm and better results succeeded, showing that FCM-NHL gives better outcomes compared to the basic FCM model.

In **education**, the weight matrix of the FCM has been used in combination with Interactive Evolutionary Computing (E-FCM). This model uses as basis the FCM, but the E-FCM allows a different update of the concepts' values.This model incorporates characteristics from Evolutionary Computing (mutation, crossover) but it demands expert to choose candidate E-FCMs in order the optimization process be completed. It can model not only fuzzy causal relationship but also probabilistic causal relationship among variables. E-FCMs have been applied to a serious game for science learning, which let children learn about different diseases by exploring in a virtual world (Cai, et al. 2010). The E-FCM shows the evolution of the state in real-time. Concepts of this model represent the variables of interest in a real-time system. Generally, E-FCMs use attributes from both FCMs and Bayesian network (use and the conditional probability for representing the causality). The output is converted into linguistic when steady state is reached.

In **engineering** FCMs learning with Hebbian algorithm have been used to model structural damage detection (Beena and Ganguli 2011).For this application some concepts include the difference between measurement frequencies that declare damage and those for undamaged, while others contain the possible damage location. It is simulated with the basic FCM approach and FCM using Hebbian learning with the second one have better results. The output gives with high success rate the damage location. However, this approach depends on the input and structure selection and as the number of input and outputs are increased the system is becoming more complex.

For every application area, experts or non-experts contribute differently to the result. As not all experts/non-experts have the same experience and background, a 'credibility' parameter should be inserted in order to become a more reliable model. Additionally and merely for medical and business-management applications, time may be a major factor that can change the output. Therefore, the lack of the concept of time, regarding the order and the reaction time of a change, may provoke important changes in patient state or influence the output in a strategic/economic problem.

5. CREATING SYNERGISTICAL MODELS BASED ON FCMS

For improving modeling and simulation results the basic form of FCM has been supplemented with other approaches, such as Case Base Reasoning (CBR), evolutionary algorithms, Decision Trees (DT). Synergistical models can handle the data in a more efficient way as they can combine and take advantage of the characteristics of two or more methods in order to optimize a process and obtain more reliable results. The models that have been proposed succeeded in making FCMs less human independent, overcoming one of the main FCMs' weaknesses. The use of CBR and evolutionary algorithms wield the historical data, while Decision Trees can enhance FCMs by letting processing both qualitative and quantitave data.

Modeling using Competitive FCMs (Georgopoulos, Malandraki and Stylios 2003) has been used for decision making, ensuring that there will be only one result. CFCMs are capable on their own to perform a comparison and lead to a decision based on expert knowledge and experience. They are based on 'competitiveness' which will give a 'winner' concept. They consist of two types of concepts: factor and decision. These concepts are determined by experts. The output of modeling is linguistic. CFCMs have been enhanced with various methods in order to infer more reliable results, overcome weaknesses that have the initial model, cope with the increasing number of concepts and become less human dependent. FCMs supplemented with CBR can use information from previous cases and in that way they can face problems such as no activation of nodes because of human underestimation. CBR bases on the fact that similar problems have similar solution. This model has been enhanced with additive methods in order to reduce the simulation time. Another enhancement is the combination of FCMs with Evolutionary Algorithms which are population-based algorithms, and are efficient when they are applied to solve optimization problem. Decision Trees have been also used in order to face the amount of data that may be qualitative and quantitative.

Synergistical models have been used for **medical** circumstances. CFCMs have been used for describing differential diagnosis among Specific Language Impairment, dyslexia and autism (Georgopoulos, Malandraki and Stylios 2003). The simulation reaches a decision, however, this may not be a clear one since in certain situations the output concepts have very close values. CFCMs supplemented with CBR giving the Augmented Competitive FCM (Georgopoulos and Stylios 2005). The main idea of CBR is the assumption that similar problems usually have similar solutions. Thus, this model takes in consideration historical data as it assumes that similar problems usually have similar solutions, reducing the human intervention and making a more automated model. CBR is not called every time, thus it can decrease simulation time. CFCM-CBR has been applied for diagnosis in speech and Language pathology and specifically developed as a differential diagnostic System for Specific Language Impairment, Autism and Dyslexia. It is applied in comparison with the results without CBR and the results showed the advantages of the new system. The difficulty in inferring a distinct result in some cases led to the Complementary CFCM-CBR (CBR enhanced), which uses lateral inhibition and gives an even clearer decision. This model uses an additive method in order to enhance the differences between different decisions/diagnoses and emphasize boundaries. It has been used applied successfully to model and test two decision support systems, one a differential diagnosis problem from the speech pathology area for the diagnosis of language impairments and the other for decision making choices in external beam radiation therapy (Georgopoulos and Stylios 2008). As regard the speech pathology, the simulation of the Complementary CFCM-CBR with the same concepts as the previous CFCMs resulted to better diagnosis of the most probable disorder. The External Beam Radiotherapy

Decision Support is another example that CBR-enhanced CFCMs contribute to the final choice for the optimum distribution of beam so as the healthy cells are not be affected. The use of CFCMs with GA decreases the human intervention. GAs are designed to evaluate existing potential solutions as well to generate new (improved) solutions to a problem for evaluation. Based on this method the Genetic Algorithm Factor Interaction Competitive FCM (GAFI-CFCM) a diagnostic support model has developed (Georgopoulos and Stylios 2009) giving even better results. GAFI-CFCM is also applied for labor modeling (Stylios and Georgopoulos 2010).In this case the result was promising.

FCMs have been also combined with Decision Trees(DT) FCM (Papageorgiou, Stylios and Groumpos 2006). This technique includes a DT (created by any decision tree algorithm) with the FCM. It can handle different types of initial data and can be used differently depending on the type of input data, that is, if data include only quantitative or only qualitative or both. Depending on the type of input data, it is activated with the use of DT or the construction of FCM according to experts' opinions or both; the outputs can be combined in order to reach decision. For a large number of input data, qualitative and quantitave data are used to construct a FCM separately. Their combination constructs the enhanced FCM model. The FCM enriched with IF-THEN rules to assign weights direction and values. The NHL unsupervised training algorithm is used to reach to the proper decision. This model offers better handling of large data, while the FCM's flexibility is being enhanced by the introduction of the decision tree rules that specify weight assignment through new cause-effect relationships. This approach reduces the human intervention however it remains highly dependable on it. It has been used for medical purposes, too (grading bladder tumor).Concepts derived from experts, while quantitative data from the DT. The inductive knowledge from the DT has been used for deriving a set of association rules. This tool has been applied under the same conditions with the FCM tool and the results showed that the FCM-DT approach succeeded more accurate and clear results. The output is linguistic.

These models that have been developed for medical purposes lack the temporal concept. This may be important for certain medical application.

For **political and strategic** issues, FCMs have been applied for crisis management and political decision. The flexibility of FCM has been improved by allowing a variety of Activation Levels (AL) of each concept thus creating Certainty Neuron Fuzzy Cognitive Maps (CNFCM) (Andreou, Mateou and Zombanakis 2005). This model has been also enhanced with GA and applied for the Cyprus issues trying different scenarios. It offers the ability not only to design multi-objective scenarios, but also to predict the dynamics of a future realization. The advantage of this model is that GAs are used and aim at solving the problem of the invariability of the weights and the inability of the method to model a certain political situation following the change of a certain weight or group of weights. Concepts derived from questionnaires and interviews and experts determined the final concepts for modeling. The decision-maker is able to consider hypothetical scenarios by defining the target activation level of a concept in focus and to study the resulting weight values and AL once the model has reached equilibrium. However, it is possible to get into limit cycle or chaotic behavior. This model can be used as an assistant tool for the political analysts and decision makers.

These models are based on human (expert or non-expert). However there is no credibility parameter, as with the most basic models, discussed above.

6. HIERARCHICAL STRUCTURES

For better handling cases of large complex systems, an approach is the decomposition into sub-systems. This technique has been used extensively on conventional modeling and simulation approaches. When subsystems have many elements in common decomposition is not easy and that prohibit the simplified approach of summing up the individual components behavior.

Hierarchical models consist of a number of levels. In theory, the levels can be infinite; in practice, however, they have a limited number. The output of a level is usually the input to another one, which can activate another part of the system. FCMs have been used to construct subsystems of a larger system. The generic purpose of FCMs as subsystems is to exchange information among all the subsystems in order to accomplish a task, make decisions and to plan strategically. Hierarchical models are ideal for processes that involve a large number of factors with complex interrelations. FCM modeling and simulation offers a tool to cope with complexity of large systems.

The advantage of a multi-level system is that factors that correspond to a process can be organized into groups and each group constitutes a (sub)FCM, reducing the complexity. The sub-FCM should be handled both as an autonomous FCM system and as part of a general interactive system. Human intervention is needed. Hierarchical models have been in various application areas, in both medicine and business. The output can be linguistic or real numbers and can be used either to reach a decision or to compare FCMs' values to those estimated by experts.

In **medicine**, the hierarchical architecture has been used in obstetrics, for making a decision whether a natural delivery or caesarian section is to be applied. This model also has been used for decision making in radiation therapy (Papageorgiou, Stylios and Groumpos 2003). The hierarchical models that have been developed for medical purposes use up to two levels: the lower and the upper, which is referred to as a Supervisor-FCM. Thus, the upper level –the supervisor- can perform some of the tasks that a human operator successfully performs in supervising systems. It can handle and express qualitative information and have knowledge about the process structure and determine about the acceptance of a result. Especially, in a two-level hierarchical structure the FCM at the upper level can receive inputs from the lower, interact with the whole FCM and send back to the lower level new set of values until steady state is reached.

Another medical application is in radiotherapy. The hierarchical architecture is used to make decisions about the final dose of beam for radiation therapy. Concepts are determined by radiotherapists and physicists taking under consideration the basic beam data from experimental measurements and patient information. The concepts of the FCM model for radiotherapy treatment are divided into three categories: Factor-concepts, Selector-concepts, and Output-concepts. Input (factors and selectors) concepts; represent treatment variables with given or measured or desired values and taking their values from the real system and/or sensors and their measurements, with transformation to fuzzy interval. On the other hand, there are the output concepts that their value is influenced and determined by the value of the input concepts with the corresponding causal weight and the decision making process is the determination of their value. The values of the output concepts lead to the final decisions. Values of concepts are described using linguistic variables and they are transformed in numerical values using a defuzzification method.

In the **business** and management domains a hierarchical model has been used to propose an effective business modeling support tool that can also drive process change activities (Xirogiannis and Glykas 2004). In contrast to the proposed two layer hierarchical model for medical applications, the proposed model for Business Process Reengineering (BPR) consists of four layers. Each layer can contain one or more sub-FCMs that represent the map categories. Business models and strategic BPR plans are used as input and during the process an expert - redesigner is called to determine business scenarios thus modifying the fuzzy weights and then reasoning about the business performance. Interconnections are determined using linguistic notion by experts and a defuzzification method is used to produce weights. Each sub-FCM has an output that triggers another sub-FCM. This tool aid supplements the strategic planning and business analysis phases of typical BPR and simulates the operational efficiency of complex process models with imprecise relationships and quantifies the impact of the reengineering activities to the business model. The outputs of the proposed model were real numbers that were examined and compared with the values of some concepts, between the FCM approach and the experts' decision. The results gave very close results. However, more real life experiments are needed. Another application is the modeling of e-business maturity (Xirogiannis and Glykas 2007). This model was developed according to the previous hierarchical model for BPR. It consists of four levels and each level has one or more sub-FCMs that group the relative characteristics of each category. Each level is abstract, while each sub(FCM) can be dynamically reconfigurated. The modeling and simulation for this case aim at simulating complex strategic models with imprecise relationships while quantifying the impact of strategic changes to the overall e-business efficiency. Concepts and weight values are obtained by business models and/or financial planning. A team of experts provide linguistic variables for the causal weights, the concept values and the coefficients values to let the FCM algorithm reason about the impact of potential change initiatives. The experts also provide their independent expert estimates (using similar linguistic variables) of the impact of the strategic change choices to specific maturity metrics. The output of the model is expressed in real numbers as described previously.

Hierarchical models in both application areas demand human intervention during the process. In medicine it is needed from the beginning to construct the concepts, while in business it is needed during the important phase of redesigning.

In **education,** hierarchical structure has been used to model an adjustable tool for Learning Style Recognition (Georgiou and Botsios 2007). It is a three layer FCM Schema that allows educators to interfere, tune up and adjust the system parameters in order to order to contribute on the accuracy of the recognitions. The inner layer contains the learning styles, the middle one the learning activity factors and the outer the 48 statements of the learning style inventory. The factors come from the literature. The teacher can tune up system's weights using his/her own diagnosis on a learner's Learning Activity Factors. An algorithm has been used in order to eliminate fault implication, enhancing the outcome. The possible output concepts comes from Kolb's learning theory (Kolb 1984). The result is linguistic.

In **engineering** field, (Stylios and Groumpos 2004) used FCMs to model a heat exchanger system. This FCM has been used as the supervisor of a hierarchical model. Concepts were defined by experts as well as the connections between the concepts. The supervisor-FCM model can be expanded to include advanced features or planning and decision making characteristics, improving the overall performance of system's performance. A two-level hierarchical structure was also proposed to handle modeling of complex systems, where the supervisor is modeled as a FCM. The simulation gives results, if they are not acceptable experts have to redesign the model. The proposed supervisor-FCM contains few concepts however its simulation gave satisfactory results. This model demands experts' opinion for the overall construction of the system.

Hierarchical models can control the lower levels that they may consist of individual FCMs, grouped according to their similar characteristics. This approach gives the opportunity to better handle more complex and as result more realistic models with better observation and control.

7. CONCLUSION

This paper compares FCM modeling and simulation approaches for various non-overlapping application areas, which have different requirements in data handling and concept outputs. FCMs provided the opportunity to model and simulate many problems that require decision making or classification or predicition/checking of scenarios. The fact that FCMs can handle vague, missing or not available information renders them a versatile tool. The table in appendix gathers the described applications according to the used FCM approach for modeling and simulation.

For each field there are different problems as each one has different requirements. Time, for example, with respect to the concepts' content and simulation time, in medical and business applications is one significant factor that contributes and may change the final result. For the other applications, however, time is not such an important parameter. In contrast, a credibility parameter, proportional to experts' experience and knowledge, is a common requirement for all the fields. Generally, FCMs offer a tool that should be used as assistance to decision makers as this methodology may not be a sufficient model of the system because the human factor is not always reliable.

ACKNOWLEDGEMENT

This work was supported by the E.U. FP7–PEOPLE–IAPP–2009, Grant Agreement No. 251589, Acronym: SAIL.

APPENDIX

Models based on FCMs	Applications area	Application	Solving problem/type of output
Basic FCM	Business	3PLs	Predict company's survival; linguistic result
		SISP	Decision making; applying various scenarios; linguistic output
	Education	Evaluation teaching-learning process	Didactic tactics; linguistic output
		Engineering education assessment	Observes tendencies by provoking a situation; analyze the outcome linguistically
		Modeling educational software adoption	Visual medium for investigating factors that affect educational software; Linguistic output
	Technology	Modeling IT project success for Mobile Payment System(MPS)	Decision making; Critical Success Factor (indicators); Linguistic output
		Team-centric peer selection scheme for distributed wireless P2P Networks	Decision making; real positive output
	Environment	Define management objectives for the Lake Erie ecosystem	Decision making; linguistic output; complementary method
FCMs models using learning methods : - Hebbian learning	Engineering	Structural damage detection	Decision making; linguistic result
- FCM-NHL	Medicine	Radiotherapy	Decision making; Linguistic output
		Tumor grading	Classification; linguistic output
	Agricultural	Yield prediction	Make decision; linguistic output
- FCM-AHL	Medicine	Tumor grading	Classification; linguistic output
		Predict autistic disorders	Prediction; linguistic output
- FCM-GA	Medicine	Prostate cancer (RCGA)	Prediction; Real number output
	Business	Forward-backward of RFID supply chain	Evaluation; Fuzzification error

- FCM-PSO&GE	Medicine	Radiation therapy	Optimize Supervisor’s weight matrix
- Evolutionary-FCM (with Interactive Evolutionary Computing)	Education	Serious game for science learning	Explore virtual world; linguistic output
Synergistic models : - CFCM - Augmented CFCM with CBR	Medicine	Dyslexia and autism	Differential diagnosis; linguistic output
- Complementary CFCM-CBR		Language impairment	
		External beam radiation	Decision making; Linguistic output
- GAFI-CFCM		Labor modeling	
- DT-FCM		Tumor grading	Classification; handling both qualitative and quantitative input data; linguistic output
- Genetically Evolved Certainty Neuron FCM	Political and Strategic issues	Cyprus issues	Decision making; linguistic output; applicable to many strategic scenarios
Hierarchical structure	Medicine	Labor Radiotherapy	Decision making ; linguistic output
	Business	Business modeling support tool (Business Process Reengineering-BPR)	Compare bibliographic and expert values; Real numbers output
	Education	Learning Style Recognition	Decision making;Linguistic output
	Engineering	Heat exchanger system	Decision making;Linguistic output

REFERENCES

Andreou, A. S., Mateou, N. H. and Zombanakis, G. A., 2005. Soft computing for crisis management and political decision making:the use of genetically evolved fuzzy cognitive maps. *Soft Comput.,9,*194–210.

Beena, P. and Ganguli, R., 2011. Structural damage detection using fuzzy cognitive maps and Hebbian learnin. *Applied Soft Computing 11.* 2011. 1014–1020.

Cai, Y., Miao, C., Tan, A.-H., Shen, Z. and Li, B., 2010. Creating an Immersive Game World with Evolutionary Fuzzy Cognitive Maps. *IEEE Journal of Computer Graphics and Applications*, 30(2), 58-70.

Froelich, W., Papageorgiou, E., Samarinas, M. and Skriapas, K., 2012. Application of evolutionary fuzzy cognitive maps to the long-term prediction of prostate cancer. *Soft Computing*, 3810–3817.

Georgiou, D. A. and Botsios, S.D., 2007. Lerning Syle Recognition A Three Layer Fuzzy Cognitive Mao Schema. *IEE International Confererence on Fuzzy Systems*, 2202-2207.

Georgopoulos, V.C. and Stylios, C.D., 2008. Complementary case-based reasoning and competitive fuzzy cognitive maps for advanced medical decisions. *Soft Comput.12(2),*: 191-199.

Georgopoulos, V. C., Malandraki, G. A. and Stylios, C. D., 2003. A Fuzzy Cognitive Map Approach to Differential Diagnosis of Specific Language Impairment. *Journal of Artificial Intelligence in Medicine* v.29, 221-278.

Georgopoulos, V.C. and Stylios, C.D., 2005. Augmented fuzzy cognitive maps supplemented with case based reasoning for advanced medical decision support. In *Soft Computing for Information Processing*, by M. Nikravesh, L. A Zadeh and J. Kacprzyk, 391-405. Springer.

Georgopoulos, V.C. and Stylios, C.D., 2009. Diagnosis Support using Fuzzy Cognitive Maps combined with Genetic Algorithms. *31st Annual International Conference of the IEEE EMBS.*

Hobbs, B. F., Ludsin, S. A., Knight, R. L., Ryan, P. A., Biberhofer, J. and Ciborowski, J.J.H., 2002. Fuzzy cognitive mapping as a tool to define management objectives for complex ecosystems. *Ecolog.Appl. 12.* 1548-1565.

Hossain, S. and Brooks, L., 2008. Fuzzy cognitive map modelling educational software adoption. *Computers & Education* 51, no. 4. 1569-1588.

Huang, Y.K., Feng, C.M., Yeh, W.C. and Lin, L.Y., 2010. A fuzzy cognitive map modeling to explore the operation dynamics of third-party logistics providers. *Logistics Systems and Intelligent Management.* 1266 - 1270.

Kardaras, D. and Karakostas, B., 1999. The use of fuzzy cognitive maps to simulate the information systems strategic planning process. *Information and Software Technology,* 197-210.

Kim, M.C., Kim, C.O., Hong S. R. and Kwon, I. H., 2008. Forward-backword analysis of RFID-enabled supply chain using fuzzy cognitive and genetic algorithm. *Expert Systems with Applications,* 1166-1176.

Kolb, D., 1984. Experiential learning: Experience as the source of learning and development. *Englewood Cliffs, NJ: Prentice-Hall.*

Kosko, B., 1986. Fuzzy Cognitive Maps. *International Journal of Man-Machine Studies*, 65-75.

Laureano-Cruces, A. L., Ramírez-Rodríguez J. and Terán-Gilmore, A., 2004. Evaluation of the Teaching-Learning Process with Fuzzy Cognitive Maps. *Lecture Notes in Computer Science* 3315, 922-931.

Li, X., Ji, H., Zheng, R., Li, Y. and Yu, F. R., 2009. A Novel Team-Centric Peer Selection Scheme for Distributed Wireless P2P Networks.*Wireless Communications and Networking Conference,WCNC*.

Özesmi, U. and Özesmi, S. L., 2004. Ecological models based on people's knowledge: a multi-step fuzzy cognitive mapping approach. *Ecological Modelling*, 43-64.

Pacheco, R. L., Carlson, R. and Martins-Pacheco, L. C., 2004. Engineering Education Assessment System Using Fuzzy, 4867-4881.

Papageorgiou, E. I., Markinos A. and Gemptos, T., 2009. Application of fuzzy cognitive maps for cotton yield management in precision farming. *Expert Systems with Applications*, no. 36,12399–12413.

Papageorgiou, E. I., Stylios, C. D. and Groumpos, P. P., 2003. An Integrated Two-Level Hierarchical System forDecision Making in Radiation Therapy Based on Fuzzy Cognitive Maps. *IEEE Transactions on Biomedical Engineering*.

Papageorgiou, E. I., Spyridonos, D. D., Stylios, C. D., Nikiforidis, G.C. and Groumpos, P. P., 2003. Grading Urinary Bladder Tumors Using Unsupervised Hebbian Algorithm for Fuzzy Cognitive Maps. *Biomedical Soft Computing and Human Sciences Vol.9, No.2*, 33-39.

Papageorgiou, E., Stylios, C. and Groumpos, P. 2003. Fuzzy Cognitive map learning based on nonlinear Hebbian Rule. *Gedeon, T.; Fung, L.C.C.;*. Heidelberg: Springer, 256-268.

Papageorgiou, E., Stylios,C. and Groumpos P., 2006. A Combined Fuzzy Cognitive Map and Decision Trees Model for Medical Decision Making. *IEEE EMBS Annual International Conference.* New York,6117-6120.

Rodriguez-Repiso, L., Setchi, R. and Salmeron J. L., 2007. Modelling IT projects success with Fuzzy Cognitive Maps. *Expert Systems with Applications 32*, 543–559.

Stylios, C. D. and Groumpos, P.P., 2004. Modeling Complex Systems Using Fuzzy Cognitive Maps. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans.*155-162.

Stylios, C.D. and Georgopoulos, V.C., 2010. Fuzzy Cognitive Maps for Medical Decision Support – A Paradigm from Obstetrics. *32nd Annual International Conference of the IEEE EMBS.* Buenos Aires, Argentina.

Xirogiannis, G. and Glykas, M., 2007. Fuzzy Cognitive Maps in Business Analysis and Performance-Driven Change, *IEEE Transactions on Engineering Management*, 334-351.

Xirogiannis, G. and Glykas, M., 2007. Intelligent Modelling of e-Business Maturity. *Experts Systems with Applications*, 687-702.

AUTHORS BIOGRAPHY

Evangelia Bourgani is collaborator at Knowledge and Intelligent Computing Lab, Dept. of Informatics Engineering, TEI of Epirus and she is a Ph.D student in Depart. of Computer Science & Engineering, University of Ioannina. She received her diploma in Electrical & Computer Engineering and her M.Sc. degree in Information Processing from Depart. of Computer and Informatics Engineering and Physics, University of Patras. Her research interests are Soft Computing and Decision Support Systems.

Chrysostomos D. Stylios is an Associate Professor at Dept. of Informatics Engineering, TEI of Epirus; he is a senior researcher at Telematics Center Department of Computer Technology Institute & Press. He received his Ph.D from the Dept. of Electrical & Computer Engineering University of Patras (1999) and diploma in Electrical & Computer Engineering from the Aristotle University of Thessaloniki (1992). He has published over 100 journal and conference papers and book chapters. His main scientific interests include: Fuzzy Cognitive Maps, Soft Computing, Computational Intelligence Techniques, Neural Networks, Knowledge Hierarchical Systems and Decision Support Systems

George Manis is an Assistant Professor at Dept. of Computer Science & Engineering, University of Ioannina. He received his Ph.D from the Dept. of Electrical & Computer Engineering, National Technical University of Athens (N.T.U.A). He received his M.Sc. in Advanced Methods in Computer Science from QMW College, University of London and diploma in Electrical & Computer Engineering from the N.T.U.A. His main scientific interests include: Biomedical Engineering and Computing Systems.

Professor Voula Georgopoulos holds a Diploma Engineer, from the University of Thrace, Greece, an M.S., from MIT, USA, and a Ph.D., from Tufts University, USA, all in the field of Electrical Engineering. She is Professor of Informatics in the School of Health and Welfare Professions of TEI of Western Greece. Her current research interests are in Medical Applications of Artificial Intelligence Systems.