University of Cyprus

Department of Computer Science

PhD Thesis

A Framework for Developing Intelligent Information Systems to Support Decision Making in Complex and Uncertain Environments

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A FRAMEWORK FOR DEVELOPING INTELLIGENT INFORMATION SYSTEMS TO SUPPORT DECISION MAKING IN COMPLEX AND UNCERTAIN ENVIRONMENTS

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The main goal of this research work is to develop an innovative Intelligent Information System (IIS) aiming at increasing the capabilities of Expert Systems (ES) and Decision Support Systems (DSS) by expanding their capabilities and domain applications. The methodology completes a framework for developing a new category of intelligent decision support systems to be applied in complex and uncertain environments which at the same time being capable of forecasting. Fuzzy Cognitive Maps is an alternative approach to decision making processes which expand the capabilities of DSS and ES and supports scenario analysis and forecasting. During this research, several drawbacks of FCM were identified and addressed. More specifically, the methodology is based on encoding experts' assessment in problems with rich numbers of explanatory variables, large degrees of freedom and rapidly changing and uncertain environments. The assessment is inputted in a dedicated fuzzy knowledge base specifically design to handle linguistic variables. This knowledge is modelled and processed using Fuzzy Cognitive Maps, which, however, suffer from two weak nesses. The first one involves the invariability of the weights that participate in the configuration of a given problem. The second lies with the inability of the method to model a certain situation by performing all possible computational simulations following the change of a certain weight or group of weights. We addressed this issue by combining FCM with Genetic Algorithms (GA), thus creating an Evolutionary Fuzzy Cognitive Map hybrid model.

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Another two important improvements of the FCM theory were also proposed in the present thesis. The first concerns the handling of the “Limit Cycle phenomenon” attempting to improve the inference procedure, while the second improvement refers to the use of a new structured approach named Multilayered-Fuzzy Cognitive Maps for the development of FCM-based systems that are able to handle large-scale, complex systems.

The methodology was successfully applied in practice where several real world problems were modelled using the proposed framework, based mostly on the fields of crisis management, political decision-making and strategy definition. More specifically, the Cyprus issue was modeled several times following its different stages over the last six years, the 2002 tension in Cyprus due to Turkey’s threats as regards Cyprus’s bid for full membership in the EU, the S-300 missiles crises and finally the settlement of the Cyprus issue through the Annan Plan. The later model made use of a multilayer structure consisting of 56 concepts. Furthermore, the methodology was also successfully validated using the Prisoner’s Dilemma, a well known example from the area of game theory.

The application of the proposed methodology is not limited only to political or crisis management problems but can be further extended, without any restrictions, to other domains due to its generic nature and simple and straightforward steps. Therefore, it is clear that the proposed methodology may enable the study and modelling of a number of different problems provided that the basic principles of interrelated parameters (concepts) and uncertainty are satisfied.

A FRAMEWORK FOR DEVELOPING INTELLIGENT INFORMATION SYSTEMS TO SUPPORT DECISION MAKING IN COMPLEX AND UNCERTAIN ENVIRONMENTS

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LIST OF ACRONYMS

IIS	Intelligent Information Systems
DSS	Decision Support Systems
ES	Expert Systems
FCM	Fuzzy Cognitive Maps
FKB	Fuzzy Knowledge Base
AL	Activation Level
ML-FCM	Multilayer Fuzzy Cognitive Maps
GE-FCM	Genetically Evolved Fuzzy Cognitive Maps
PD	Prisoner's Dilemma
HML-FCM	Hybrid Multi Layer Fuzzy Cognitive Maps
SC	Soft Computing
ANN	Artificial Neural Networks
NN	Neural Networks
CW	Computing with words
GA	Genetic Algorithm
FL	Fuzzy Logic
MF	Membership Function
CM	Cognitive Maps
USSR	Union of Soviet Socialist Republics
PLO	Palestine Liberation Organization
DHL	Differential Hebbian Learning
NHL	Nonlinear Hebbian Learning
BDA	Balanced Differential Algorithm
EU	European Union
T/C	Turkish Cypriots
G/C	Greek Cypriots
UK	United Kingdom
USA	United States of America
UN	United Nations
NATO	North Atlantic Treaty Organization
BBN	Bayesian Belief Network

Chapter 1: Introduction

1.1 Objectives
1.2 Research methodology
1.3 An outline of the main research activities. Statement of the problem
1.4 Thesis structure

1.1. Objectives

The objective of this research lies with the development of a new category of Computational Intelligent Decision Support Systems (CI-DSS) used to model complex real world problems which are characterized by imprecision, uncertainty, partial truth, and approximation [83]. A new methodology is implemented for supporting problem-solving and decision-making processes in the domain of Soft Computing [189], using as its basic elements different methods of Artificial Intelligence, such as Fuzzy Cognitive Maps, Fuzzy Logic, Neural Networks and Genetic Algorithms. The methodology can be applied to model problems requiring a decision making process, but is also well applied to issues related to crisis management, political decision-making and strategy definition [16]. Following a number of certain minor modifications, the methodology may be used, in addition, to face other complex problems with certain properties that require decision-making under uncertainty and predict the strategy that needs to be followed based on scenario analysis [36]. The new methodology uses the Evolutionary Fuzzy Cognitive Maps [14] as a new approach for creating a special type of CI-DSS using the cognitive science to evolve both Decision Support and Experts Systems [176]. The latter is a decision–making software tool that mimics human experts' knowledge, its performance being comparable or even exceeding that of a human expert on a specific scientific area. It is thus used to transfer human expert knowledge to a computer and subsequently process and extract it using artificial intelligent technology [140], aiming at arriving at specific policy conclusions and recommendations.

The term Decision Support Systems (DSS) is used to describe any computational system that supports in some way the decision-making process [175]. In early 1970's Scott Morton gave a definition for DSS stating that "DSS is as an iterative computer based system, which help decision-makers to handle unstructured problems" [152]. During the last few years the term DSS is used as a super set describe any computerized system that supports decision making in an organization. Their use, however, requires particular attention, given that their forecasts rely on extrapolations of existing data that introduce the underlying assumption of a stable and repeatable environment. The fact remains, in any case, that DSS can provide a source for data collected on a regular basis and support the decision making process both in identifying the decision to be made, as well as in monitoring results. Decision support systems have a supporting role to play in the decision making process, with the aim to support and improve its effectiveness [31]. The advantage introduced by the DSS is that decision makers can use them interactively to build and, what is more important, to modify analytical models of decision systems. This interactive facility allows immediate changes with rapid feedback, encouraging a learning process that would have been impossible if the decision maker had to wait for prolonged time periods before the effectiveness of the initial policy measures taken would be evaluated. DSS allow decision makers to utilize a wide variety of techniques of analysis, tapping either the central or the DSS special database to acquire specific information in a timely manner and display the resulting output in any format required.

Expert systems can replace human judgment by transforming expert knowledge to a large rule knowledge base; on the other hand regular DSS play a more passive role in human-computer interaction [7]. In other words, DSS may execute computations, present data and respond to standard commands, but cannot replace an intelligent assistant to the decision maker, given their lack of flexibility required to face the effects of daily unexpected changes and discontinuities. Turning to Expert Systems (ES) the study of artificial intelligence uses them to simulate the human brain functions [141]. In fact, expert systems attempt to emulate the decisions of an expert on a particular problem domain and include ways to automate decisions in repetitive environments. Such systems are useful in cases in which rare expertise or fine-tuning of complex policy manoeuvres is required. This task, however, is rather demanding, requiring constant revision of complex decisions depending on the environment instability. This accounts for the use of a wide variety of expert systems, some of which are very effective rule-based systems that classify objects in a complex environment [42].

While the motivation of an expert system is the computerization of rare expertise to the point of actually replacing the human expert, in practice the general idea is much simpler: Expertise is transferred from the expert to a computer. This knowledge is then stored in the computer and users run the program for specific advice as needed. To build expert systems a considerable amount of time to programme, test and store expert information for further use is needed [93], thus requiring a lot of effort to time develop a reliable system that can face a complicated task.

The above indicate the differences between DSS and ES, the most significant one being that ES are mainly used for repetitive tasks while DSS aim at coping with unstructured environment involving specific decisions [141]. It follows therefore, that DSS require flexibility in order to respond to a changing environment while ES tend to stick closer to the process paradigm of cognitive decision theory. In fact they are not structure related, with much smaller domains of application than DSS. The knowledge in ES is represented not as tables and data but in many different ways, such as, linguistic terms, frames, rules etc [32]. The new technologies make the borders between ES and DSS very narrow, some scientists believe that ES are part of DSS while others see DSS and ES as two completely different systems. Moreover others combine the two approaches into a new form termed “Knowledge-based systems” [101].

A cognitive approach using Fuzzy Cognitive Maps (FCM) has been praised for the radically different stance it takes towards environmental uncertainties [100]. In fact, whereas trend-projecting forecasting techniques attempt to remove uncertainties by providing one specific forecast at a time, FCM use scenario analysis that faces environmental uncertainties by considering several alternative forecasts [107]. They, thus, aim at influencing the decision makers’ reasoning by pointing to a feasible future state of the issue under consideration.

Computational Intelligent DSS extent the concept of a typical DSS by adding Computational Intelligence techniques [76], such as genetic algorithms, fuzzy logic and neural computing, aiming to assist decision-making [178].

Genetic Algorithms solve problems in an evolutionary way by searching for an optimal solution through the process of evolution [130]. The Fuzzy Logic approach, on the other hand, is closer to the human pattern of information communication, providing for ways to face the lack of precision involved in human value judgments by relying on other artificial methods, such as expert systems and artificial neural networks [75]. Neural computing [111], in particular, is a concept that attempts to emulate the basic structure and functionality of the human brain, thus being able to support the knowledge acquisition process during the development of an expert system [176].

One of the main objectives of this research is to develop a Computational Intelligent DSS aiming at increasing the capabilities of expert systems by expanding their capabilities via the use of Fuzzy Cognitive Maps (FCMs) [3]. The use of FCMs helps to create an efficient, and at the same time easy to build, fuzzy knowledge base system using simulation techniques [27].

The proposed research is based on encoding experts' assessment on the parameters and their interdependencies which describe large scale complex problems. This assessment is inputted in a Fuzzy Knowledge Base (FKB) [21] using a linguistic form; this knowledge is modelled and processed using Fuzzy Cognitive Maps [107]. A new technique is proposed for encoding the linguistic variables in a FKB, while a fuzzification and defuzzification process is implemented and used to interpret the results along the lines of human reasoning pattern. This type of defuzzification allows decision-makers to define their strategy in order to promote a future desired state, or to plan certain actions to avoid an undesirable development.

Furthermore, with the use of a genetic optimisation algorithm, the user is able to hypothesise different scenarios aiming at choosing the most appropriate strategy. In that sense, this research deals with the optimisation technique not only for proving the reliability of the underlying method, but also for its expansion when the problem becomes more complicated or multidimensional. Thus, in this case, modelling is achieved through a new methodology, which produces a Multilayer Hybrid System comprising of layers of Fuzzy Cognitive Maps and Genetic Algorithms [168].

1.2. Research methodology

The steps taken to develop the hybrid model include a number of phases which also take into consideration the usability and reliability of the proposed Computational Intelligent Decision-Support model:

The first phase of the methodology requires on the collection and coding of expert knowledge on the specific issue under study. More specifically this phase is supported by the utilization of experts to determine the factors influencing the problem and the interaction between these factors for the creation of the initial analysis part of the model. The coding of experts' knowledge presumes the development of a fuzzy knowledge base, which encodes this knowledge in the form of linguistic variables [114]. The type of encoding and the fuzzification/defuzzification process to support inference is studied and analyzed in detail during this phase.

The next phase relates to the processing of information, the conversion of linguistic variables to mathematical variables, and the processing of the latter so that they can be inserted into mathematical equations that will computationally support the model. The use of Genetically Evolved Fuzzy Cognitive Maps (GE-FCMs), which essentially constitute an extension of FCMs, comprises the computational basis of the methodology. Genetic Algorithms are used for the simulation of future states and for the creation of multiple scenarios with the involvement of one or more of the states in any scenario outlining a problem on which decisions must be taken [165]. The use of various algorithms, the reliability of the results provided and also their use in a multi-level decision-making model is the subject of thorough investigation in this phase.

Previous research studies in the field of Fuzzy Cognitive Maps have shown that when a problem is complicated and multidimensional it requires a novel methodology for the clustering of the various participating factors, as well as for their structuring in a multilevel decision-making model. The use of multilayered Fuzzy Cognitive Maps constitutes the next phase. A dedicated software tool is developed which executes a new algorithm that supports the development and execution of Multilayer Fuzzy Cognitive Maps (ML-FCM) [121].

Scenario analysis and the interpretation (conversion) of mathematical results to linguistically understandable results comprise the final phase of the methodology. Emphasis is placed on how to reach conclusions safely and on the selection of indications produced by the simulations that can point to the right decisions depending on the problem under study.

The phases described above comprise a new methodology for developing a specific type of Computational Intelligent DSS having the ability to handle real-world complex problems, thus contributing to the broader area of Decision Support Systems and promoting the decision making process under uncertainty [122].

1.3. An outline of the main research activities. Statement of the problem

1.3.1. A cognitive approach to identify and formulate domain variables

One of the most important requirements of a Computational Intelligent DSS is the identification of the problem variables using expert knowledge, a task that heavily depends on the effectiveness of the identification and description methods used e.g (questionnaires, formal consultations, texts etc). The importance of this task, however, is crucial given that it provides a descriptive overview of the system. Once this is established, Fuzzy Cognitive Maps methodology, we treat variables and the causal relationships among them as concepts (nodes) and directed arcs participating in the CI-DSS model [91].

The proposed CI-DSS works in discrete steps. When a strong positive correlation (i.e. effect, dependency) exists between the current state of a concept and that of another concept, the former exercises a positive influence on the latter, this indicated by a positively weighted arrow directed from the causing to the influenced concept. On the other hand, when a strong negative correlation exists, a negative weighted arrow will indicate the existence of a negative causal relationship. Once the activation levels of each of the system nodes, as well as the weighted arrows, are set to a specific value as suggested by expert assessment, the system is free to execute a sequence of calculations that measure the level of interaction between nodes. This interaction continues until the model reaches a stable equilibrium, or presents a limit cycle or, even, a chaotic behaviour. The first objective of this research is the selection of the appropriate variables required and their transformation to candidate concepts of an FCM model [92]. Each concept is assigned a descriptive name while its causal relationship with other concepts is identified, and the sign and the weight value for each of these relationships are estimated. Once the concepts have been identified they are partitioned into fuzzy sets with each set assigned a linguistic value as described in the next subsection [98]. The transformation of linguistic variables to a mathematical form is studied and a new fuzzification and defuzzification technique is proposed [116].

1.3.2. Linguistic fuzzy sets encoding

The analysis of a given problem helps to determine assumption-abstracting reality, locating the required variables and transforming them to candidate concepts of a FCM model. Once the names and roles of each concept have been identified, they are described by fuzzy sets [54]. The advantage of using fuzzy sets, therefore, is that they provide a basis for a systematic way of manipulating vague and imprecise concepts and as such they are often treated as representing linguistic variables. A linguistic variable can be regarded as a variable with values appearing either as fuzzy numbers or in linguistic terms [61]. The number of linguistic variables depends on the complexity of the real-world problem described by the model and the desired model accuracy. The fuzzy set encoding is a key step in our framework because it is used to build up the most important element of the CI- DSS, namely the Fuzzy Knowledge Base [108].

1.3.3. Encoding of experts knowledge in a Fuzzy Knowledge Base

The construction of a fuzzy knowledge base system is a very complicated task requiring occasional adjustment of knowledge, especially in cases of complex applications. The integration of a Fuzzy Knowledge Base (FKB) to CI-DSS is a milestone for the success of this research, attempting to overcome the difficulty of encoding the domain experts' assessment.

The linguistic sample is encoded directly in a numerical matrix using an uncertainty fuzzy distribution and is subsequently reduced to a scalar form [114]. This linguistic matrix provided by the fuzzy encoding procedure, reflects the quantization levels of the input and output spaces, and the number of fuzzy set values assumed by the fuzzy variables.

1.3.4. Hybrid FCM

Promising as they may appear, the FCMs have two weak points: The first involves the invariability of the weights, which leaves only the activation levels to participate in the configuration of a problem. The second lies with the inability of the method to model a certain complex situation by performing all possible computational simulations following the change of a certain weight or group of weights [128]. This research aims at solving these problems by combining FCMs with Genetic Algorithms (GAs) [131], thus creating a hybrid model we named Genetically Evolved Fuzzy Cognitive Map (GE-FCM) and applying it in real-world problems [118].

In this context, the FCM part of the algorithm computes the final activation levels given the weights and relationships between concepts, while the GA part develops the weight matrix attempting to find the optimal set of weights that satisfy a predefined activation level for a specific concept. A hybrid model of this type is able to trace the degree of the causal relationships between the various concepts so that it can "force" them to be activated to a certain level. Such hybrid models are expected to contribute to the effectiveness of decision-making by defining, for each possible concept selected, the activation level achieved with a certain set of weights evolved by the GA [15]. The resulting simulations retrieve the final activation levels of the rest of the concepts, as well as the strength of the causal relationship between them. The analyst is thus able to proceed to tactical movements in his decision-making exercise by varying the degree of such relationships in line with the final activation levels the model has suggested.

1.3.5. Multi-objective Hybrid FCM

In cases of multiple scenario analysis the methodology is unable to support multi-objective decision-making due to the fact that the GA may compute a weight matrix only for one particular concept. The proposed methodology outlined thus far was improved in order to overcome this limitation and was based on a new Genetic Algorithm especially designed to support a multi-objective decision-making environment [120].

In general, finding an optimal weight matrix, which will guide a FCM to desired AL values for specific concept, is a task which may be performed using a variety of algorithms. The selection of GAs is driven by the functional characteristics of FCMs, with the algorithms adopting a stochastic methodology for solving problems, being based primarily on the generation of random values.

1.3.6. Limit Cycles

As previously mentioned, the development of the FCM is based on the utilization of domain experts' knowledge that defines the active concepts and the degree of influence between them in the form of numerical values. The activation level of the nodes participating in an FCM model can be calculated using specific updating equations in a series of iterations [100]. As a result, the model can either reach equilibrium at fixed points in a direct way with activation levels ranging in the interval [-1, 1] or, exhibit limit cycle behaviour or present chaotic behavional characteristics [70]. Once the system reaches equilibrium, the decision-makers use this information to make decisions leading to the desired simulated solution. In cases, however, in which the system reaches limit cycle decision-making is practically impossible. Once in a simple FCM environment, one approach to overcome this problem is to resort to the experts' contribution once again, asking them to estimate the exogenous disturbance which causes the instability of the system by influencing one or more concepts. When a GE-FCM is used, domain experts are not able to help since the weight recalculation is performed with the involvement of GAs as previously mentioned, thus creating a hybrid model. An extension of the GE-FCM algorithm is proposed aiming at increasing its reliability by overcoming the weakness appearing in cases of limit cycle behaviour [123]. An additional contribution that faces the difficulties arising in limit cycle cases is suggested by means of a new fuzzification technique which will be introduced later in this thesis. This modification is integrated in the defuzzification process to give credibility to the results by introducing a confidence rate for each result.

1.3.7. Multi-Layer FCM

Large-scale problems are characterized by a large number of parameters, concepts, variables, nonlinearities and uncertainties that make their analysis and modelling a very difficult task. Facing such complications requires the design of a new computational algorithm that supports the creation of parameter and variable layers describing the system under study, as well as the simulation of its evolution dynamics.

The present work proposes a new structured approach we called Multi-Layer Fuzzy Cognitive Map (ML-FCM) [121]. The ML-FCM algorithm supporting this approach is used to improve the decision making process in problems which are modelled using the Fuzzy Cognitive Maps approach. The main issue is the decomposition of the parameters into smaller, more manageable quantities organized in a hierarchical structure forming a model, which consists of subsystems working together and supporting a central objective. The latter is related to the modelling of a particular system and is represented by a main, central FCM, with distinct sub-models (layers) implemented also as FCMs and linked together in a hierarchical structure. The sub-models represent and implement (in computational terms) the decomposed parameters and variables of the system, thus offering the ability of isolating and studying its critical parts.

1.3.8. Multi-layer Hybrid FCM

The use of a Multi Layer hybrid approach reflecting both the implementation of the GA and the multilayer methodology applied for solving large scale problems aims at obtaining the optimal values of the weights corresponding to the ALs in any FCM Layer. This is very useful for the simulation process and helps the decision maker to develop scenarios with the involvement of more than one concept in any place of the Multilayer FCM.

Given that Fuzzy Cognitive Maps have the potential to be used as a tool for creating separate sub-models [124], the Hybrid Multi Layer FCM (HML-FCM) algorithm improves the decision making process in cases in which the approach takes the following steps: First, the parameters are decomposed into smaller, more manageable parts, organized in a hierarchical form resulting in a model. Thus, this model consists of sub-systems working together and supporting the main objective of the system which is represented by the main FCM model. Second, the HML-FCM is used for scenario analysis through simulation techniques, which gives the ability to perform forecasting activities.

1.4. Thesis structure

Chapter 2 presents a detailed review of the relevant literature. First, an introduction to soft computing is presented, followed by a short reference to Neural Networks and detailed description evolutionary algorithms and genetic computing. The presentation includes, in addition, Genetic algorithms and how these are integrated in neural networks and fuzzy logic. Fuzzy logic is described next, divided into two sections; (i) the foundation of fuzzy logic including fuzzy logic principles, membership functions, fuzzy sets and linguistic variables and (ii) the fuzzy inference system in which fuzzification/defuzzification techniques are presented. The final section presents the combination of fuzzy logic and neural networks yielding neuro-fuzzy systems.

Chapter 3 is devoted to the theory of Cognitive science and Fuzzy Cognitive Maps, starting with a historical overview about Cognitive science and the theory of Fuzzy Cognitive Maps with the enclosure of examples. Following the description of other related work and different applications using the FCM theory, this chapter introduces the main activities of this research work that will be described in detail in chapter 4.

This makes chapter 4 a key chapter as the research activities are described in details through real examples. It starts with a case study, namely “The solution of the Cyprus issue”. To begin with, the issue is analyzed in parameters followed by manual static analysis of the model aiming at pointing out the limitations of FCMs. The next subsections present the various improvements in the FCM theory and methodology showing how a hybrid FCM solves the problem of recalculating the weights corresponding to each concept every time a new strategy is adopted by combining FCMs with Genetic Algorithms. The application of the hybrid model is presented on a new case study, namely the S-300 crisis. The improvement of the hybrid methodology is demonstrated through the introduction of a Multiple Scenario Analysis algorithm that enables the experts to deal with combined scenarios using Genetically Evolved Fuzzy Cognitive Maps.

The next part introduces the integration of Fuzzy Knowledge Base with Fuzzy Cognitive Maps and describes the encoding of linguistic fuzzy sets, as well as the Fuzzification and Defuzzification processes using the FKB and the Fuzzy Sets encoding. The next subsection deals with the automatic drawing of FCM, which improves the time needed to construct an FCM and presents the handling of Limit Cycles to improve the inference procedure of FCM while proposing a way to eliminate the phenomenon of the limit cycle. Then the methodology is summarised and the results of the case study, using the Cyprus issue case study are presented. Finally the chapter is concluded with some discussion with emphasis to two major issues that were fazed during this research activity. The first one compares the FCM proposed methodology with other methods and particularly with the Bayesian methodology applied in politics and the second one is giving the performance of the FCM methodology in respect of time.

Chapter 5 introduces the Multilayer Fuzzy Cognitive Maps (ML-FCM) algorithm which is used to improve the decision-making process in large scale problems. The selection of a very complicated case study, namely the Cyprus issue, aims at validating this methodology. The identification of fifty-six (56) concepts grouped in seven FCMs and connected together in a hierarchical structure is followed by a discussion of the results and the characteristics of the models used. Appendix A describes fully the fuzzy knowledge base for the 56 concept followed by the presentation of the results of the initial state of the case study. An example of scenario analysis for layer 1 and 2 and sub-graphs FCM1, FCM2 and FCM5, is also presented there.

The final part of this research, Chapter 6, provides a comprehensive summary and draws the appropriate conclusions, proposing future work and new research steps while suggesting improvements for the decision making process in problems with even higher complexity [26].

In Appendix B validation of this methodology is introduced, using a well known game theory problem, the classical Prisoner’s Dilemma (PD) paradigm. Starting with the Fuzzy interpretation of the PD and an introduction to game theory the PD is transformed to a Fuzzy Cognitive Maps formulation.

The next step is the validation of the problem evaluating all steps of the FCM methodology, with the results proving that the methodology is appropriate and reliable in such game theory problems. The application of the PD to the case of the Cuban Missile Crisis of 1963 validates both the PD and the FCM methodology.

Chapter 2: Background Theory

2.1 Soft Computing
2.2 Artificial Neural Networks
2.3 Evolutionary Computing
2.4 Fuzzy Logic
2.5 Neuro Fuzzy Systems

2.1 Soft Computing

A way to describe the term "Soft Computing" is by using the original definition given by Lotfi Zadeh [189]:

"Soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty, and partial truth. In effect, the role model for soft computing is the human mind. The guiding principle of soft computing is: exploit the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, and low solution cost."

Generally Speaking Soft Computing (SC) is a collection of computational methods in artificial intelligence, which attempt to study, model and analyze complicated problems. It involves the use of theories like fuzzy logic, neural networks and evolutionary computing to solve real-world problems for which conventional computing techniques can not provide satisfactory solutions [59].

Soft computing represents a set of computational intelligence-based methodologies which are used to deal effectively with systems that are characterized by complex structures, incomplete knowledge and uncertainties [21]. The above approaches can contribute to the design and development of intelligent information systems.

Most of the solutions in "hard computing" are predictable while solutions in SC are not programmed for each and every possible situation. As an alternative, the problem is represented in such a way that the system can be measured and compared to a certain desired state. The superiority of a SC system is the adaptation of its parameters, which slowly converge towards a solution. This is the basic approach employed by genetic algorithms and neural networks.

Soft-computing is more efficient under an environment with uncertainty which is characterized by imprecision present among the data on which it operates. Lotfi Zadeh, founder of Fuzzy Logic, says for Computing with Words (CW) "Computing, in its usual sense, is centred on manipulation of numbers and symbols using as an object of computation words and propositions coming from natural language" [146]. Computing with words is essential when the available information is not precise, it is too general or abstract and its association with numbers is quite difficult. Many applications [177] and research studies are developed and implemented using soft computing techniques [10]. The present research work is one of them presenting a comprehensive and consistent utilization of soft computing in the form of Fuzzy Cognitive Maps [81].

Fuzzy Cognitive Maps, as a Soft Computing technique, allow the system designer to take advantage of the knowledge accumulated by the system either in linguistic or data form [160], in order to utilize a continuous learning process based on operating experience, and optimize the operation by making use of state-of-the-art evolutionary computing algorithms [129]. It is important to point out in this case that evolution is the process by which life adapts to changing environments while Evolutionary Fuzzy Cognitive Maps is a new methodology proposed in this research work which combines the advantage of evolutionary computing and Fuzzy Cognitive Maps [18]. This combination is used to design a new category of Computational Intelligent Decision Support Systems the main advantage of which is the ability to perform forecasting and scenario analysis [36]. In this sense, evolutionary computing represents another tool of soft computing techniques based on the concepts of artificial evolution [57].

2.2 Artificial Neural Networks

Artificial Neural Networks (ANN) aim at reproducing at least some of the functioning and power of the human brain [78]. ANN consist of many simple computing elements linked by connections of varying strength [105]. ANN assist in solving problems relying on natural mechanisms of generalization like signal processing, speech recognition, visual perception, controls, robotics etc. To oversimplify, suppose we represent an object which is part of a network, as a pattern of activation of several sub-networks. In case that a sub-network responds incorrectly then the overall pattern stays almost the same, and the network still responds correctly [88]. When ANN operate, similar inputs naturally produce similar outputs [8].

ANN structure refers to the ordering and organization of the nodes from the input layer to the output layer. The choice of how to build or how to structure an ANN is mainly dictated by the type of problem being considered or in some cases how the nodes are organized and therefore how data is processed through the network [5]. A feedforward ANN is a network that has its nodes hierarchically arranged in layers starting with the input layer and ending with the output layer [78]. A number of internal layers called "hidden" layers provide the computational power of ANN. Unlike Feedforward (FF) ones, recurrent networks allow for feedback connections among their nodes. They are structured in such a way so as to permit storage of information in their output nodes through dynamic states providing the network with some sort of memory [81].

Learning in neural networks is highly important and has been the subject of intense research in both biological and artificial networks [88]. Learning is the process by which the neural network adapts itself to a stimulus, and after making adjustments in the parameter, it produces a desired response. In fact during the process of learning, the network adjusts its parameters, the synaptic weights, in response to an input stimulus so that it's actual output response converges to the desired one, in which case the network has completed the learning phase [182]. As the neurons may be interconnected in different ways, the learning process may not be the same for every neuron.

ANN and Fuzzy Systems have many similarities but they are also very different in their details [103]. The main features of ANN are located in the structure of the networks, their dynamics and their data representation. Fuzzy systems deal with real world problems having imprecise information described in natural language, which is then transformed in linguistic variables used for computational purposes [103]. Therefore the theory of fuzziness developed in a system may sometimes be easier to use and simpler to apply to a particular problem than ANN while the opposite may also apply. The combination of the two depends particularly on the application and good engineering judgment. Fuzzy Cognitive Maps actually combine the technology of ANN and Fuzzy Systems to design structures that utilize the strong features of each approach [1].

2.3 Evolutionary Computing

Computerisation has created a rapidly growing demand for problem-solving automation and development of well performing new algorithms applicable to a wide range of problems. Evolutionary algorithms satisfy the need to design new algorithms that will handle complex problems in shorter time [18]. Evolutionary computing can be characterized as another tool of soft computing based on the concept of natural evolution [29]. Evolutionary processes are the subject of scientific studies that focus on understanding how evolution works and can be simulated by a computer, with millions of generations executed in just minutes, hours or days and repeated under various circumstances.

The essence of Evolutionary Algorithms is based on evolution observed in nature where the survival of species depends on the natural selection and evolution processes to produce a better representative [19]. The basic idea is to represent every individual of the potential solution as an array of sequences of chromosomes. The encoding string or array in the chromosome is called gene and has a particular position in the chromosome called locus [23].

The basic functioning of evolutionary computation is as follows: Firstly the Initialization phase is used to create the initial population of the potential solutions. The initial population normally is generated randomly. Then the evolution is performed using selection, recombination or crossover, and mutation operations in which every chromosome in the population is evaluated and receives a fitness value [35]. During crossover and mutation operation the new offspring is created using the chromosomes with the most successful chromosomes. Then the encoding mechanism is used to present the population of potential solutions. Different mechanisms are used dependent of the problem being addressed. The most frequently used are binary and floating point encoding [49].

2.3.1 Genetic Algorithms

Genetic Algorithms (GA) represent a very popular, well defined and important class of evolutionary computing techniques [24]. GA is a non-comprehensive search technique used to determine, among other things, the global optimum of a given function (or process) that may or may not be subject to constraints. The origin of GA dates back to the early 50s, while Holland was the first to introduce the methodology in a more formal way [74]. He proved that genetic algorithms have sound theoretical roots and they are able to solve a wide range of optimization problems accurately [67]. This is done through a procedure inspired from the biological process of evolution and the survival of the fittest concept [37].

GA have enjoyed a wide interest from researchers in the field of mathematics, connectionist modeling and approximate reasoning in recent years [7]. The search procedure of GA is stochastic in nature and doesn't usually provide the exact location of the optima as some other gradient-based optimization techniques do [136]. However, GA-based techniques possess two attractive features putting them at an advantage with respect to their derivative-based counterparts. In fact, given their discrete search nature, they could be easily applied to continuous as well as to discontinuous functions. The inputs to the GA are candidate solutions (population) which initially are randomly generated. The GA then evaluates each candidate according to its fitness function and only the more fit candidates pass to the next generation. These candidates are combined, reproduced or slightly altered in a random way and the offspring pass to the next generation, creating a new group of candidate solutions which is subjected to fitness evaluation as in the previous generation. Those candidate solutions which did not improve their fitness are not selected for evaluation and thus “die”. The process continues until the overall fitness function of the population, which normally is increased in each cycle (generation), does not improve further or until the target value is reached attaining very good solutions to the problem [24]. A GA may also terminate if it reaches a predefined maximum of generations. GA has been used in a wide variety of fields to develop solutions to problems equally, or even more difficult compared to those faced by human designers [19]. The solutions given by the GA are often more efficient and more complicated than any engineer would produce.

2.3.2 Representation of individuals – genotype

As mentioned earlier, the basic principle of Evolutionary algorithms derives from the real world. When attempting to map natural evolution into the framework of artificial evolution, we must first consider the "data" for the system. In the natural environment, this data consist of living creatures [29]. Each individual represents a potential solution to the problem of survival. Similarly, in genetic algorithms, we consider a set of potential solutions, which are referred to collectively as “population” with each single solution called an “individual”. Each individual in nature has a form determined by its DNA and its collection of genetic character is commonly known as a “genotype”. In genetic algorithms, the term “genotype” is used to describe the encoding of a problem solution represented by an individual. Thus, each individual has a genotype, which encodes a solution while many individuals in a population may have the same or similar genotypes. In the GA literature, an individual's genotype is often referred to as its chromosome [130].

Genotypes in genetic algorithms are typically represented by strings, sometimes called “bits” or “characters”. Each element of the string represents a gene, which is a single unit of genetic information. In the natural environment genes control, various traits of the individual directly or indirectly [35]. For example, in the case of humans there are genes to determine eye and hair color, and genes for determining other characteristics. It is important to note that in nature, several genes often collectively determine a physical attribute, and that they are not necessarily independent. This is true in genetic algorithms as well, where a solution encoding may make use of several interacting genes.

2.3.3 Fitness function or evaluation function

Fitness assessment is a procedure that plays the role of evaluation to genotype (Chromosomes) and is the basis of selection of the new candidates that will pass to the next generation in case that the predefine requirements are met. The fitness function is a collection of quality measures applied in the chromosome [23]. The best chromosomes using minimization or maximization techniques are mixed (crossed) with other, less fit chromosomes, hoping that the characteristics of the resulted chromosomes are better than the previous ones. The fitness function is very important step in the evolutionary procedure and special attention should be given in cases where a contradiction might arise if the original problem requiring minimization of the fitness is associated with maximization. Generally speaking the fitness function is a measure that indicates the evolution success of a set of individuals in a given environment [18].

2.3.4 Selection

The new set of individuals which are generated during the evolutionary process consist the new population that will be evaluated during the next generation. This population, which in most of GA is constant, contains the possible solutions for the optimal solution [130]. The entire population is taken into consideration during evaluation process and the selection criteria are applied to all individuals.

Several techniques are used for the selection of the new individuals. The most popular techniques are the followings: The “Elitist selection” in which the best individuals of each generation are selected for further evolution and the “Fitness-proportionate selection” according to which the individuals are selected based on their fitness value [74]. Within the latter, other approaches for selection of the best individuals are the roulette wheel, the tournament and the rank-based. In the “Roulette-wheel” the form of fitness-selection is proportional to the amount by which an individual’s fitness is greater or less than its competitor’s fitness. “Tournament” selection is based on the creation of subgroups of individuals and the “leading” individual is selected for reproduction. Finally in “Rank” selection the individuals are ranked in accordance to the fitness function and their selection criterion is based on this ranking instead of absolute difference in fitness [19].

2.3.5 Methods of change – Mutation and Crossover

Mutation is very important operator in genetic algorithm helping the creation of offspring. The method to create new individuals is based on the biological mutation and is used to preserve genetic diversity from one generation to another. Mutation delivers the modified offspring depending on the outcome of random variable for each bit. The objective of this randomness is to identify the particular bits that will be changed. The principle is to avoid the phenomenon of local minimum by allowing the mutation operator to "jump" everywhere in the offspring preventing chromosomes becoming too similar each other [35].

Although several techniques are used for mutation the most common is binary encoding which considers each gene separately and allows each bit to flip. It basically inverts the value of a gene from 1 to O or O to 1 with a small probability P_m. Figure 2.1 illustrates the case where the third, fourth, and eighth random values generated are less than the bitwise mutation rate P_m [24].

1	0	***1***	***0***	0	0	0	***1***	0
1	0	***0***	***1***	0	0	0	***0***	0

Figure 2.1: Mutation rate for small probability

Other mutation operator is boundary that replaces randomly the new gene by the upper or lower bound of the particular gene. Uniform and Non uniform operator are other popular methods of mutation in which in the uniform method the value of the chosen gene is substituted by random value among specified gene. In the Non-uniform operator during the evolutionary process and while the number of generation increases the mutation is kept close to 0. This allows GA to make fine turning in the last states of evolution [29].

The second method of change is called crossover which is used to diverge the programming of chromosome from one gene to the other, involving two individuals to swap segments of their code. The offspring produced is a combination of their parents. This process is also called recombination because the new individual solution is created from the information contained within two (or more) parent solutions [48]. The intention here is to simulate the process of recombination that occurs to chromosomes during reproduction. Figure 2.2 indicates a single point crossover technique between two individuals.

Another crossover technique is the two-point crossover in which all bits between two setting points are swapped. Uniform and half uniform are also very popular crossover technique. In the uniform crossover, bits are swapped with probability rate while in half-uniform half of the non matching bits are swapped [105].

0	0	1	0	1	1	0	1
1	***0***	***1***	***1***	***0***	***0***	***1***	***1***
1	***0***	***1***	***1***	***0***	1	0	1

Figure 2.2: Crossover and Mutation

2.3.6 Termination

The genetic Algorithm terminates if a criterion is met or the number of execution or predefine time elapsed. Several criteria can be setup that is examined after the formation of each generation. Fitness function is the most common one with the evolutionary process to stop if the best fitness in the current population becomes greater or less than the specified fitness threshold when the objective is to maximize or minimize the fitness respectively [35].

2.4 Fuzzy Logic

2.4.1 Introduction

To understand how fuzzy systems [45] provide improved information modeling, we need to go back to its origin. The concept of Fuzzy Logic (FL) was envisaged by Lotfi Zadeh in an attempt to explain and reducing system complexity [190]. He was concerned with extreme increase of information afforded by traditional mathematical models as the complexity of a system increased. He introduced the term imprecision in which most of the phenomena we come across everyday are imprecise, that is, they carry a certain degree of fuzziness in the description of their nature [190]. This imprecision may be associated with their shape, color, texture, environment or even the semantics that describe their nature. In many cases the same concept has a different meaning in different contexts of time. Thus, a hot day in winter is not exactly the same as a hot day in summer simply because the boundary line between warm and hot is imprecise. This kind of imprecision or fuzziness associated with continuous phenomena is common in all fields of study, in modeling real world problems as well as in every day life [50].

In most of the cases imprecision is not something we pay too much attention to, even if we use it extensively in our daily life because we accept it as a natural consequence of the way things happen. The precision of mathematical modelling in which involve uncertainty of the "real world" is generally not addressed by scientists. We simply approximate these events as numerical functions and choose a result that either makes sense from the empirical point of view. More over we process and understand imprecise data easily, from morning traffic reports to complex business analyses [30].

FL is theoretically easier to understand because the mathematical concepts behind fuzzy reasoning are very simple [45]. The methodology is very flexible and it is easy to mix with other conventional control techniques [186]. But what makes FL very attractive and easy to understand is the simplicity of the language used which is a close approximation of human reasoning [20]. In fact, FL is based on natural language and its basis is actually the basis of human communication that uses common daily natural language [191]. This innovative design and the strong features of FL make it a very flexible and powerful tool dealing with imprecise data and uncertainties, in a quick and cost effective way [133].

2.4.2 Membership function

A membership function (MF) as proposed by Lotfi Zadeh [188] extends the bivalent indicator function of I_A of a non fuzzy set to multi value called membership $\mu_A : \rightarrow [0,1]$.

$\mu_A(x)$ measures the degree to which element x belongs to set A by $\mu_A(x) = Degree\ (x \in A)$. If X defines a set of universe and A is fuzzy set then let $x \in X$ be an arbitrary element in this universe set. For the Crisp value Set we have the characteristic function of A as follows:

$$\left.\begin{aligned} &f_A: X \rightarrow \{0, 1\} \text{ such that} \\ &\quad f_A(x) = 1 \text{ if } x \in A \\ &\quad f_A(x) = 0 \text{ if } x \notin A \end{aligned}\right\} \qquad 2.1$$

Recall that the notation $f_A: X \rightarrow \{0, 1\}$ implies that either $f_A(x) = 0$ or $f_A(x) = 1$, with no other options, a restriction which we must be more loose in the case of a fuzzy set. Figure 2.3 indicates the relation between crisp set and fuzzy set. The membership function [137] representing a fuzzy set normally is represented by μ_A. For example for an element x of X, the value $\mu_A(x)$ is called the membership degree of x in the fuzzy set A

[181]. In Fuzzy sets the membership degree $\mu_A(x)$ gives the degree in which an element x of o the fuzzy set is member of the set. For instance the value 0 means that *x* is not a member of the fuzzy set while the value 1 means that *x* is 100% full member of the fuzzy set [188].

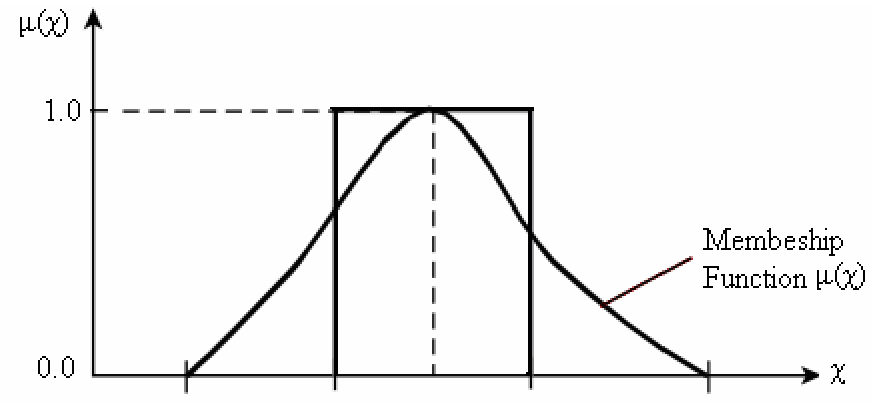


Figure 2.3: Relation between crisp and fuzzy value

2.4.3 Fuzzy set

Before entering in the analysis of fuzzy sets we need to distinguish the main differences between classical set theory and fuzzy sets. In a classical set an element of a set *x* either belongs or does not belong to the set. On the other hand, fuzzy set theory allows partial membership of elements in a set. As it was explained earlier this is achieved with the help of a membership function [184].

For a fuzzy set *A*, we have the membership function of *A*

$\mu_A: X \rightarrow [0, 1]$, which is to say that for all $x \in X$, we have $0 \leq \mu_A(x) \leq 1$.

The values obtained by the membership function are as follows [61]:

$\mu_A(x) = 0$	if *x* is not in the set *A*
$\mu_A(x) = 1$	if *x* is totally in the set *A*
$0 < \mu_A(x) < 1$	if *x* belongs partially to *A*

The example of tall men is a classic example in fuzzy set theory. Consider the set of tall men, with *x* being the height of an individual, in meters. We may say the following.

$\mu_A(2.26) = 1.0$	John is absolutely tall
$\mu_A(1.85) = 0.83$	Nick is to some extent tall
$\mu_A(1.40) = 0.0$	Mario is not tall

Taking into consideration the set of tall men, we can define the boundaries of this set which it might say that all people taller than 1.80 cm are considered to be tall. But such a distinction does not seem very logical. Figure 2.4 below shows the crisp values and Figure 2.5 a smoothly varying curve passing from not-tall to tall. The output axis known as membership function (μ) defines the transition from “not tall” to “tall”. Both people are tall to some degree, but one is less tall than the other.

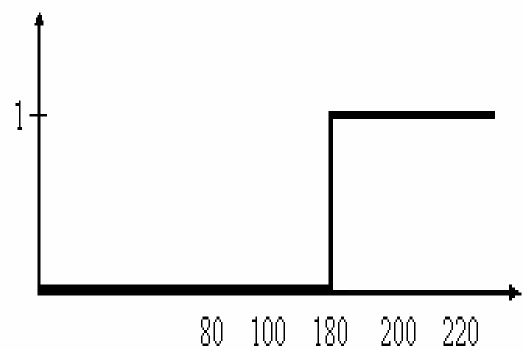


Figure 2.4: Crisp value

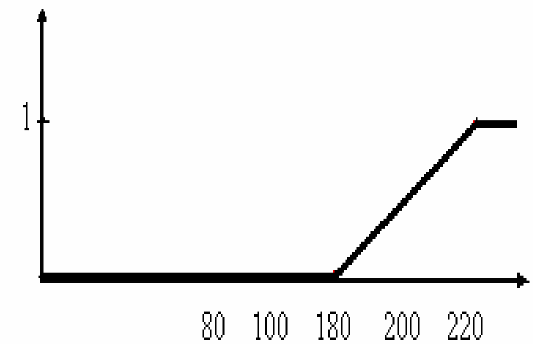


Figure 2.5. Membership function,

Example: Fuzzy set TALL that would answer the question:

"To what degree a person is tall?"

$$\mu_{TALL}(x) = \begin{cases} 0 & \text{if } height(x) < 180 \\ (height(x) - 180)/140 & \text{if } 180 \le height(x) \le 220 \\ 1 & \text{if } height(x) > 220 \end{cases}$$

Person	***height***	***$\mu_{TALL}(x)$***
Peter	*140*	*0*
John	*190*	*0.25*
Mario	*195*	*0.37*
Kostas	*210*	*0.75*
Andreas	*220*	*1*

$\mu_{TALL}(x)$ is considered the true value of the statement: *x* belongs to the set of TALL people. For example John has a height of 190cm. We can consider John as TALL with a truth value of 0.25

2.4.4 Fuzzy sets and linguistic variables

A fuzzy set indicates to which degree a value may be a member of the set. The element of fuzzy set has degree of membership [102]. It takes values between zero and one indicating its actual degree of membership with zero value meaning that it is completely representative of the set [45]. As an example consider the concept of a long project with Figure 2.6 illustrating the degree of membership function for such a concept.

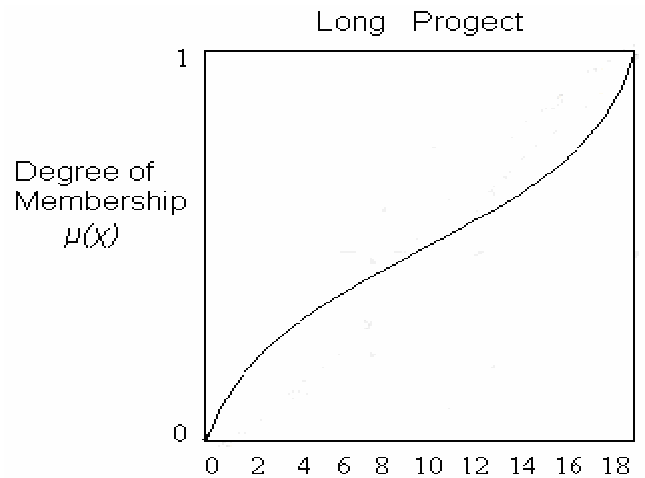


Figure: 2.6: The idea of a long project

The members of this set are duration period of the project in weeks, required for the completion of a project. The fuzzy set indicates to what degree a project of a specified duration is a member of the set of LONG projects. As the number of weeks increases our belief that the project is indeed LONG increases. A project 2 weeks in duration would not be considered LONG, a project ten weeks in duration would have a moderate membership in the set of LONG projects, and a project of more than 15 weeks in duration is most certainly a LONG project. Of course, the actual definition of what a LONG project actually is depends on the context in which it is used. For some models even a one- or two-day project might be LONG, and for others, for example projects performed by movement contractors, the idea of LONG only begins to make sense at some distant point in the future (e.g. one year).

The centre of the fuzzy modelling technique is the idea of a linguistic variable. At its root, a linguistic variable is the name of a fuzzy set. In the previous example, the fuzzy set LONG is a simple linguistic variable and could be used in a rule-based system to make decisions based on the length of a particular project:

IF *project duration* is LONG

THEN the *completion risk* is INCREASED

In terms of linguistic variables using the same example of Long project the fuzzy set "LONG"- "very LONG", "somewhat LONG", "slightly LONG", and "positively not very LONG" are identified. We interpret these expressions using the same rules of precedence as English; thus, "not very LONG" and "very not LONG" are two distinct statements. Linguistic variables permit the fuzzy modelling language to express directly the shades of semantic meanings used by experts. This is illustrated in the following rule,

IF *project-duration* is positively not very LONG.

THEN the *completion-risk* is somewhat REDUCED

Qualifiers may also be applied to fuzzy sets in an easy way; for example we can say "most LONG projects are usually LATE". This has important representational implications for time-series-based fuzzy models. A linguistic variable summarizes the properties of approximate or imprecise concepts in a systematic and computationally useful way, while reducing the apparent complexity of a system bum matching a semantic tag to the underlying concept [97].

2.4.5 Fuzzy "IF–Then" rule

In most fuzzy problems fuzzy rules are generated using past experience. In case where rules are expressed by a single input variable, a simple fuzzy If-Then rule [139], assumes the form IF x is A then y is B where A and B are linguistic values defined by fuzzy sets on the ranges (universe of discourse) X and Y, respectively. In most of the cases fuzzy logic problems involve more than one variable.

The If-Then rule becomes more difficult to put it into a table, if the fuzzy statements have more variables [148] such as,

If A_i and B_j and C_k, Then H_{ijk}

This statement is decomposed as,

If A_i and B_j, Then H_{ij}

If H_{ij} and C_k, Then H_{ijk}

The above statement can be further extended to include many variables and applications. Fuzzy rules have many applications and are used in Expert Systems forming in a Fuzzy Rule Base [48].

2.4.6 Fuzzification

The fuzzification process starts by taking the inputs and determining the degree to which they belong to each of the fuzzy sets identified through membership functions [45]. The input value is always numerical and the output is a degree of membership in the fuzzy set. This encoding is a very important step of the entire process and the success of correct fuzzification will reflect to the reliability of the results during the execution of the defuzification process.

The fuzzification process consists of two basic steps. During the first step the interval of each concept is analyzed into known membership function (e.g. trapezoidal or triangular). A number of intervals can be used during the fuzzification process depending on the complexity of a problem [98]. The minimum number of intervals is two. This number can be increased up to twelve or even higher.

Figure 2.7 in particular, shows how the fuzzification of three crisp values causes the distribution of the variables according to a certain profile. It is interesting to point out that this distribution produces two overlapping areas, an outcome which has been regarded as rather common and even desirable on certain occasions. In such a case the problem arising when values that fall within an overlapping area must be allocated is handled during the defuzzification process [102].

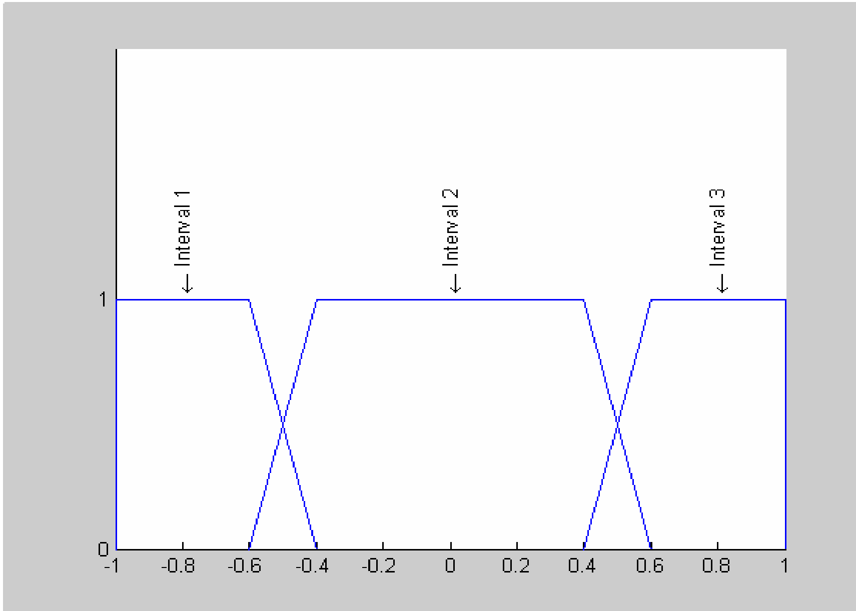


Figure 2.7: Parameter with 3 membership functions of variable width

2.4.7 Defuzzification

Defuzzification is the last step of the process and is very important because the output results define the level of success for the fuzzy model [164]. Generally speaking, Defuzzification is the process that uses the membership functions to find the degree of membership that defines an outcome. As it was mentioned earlier, a fuzzy set is used as an input for the defuzzification process and the output is a number within the fuzzy set interval. Several techniques have been developed to produce an output. The most common ones are, the “maximizer" by which the maximum output is selected, the “weighted average” by which the averages weighted possible outputs and the “centroid calculation” which returns the center of the fuzzy area [137].

As we have already pointed out, the defuzzification process is more complicated than the fuzzification one and follows the next steps [116]: The first is the determination of the technique that will be used. For example, if we use the Max-Min and Mean Computation we need to compute the minimum, maximum and average values for each concept, while the various levels are matched according to the membership functions of each parameter. Then the matching process starts and the value of the parameters fall into a particular interval as a result of the fuzzification process.

2.5 Neuro Fuzzy Systems

2.5.1 Introduction

Artificial Neural Networks and Fuzzy Systems have been recognized as promising alternative approaches to Intelligent Information processing [1]. The two technologies have certain advantages in the case of imprecise data or when prior knowledge is involved. Neuro-fuzzy systems have been proposed so as to take advantages of both technologies and complement each other [58]. This combination allows overcoming some of the individual weaknesses, while offering some strong features in developing a new class of intelligent systems [111]. The main objective is to avoid difficulties appearing in fuzzy logic for systems represented by numerical knowledge (data sets), or similarly in applying neural networks for systems represented by linguistic information (fuzzy sets) .

Fuzzy Logic and neural networks are not capable to address successfully specific types of problems due to their inability to handle numerical and linguistic variables at the same time [81]. For instance, while fuzzy logic theory permits the accurate representation of a given system behaviour using a set of simple "IF-Then" rules, it is nevertheless unable to tackle knowledge stored in the form of numerical data. For this particular type of system, "IF-Then" rules have to be extracted manually from the data sets, a process that becomes very tedious or even impossible to achieve for data sets with large numbers of patterns. The problem becomes even harder when the knowledge about the system is stored in both forms: linguistic (fuzzy sets) and numerical (data sets).

Neural networks on the other hand have been shown to be universal approximators capable of learning virtually any (smooth) non-linear mapping with a high degree of accuracy, while also being excellent classifiers and predictors. As it was previously described they accomplish this through a learning process in which numerical data are presented to the system for training under a computational structure composed of neurons and weighted links. Once a network has been trained, computation is then carried out in a parallel and distributed manner. But despite their versatility, neural networks suffer from several weaknesses among which are the implicit representations of knowledge (known among researchers as the black box structure). It is, for instance, very difficult to explicitly quantify the meaning of weights among the nodes of the network once the systems have been trained. As such, neural networks are not very "transparent" at explaining their decision-making process [26]. In addition, it is difficult to incorporate additional knowledge into the system without retraining it, or to extract linguistic representation patterns of knowledge from the data.

2.5.2 Combining Artificial Neural Networks and Fuzzy Systems

To overcome the limitations of both system representations (fuzzy and neural), researchers in the area have proposed incorporating fuzzy logic reasoning [20] within a learning architecture of some sort, a task for which ANN have been shown to be an excellent candidate [1]. Fuzzy logic and artificial neural networks paradigms have originated from totally different mathematical formalisms; it has been shown that both these methodologies are universal approximators for a large class of nonlinear mappings [45]. It has also been shown that they can be combined to form a hybrid structure [154] powerful enough to deal with a wide range of systems involving different types of knowledge, both numerical and linguistic.

The combination of fuzzy systems and neural networks can help avoiding the drawbacks of both approaches when used individually. Therefore, neuro-fuzzy methods are especially suited for applications that desire user interaction in model design or interpretation.

Fuzzy Cognitive Maps are combinations of neural networks and fuzzy logic but as they are also directed graphs with closed loops they cannot be strictly classified as neuro-fuzzy systems. There are a lot of common features in the layers of neuro-fuzzy system [179], but there are also some significant differences that permit simulation and forecasting, which are very important tools in the hands of decision makers and strategic planners. Fuzzy Cognitive Maps will be described in detail in the next chapter, while the proposed methodology for a new class of Intelligent Decision Support System will be presented in Chapter 4.

Chapter 3: Fuzzy Cognitive Maps

3.1 Introduction
3.2 Cognitive Maps
3.3 Technical background on Fuzzy Cognitive Maps
3.4 Overview of FCM applications.

3.1 Introduction

A Fuzzy Cognitive Map introduced by Kosko as an extension to Cognitive Maps in 1986 [100] is a technique incorporating and adapting human knowledge by combining fuzzy logic and neural networks. During the past twenty years, there has been a large and active improvement in research efforts aiming at synthesizing fuzzy logic with neural networks, thus leading to FCM models [103]. The combination of fuzzy logic and neural networks is essential because the two approaches view the design of "Intelligent'' systems from different angles and one complete the other [83]. The strong features of neural networks providing algorithms for learning, classification, and optimization associated with fuzzy logic which deals with high level reasoning issues and uncertainty in a linguistic form create a new type of systems. [192].

The combination of neural networks with fuzzy logic takes place by means of a dynamic fuzzy system in which certain processing stages are implemented with neural networks while others with a fuzzy inference system [46]. An example of such a system would be a tree classifier in which classification at some node can be carried out with a fuzzy inference system and classification at some other node could be performed using a neural network [111]. In general, we cannot combine two or more trees to produce a new tree, while the problem increases with the number of trees combined [77]. It is evident that these difficulties limit the number of knowledge sources or experts who can build the search tree in an environment in which a larger expert sample size should produce a more reliable knowledge structure [162].

Kosko suggested the Fuzzy Cognitive Map model as a technique to overcome the limitations of representing knowledge as a search tree [99]. Thus, instead of viewing FCM as graph search can be viewed as a dynamical system represented by an acyclic graph while its equilibrium behaviour may be used an inference mechanism [128]. The advantage of this qualitative dynamic model when compared with other quantitative models is its simplicity in both model representation and execution [146]. It is interesting to point out, that the main restriction of quantitative models is the fact that they require substantial effort and specialized knowledge from outside the application domain to develop a correct model, which is practically eliminated in an FCM model.

3.2 Cognitive Maps

The origin of Cognitive mapping derive from graph theory put forward by Euler in 1736, while Tolman in 1948 laid the basis for cognitive psychology research in which cognitive maps are considered as schemes inside the human mind [169]. Cognitive mapping is essentially a part of our expression of the physical world and participates in the formulation of our decision and attitudes [156]. In early sixties, this theory was put into use in quantitative measures in order to make a structural analysis of observations. Such types of a structural analyses produced maps called “digraphs” which, later on, were modified by the political scientist Robert Axelrod [8,17] from the subjective interpretations of anthropologists to the observations of individuals and called “Cognitive Maps” [55].

Cognitive Maps (CM) have also been used to support knowledge acquisition, specifically in structuring problems that need qualitative modelling performed by human decision analysts [34]. Cognitive maps are interesting for their potential practical relevance to social science [47], political science and cognitive modelling. Successful application in those areas enhanced their suitability for decision support [26], as they form a bridge between graph theory models and encoding of subjective beliefs and preferences. Finally, CM possesses historical interest as a relatively early attempt to formalize a form of qualitative reasoning in a decision-making context [95].

The basic principle and elements of a CM are simple: The concepts used by an individual decision-maker are represented as nodes, and the causal relationships between these concepts are represented as directed arrows [92]. Each arrow is characterized by a weight, a real value that indicates the effect of the causal relationship between nodes. This representation gives a figure of nodes and arrows called “cognitive map” in which the various concepts are considered as variables of the system. The advantage of this scheme is that it offers a global view of the different links between causal relationships and concepts in the model. The map offers three different types of causal relationships between two nodes p and q ($p \rightarrow q$) indicating all possible causality directions as follows:

- Positive (+) causality, in cases in which p promotes q meaning that an increase in the cause variable will bring about an increase in the effect variable, while a decrease in the cause concept will result to a decrease in the effect concept.
- Negative (-) causality, in cases in which p prevents, or is harmful to q, in which case an increase in the cause variable will result to a decrease of the effect variable and vice-versa.
- No effect (0), when p has no effect on, or does not matter for q.

Axelrod was the first to introduce a slightly modified form of cognitive map in terms of interpretation and representation in political modelling [16]. In fact, Figure 3.1 shows causal relationships that were identified by Henry Kissinger in 1982 trying to model the Middle East Crisis [102]. However, this first approach of modelling real-world problems using positive and negative causality suffered from the inability of experts to extract precise results giving just indications of how the model should behave in certain changes. In the case, let us say, of the relation between two causes, Soviet imperialism, until the fall of the USSR in the beginning of the nineties, and Arab radicalism, this depended on how they interacted to produce the effect which was the Syrian Control on Lebanon for the former and PLO terrorism for the latter. In cases in which two causes are competing, and then establishing one would tend to decrease the other, while if they are complementary, then positions for both causes are directly related. Take, for example, the case depicted in Figure 3.1, which may only have a historical value, however it describes the causal relations very clearly: If the Islamic Fundamentalism increased in the Middle East, the answer according to the map is that the Arab Radicalism would also increase, but the Soviet Imperialism would decrease. In this case, then the control of Syria to Lebanon would decrease to a certain level leading to the strengthening of the Lebanese government. On the other hand, the increase of the Arab Radicalism would make PLO terrorism more powerful, encouraging more attacks in Lebanon, thus weakening the Lebanese Government.

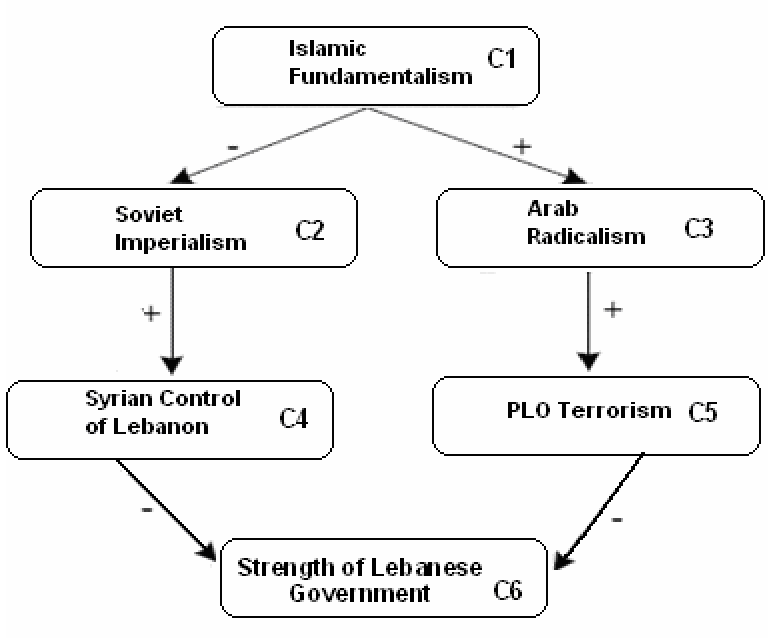


Figure 3.1: Henry Kissinger's CM modelling of Islamic Fundamentalism [102].

It is clear that the introduction of fuzzy logic [45] gave new capabilities to CMs, enabling the indication of both the type of representation of the causal relationships between concepts (i.e. positive, negative, zero) and the degree or strength of this relationship. The most significant improvement concerns the representation of the relationships involved which were fuzzified. This means that their description is improved by numerical values instead of just signs, permitting the application of varying degrees of causal inferences. The main difference, when compared with cognitive maps, being that each directed edge is associated with a number that expresses relationship [95]. Our research work moves to this direction aiming at improving the FCM theory to such a degree that will allow us to develop an Intelligent Decision Support System [135] using FCM as an inference machine.

3.3 Technical background on Fuzzy Cognitive Maps

3.3.1 Introduction to FCM

Each concept node possesses a numeric state, which denotes the qualitative measure of its presence in the conceptual domain. Thus, a high numerical value indicates that the concept is strongly present in the analysis, while a negative or zero value indicates that the concept is not currently active or relevant to the conceptual domain. This value is usually normalized to the interval [–1, 1]. The value of -1 represents a full negative causality and creates inhibiting effects, while +1 represents full positive causality creating a promoting effect. Zero value denotes a neutral causal effect. Other values correspond to different intermediate levels of causal effect [128]. When a strong positive correlation exists between the current state of a concept and that of another concept in a preceding period, we say that the former positively influences the latter, indicated by a positively weighted arrow directed from the causing to the influenced concept. By contrast, when a strong negative correlation exists, it reveals the existence of a negative causal relationship indicated by an arrow charged with a negative weight. Two conceptual nodes without a direct link are, obviously, independent.

The principle of how simple FCMs works is explained via an example, consisting of two connected concepts as depicted in Figure 3.2.

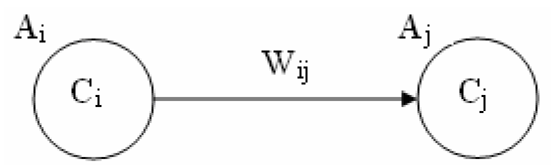


Figure 3.2: Connection between nodes

The directed edge W_{ij} from concept C_i to concept C_j indicates how much C_i causes C_j. The edges W_{ij} take *va1ues* in the fuzzy causa1 interva1 [-1, 1]. *Wij=0* shows no causa1ity $W_{ij} > 0$ indicates causal increase: C_j increases as C_i increases, and C_j decreases as C_i decreases. $W_{ij} < 0$ indicates causa1 decrease or negative causa1ity: C_j decreases as C_i increases, and C_j increases as C_i decreases.

The calculation of AL of each node indicates the degree to which the concept is active in a model. This value is a floating-point number from -1 to +1, explicitly defined by equation 3. 1.

$$A_i^{(t)} = f\left(\sum_{\substack{j=1 \\ j \neq i}}^{n} A_j^t W_{ij} \right) \qquad 3.1$$

where: $A_i^{(t)}$ the activation level of concept C_i at iteration t

W_{ij} the strength of relation from concept C_i to concept C_j

f the transformation function

The main purpose of the transformation function f is to reduce the weighted sum to a certain value range i.e. from -1 (negatively inactive) to +1 (Positive active). The most commonly used transformation functions are the following [102]:

Bivalent :

$$f(x) = \begin{cases} 0, & x \leq 0 \\ 1, & x > 0 \end{cases} \qquad 3.2$$

Trivalent :

$$f(x) = \begin{cases} -1 & x \leq -0.5 \\ 0 & -0.5 < x < 0.5 \\ 1 & x \geq 0.5 \end{cases} \qquad 3.3$$

Sigmoid function:

$$f(x) = \frac{1}{(1 + e^{-cx})} \qquad 3.4$$

An FCM works in discrete steps and the activation level of each of the system nodes as well as the weighted arrows are set to specific values based on expert assessment.

Thereafter, the system is free to interact and this interaction continues until the model:

- Reaches equilibrium at a fixed point, with the activation levels, being decimals in the interval [-1, 1], stabilizing at fixed numerical values.
- Exhibits a limit - cycle behaviour, with the activation levels falling in a loop of numerical values under a specific time-period.
- Exhibits a chaotic behavior, with the activation level reaching a variety of numerical values in a non-deterministic, random way.

Since the system follows an iteration process, the calculation of the new activation level should take into consideration the previous value of the AL. For a given concept, the AL can be calculated taking into account the activation levels of all the concepts that have exerted influence on it at the previous iteration and Equation 3.1 is transformed as follows:

$$A_i^{new} = f\left(\sum_{\substack{j=1 \\ j \neq i}}^{n} A_j^{new} W_{ij}\right) + A_i^{old} \qquad 3.5$$

A^{new} is the new activation level of concept C_i at time $t+1$, A^{old} is the activation level of concept C_j at time t.

The graph representation of a FCM may be described also by a square matrix. This matrix contains the weight values of connections between corresponding concepts. Thus we can write the FCM function of equation 3.5 in an even simpler way by writing the status of all concepts as a row-vector S, with notation { C_1, C_2, … , C_n } for n concepts, and the weights of the edges in a $n \times n$ matrix W, where each element A_{ij} gives the weight of the edge from concept C_i to C_j . If there is no causal link between two concepts, the value of that link A_{ij} is zero. The general form of a weight matrix is the following:

$$W = \begin{pmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{pmatrix} \qquad 3.6$$

where, W_{12} is the weight of the causal relationship between C_1 and C_2.

3.3.2 Methods for developing FCMs

There are several techniques to create FCM models, but we can distinguish them in two main categories, manual and semi-automatic methods [3]. Despite the fact that some trials have been made on pre-existing data trying to develop an automatic FCM, until now, to the best of our knowledge, no fully automatic method has been proposed and applied to general problems Mainly due to the difficulties encountered during the automatic estimation of the Activation levels and weights [171]. The manual method, by contrast, covers techniques that exploit only human (expert) knowledge and for a long time this was practically the only way for establishing FCM models, in the absence of automated or semi-automated approaches that would support this process. Recently, however, several attempts were made for the development of semi-automatic computational Fuzzy Cognitive Maps.

3.3.2.1 Manual method

One of the advantages of FCM modelling is its easiness concerning expert knowledge aggregation [25], given that it enables a whole group of experts, instead of just one, to work on the model, something which improves its reliability. Once this is performed then at a second stage, all individual expert models are combined together.

The experts are required to build up a model using a specific procedure. Firstly they are asked to identify the main parameters influencing a problem, transform them in concepts and identify the causal relationships among them. Finally they estimate the causal relationships' strength and the initial activation level for each concept [91]. Since the number of possible connections among concepts increases at a quadratic rate with the increase of the number of concepts, expressing complex systems that consist of a large number of nodes is often very difficult or even impossible to perform by humans and if it must be done by humans, it may result in simplifications, which eventually lead to inaccuracy or inefficiency, given that the development process often requires many iterations and simulations before a suitable model is established [104].

In case of group development, the quality of the final model can be improved by varying the impact of a given expert model on the final one based on the reliability of the particular expert in each case. The reasoning behind this modification is that combining incomplete, conflicting opinions of different experts may cancel out the effect of oversight, ignorance and prejudice [25]. However, such an extension requires additional parameters, like for example the credibility coefficient of each individual expert, which complicates the FCM development task. This parameter reflects the fact that some experts may be more credible than others [163].

If S_i is the score of experts i and W_i is the weight matrix according to a certain expert, the final weight matrix is then given by a normalized sum according to equation 3.7. This equation improves the accuracy and reliability of an FCM model by minimizing the possibility of bias results. This formula eliminates the opposite opinions and a more general weight is accepted:

$$W = \frac{\sum_{i=1}^{N} S_i W_i}{\sum_{j=1}^{N} S_j} \qquad 3.7$$

Manual methods for developing FCM models also share the major disadvantage of relying on human knowledge, meaning that it is very difficult to assess the model's accuracy in an unbiased way [45]. What is more, even if historical data are available to justify the model's quality, obtaining an appropriate model that mimics the data requires a lot of effort, which is performed by drawing and simulating successive models.

3.3.2.2 Semi-automatic methods

Different semi-automatic methods are proposed in literature [3]. A class of semi-automatic methods uses the simple Differential Hebbian Learning law (DHL). Dickerson and Kosko proposed DHL to be applied in the learning process of FCM [52].

The updating function of this learning process is based on the change of the values of weights of all edges on the FCM graph until the desired structure is found. Considering that value ΔC_i, which is defined as the difference between the concept's values in two successive states, ranges between -1 and 1, the C_i and C_j concept values increase or decrease only when $\Delta C_i - \Delta C_j > 0$. Then, if one of the concept values decreases while the other increases. Generally speaking, the weights of outgoing edges for a given concept node are modified when the corresponding concept value changes. The weights are updated according to equation 3.8:

$$e_{ij}(t+1) = \begin{cases} e_{ij}(t) + c_t[\Delta C_i \Delta C_j - e_{ij}(t)], & \text{if} \quad \Delta C_i \neq 0 \\ e_{ij}(t), & \text{if} \quad \Delta C_i = 0 \end{cases} \qquad 3.8$$

where t is the current iteration number, and a parameter n is chosen to ensure the learning coefficient C_i. This parameter is always positive and is usually equal to the number of iterations or generations of observed states used for learning. The results of the experiments performed using this learning method were very promising [143]. The main problem in this type of learning on one hand is that weights measure the causal-effect strength between two concepts C_i, C_j, and thus take into consideration only these two and on the other hand it turned out that the learning process is highly sensitive to the order of data presentation.

To overcome the above limitations, an extension to the DHL algorithm was proposed introducing new rules to update edge values [178]. This new algorithm, called Balanced Differential Algorithm (BDA), eliminates the drawback of the DHL method in which weight updating for an edge connecting two concepts (nodes) depends only on the values of these two specific concepts. In BDA, by contrast, during the learning process weights are updated taking into account all concept values that change at the same time. This means that the formula for calculating $e_{ij}(t+1)$ takes into consideration not only the changes ΔC_i and ΔC_j but also the changes in all other concepts if they occur at the same iteration and in the same direction. The BDA algorithm was applied to FCM models which use bivalent transformation function, based on historical data consisting of a sequence of state vectors. The goal was to develop FCM that is able to generate identical sequence of state vectors given the same initial state vector.

Another method based on Hebbian learning was proposed in 2003 by Papageorgiou et al. who developed an algorithm, called Nonlinear Hebbian Learning (NHL) [143]. The main contribution of this method is a nonlinear extension to the basic Hebbian rule, using a semi-automated approach, since it requires initial human intervention. The main idea behind this method is to update weights associated only with edges that are initially suggested by expert(s), i.e. non-zero weights. Additionally, the experts have to indicate the signs for each non-zero weight according to its physical interpretation. Weight values are updated at the same time, yet they bear fixed signs for the entire learning process. As a result, the NHL algorithm allows obtaining models that retain their structure, which is enforced by the expert(s), but at the same time it requires human intervention before the learning process starts.

Finally, in 2003 Mateou and Andreou developed a hybrid methodology offering a solution to the problem of the participation of the weights in the forecasting process [118]. This problem is solved through the introduction of Genetic Algorithms which produce a set of solutions and new weights following a strategy change. The methodology has two stages, the first one being the consideration of expert judgment under a semi-automatic method and the second involving the recalculation the of weight matrix via a Genetic Algorithm as a fully automated method [90]. The advantage of this methodology is that it is based on experts for the development of the model's initial condition which reflects the current environment describing a real world problem thus ensuring the reliability and credibility of the model. Then the experts are disengaged from the process and an automatic method performs forecasting through the development of a number of scenarios [66]. Since 2003 this methodology as part of this Phd work was developed in such a way to constitute a complete methodology of the new category of Intelligent Decision Support Systems. The different steps of this development is fully explained and demonstrated in chapter 4.

3.4 Overview of FCM and applications

Due to enormous increase of research work related to FCM theory, we decided to present also studies that are not confined to the period prior to this thesis, but also to make an overview of FCM applications up-to-date so as to give a more complete and comprehensive picture of current research trends. In this section we briefly describe or make reference to selected studies and applications on Fuzzy Cognitive Maps [68]. At present, there are several applications in different domains and new studies (dynamical characteristics, learning procedures, etc.) aiming to improve the performance of FCMs [146]. The number of applications and their diversity indicate that FCMs are indeed very promising. In fact, the encoding of knowledge in FCMs is a very important issue examined by researchers [147]. The notion of "time" is also very important for dynamic systems and requires additional research, whiles the automated construction of FCMs, is a new and growing field [34].

Lee et al. [106] suggested a FCM methodology that may be used by decision makers to understand the parameters influencing complex dynamics associated with certain strategic goal related environmental factors [60]. The main issue was the development of a cognitive causal knowledge to identify those factors relevant to the strategic goals being considered. They proposed the classification of environments into three categories: Uncontrollable, Semi-controllable and Controllable.

Carlsson and Fuller in their work [38] proposed that the theory of strategic management, using the Fuzzy Cognitive Maps approach, can be represented with a “Hyper-knowledge based support system”, consisting of a set of interrelated concepts. More precisely they proposed a hyper-knowledge support system using Adaptive FCM in which during the adaptation process a system changes its operation in a dynamically changing environment [52].

An indication, to which extent the FCM is in balance, is given by the notion of the Balance Degree. In case that some strong paths between the same nodes are of different signs then the system has some strong possibilities to be unbalanced. To identify if a FCM is imbalanced two methods were proposed. The first one uses the principle of the shortest path between two nodes and the total effect of the sign of the shortest path. In the second one, Tsadiras and Margaritis introduce a new approach for measuring the balance degree of FCM, stating that “the sign of the total effect should be the sign of the most important path where the most important path is the one that passes through the most important nodes” [172].

Tsadiras and Margaritis [173] also addressed the problem of the natural behaviour of a node. The concept node can be imagined as a living entity (cell) that is positively or negatively activated and can be influenced by cells in its neighborhood. The natural behaviour for that cell would be to lose some of its activation when there is no stimulation to maintain the activation. They introduced Certainty Neuron FCMs [174] that can be defined as a neuron having the new activation level depending not only on the sum of weight influences that it receives but also on their previous state. While the classical FCMs allows two values for the activation function of FCM [0,1] the Certainty Neuron FCM may allow any value within the interval of -1 to +1.

Another work has been presented by Stylios and Groumbos [159] related to the use of FCMs in Control Systems. Control systems are an interesting area of industry that FCMs can handle specific types of problems. They proposed a new methodology for modelling the supervision of a complex control system using Fuzzy Cognitive Maps [70]. This methodology uses a two-level structure where the FCM is the upper level for more complicated supervisory control of manufacturing systems and the other is the control system itself. In another work Stylios and Groumbos addressed the issue of modeling large scale complex systems [158], while M. Mohammadian proposed a Self-Learning Hierarchical Fuzzy Logic for Guidance and Control of Multirobot Systems [132].

During the past few years a lot of research has been devoted to different FCM applications. FCMs are applicable for modelling scientific, political and social problems [171]. The implementation of FCMs for modelling mobile robot motion, in computer assisted learning check, and the extent to which students understand their lessons are just a few scientific applications of FCMs [161]. In addition, introducing FCMs to the public business can be used for strategic planning [87], while in economics exchange rate [9] and stock investment [108]; FCMs may support the use of game theory in more complex settings [96]. Some other important applications where FCMs are used is business performance [193], the designing of hybrid models for complex systems, studies related to virtual world [144], advanced robotics, assessing business performance [86], diagnosis problem [64], fault diagnosis problems [106], radiation therapy [142], Fuzzy PI+ D controller [110], Pattern recognition [187], financial modelling [134], prediction of interest rate [94], diagnosis of bone diseases [185].

It is important to mention that FCM models have also been applied in politics and particularly in crisis management problems and modelling of political, issues which is a very sensitive and demanding area. Tsadiras and Margaritis created a dynamic model of the Former Yugoslavian Republic of Macedonia (FYROM) Crisis in March 2001 [170].

Neocleous and Schizas studied the political dynamics of a Fuzzy Cognitive model in the case of the Cyprus problem [138]. The system that has been developed was used to study the effects of a change in the parameter influencing the solution of the Cyprus problem in relation to the stability and growth of some other parameters.

Mateou et. al created several political models examining the possibilities of a solution to the Cyprus issue during the last five years, starting from 2002 and concluding with Cyprus obtaining full EU membership status [117]. Additional issues considered have been the S300 crisis in 2003 and the possibilities of a solution according to the provisions of the Annan plan [11]. The results derived were very promising and the methodology developed aims at a new category of Intelligent Decision Support Systems [115].

Chapter 4: Intelligent Decision Support Systems - Research Contribution

4.1 Research challenges – Open issues
4.2 Initiating the problem
4.3 Dynamic Analysis of a model related to the Cyprus issue
4.4 Hybrid model
4.5 Multiple scenario analysis using Genetically Evolved FCMs
4.6 Fuzzy knowledge Base
4.7 Automatic drawing of FCM (simplification)
4.8 The limit cycle phenomenon
4.9 Genetically Evolved Fuzzy Cognitive Maps as the basic for developing Intelligent Decision Support systems
4.10 Application of a GEFCM Intelligent DSS: The case of the Annan plan
4.11 Discussion

4.1 Research challenges – Open issues

When this research was initiated, different objectives were set out. Entering deeply in the area of Fuzzy Cognitive Maps and working to develop a new category of Intelligent Decision Support Systems [39] applied in problems with a very high degree of uncertainty were among the first objectives.

One of the aims of chapter 3 was to present the recent advances in the theory of fuzzy cognitive maps, the work of other researches and some applications of FCM. Currently, several applications in different domains and studies are in progress to improve the performance of Fuzzy Cognitive Maps (dynamical characteristics, learning procedures, etc) [108]. In this chapter a more detailed explanation of the development of a new Intelligent Decision Support System will be given [76] using as an inference engine the Fuzzy Cognitive Maps approach. The following sections describe the major drawbacks of FCMs and offer a brief discussion on how these drawbacks may be addressed and tackled. We start with presenting the FCM weaknesses and the solutions given in the context of the present thesis.

4.1.1 The inability of FCMs to encode linguistic variables in a Fuzzy Knowledge Base

A FCM can avoid many of the knowledge extraction problems which are usually posed by rule based systems, by integrating with a Fuzzy Knowledge Base (FCM) [41]. The classical knowledge representation in expert systems is made through a decision tree. The most difficult part when designing a Fuzzy System is knowledge acquisition and representation via fuzzy values that may then be used as input to model a real-world problem [21]. To the best of our knowledge there is currently no systematic way of constructing and utilizing a FKB that could complement the modeling framework of FCMs, by enabling it to translate fuzzy knowledge on key issues of a problem to numerical values and vice-versa [101].

The absence of a FKB in FCMs was due to the lack of linguistic encoding in the fuzzification and defuzzification processes, something which made inference very difficult or even impossible without the help of programmers. The construction of the FKB is primarily based on producing fuzzy information provided by a group of experts [33] which is utilized to identify and assess the significance of the various concepts describing a problem under study and define the relations among them. Based on this information, the various activation levels of the FCM concepts, which are used to model the specific problem, are classified, labeled, coded and stored in the form of a Fuzzy Knowledge Based System. When the FKB is introduced in the system the experts may be automatically informed about the results without the need to transform numbers in linguistic form understandable to anyone. This improvement is a very important step in the development of a system that could be used also by domain experts. Part of this thesis was devoted to this issue, achieving to provide a system that combines numerical information describing activation levels and weights calculated during the interaction cycles of the model with linguistic values of the fuzzy knowledge representation reflecting the behavior of the system under study. In our FCM extension the number of linguistic variables depends on the complexity of the problem. The linguistic sample is encoded directly in a numerical matrix using an uncertainty fuzzy distribution and is substantially reduced to a scalar form [13].

4.1.2 A Weakness in the forecasting process: The presence of weights in the simulation experiments

When we are dealing with forecasting with FCMs we come across two weak points: The first involves the invariability of the weights, which leaves only the activation levels to participate in the configuration of a given problem. The second lies with the inability of the method to model a certain situation by performing all possible computational simulations following the change of a certain weight or group of weights. We addressed these issues by combining FCMs with Genetic Algorithms (GAs) [90], and the weak points were resolved, thus creating an Evolutionary Fuzzy Cognitive Map hybrid model able to perform forecasting activities, something that was not possible in the past. More specifically, the hybrid model was the solution to the above limitations expecting to contribute to the effectiveness of decision-making. As the main part of this research, the hybrid model was first proposed in [14] and validated in real world political problems. During this validation process another weak point was identified when multiple scenario analysis was involved. The methodology was unable to support multi-objective decision-making due to the fact that the GA could compute a weight matrix only for one particular concept. Thus, the methodology was further improved, to overcome the above weakness based on a new Genetic Algorithm specially designed to support a multi-objective decision-making environment [120]. FCM hybrid models are expected to contribute to the effectiveness of decision-making by defining for each concept the desired activation level, achieved with a certain set of weights evolved by the GA. When multiple scenario analysis is involved, the methodology will be able to support multi-objective decision-making.

4.1.3 The inability of FCMs to handle large-scale problems

Modelling complex systems in an effective way is very difficult, especially when trying to formulate a mathematical model which is very costly to design and difficult to adopt in a new environment. None of the current FCM approaches has been tested and proved as capable to handle models consisting of a large number of concepts. These approaches were applied only to relatively small models, i.e. consisting of up to ten nodes.

In a given problem consisting of a rich number concepts, it is very difficult or even impossible to create a single map and identify each interaction between concepts. This is exactly what the present research aspired also to tackle, by proposing a new methodology using Multi-Layer Fuzzy Cognitive Maps to handle the complexity of such a problem [121]. The layered structure, along with a new algorithm named ML-FCM, were designed and proposed to serve the above methodology. The purpose of the new algorithm was to form layered Fuzzy Cognitive Maps in a hierarchical structure, to compute the activations levels of the children FCMs in each layer and to update the activation list of the decomposed father FCM in the upper layer.

The essence of the methodology lays with grouping a number of concepts in a way that each group is associated with a concept of interest in the upper level, which corresponds to a crucial, complex parameter of the system. The group of concepts creates logically a "local" FCM, which is dedicated to the concept of interest properly expanded for further analysis. This grouping may be performed for a number of concepts of interest and may decompose a concept using a stepwise approach. Each step gives birth to a new discrete level, which includes in its turn a new FCM corresponding to an expanded form of the central concept in the previous level.

The international literature includes some studies and applications of FCM in scientific, political and social problems (see chapter 3) [22] but not in large complicated issues like the solution of the Cyprus issue [12]. The Cyprus issue has been a source of international discussions and friction between Cyprus, Greece and Turkey. The Annan Plan, as it was shaped in 2004 and rejected by Greek Cypriots, was the basic for designing a complicated FCM model to be used as a validation to the Multilayer methodology. We believe that this application, using a novel software tool especially designed for this purpose, is among the first (or even the only) complete application in the field.

4.1.4 The limit cycle phenomenon

In cases where a dynamic system like a FCM reaches a limit cycle (LC), decision-making is practically impossible [69]. This research also deals with the phenomenon of limit cycle and proposes an extension of FCMs aiming at increasing their reliability by overcoming the weakness realized in cases of limit cycle behaviour.

The limit cycle phenomenon results from a certain combination of weight values in a specific FCM, which drive the map away from reaching equilibrium. The main reason for this phenomenon is a set of weight value(s), that, when combined with the rest of the weights connecting concepts form positive or negative cycles in the FCM (loops starting and ending to the same node) and give rise to a limit cycle.

Two approaches are suggested to handle the limit cycle phenomenon. The first one is to design an evolutionary algorithm based on the correction of the weight matrix the origin of which is responsible for the limit cycle [123]. The system traces the presence of a limit cycle or chaotic behaviour [72] and searches the weight matrix using evolutionary techniques to identify which weights or group of weights are responsible for the cause of limit cycle. The second approach to handle this phenomenon is a defuzzification method applicable to the limit cycle behaviour [15]. The proposed method calculates the mean value of the levels that fluctuate on a limit cycle and evaluates the reliability of the corresponding results.

4.1.5 Creation of new category of Computational Intelligent Decision Support Systems (CI-DSS)

Decision makers and policy proponents face serious difficulties when they have to design dynamic systems because it requires special knowledge outside their domain of interest. In addition, formulating a mathematical model may be difficult, costly and even impossible for some of them. Numerical data may be hard to be transformed in a linguistic form. In order to understand a system an expert may need to deal with natural language arguments [191]. Our research work moves along this direction aiming to built such a system that will be easier to use by an expert, and will also be easy to modify and adopt in a changing environment. What is also important to emphasise is the interpretation of the results which are self explanatory without the need to transform mathematical values into natural language.

The final research aim of this thesis is to propose a new Computational Intelligent Decision Support System (CI-DSS), extending the concept of a typical DSS by adding

Artificial Intelligence techniques as reasoning systems, natural language processing, knowledge representation etc. These techniques use the CI-DSS terminology [60] and include genetic algorithms, neural computing and fuzzy logic [31].

4.2 Initiating the problem

This section provides a detailed description of the first part of the research work conducted in this thesis. It starts with the static analysis of a given real-world problem, then the dynamic analysis is presented and the various improvements and contributions to this sub-area work are presented in a detailed and comprehensive way.

4.2.1 Static Analysis and dynamic models

In every FCM model, the dynamic behavior should be measured in order to identify its density [100]. This is achieved through the static analysis which is based on studying the characteristics of the weighted directed graph that represents the model. One way to receive an insight of the behavior of the model is by calculating its density. Basic analysis of the FCM structure includes the number of concepts (*N*) and the maximum number of connections (relationships) (*R*). The density (*D*) is an index of the degree of connectivity, calculated as:

$$D = \frac{R}{N^2} \tag{4.1}$$

Density is very useful indication of the complexity of a dynamic model. High density indicates increased complexity of the problem the model represents. Typical values of density are in the interval [0.05, 0.3]. Equation 4.1 assumes that concepts are allowed to have a causal effect on them.

A higher density indicates a view which recognizes more relationships among concepts. The types of concepts included and their relative role in FCM are also important in detecting differences among views. For any concept C_i, the in-degree id_i, is the sum of the weights affecting (feeding) a concept and is given by equation 4.2. The out-degree od_i (equation 4.3) is the sum of the outgoing weights of a concept to other concepts connecting it to them.

$$id_i = \sum_{j=1}^{n} \left| e_{ji} \right| \tag{4.2}$$

$$od_i = \sum_{j=1}^{n} \left| e_{ij} \right| \tag{4.3}$$

The in-degree represents the increasing influence received concept *i*. The overall effect of the concept can then be represented by the total degree or centrality td_i, which is the sum of the in-degree and out-degree, calculated as:

$$td_i = id_i + od_i \tag{4.4}$$

Centrality gives a measure of the significance of any concept in the system. This is based on the strength of both the effects it produces and receives [173]. The in-degree and out-degree also indicate the role of the concept in the system and concepts may be classified as being input ($id > 0$, od = 0), output ($od > 0$, id = 0) or normal variables (*id* and *od* > 0).

4.2.2 Model related to the Cyprus Issue

A FCM as an acyclic graph, with multiple cycles each representing a possible decision making path. Dynamic testing of an application requires a proper static analysis at an earlier stage in the development of the cycle, which allows finding and correcting problems that might be difficult to manage during the dynamic test phase. Through the static analysis of a problem, the verification of the correctness of the map and an analysis of the components and resources of an application is executed.

The main concepts that influenced the Cyprus problem in 2002 are used as an example to simplify things and describe better the key notions of the proposed approach. As shown in Table 4.1 sixteen concepts have been identified with the help of a team of domain experts. These experts have filled in a questionnaire concerning the causal relationships and the weights involved, i.e. the degree to which concepts influence each other, using a positive (+) or negative (-) number between zero and seven, to indicate the direction and intensity of the causal relationships between the concepts. For computational purposes, each number corresponded to the intensity of the casual relationship as follows: Absent 1 (0), very weak 2 (0.18), weak 3 (0.36), average 4 (0.54), strong 5 (0.72), very strong 6 (0.9) and decisive 7 (1.0). The resulting general model (Figure 4.1) manually designed, focused on the instability/intensity in Cyprus (C1) as its central concept, with all model concepts interacting with one another. On the left hand side of Figure 4.1 the weights are presented in a form that indicates the link from the starting to the ending concept.

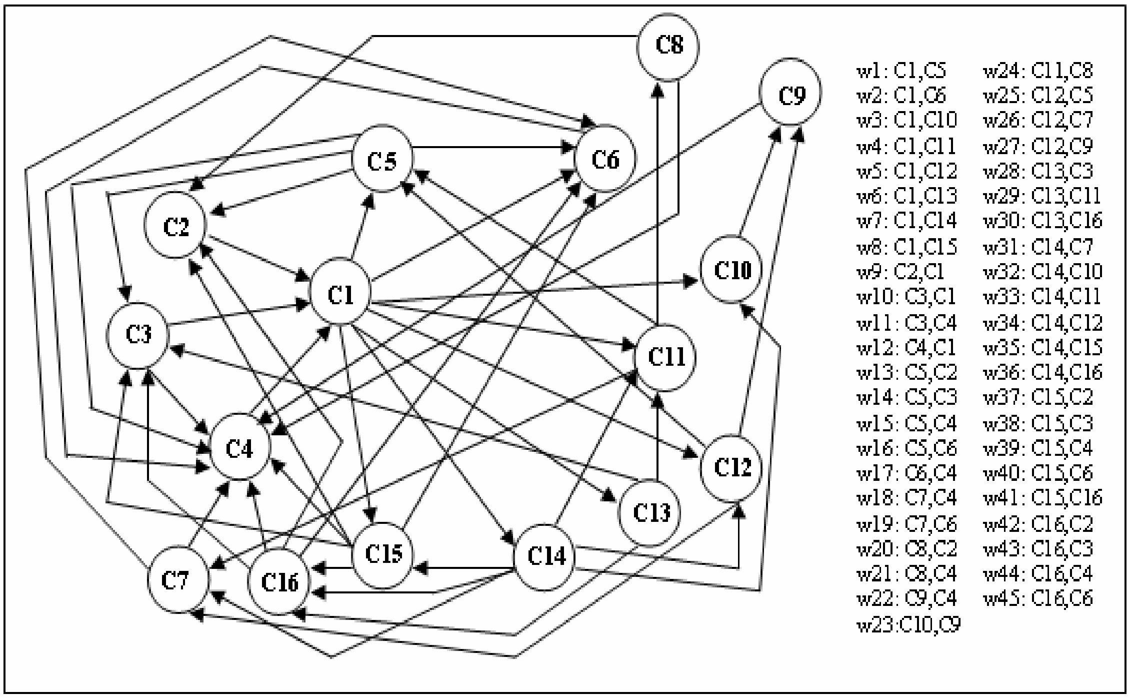


Figure 4.1: The Cyprus issue FCM model

Table 4.1: Description of the concepts employed in the Cyprus issue model

C1	Instability /Intensity in Cyprus	C9	Support to the Greek-Cypriot Army
C2	Turkish Forces Actions in Cyprus	C10	Reinforcement of the Greek Army
C3	Turkish Threats	C11	Reinforcement of the Turkish Army
C4	Solution of the Cyprus Problem	C12	Stability of the Greek Government
C5	Greek Political Support	C13	Stability of the Turkish Government
C6	UN Talks for the Cyprus Problem	C14	EU/NATO Economic, Military and Political Support
C7	Stability of the Cyprus Government	C15	International Influence
C8	Support to the Turkish Forces	C16	Turkish-Cypriot Reactions

The opinion of the experts, used to determine the weights of the different causal links and the initial activation level for each concept, was given a degree of reliability expressed by a value between 1 and 10 representing the relevance of the expert to the subject and his credibility [33]. Multiplying the degree of reliability of each expert by every weight determined by the expert and then averaging the two or more partial weight matrices resulted in the final weight matrix [163]. This is the usual practice followed for obtaining a normalized weight matrix, which can be considered more representative and objective as optimistic or pessimistic expert characteristics are better taken into consideration according to the degree of expertise. In this case study we employed two experts. The weight values of the normalized weight matrix for the Cyprus issue modelling attempt are given in Table 4.2.

Table 4.2: Normalized weight matrix for the Cyprus issue model

w1	**w2**	**w3**	**w4**	**w5**	**w6**	**w7**	**w8**	**w9**	**w10**	**w11**
0.10	0.29	0.03	0.32	-0.06	0.10	-0.16	0.13	0.21	0.21	-0.23
w12	**w13**	**w14**	**w15**	**w16**	**w17**	**w18**	**w19**	**w20**	**w21**	**w22**
-0.21	0.34	0.29	0.06	0.10	0.13	0.23	0.26	0.34	-0.19	0.26
w23	**w24**	**w25**	**w26**	**w27**	**w28**	**w30**	**w31**	**w32**	**w33**	**w34**
0.23	0.19	0.19	0.06	0.10	0.10	0.10	0.19	0.13	0.23	0.16
w35	**w36**	**w37**	**w38**	**w39**	**w40**	**w41**	**w42**	**w43**	**w44**	**w45**
0.16	0.13	-0.23	-0.19	0.23	0.26	0.19	0.13	0.13	-0.03	-0.03

As previously mentioned, the static analysis of the model focuses on the characteristics of the weighted arrows presented in the model using techniques from graph theory. The first important characteristic is that the density of the model according to equation 4.1 is 0.23 indicating that the model is in balance. Another important element to consider is the feedback cycles that exist in the graph. We consider a cycle in a FCM the path which starts from a concept, passes through other concepts and terminates at the concept it started. Each cycle is accompanied by a sign, which is determined by the multiplication of the signs of the arrows participating in the cycle. If all signs in a cycle are positive, or the number of negative signs in the same cycle is even, then the behavior of the entire cycle is positive. Positive cycles are those that behave as amplifiers: A positive change in the activation of a node in the cycle leads to a constant increase of the activation at the end of the cycle. The negative cycles on the other hand may neutralize the activation at the end of the cycle or even deactivate the cycle all together. This means that the activation level of the ending node will be decreased in cases in which an increase is introduced in the activation of any node in the cycle.

The model of Figure 4.1 has a plethora of cycles: 59 cycles exist, 32 of which are positive and 27 negative. The close numbers of positive and negative cycles leads to characterizing the model as rather complex. An example of a positive cycle, the identification of which is performed manually, as this appears in Table 4.3, is C1+→ C11+→C8 +→C2+→C1. This cycle begins with concept C1 (Instability/Intensity in Cyprus). Concept C1 exercises a positive effect on the Turkish Forces represented by concept C11 that any form of instability in Cyprus will lead to reinforcing the Turkish Army. C11 influences the support to the Turkish forces in Cyprus (C8) positively and this, in its turn, affects Turkish actions in Cyprus (C2) in a positive way. Concept C2 leads to an increase of concept C1 revealing increased instability in Cyprus. It is easy to see that if this cycle persists, then instability in Cyprus will constantly increase. An example of a negative cycle as this appears in Table 4.3 is C1+→C5+→C6+→C4−→C1. The cycle begins with concept C1, which exercises a positive effect on the concept representing the Greek Political Support (C5). This situation influences positively the UN talks for the Cyprus problem (C6), which in its turn affects the solution of the Cyprus Problem (C4) favorably, while C4 influences the Instability in Cyprus adversely. Via this cycle the Instability in Cyprus will constantly decrease if a positive change in the activation of any node in the cycle takes place.

The examples that follow attempt to show the effect of a weight changing gradually from negative to positive; weight w12 from its negative value given by the experts is changed to its positive equivalent, hence we expect a modification in the cycle status of the model as follows: The negative effect of concept C4 (Solution of the Cyprus Problem) on concept C1 (Instability in Cyprus) expressed by w12 will now be altered to positive, expecting an increase of the intensity and instability in Cyprus as a consequence of a solution to the problem. Indeed, when weight w12 becomes positive the number of positive cycles is greater than the number of the negative ones (now 33 positive and 26 negative cycles) meaning that an augmentative tendency is amplified in the model. The point of this example is that the intensity will not necessarily recede in the case in which the solution of the Cyprus problem promotes it.

Table 4.3: Examples of cycles starting and ending at concept C1

C1	w1	+	C5	w13	+	C2	w9	+	C1			
C1	w1	+	C5	w14	+	C3	w10	+	C1			
C1	w2	+	C6	w17	+	C4	w12	-	C1			
C1	w1	+	C5	w15	+	C4	w12	-	C1			
C1	w1	+	C5	w16	+	C6	w17	+	C4	w12	-	C1
C1	w1	+	C5	w14	+	C3	w11	-	C4	w12	-	C1
C1	w3	-	C10	w23	+	C9	w22	+	C4	w12	-	C1
C1	w4	+	C11	w24	+	C8	w21	-	C4	w12	-	C1
C1	w4	+	C11	w24	+	C8	w20	+	C2	w9	+	C1
C1	w5	-	C12	w25	+	C5	w13	+	C2	w9	+	C1
C1	w5	-	C12	w25	+	C5	w14	+	C3	w10	+	C1
C1	w5	-	C12	w26	+	C7	w18	+	C4	w12	-	C1

A second example of static analysis involves a manual change of the positive sign of weight w10, which links the concept of the Turkish Threats (C3) to that of Instability/Intensity in Cyprus (C1). A negative w10, involving constructive Turkish statements rather than threats (C3) will lead to counting 28 positive and 31 negative cycles, which suggests a clear receding tendency in the model and a decrease of the intensity in Cyprus, a development that contributes to the solution of the Cyprus issue.

The problem with static analysis, though, is that it involves a large number of restrictions while it is very difficult to identify which of the numerous cycles in a model, 59 in our case, will finally prevail and which are the ones with the strongest effect on the model. In other words, calculating the interactions between the cycles, altering the weights each time a new scenario is introduced and trying to identify which concept(s) and which weight(s) will eventually prevail can be very complicated even for models with a much smaller number of concepts than the one currently studied. These problems can be overcome by the use of dynamic analysis based on computational simulations. This issue is covered in the next section.

4.3 Dynamic analysis of a model related to the Cyprus issue

The dynamic analysis involves using our model in the context of a scenario approach as a technique for strategic management and decision-making. In broad terms a scenario is taken to describe some feasible future state of the environment under study by modeling the dynamic sequence of interacting events, conditions and changes required to reach that state. Such an approach is particularly suitable for the evaluation and selection of strategies, decision-making and identification of future possibilities in face of uncertainties.

4.3.1 Model initialization

The first step of dynamic analysis is the initialization of the model meaning that the model is stabilized and the results reflects the initial condition of a given problem. In the example of Figure 4.1 the new activation levels of the sixteen concepts are calculated with equation 3.5 of chapter 3, following which the model can simmer down to either a state of coverage or when it reaches in a final immutable situation, which can be either an equilibrium, or a limit cycle, or even chaos. Using as input the weights (W_i) and the activation levels (A_i) defined by the experts we allow the concepts of the system to interact. The activation levels calculated after 250 iterations are presented in Table 4.4, while Figure 4.2 indicates that the model reached an equilibrium state.

Table 4.4: Activation levels (A_i) calculated by the Cyprus issue

C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
0.69	0.59	0.75	-0.59	0.79	-0.44	-0.74	0.78
C9	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**
-0.65	-0.62	0.60	0.30	0.67	0.56	-0.81	0.54

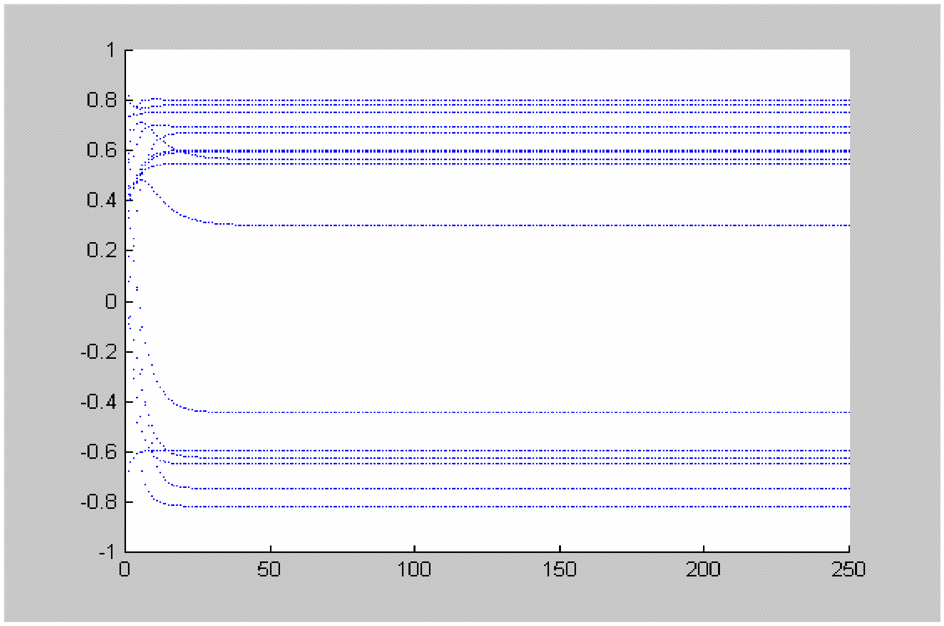


Figure 4.2: Stabilization of the model at equilibrium after 250 iterations

4.3.2 The Politics of the initial state

After running the FCM, the model outlined the current political situation of Cyprus as follows: The current activation level of concept C1, which is the Instability in Cyprus, was found to be at a high level (A_1=0.69), influenced by the Turkish Actions in Cyprus (C2). This assumed a value of A_2=0.59, a rather high value explained by the continuous support and reinforcement of the Turkish troops in Cyprus by Turkey and the continuous violations of the Greek and Cypriot FIR. The instability is also influenced by the Turkish threats (C3) with A_3=0.75, a remarkably high figure given the continuing threats expressed by various Turkish officials following the Cyprus full EU membership. The third concept which relates to the instability in the island is the solution of the Cyprus problem (C4) with A_4=-0.59, a concept inversely related to the intensity in Cyprus as long as the Cyprus problem remains unsolved. Concept C15 which is the International Influence comes up with an activation level of A_{15}=-0.81, indicating that the current status leaves a lot of room for pressure upon the factors that contribute to the decrease of the instability in Cyprus . The UN talks on the Cyprus problem represented by C6 bear a negative activation level (A_6=-0.44), as it appears that the UN alone is not in a position to contribute to the solution of the Cyprus problem effectively. A final concept that appears to exercise an important positive effect is the NATO/EU economic, military and political support represented as C14, with an activation level of A_{14}=0.56

A straightforward conclusion drawn on the basis of these results is that there is a high level of instability in Cyprus, suggesting that as things are described at this initial state a solution to the problem is just a remote possibility. These results reflected exactly the political situation in 2002.

Scenario analysis is a process of analyzing possible future events by considering different possible outcomes. Here it is used in to indicate the inability of static analysis to perform dynamic and reliable scenarios due to the fact that only one or a limited number of weights take part in this process. It can be difficult to foresee what the future holds in an FCM system using only static analysis due to the fact that FCM works in discrete steps for a number of iterations. To verify the above indicative scenarios are given below.

4.3.3 Solving of the Cyprus problem: First scenario

This scenario involves differentiating the probability of solution of the Cyprus problem and changing the weight w12, which is the causal link between concepts C4 and C1, from negative to positive. The value of the weight w12 has been changed from -0.21 to the strongly positive value of 0.7. The meaning of this change is that the solution to the Cyprus problem (C4) is expected to contribute (strongly as the selected value of 0.7 indicates) to the climate of intensity promoting stability in Cyprus (C1). The calculated activation levels reflecting this scenario are given in Table 4.5 and presented graphically in Figure 4.3, indicating that the model again reaches equilibrium.

Table 4.5: Scenario 1: Calculated activation levels (A_i) for W12=0.7

C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
0.67	0.58	-0.19	0.69	0.72	0.48	0.77	0.46
C9	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**
0.68	0.63	0.47	0.73	0.48	0.85	0.73	0.42

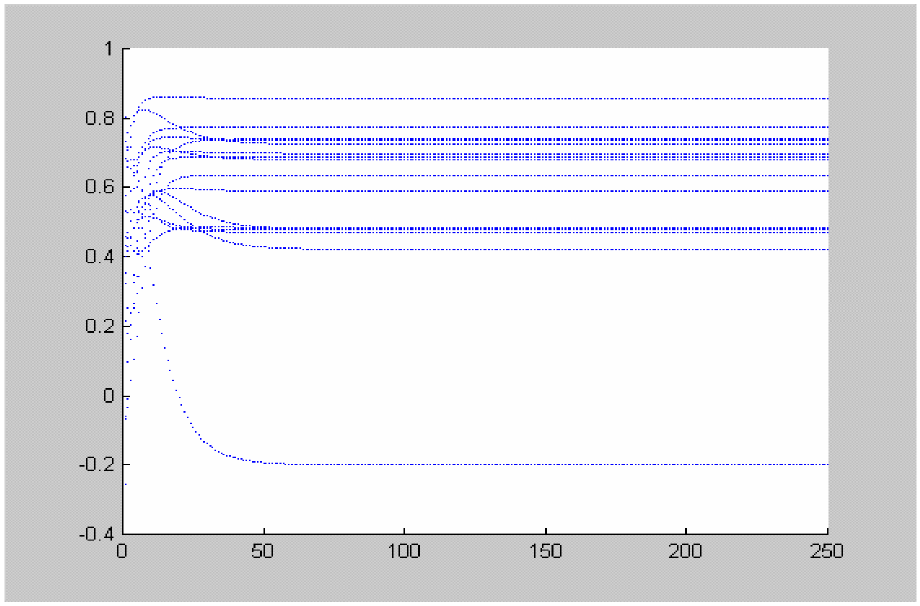


Figure 4.3: Scenario 1: Equilibrium for W12=0.7

The first conclusion drawn based on this scenario is that there is a considerable chance of a solution to the Cyprus problem, given that the activation level of concept C4 has assumed a quite substantial positive value (A_4=0.69). This calls, however, for a requirement that the Turkish side changes its attitude from being aggressive to contributing through a series of positive statements to solving the Cyprus problem. This radical change of attitude is reflected in the dramatic change of the activation level of concept C3 (Turkish threats) down to A_3=-0.19. Moreover, it is interesting to mention that the rise of the activation level of the talks under the UN auspices (C6) to A_6 =0.48 indicates that such talks can be quite helpful and must be continued, together, of course, with the exercise of what we term "International Influence" (C15). The sign of the latter changes and its value becomes strongly positive, indicating its decisive effect upon the possibility of tracing a solution of the Cyprus Problem. Likewise, concept C14 representing the political, economic and military support by the NATO and the EU, assumes an increased activation level of A_{14}=0.85. This last conclusion points out the possibilities that may be offered by the contribution of these two powerful entities on reaching a solution to the Cyprus issue. Concerning the government stability in all three countries directly involved in this issue (C7, C12, C13) the activation levels are considerably high, indicating its essentiality in all cases.

A further interesting finding in this scenario concerns the reinforcement of the Greek Army (C10) and the military support to the Greek-Cypriots (C9), that if the Greek Army is strengthened (A_{10}=0.63) wile more military support is given to the Greek-Cypriot Army (A_9=0.68), then this may support a solution of the Cyprus issue in the context of a "si vis pacem para bellum" policy (the Latin for "if you want peace prepare for war"). It seems that the unstable environment in Cyprus will continue prevailing given its high activation level (A_1=0.67), combined with an almost equally high activation level of the Turkish military activity on the island (A_2=0.58). This simply means that a solution to the Cyprus issue will not necessarily lead to stability, the latter being adversely affected by the strong presence of the Turkish troops on the island. It is necessary to recall here that the results reflected the 2002 political situation in Cyprus.

4.3.4 Solution of the Cyprus problem: Second scenario

To face the adverse repercussions predicted by the first scenario we have resorted to asking the model to forecast the political impact in cases in which all Turkish forces activity is neutralised. This is introduced by setting the weight w9, which represents the causal link between concepts C2 and C1, to zero. As a result the model has reached a mixed state of equilibrium and limit cycles as depicted in Figure 4.4.

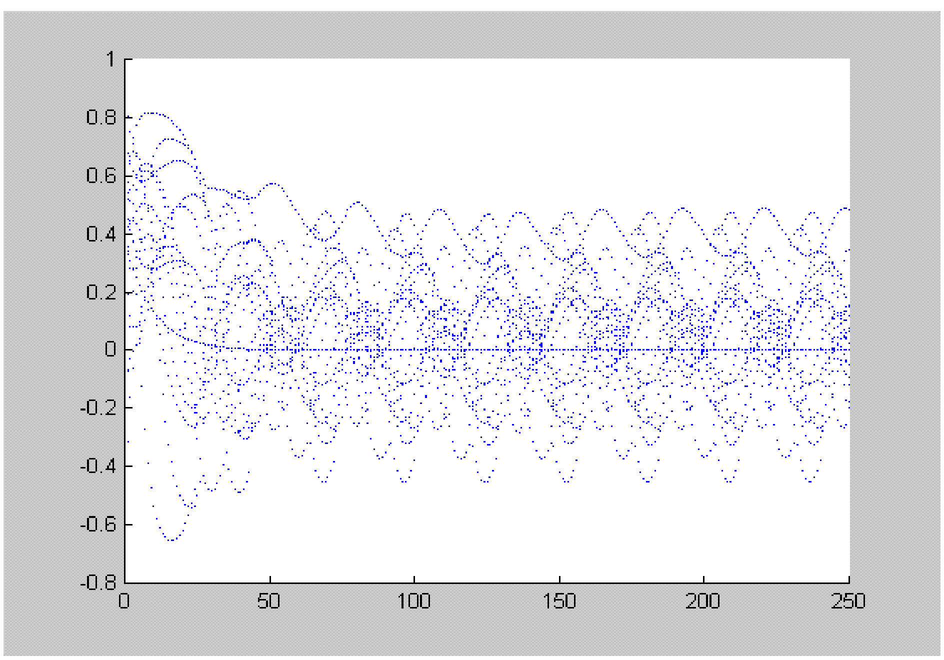


Figure 4.4: Scenario 2: Limit Cycle and equilibrium for W9=0.0

It is impressive to notice in Table 4.6 that the relevant activation level has turned to negative (A_1=-0.11) meaning that there are chances for attaining a stable equilibrium in Cyprus after all! However, combining the concept solution of the Cyprus Problem (C4) with an activation level of A_4=0.07 leads to a neutral environment implying that in this scenario the Cyprus issue appears to be "frozen" possibly due to the absence of events causing a general instability that could trigger a process leading "wake-up" the public opinion and give the necessary momentum to the settlement of the problem. This leads to a conclusion very much similar to that of the previous scenario, i.e. that the solution of the Cyprus problem may not contribute to the stability in Cyprus meaning that after the solution it may be a period that the two communities will be in conflict until a mutual trust will be built. Regarding the International Influence (C15), this assumes a lower activation level compared to the first scenario (A_{15}=0.34) Generally speaking, the main conclusion of this scenario refers to the tendency of most concepts to assume a neutral attitude, given the absence of actions on behalf of the Turkish troops in Cyprus.

Table 4.6: Scenario 2: Final activation levels (*Ai*) for W9=0.0

C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
-0.11	0.00	0.17	0.07	-0.19	0.06	0.15	-0.09
C9	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**
0.15	0.07	0.02	0.14	0.12	0.48	0.34	-0.05

The conclusions drawn above have been reached to their largest extent on the basis of quantitative analysis in order to avoid personal evaluations and normative biases. The method, as previously described (section 4.1.2), suffers from two main limitations: The invariability of the weights to participate in the process and the inability of the method to model a certain political situation by performing all possible computational simulations following the change of a certain weight or group of weights. The GA part will be responsible for developing the weight matrix attempting to calculate the optimal set of weights that satisfy a predefined activation level for a specific concept. The use of the GA will allow exploiting the potentials of forecasting leading some times to entirely unexpected results.

4.4 Hybrid model

4.4.1 Introduction to evolutionary strategy

The objective of the Genetically Evolved Fuzzy Cognitive Map (GE-FCM), is to overcome the main weakness of FCMs, which relates to the recalculation of the weights corresponding to each concept every time a new strategy is adopted [10]. This approach aims at solving these problems by combining FCMs with Genetic Algorithms (GAs) thus creating a hybrid model much more suitable, bearing in mind the complication of real world problems. In this context, the FCM part of the algorithm computes the final activation levels given the weights and relationships between concepts, while the GA part develops the weight matrix attempting to find the optimal set of weights that satisfy a predefined activation level for a specific concept. The GA concepts are very appealing since they offer the optimal solution without a problem-solving strategy, once the requirements are defined [154]. It is interesting to point out that the hybrid approach is reflected in both the implementation of the GA and in the methodology applied for solving the problem. In fact, the reasoning behind this hybrid methodology is to use it for obtaining the optimal values of the weights corresponding to the variables of the model rather than the optimal values of the variables themselves.

More specifically, the GA evolves a population of individuals each of which is encoded as a weight matrix structure describing the degree of causal relationships between the participating concepts [37]. The initial generation contains weights matrices with random values. The evolution of the individuals is performed with the help of the FCM model, which computes the final activation levels of the concepts. The activation level of a certain concept in focus denoted by $AL_{d,i}$ is used to calculate the fitness of each individual-weight matrix W_i according to the following equation:

$$\text{Fitness}\ (W_i)=1/(1\text{-abs}(AL_{d,i} - \text{mean}_{50}(AL_{a,i})) \qquad 4.5$$

where $AL_{d,i}$ is the target (desired) value of the activation level for the concept in focus C_i and $\text{mean}_{50}(AL_{a,i})$ is the mean value of the last fifty actual activation levels of concept C_i as these are computed by the FCM. It is clear from equation 4.5 that the closer to the target value this mean is, the more appropriate the weight matrix. In fact, the fitness function uses the average values of the last fifty activation levels to account for limit-cycles, that is, a state in which the $AL_{d,i}$ exhibit periodic fluctuations and do not stabilize at equilibrium values as previously described. Thus, if the activation level of the concept in focus reaches equilibrium then the corresponding weight matrix in this case can be considered to be more appropriate compared to another individual-matrix that has resulted to limit cycle [69].

Genetic algorithms are used to find optimized values for the membership function parameters, particularly when manual selection of their values becomes difficult or takes too much time to attain [18]. Using GAs for the purpose of enhancing the learning capabilities of neural networks has been suggested since the early days of the back-propagation learning algorithm. But it was only recently that powerful and more formal algorithms have been developed for integrating the optimization tools [150] of GAs with the learning schemes of a large class of neural networks [67].

Table 4.7: The Cyprus issue: Weight matrix

w1	**w2**	**w3**	**w4**	**w5**	**w6**	**w7**	**w8**	**w9**	**w10**	**w11**	**w12**
0.10	0.29	0.03	0.32	-0.06	0.10	-0.16	0.13	0.21	0.21	-0.23	-0.21
w13	**w14**	**w15**	**w16**	**w17**	**w18**	**w19**	**w20**	**w21**	**w22**	**w23**	**w24**
0.34	0.29	0.06	0.10	0.13	0.23	0.26	0.34	-0.19	0.26	0.23	0.19
w25	**w26**	**w27**	**w28**	**w29**	**w30**	**w31**	**w32**	**w33**	**w34**	**w35**	**w36**
0.19	0.06	0.10	0.10	0.16	0.10	0.19	0.13	0.23	0.16	0.16	0.13
w37	**w38**	**w39**	**w40**	**w41**	**w42**	**w43**	**w44**	**w45**			
-0.23	-0.19	0.23	0.26	0.19	0.13	0.13	-0.03	-0.03			

All simulations conducted in the next section use the following variable values: The population size has been set equal to 100 and the number of generations equal to 400. The weight values were initialized in the range [-1.0, 1.0] while the probability of applying the genetic operator of crossover was set to 0.25 and that of mutation to 0.01.

4.4.2 Experimental results

New simulations for the Cyprus issue case study were performed as follows: The first step involved the calculation of the activation levels by the FCM model (Table 4.4) at equilibrium using the initial weight matrix shown in Table 4.7. The next step simulated different scenarios by asking the model to reach a desirable activation level for a certain concept the policy–maker focuses on. The GE-FCM model calculated the new optimal weight matrix, which was then used by the FCM model to recalculate the new activation levels of the 16 concepts participating in the model of the Cyprus issue [12]. In fact the recalculation of all weights that participate in the simulation process constitutes the most important difference between the GE-FCM and the simple FCM models. Its importance is underlined by the fact that the policy-makers will not base their decision only on experts' evaluation, but also on the optimal weights that lead a concept to be activated to a certain predetermined degree. This means that decision-makers are able to introduce hypothetical cases which are represented by a target activation level for a certain concept in the model. Then the corresponding weights and activation levels for the rest of the concepts are studied. Based on this information, the policy-maker is in position to take decisions leading to the desired simulated solution and is to assess the consequences of such a decision.

4.4.2.1 Scenario 1: An environment of increased instability

Rising instability in Cyprus is introduced by increasing A_1 from 0.69 (Table 4.4) to 0.95. The final activation levels of Table 4.10 were obtained using the optimal weights calculated by the GE-FCM listed in Table 4.8. As depicted in Figures 4.5 and 4.6, the model has reached equilibrium showing a reliable fitness. The simulated results pointed out that the cause of the increased instability in Cyprus (A_1=0.88) are concepts C2 and C3, representing the Turkish provocative actions (w9=-0.75; A_2=-0.75) and the Turkish threats (w10=-0.53; A_3 =-0.59) respectively. The environment instability is further aggravated given the combination of the negative activation levels of C2 and C3 to the weights that link them with C1 which have turned from positive (Table 4.4), to negative (Table 4.9). The activation level of 0.76 assumed by C4 (solution of the Cyprus problem) can only contribute to this instability.

Table 4.8: Increased instability (A_1=0.95): GE-FCM optimal weight matrix

w1	w2	w3	w4	w5	w6	w7	w8	w9	w10	w11	w12
0.89	0.90	0.98	-0.03	-0.19	-0.21	0.02	-0.15	-0.75	-0.53	0.18	0.81
w13	**W14**	**w15**	**w16**	**w17**	**w18**	**w19**	**w20**	**w21**	**w22**	**w23**	**w24**
0.05	-0.33	0.91	0.42	0.89	0.39	0.28	0.73	0.11	-0.59	-0.24	0.88
w25	**W26**	**w27**	**w28**	**w29**	**w30**	**w31**	**w32**	**w33**	**w34**	**w35**	**w36**
-0.76	-0.68	-0.37	-0.28	-0.40	0.32	-0.78	0.07	-0.84	-0.78	-0.69	0.35
w37	**W38**	**w39**	**w40**	**w41**	**w42**	**w43**	**w44**	**w45**			
-0.52	-0.49	0.71	-0.01	-0.50	-0.02	0.07	0.34	-0.04			

Table 4.9: Increased instability (A_1=0.95): GE-FCM's AL with optimal weights

C1	C2	C3	C4	C5	C6	C7	C8
0.88	-0.75	-0.59	0.76	0.84	0.75	0.69	-0.67
C9	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**
-0.67	0.41	-0.72	-0.79	0.73	0.63	0.81	0.50

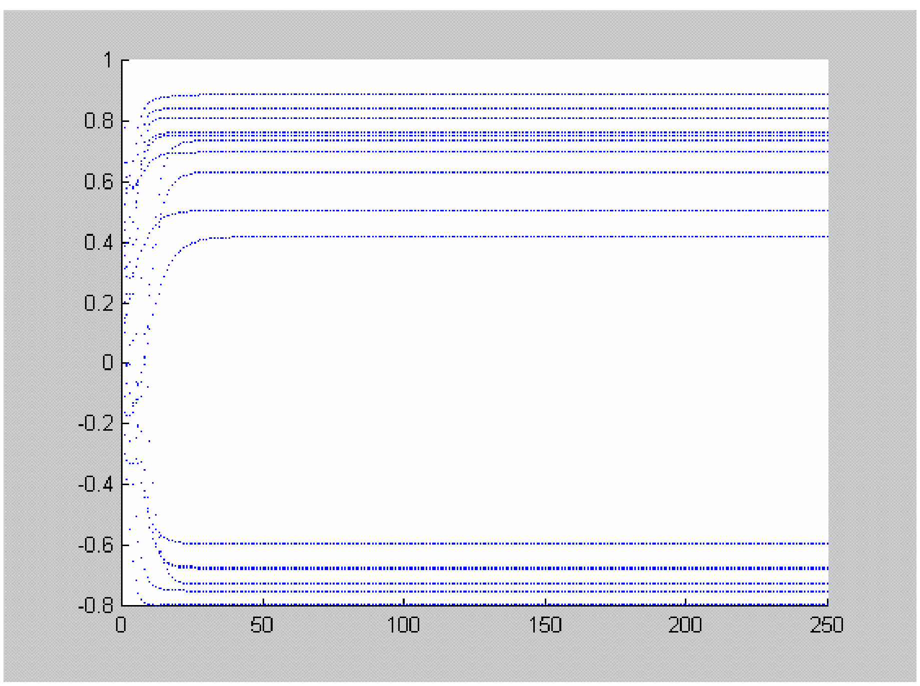


Figure 4.5: Equilibrium for target concept $A_1 = 0.95$

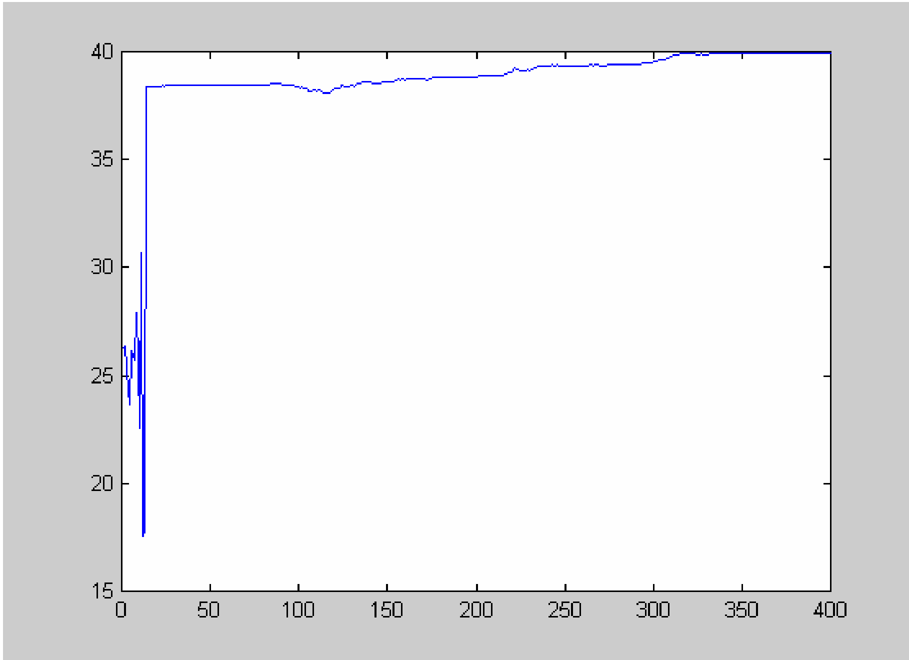


Figure 4.6: Fitness evolution generations for target A_1=0.95

A further interesting point regards the consequences of a reduced support offered to the Turkish forces on the island, a possibility indicated by a decrease of the appropriate activation level down to A_8=-0.67 from 0.78 and the results of which is a reduction of the provocative statements, threats and actions from the part of Turkey. It is important to point out that the effectiveness of reducing the support to the Turkish forces is revealed by the increase of the corresponding weight (w20) to twice its original value due to the reduction of the Turkish forces, as indicated by the relevant weights and activation levels. Concluding the experiments involving an unstable environment, it is interesting to observe that the pronounced activation level of the international influence (C15) has turned from negative to positive, while its impact upon solving the Cyprus problem (w39) has risen to three times as much as its baseline value, underlining the importance of the pressure exercised by international organizations or superpowers.

4.4.2.2 Scenario 2: How to solve the Cyprus problem

This scenario examines the solution of the Cyprus problem in two ways: The first involves simulating the situation under which the potential of a solution to the problem is decreased, while the second investigates the scenery in case this potential is marginally increased. In the former case the simulations were performed with a target activation level A_4=-0.9, while in the latter case this level was equal to A_4=-0.2.

Table 4.10: Solving the Cyprus problem: GE-FCM optimal weight matrix for target A_4= -0.9

w1	**w2**	**w3**	**w4**	**w5**	**w6**	**w7**	**w8**	**w9**	**w10**	**w11**	**w12**
0.43	-0.85	-0.98	0.98	-0.04	-0.82	0.63	-0.98	-0.81	-0.61	-0.70	-0.93
w13	**w14**	**w15**	**w16**	**w17**	**w18**	**w19**	**w20**	**w21**	**w22**	**w23**	**w24**
-0.23	-0.94	-0.44	-0.90	0.76	-0.79	-0.73	0.33	0.55	0.30	-0.81	-0.43
w25	**w26**	**w27**	**w28**	**w29**	**w30**	**w31**	**w32**	**w33**	**w34**	**w35**	**w36**
0.57	-0.41	-0.58	-0.28	0.55	0.90	-0.40	0.39	-0.64	-0.96	-0.20	-0.76
w37	**w38**	**w39**	**w40**	**w41**	**w42**	**w43**	**w44**	**w45**			
-0.09	-0.21	0.81	0.63	0.20	0.99	-0.76	0.01	-0.22			

Table 4.11: Solving the Cyprus problem: GE-FCM Activation levels for target A_4= -0.9

C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
0.93	-0.84	0.18	-0.86	0.89	-0.83	0.90	-0.84
C9	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**
-0.66	0.79	0.73	0.79	-0.75	-0.77	-0.83	-0.85

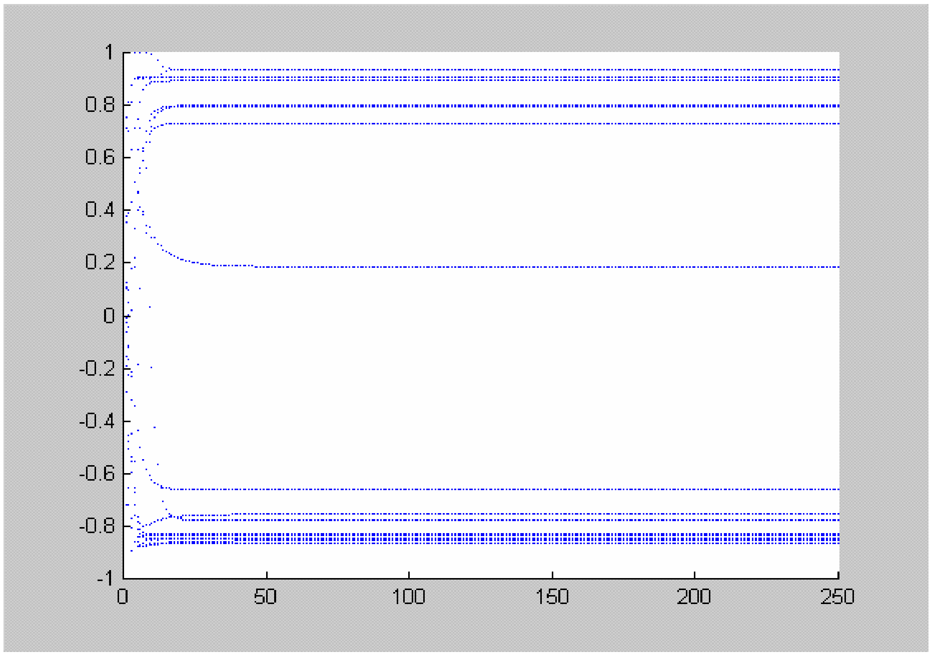


Figure 4.7: Equilibrium for target A_4=-0.9

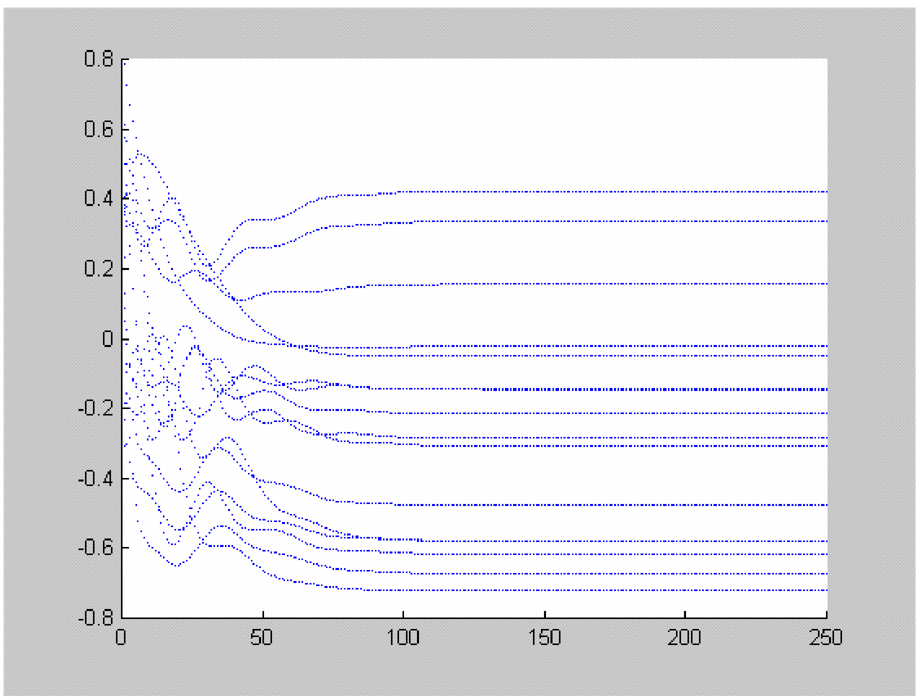


Figure 4.8: Equilibrium for target A_4=-0.2

Table 4.12: Solving the Cyprus problem GE-FCM weight matrix for target A_4=-0.2

w1	w2	w3	w4	w5	w6	w7	W8	w9	w10	w11	w12
-0.81	0.27	0.76	0.27	-0.86	0.15	-0.09	0.96	0.75	-0.57	0.95	0.52
w13	**w14**	**w15**	**w16**	**w17**	**w18**	**w19**	**W20**	**w21**	**w22**	**w23**	**w24**
0.58	-0.15	0.41	-0.70	-0.64	-0.60	-0.52	0.33	-0.40	-0.93	-0.89	0.62
W25	**w26**	**w27**	**w28**	**w29**	**w30**	**w31**	**W32**	**w33**	**w34**	**w35**	**w36**
-0.10	-0.12	-0.79	0.69	0.53	-0.91	0.55	0.57	0.25	0.02	0.65	0.68
w37	**w38**	**w39**	**w40**	**w41**	**w42**	**w43**	**W44**	**w45**			
0.01	0.45	0.57	-0.62	-0.60	-0.12	-0.01	0.52	0.37			

Table 4.13: Solving the Cyprus problem: GE-FCM final activation levels for target *A4*=-0.2

C1	C2	C3	C4	C5	C6	C7	C8
-0.14	-0.28	-0.30	-0.21	-0.61	0.33	-0.14	-0.02
C9	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**
0.42	-0.57	-0.04	-0.47	-0.58	-0.72	-0.27	0.15

Decreasing the activation level of C4 to –0.9 the GE-FCM yields the optimal weight matrix depicted in Table 4.10 which activates the concept almost to its equilibrium target value (C4=–0.86; Table 4.11, Figure 4.7). In this case concept's interactions are the following: Intensity in Cyprus climbs to A_1=0.93, while the Turkish hostile decrease to A_2=-0.84 with the Turkish threats almost neutralized. This high level of intensity comes as a result of the negative A_2 and the negative w9 linking C2 with C1, the multiplication of which contributes to increasing A_1 to the previous directions. The same holds for A_4 and w12, linking C4 with C1, while the international influence (C15) is negatively activated (A_{15}=-0.83), thus affecting the solution to the Cyprus problem adversely given its positive link to C4. The Turkish government appears quite unstable (A_{13}=-0.75), while the Turkish army is substantially reinforced (A_{11}=0.73). These levels are certainly expected to contribute to raising tension in the area, given the tendency of the Turkish authorities to “export” their domestic economic, political and social problems in a crises form.

Turning to our second policy, setting the target A_4=-0.2 seems to be more fruitful as the equilibrium values of the results indicate (Tables 4.12 and 4.13, Figure 4.8). While A_4 rises to -0.21, intensity appears to be significantly decreased to the value of A_1=-0.14, unlike the previous case, given the drop of both the level of the Turkish forces actions in Cyprus and that of the Turkish threats.

4.4.2.3 Application of the hybrid model on a real case: The S-300 crisis

Unlike the hypothetical cases examined thus far, the hybrid model is tested in an environment of a crisis between January 1997 and December 1998, namely that of the S–300 missiles, involving installation of such an efficient long-range ground to air missile on Cyprus that was considered a threat to Turkey, improving the effectiveness of the Greek and Cypriot armed forces in the context of the Integrated Defence Doctrine, while, in parallel, compelling Turkey to resort to purchasing expensive countermeasures to such an alleged threat.

Table 4.14: S-300 crisis weight values defined by the experts

w1	**w2**	**w3**	**w4**	**w5**	**w6**	**w7**	**w8**	**w9**	**w10**	**w11**	**w12**
0.0	-0.1	0.0	0.0	0.0	-0.4	0.0	0.0	0.8	0.1	-0.3	-0.4
w13	**w14**	**w15**	**w16**	**w17**	**w18**	**w19**	**w20**	**w21**	**w22**	**w23**	**w24**
0.0	0.1	0.1	0.1	0.2	0.0	0.1	0.1	-0.8	-0.1	0.2	0.2
w25	**w26**	**w27**	**w28**	**w29**	**w30**	**w31**	**w32**	**w33**	**w34**	**w35**	**w36**
0.0	0.1	0.0	0.25	-0.3	0.1	0.2	0.0	0.0	0.1	0.1	0.0
w37	**w38**	**w39**	**w40**	**w41**	**w42**	**w43**	**w44**	**w45**			
-0.5	-0.3	0.3	0.9	-0.3	0.3	0.1	0.4	0.1			

The Greek side, in its turn, claimed that the installation of the S-300 would not be enough to shift the balance of power in the area to its favour, given that these missiles would be exposed to a sudden blow from the part of Turkey to which they would be able to respond only if they survived. In such a case, therefore, any form of destabilizing action in the area would only come from the Turkish side, given that the role of the S-300 would have been purely defensive. The strong opposition to this purchase by the USA and Great Britain finally led to the installation of the missiles on the island of Crete and to the purchase of just a short-range ground to air system for Cyprus.

Table 4.15: S-300 crisis: FCM calculated activation levels

C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
0.79	0.87	0.77	-0.77	-0.41	-0.63	-0.41	0.88
C9	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**
0.70	0.00	0.66	0.60	-0.71	0.58	-0.85	-0.27

In order to analyze the environment described above, we first simulated the S-300 incident using the weight matrix presented in Table 4.14. The final activation levels of the sixteen concepts involved are shown in Table 4.15 and depicted graphically in Figure 4.9 reflecting a picture characterised by increased tension (A_1=0.79) and strong reactions and threats from the part of Turkey (A_2=0.87 and A_3=0.77 respectively). It is reminded that these threats included attacking and destroying the system once installed and was accompanied by sending F16 fighters to the occupied airport of Lefkoniko aiming at reinforcing the Turkish position on the island. In short, the results obtained recreate the atmosphere prevailing on the island during the actual crisis period, when the FIR violations, the reinforcement to the Turkish forces on the island and the intense diplomatic activity from the part of Turkey were culminating. These seem to lead to adverse repercussions as regards the possibilities of a solution to the Cyprus problem (A_4=-0.77) and chances for peace talks (A_6=-0.63), while both the Cypriot and the Turkish governments suffer destabilizing effects (A_7=-0.41 and A_{13}=-0.71 respectively), results which are strongly supported by historical evidence referring to the period under study. The incident, however, does not appear to affect the stability of the Greek government (A_{12}=0.60), the support of which to the Greek-Cypriot army appears to be considerable (A_9=0.70), as it has been the actual case. The support to the Turkish forces on the island is very strong (A_8=0.88), a development sustained by the strength of the Turkish forces (A_{11}=0.66). Finally, the international influence has affected the crisis negatively (A_{15}=-0.85) given that, at least indirectly, it encouraged Turkish aggressiveness by opposing the purchase of the S-300 system.

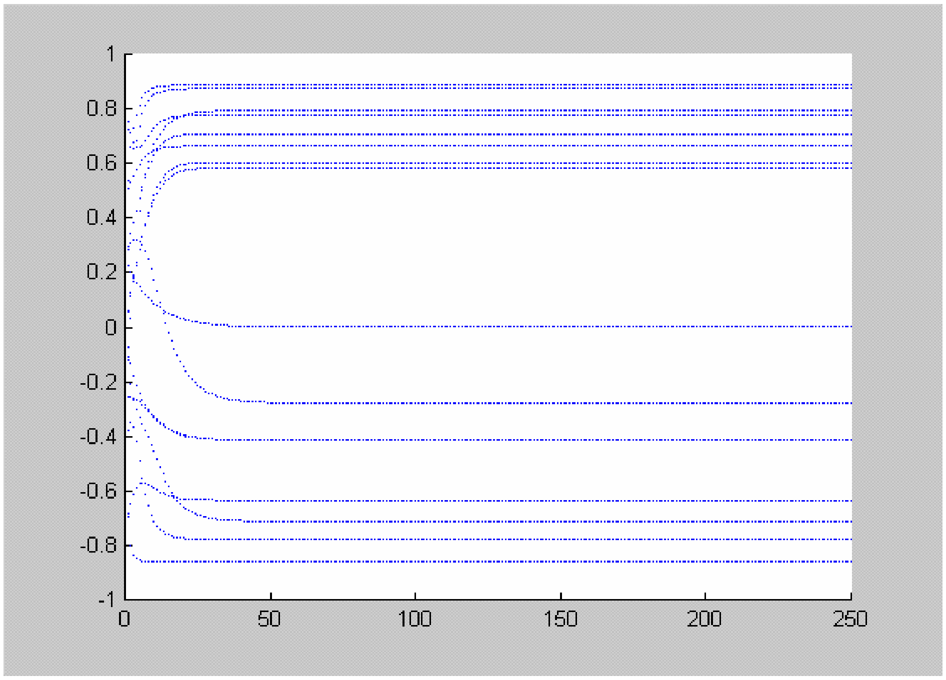


Figure 4.9: Graphical representation of S-300 crisis baseline simulation

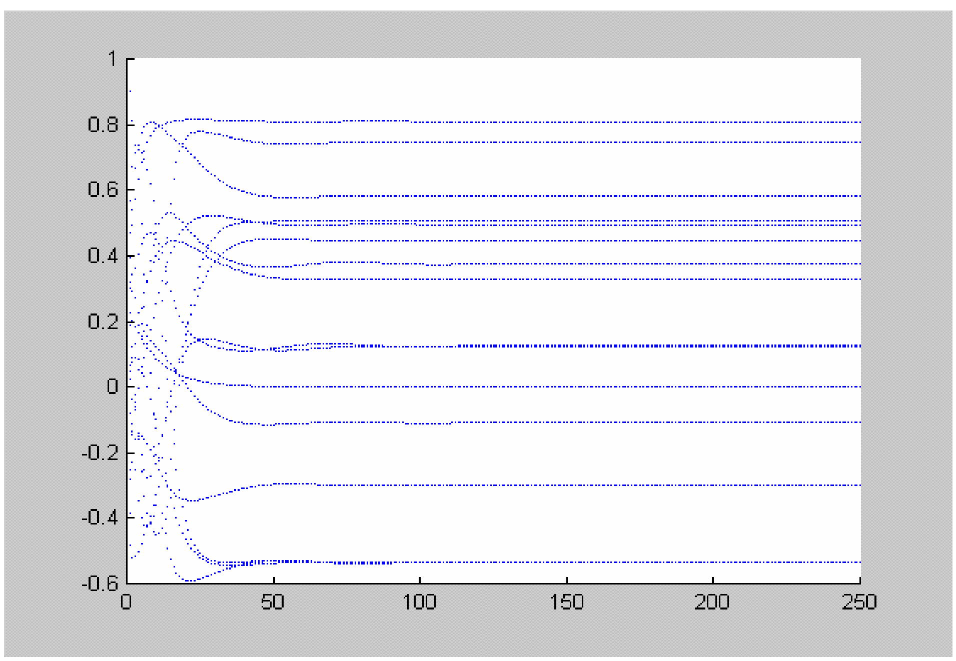


Figure 4.10: Scenario 1: Tension reduction for the S-300 crisis

4.4.2.4 Coping with the S–300 crisis: Tension reduction

At this stage we requested the model to consider a 50% reduction of the intensity on the island, aiming at evaluating the extent to which it can reflect the climate prevailing on the island with the tension cooling down after December 1998. The model has indeed reached the intensity-reduction target by attaining equilibrium at A_1=0.37 (Table 4.17 and Figure 4.10). The role of the international influence, climbed from A_{15}=-0.85 to A_{15}=0.74 indicating reluctance to approve the Turkish threats and actions in Cyprus that used to support a climate of tension, while its pressure upon the Cypriot side has also considerably contributed to the same direction. The latter is introduced in the model through the weight w40=0.27 (Table 4.16) which links the international influence C15 to the peace talks C6. The negative weight w39=-0.50 that links C15 with C4 (solution to the Cyprus issue) implies a decrease of the international support to the solution of the problem, something which reflects the shift of emphasis placed during the crisis period from solving the Cyprus problem to facing the S-300 crisis.

The reluctance of the Greek side to provide active military support to the installation of the S-300 on the island is reflected in the relevant zero activation level (A_{10}=0.0), unlike that of the Cypriot National Guard, the strength of which had reached A_9=0.8 revealing its adherence to the S-300 project. The Cypriot government itself does not seem to be confident enough about the decision to install the missiles, since its activation level drops to A_7=-0.53, given the disagreement which took place between the military and the politicians over the issue. Finally, special attention should be drawn to w25 that links the stability of the Greek government (C12) to the Greek support to the Cyprus issue (C5), the weight linking the two assuming the impressive value of 0.99. This underlines the unanimity and confidence of the Greek side concerning the influence exercised upon Cyprus.

Table 4.16: Settling the S-300 crisis: GE-FCM optimal weight matrix for target A_1=0.4

w1	**W2**	**w3**	**w4**	**w5**	**w6**	**w7**	**w8**	**w9**	**w10**	**w11**	**w12**
0.10	0.60	-0.65	0.13	0.25	-0.24	-0.21	0.48	0.59	-0.70	-0.49	0.81
W13	**w14**	**w15**	**w16**	**w17**	**w18**	**w19**	**w20**	**w21**	**w22**	**w23**	**w24**
-0.63	-0.67	0.88	-0.41	-0.77	0.79	0.89	0.38	-0.53	-0.04	0.22	-0.32
w25	**w26**	**w27**	**w28**	**w29**	**w30**	**w31**	**w32**	**w33**	**w34**	**w35**	**w36**
0.99	-0.20	0.80	0.88	-0.52	0.01	0.05	-0.47	-0.62	-0.67	0.88	0.55
w37	**w38**	**w39**	**w40**	**w41**	**w42**	**w43**	**w44**	**w45**			
-0.73	-0.14	-0.50	0.27	-0.41	-0.13	-0.09	-0.41	-0.37			

Table 4.17: Settling the S-300 crisis: Final activation levels for target A_1=0.4

C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
0.37	-0.53	-0.10	-0.29	0.44	0.49	-0.53	-0.53
C9	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**
0.80	0.00	0.50	0.58	0.12	0.32	0.74	0.12

So far we have demonstrated that using the proposed methodology decision-makers are able to introduce hypothetical cases reflected through a target activation level for a certain concept in the model and study the corresponding weights and activation levels for the rest of the concepts compatible with the predetermined target activation level. Based on this information, the policy maker is then able to take decisions leading to the desired simulated solution. Scenario analysis using only one concept is too simplistic a case. In most of the cases multiple scenarios are required because more than one condition may change at the same time.

4.5 Multiple scenario analysis using Genetically Evolved FCMs

4.5.1 Fitness function

The purpose of the proposed methodology for planning and executing scenarios with two or more desired Activation Level (AL) values is to find a suitable weight matrix with which the FCM reaches these final AL values after a predefined number of iterative computational steps thus satisfying a multi-objective scenario [120]. In this respect, the GA part of the GE-FCM is modified to a large extent so as to correspond to the demands and characteristics of FCMs scenario analysis more accurately in the light of its use in a multi-objective environment [37]. These modifications target at a quicker, more reliable and more efficient optimal or near-to-optimal solution [85].

In our GA part each individual (chromosome) represents a specific weight matrix used by the FCM to provide the final activation values of the participating concepts in equilibrium state [35]. It is obvious that more than one target values can be used. The evaluation of each individual is performed using the following fitness function (F):

$$F = 1/(\mathrm{abs}(targetofAL_1 - (AL_1)) + \mathrm{abs}(targetofAL_2 - (AL_2)) .... (\mathrm{abs}(targetofAL_n - (AL_n))) \quad 4.6$$

where, $targetofAL_n$ represent the desired values of specific ALs and AL_n the actual values calculated by the FCM using the specific weight matrix-individual.

The fitness value for each individual is always positive. The larger this number is the better the solution to the problem the matrix-individual offers.

The computation procedure of the GA starts with the random selection of the initial individuals (weight matrices). The evaluation of the fitness of each individual is performed after the FCM is run for a specific number of iterations. According to this calculated fitness value the most suitable individuals pass to the next generation and undergo crossover and mutation operations [130].

4.5.2 Crossover (recombination) and mutation

The GA executes a recombination for each couple of the fittest individuals as a result of which two offspring are produced. The technique we use is called intermediate recombination and it is ideal for real numbers [74]. Its main operation is based on the generation of a random value a in the range [–0.25, 1.25], which corresponds to the percentage of participation of each individual in the offspring. Each new value of the offspring's weight is calculated by the following equation:

$$w_{\text{new}}(x,y) = w_1(x,y) \cdot a + w_2(x,y) \cdot (1-a) \quad 4.7$$

where, $w_1(x,y)$ and $w_2(x,y)$ correspond to the weight value located at row x and column y of the weight matrix corresponding to the first and second offspring respectively.

Following the production of the offspring of the fittest individuals among the parents, the offspring pass to the next generation. Also it should be noted that 50% of the next generation's individuals represent parents that rank top as regards fitness, while the rest 50% is chosen among the rest offspring. After this selection the mutation operation is executed on all new individuals.

The mutation is used in the GA not only for the exploration of new solution sub-spaces, which otherwise would not be explored using only the recombination operation, but also for avoiding the "trapping at local maximum" phenomenon [35]. Due to the fact that the operation of FCM is similar to Gradient methods (e.g. hill-climbing, greedy first search, etc) [105], and because the specific optimization problem may contain a rich number of local maxima that increase proportionately to the increase of the number of ALs used in the fitness function, the utilization of mutation is not only desirable but also required. From a different point of view, mutation may cause a serious problem to the evolution of the value of the fitness function we call "backtrack".

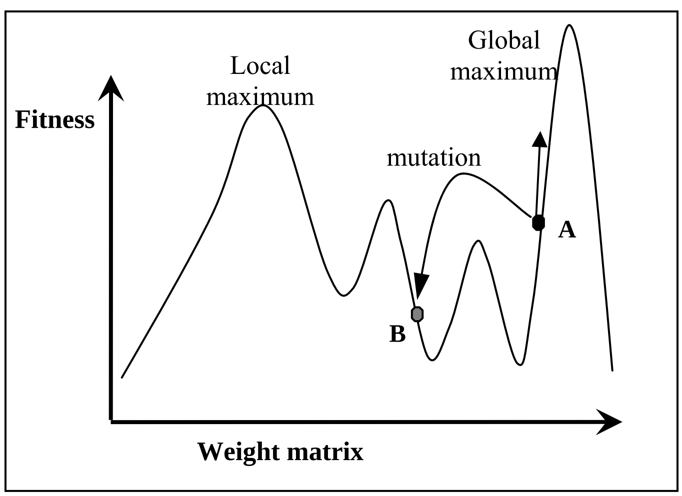


Figure 4.11: The mutation effect on the fitness value

More specifically, since one of the main characteristics of the FCM is its strong dependence on the values of specific weights (the first characteristic of an FCM as mentioned before), a random change of such a weight resulting from a mutation execution may cause a decrease of the fitness value of the specific individual [24]. Thus, the specific individual value, which gave a better fitness before the mutation (place A in Figure 4.11), and was probably a candidate optimal solution, is driven even to rejection from the next generation because its fitness is now considerably decreased (place B).

Aiming at avoiding this complication together with the loss of "good" individuals, our algorithm does not experiment only with a single mutation operation, but with a fixed number of mutations for each individual. It then selects the new individual value, which yielded a better fitness performance compared to that of the initial one and passes it to the next generation. If a better individual value in terms of fitness is not produced then the algorithm selects the best individual among the newly created after mutation.

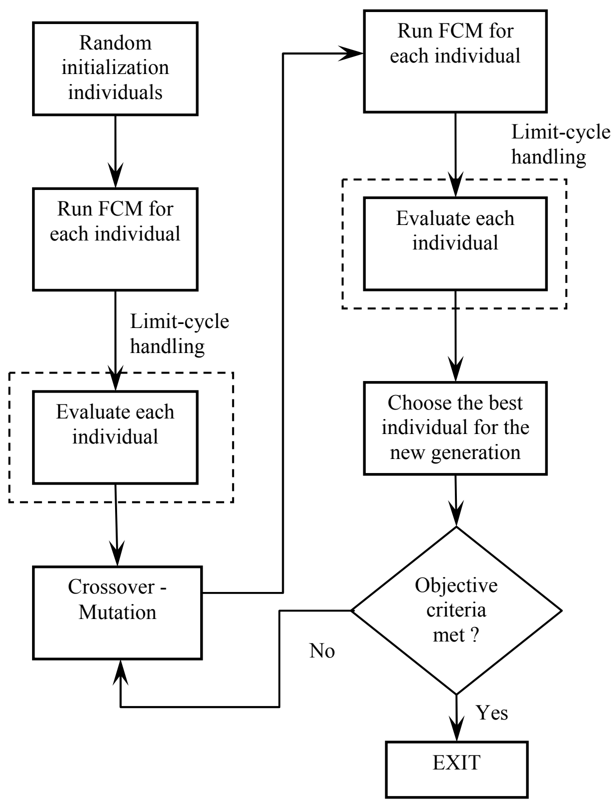


Figure 4.12: Logical diagram of the Genetic Algorithm

This means that an undesirable "local maximum" may appear in case the best individual generated yields only a small improvement or reduction in the fitness value of the initial. The process is as follows: The GA checks the progress of each individual after a specific number of epochs. If this progress is sufficient (i.e. there is an increase in fitness above a given threshold), then the GA continues its normal operation; in the opposite case it performs mutation not to just one weight but to a number of weights thus causing a significant change of the individuals, which helps exiting the "local maximum" and avoiding the loss of significant computational time [23]. The algorithm described above executes a number of iterations as depicted in Figure 4.12 and terminates when a predefined condition is met or when a maximum number of iterations (epochs) is reached.

4.5.3 Validation of the multi-optimization hybrid model on a real case: The S-300 crisis

In order to analyze the technical environment described above, we simulated the S-300 incident using the FCM model of Figure 4.1, with the initial activation levels defined on the basis of experts' knowledge. The model was adopted to reflect the 1998 S-300 missile crisis utilized to verify the methodology.

Table 4.18: S-300 crisis - Final ALs computed by the FCM

C1	Instability in Cyprus = 0.79
C2	Turkish Forces Actions = 0.87
C3	Turkish Threats = 0.77
C4	Solution of the Cyprus Problem = –0.77
C5	Greek political support = –0.41
C6	Un talks for the Cyprus problem = –0.63
C7	Stability of the Cyprus government = –0.41
C8	Support to the Turkish forces = 0.88
C9	Support to the Greek-Cypriot Army = 0.70
C10	Strengthening of the Greek army = 0.00
C11	Strengthening or the Turkish army = 0.66
C12	Stability of the Greek government = 0.60
C13	Stability of the Turkish government = –0.71
C14	EU/NATO political support = 0.58
C15	International influence = –0.85
C16	Turkish - Cypriot reactions = –0.27

The crisis between Cyprus, Turkey and Greece was started when Russia announced that they were ready to deliver the S-300 system to the Republic of Cyprus. The S-300 system was an advanced system capable of integrating and destroying aircraft at range up to 150 kilometers, and incoming missiles at range of up to 40 kilometers. With this procurement, the Cyprus government was potentially simply trying to change Turkey's air force superiority while at the same time protecting its newly built military base in Paphos. The capabilities of this system were considered that these missiles would pose a threat to its security.

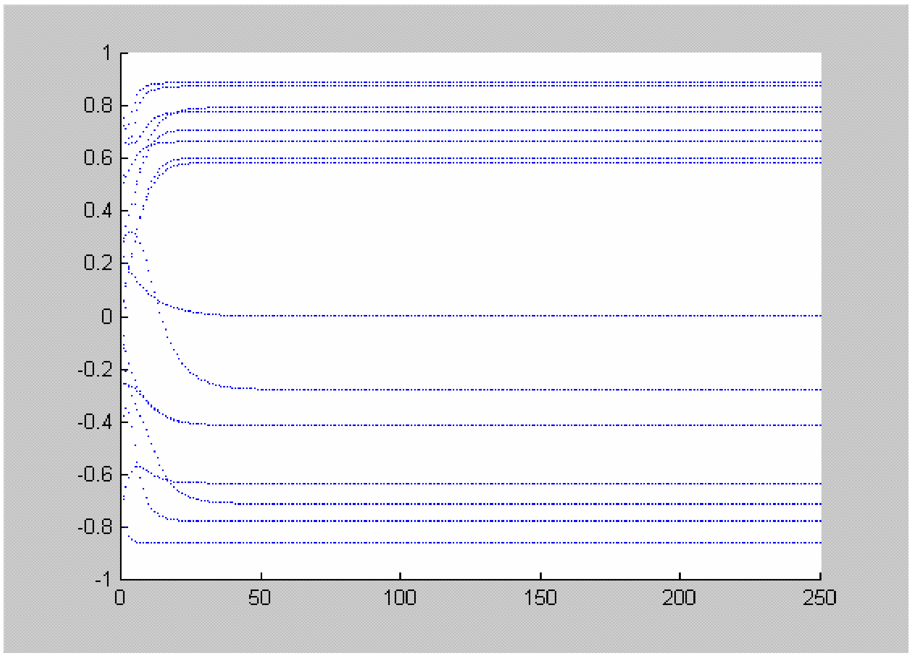


Figure 4.13: The S-300 crisis

The general political picture modeled (see figure 4.13 and Table 4.18) is characterized by increased tension (A_1=0.79) and strong reactions and threats from the part of Turkey (A_2=0.87 and A_3=0.77 respectively). It is reminded that these threats included attacking and destroying the system once installed. The results obtained reproduce the atmosphere prevailing on the island during the actual crisis period, when the FIR violations, the support to the Turkish forces on the island and the intense diplomatic activity from the part of Turkey were culminating. These seem to lead to adverse repercussions as regards to the possibilities of a solution to the Cyprus problem (A_4= –0.77) and chances for peace talks (A_6= –0.63), while both the Cypriot and the Turkish governments suffer destabilizing effects (A_7= –0.41 and A_{13}= –0.71 respectively), results which are strongly supported by historical evidence referring to the period under study. The incident, however, does not appear to affect the stability of the Greek government (A_{12}=0.60), the support of which to the Greek-Cypriot army appears to be considerable (A_9=0.70), as it has in fact been the case. The support to the Turkish forces on the island is very strong (A_8=0.88), a development sustained by the strength of the Turkish forces (A_{11}=0.66). Finally, the international influence has contributed negatively to the crisis (A_{15}= −0.85) given that, at least indirectly, it encouraged Turkish aggressiveness by opposing the purchase of the S-300 system.

4.5.4 Hypothetical Scenario: Increase of international influence and reduction of Greek political support to Cyprus

In this scenario we aim at investigating the potentials of increasing the influence of the international factor by setting A_{15}=0.8 and at the same time of reducing the political support offered by Greece to Cyprus by setting A_5=0.2. This hypothetical scenario will allow us to study the dynamics of the concepts, as well as the type of their relationships in the map (positive or negative), provided that both activation level targets are met. Under this scenario the GA will seek an optimal weight matrix, which will satisfy the hypothetically increased international influence and the reduction of the Greek support to the Cyprus government's decision to install the S-300 missile system in the island.

Table 4.19: S-300 crisis - ALs computed by the FCM

C1	Instability in Cyprus = 0.88
C2	Turkish Forces Actions = 0.77
C3	Turkish Threats = 0.80
C4	Solution of the Cyprus Problem = –0.77
C5	Greek political support = 0.19
C6	UN talks for the Cyprus problem = –0.76
C7	Stability of the Cyprus government = –0.49
C8	Support to the Turkish forces = 0.71
C9	Support to the Greek-Cypriot Army = –0.12
C10	Strengthening of the Greek army = –0.20
C11	Strengthening or the Turkish army = 0.75
C12	Stability of the Greek government = 0.62
C13	Stability of the Turkish government = 0.51
C14	EU/NATO political support = –0.46
C15	International influence = 0.7
C16	Turkish - Cypriot reactions = –0.61

The simulations are based on the following constant values for the variables involved: The population size has been set equal to 100 and the number of generations to 400. The weight values were randomly initialized in the range [-1, 1], while the probability of applying the genetic operator of recombination was set to 0.25 and that of mutation to 0.01.

Following the simulation the model reached the multiple targets yielding an equilibrium state. The final AL values calculated by the FCM using the optimal weight matrix (Table 4.19).

The analysis of the results will allow decision makers to understand the circumstances under which such a hypothesis may be realized: The instability in Cyprus is high (A_1=0.88) and this is mainly due to Turkish reactions (A_2=0.77) and Turkish threats which are increased (A_3=0.80). The role of the international influence is important in this case indicating that when pressure is exercised on Cyprus and with the role of the Greek Government almost neutral the instability can be high and no negotiations for the settlement of the Cyprus issue will exist (A_6=–0.76). The absence of negotiations keeps the solution of the Cyprus issue to the minimum level (A_4=–0.77). The Turkish Cypriots are against the decision of the Cyprus Government to purchase the missile system (A_{16}=–0.61) and do not participate to the negotiations for the settlement of the Cyprus Issue. The strengthening of the Greek-Cypriot army A_9=–0.12 and the Greek Army A_{10}=–0.20 stays at low levels in contrast to the strength of the Turkish army which is considered high (A_{11}=0.75). The reluctance of the Greek side to provide active military support to the installation of the S-300 missiles on the island is reflected in the activation level (A_{10}=–0.20), affecting the Cypriot National Guard, the support to which reached the low level of A_9=–0.12. The Cypriot government itself does not seem to be confident enough about the decision to install the missiles, since its activation level drops to A_7=–0.49, given the disagreement which took place between the military and the politicians over the issue. On the contrary, the stability for the Greek government (A_{12}=0.62) and the Turkish government (A_{13}=0.51) is high, showing that their decisions regarding this matter have already been taken. The EU/NATO withdraws its support to the Cyprus government (A_{14}=–0.46) and seems to support the International pressures to the Cyprus government not to install the S-300 system in Cyprus.

The hybrid system was validated on a well-known political crisis, that of the S-300 missiles, which took place between Turkey, Greece and Cyprus in 1997-1998, and proved its modelling efficiency. The model successfully predicted the dynamics behind a hypothetical situation giving the ability to decision makers to reach to some interesting conclusions. Thus, decision makers may study the concepts that led our model to reach this hypothetical state and plan their actions so as to work towards promoting or deteriorating the possibility for certain concepts to take the activation levels appearing in the map.

4.6 Fuzzy Knowledge Base

4.6.1 Linguistic Fuzzy Sets Encoding

Given that fuzzy knowledge-based systems [107] simulate human thinking; we have integrated a fuzzy knowledge base to GE-FCMs, aiming at capturing these aspects of human intelligence that are associated with the complexity of a real-world problem. The main focus in this case is to deal with this complexity by providing a simple methodology for constructing a GE-FCM hybrid system that bases its processing on a Fuzzy Knowledge Base, especially constructed for this particular case. This approach enables the incorporation of both symbolic and connectionist knowledge in one system and provides the means by which linguistic variables [61] are encoded in numerical values for carrying out mathematical computations with the result transformed back to descriptive values for inference purposes.

Our system is defined as an expert system [93], which uses the method of fuzzy logic and fuzzy knowledge in the form of Evolutionary Fuzzy Cognitive Maps systems using fuzzy data and fuzzy inference. The advantage of this method is the fuzzy knowledge representation reflecting the behaviour of the system [101].

The use of fuzzy sets provides a basis for a systematic way of manipulating vague and imprecise concepts which are treated in this case as representing linguistic variables [61]. A linguistic variable can be regarded either as a variable, the value of which is a fuzzy number, or as a variable assuming values defined in linguistic terms. It may be described by the quintuplet ($x, T(x), U, G, M$) in which x is the name of variable, $T(x)$ is the term set of x, that is, a set of linguistic values of x each of which corresponds to a fuzzy number defined in a set of real values *U, G* is a syntactic rule for generating the linguistic of values of *x* from their numerical counterpart, and *M* is a semantic rule for associating with each value its meaning. Each term *u* in *T(x)* can be classified in a certain fuzzy set *A* that uses a membership function $\mu_A(u) = U \rightarrow [0,1]$ which provides a real number in the interval [0, 1] indicating the degree to which *u* belongs to set *A*. A value of zero (0) means that the term is not a member of the set while a value of unity denotes complete set membership.

A rather simple example will clarify the matter: If we interpret Temperature, as a linguistic variable we may have a term set *T(temperature)={Low, Medium, High}* and each term in the term set may be characterized by a fuzzy set in a universe of discourse U=[0^{o}C, 40^{o}C]. The three crisp variables may be defined as *Low*=10^{o}C, Medium=20^{o}C and *High*=30^{o}C. This definition, though, does not cover values between the crisp variables, e.g. when temperature ranges between 0^{o}C and 10^{o}C, 10^{o}C and 20^{o}C, 20^{o}C and 30^{o}C. This is the reason why the conventional set operations must be extended to move from ordinary set theory to fuzzy set theory in order to consider cases in which, the fuzzy subsets have membership degrees. For example we may interpret *Low* as "Temperature below 10^{o}C", *Medium* as "Temperature close to 20^{o}C" and *High* as "Temperature above 30^{o}C". The terms can then be characterized as fuzzy sets whose membership functions are:

$$Low(v) = \begin{cases} 1 \ , \ if \ \ v \le 10 \\ 1-(v-10)/10 \ , \ if \ \ (10 \le v \le 20) \\ 0 \ , \ otherwise \end{cases} \qquad 4.8$$

$$Medium(v) = \begin{cases} 1-\left|v-20\right|/20 \ , \ if \ \ (10 \le v \le 30) \\ 0 \ , \ otherwise \end{cases} \qquad 4.9$$

$$High(v) = \begin{cases} 1 \ , \ if \ \ v \ge 30 \\ 1-(30-v)/10 \ , \ if \ \ (20 \le v \le 30) \\ 0 \ , \ otherwise \end{cases} \qquad 4.10$$

The fuzzification of the three crisp values as shown in Figure 4.14 describes the distribution of the variables that reflects the problem under study. It is obvious that this distribution produces two overlapping areas. Despite the fact, however, that overlapping is both common and even desirable on certain occasions, there is a problem with allocating values that fall within an overlapping area. For example, if temperature is equal to 17.5°C then this temperature belongs to both the *Low* and the *Medium* fuzzy sets, with membership values 0.25 and 0.75 respectively. Thus, we may infer that this temperature value may be considered as belonging to the *Low* interval with confidence level 25% and to the *Medium* with 75%. It is quite important to note in this case that we do not rule out the *Low* set membership of this temperature value just because its confidence level is significantly lower compared to that of the *Medium* set. In fact if fuzzy structure is used for decision-making, in particular, the two alternative classifications of the linguistic variables are equally important as indicating that we must consider more than one reaction.

The number of linguistic variables depends on the complexity of the real-world problem described by the model and the accuracy required. Along the same line in FCM the general structure of the fuzzification of a typical six-crisp variable describing the activation levels of a FCM is depicted in Figure 4.17.

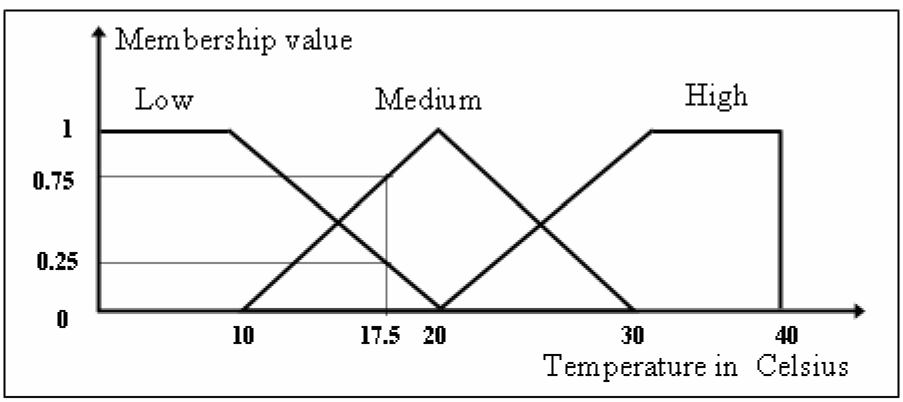


Figure 4.14: Membership Function of Linguistic Variable Temperature

The first interval begins at -1 and the last ends at +1. Each of the intervals is given a name, corresponding to a certain linguistic variable, and is subsequently stored in a fuzzy knowledge base in order to be used during the defuzzification process. The fuzzy set encoding is a key step in our framework because it is used to build up the most important element of the GE-FCM based Decision Support System, namely the Fuzzy Knowledge Base (FKB).

4.6.2 Integration of Fuzzy Knowledge Base to GE-FCM

Building knowledge-based systems is a very complicated task requiring occasional adjustment of knowledge, especially in cases of complex applications [104]. The integration of a Fuzzy Knowledge Base (FKB) to GE-FCMs as described in this section attempts to overcome this difficulty by encoding the experts' assessment concerning a given real-world problem and representing this knowledge in a graphical representation language [13]. More specifically, the linguistic sample is encoded directly in a numerical matrix using an uncertainty fuzzy distribution and is subsequently reduced to a scalar form [122]. This linguistic matrix reflects the quantization levels of the input and output spaces, and the number of fuzzy set values assumed by the fuzzy variables [54].

In Fuzzy Cognitive Maps the term set consists of specific linguistic variables describing the activation level of the concepts participating in the model. These variables are associated with values within the range [–1, +1]. The number of linguistic variables depends on the complexity of the real-world problem described by the model and the desired model accuracy. The general structure of the fuzzification of the crisp variables describing the activation levels is given in Figure 4.15.

The process of designing a GE-FCM model and integrating a FKB system is the following:

Stage 1. Identification

Verbal identification and description of the problem. Definition of the problem parameters that determine its target. These parameters will be treated in the next stage as the concepts participating in the model under construction.

Stage 2. Conceptualization

Selection of the parameters identified above as the candidate concepts of a FCM. For each concept the following must be defined:

- A descriptive name
- The causal relationships between this concept (source) and the rest of the concepts (destinations)
- The sign and weight value of each relationship

Stage 3. Formalization

Graphical representation of the FCM containing the concepts identified and their causal relationships. Implementation of the updating mechanism that calculates the new activation levels of the concepts for every iteration of the model.

Stage 4. Integration

Implementation of each concept as a linguistic variable.

For each linguistic variable definition of the following:

- The term set of the activation levels of the concept
- The range of numerical values for each member of the term set of the concept
- The membership function of each member of the term set. This will normally orient the overlapping areas

Stage 5. Experimentation

Determination of the initial levels of activation for each concept on the FCM. Calculation of the final activation levels (baseline) by running the model for a certain number of iterations and evaluation of the results. In case of a stable equilibrium then execution of next stage

Stage 6. Realization-Inference

Baseline activation levels analysis and interpretation of the results according to the Fuzzy Knowledge Base and the membership functions (i.e. the overlapping areas).

Creation of a number of scenaria with target values set for each activation level and use of the GE-FCM to drive the activation of the concept in focus to the desired level.

If the target is attained then use of the Fuzzy Knowledge Base to determine the context in which the target activation level is realized (i.e. the activation of the remaining concepts evolved by the GA that contribute to attaining the target).

Stages 1, 2 and 4 described above must be carried out with the aid of a group of experts who can determine the variables affecting the scope of the problem, and can describe the magnitude of each concept in the FCM using a linguistic fuzzy classification. Every expert proposes a fuzzy interval and its related linguistic explanation for each concept, thus identifying the important concepts or variables influencing our strategic target, as well as the various causal links between them.

4.6.3 Fuzification/Defuzzification Process

Decision-making is a task of critical importance. There is a wide variety of difficulties that decision makers face when approaching significant, real-world systems under uncertainty. For example, decision makers have to face the increased complexity which characterizes the interrelation of the various dynamic components (concepts) of a certain problem encountered. When it comes to requiring numerical data, these may be hard to trace, or unreliable, while formulating a mathematical model may be difficult and costly, or even impossible. What a FCM does, in fact, is allow the policy-maker to perform a qualitative simulation through scenario analysis [36]. In fact, policy proponents can publish a model of the system under discussion and illustrate their case using simulation experiments. The next step involves simulating different scenarios by asking the model to reach a desirable activation level for a certain concept that the policy maker focuses on [107]. The Genetically Evolved Fuzzy Cognitive Maps (GE-FCM) model calculates the new optimal weight matrix, which is then used by the GE-FCM model to recalculate the new activation levels of the concepts [14].

The fuzzification process is based on producing fuzzy information provided by a group of experts, each concept analyzed into membership functions of fixed or variable widths. Each of these intervals is labelled and stored for the defuzzification process later on. For each domain expert consulted, their activation levels and weight values are entered and normalized based on their respective ranking [163]. The defuzzification procedure takes place, where the levels are matched according to the membership functions of each concept. This process is more complicated than the fuzzification and consists of four basic iterative stages: The Iteration stage involves the determination of the initial levels of activation for each concept on the FCM and the calculation of the final activation levels. The next step computes the minimum, maximum and average values for each concept of this matrix, with the levels matched according to their membership functions. The third stage matches the average, minimum and maximum values for each concept derived during fuzzification to find the interval these three parameters fall into. The last stage is the inference stage in which, following the creation of hypothetical scenarios [66], the Fuzzy Knowledge Base is used to determine the context in which the target activation level will be realized.

4.6.3.1 Fuzzification Process

The fuzzification process consists of two basic steps [116]. During the first step the interval of each concept is analyzed into trapezoidal membership functions, as shown in Figure 4.15. Since the concept activation levels fall in the range between -1 and +1, the concept intervals themselves must also fall in this range. The minimum and maximum number of intervals used in all our models ranges between two and eight, having a fixed width or variable length, as shown in Figures 4.15 and 4.16**.** Other membership functions (e.g. triangle) may also be appropriate and can be utilised with success depending on the problem being modelled; the trapezoidal membership function is selected in our case studies on one hand due to its simplicity and efficiency with respect to computability and on the other because it is able to represent more accurately the linguistic variables used in our modelling attempt.

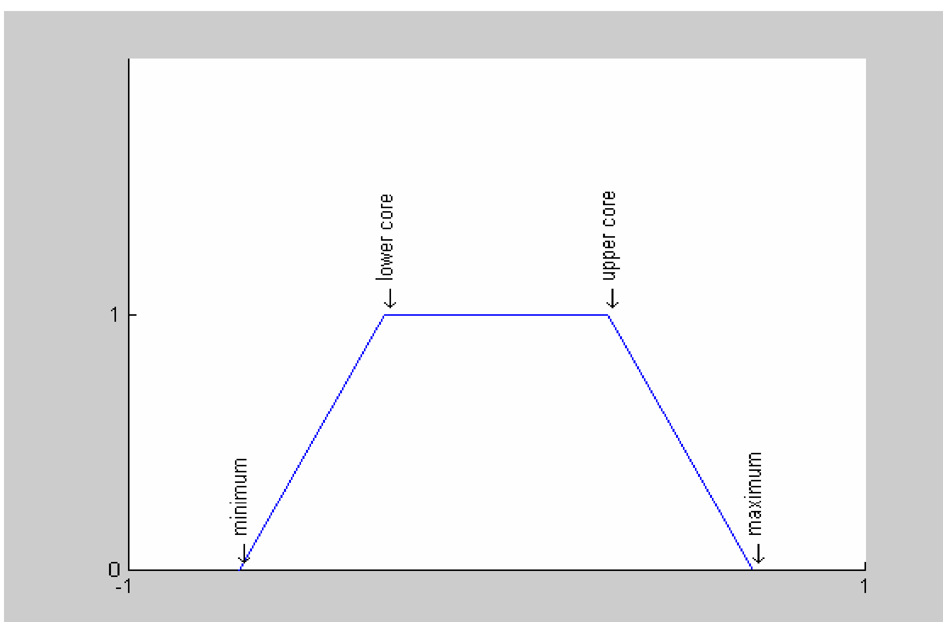


Figure 4.15: The trapezium formed by the interval limits and overlap percentage

Figure 4.16 shows how the fuzzification of three crisp values causes the distribution of the variables according to a certain profile that reflects the problem under study. In such a case the problem arising when values that fall within an overlapping area must be allocated is handled during the defuzzification process.

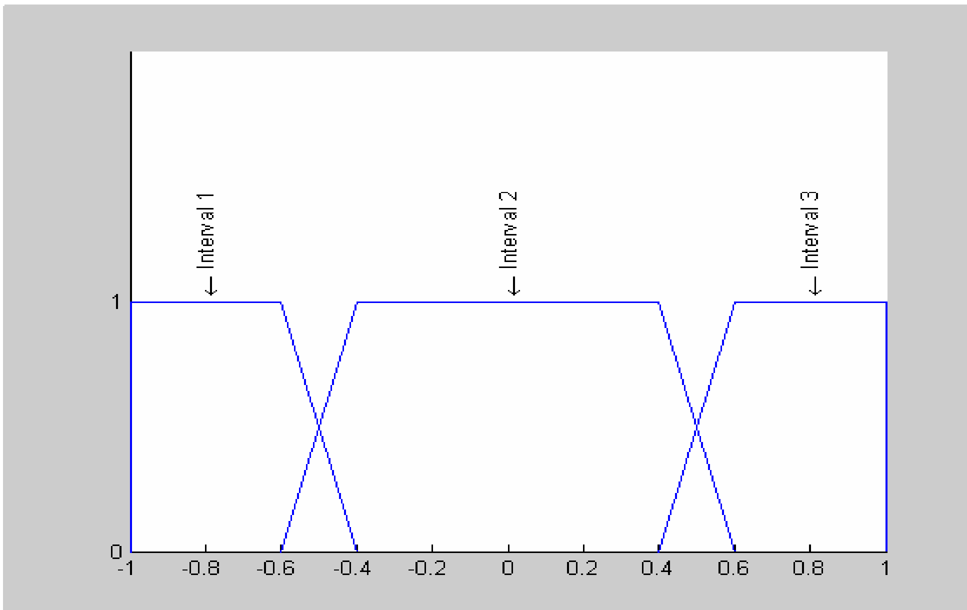


Figure 4.16: A concept with 3 membership functions of variable width

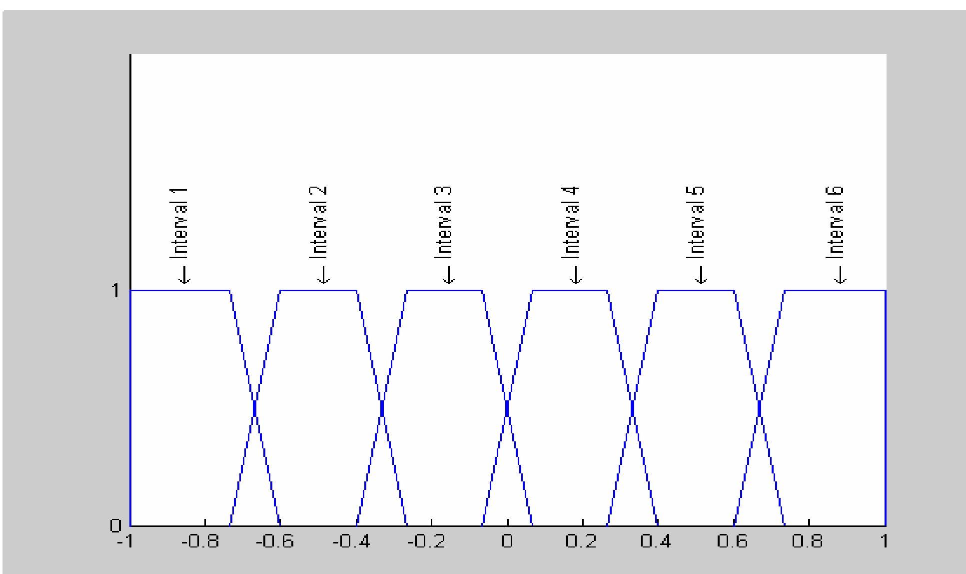
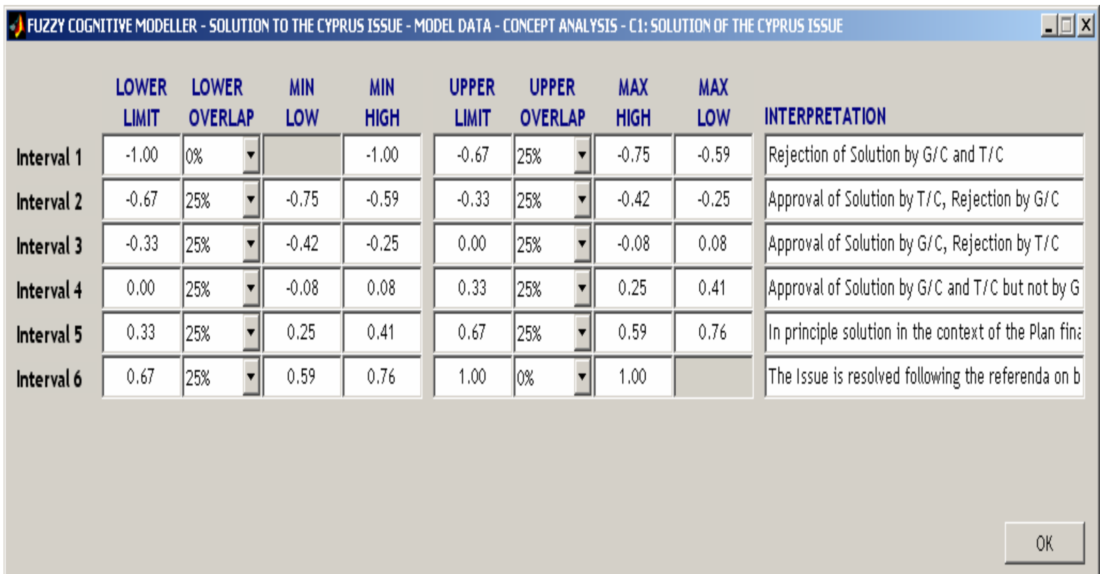


Figure 4.17: A concept with 6 membership functions

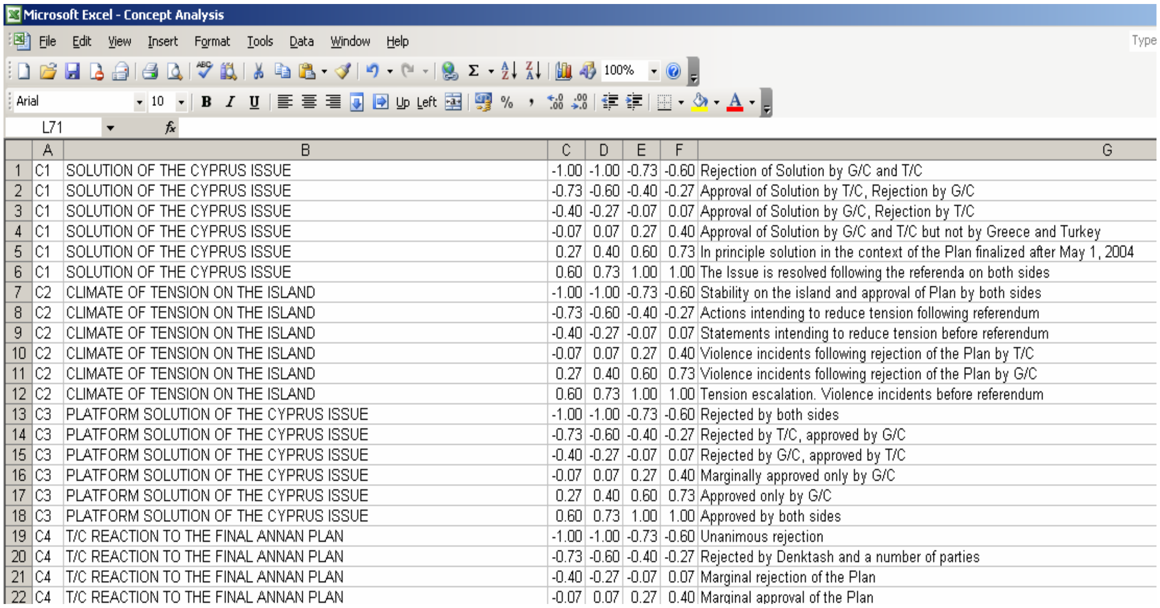
As previously mentioned in Fuzzy Cognitive Maps the term set consists of specific linguistic variables describing the activation levels of the concepts participating in the model. These variables are linked to specific values within the range of [–1, +1]. The general structure of the fuzzification of six crisp variables describing the activation levels is depicted in Figure 4.17.


FUZZY COGNITIVE MODELLER - SOLUTION TO THE CYPRUS ISSUE - MODEL DATA - CONCEPT ANALYSIS - C1: SOLUTION OF THE CYPRUS ISSUE

	LOWER LIMIT	LOWER OVERLAP	MIN LOW	MIN HIGH	UPPER LIMIT	UPPER OVERLAP	MAX HIGH	MAX LOW	INTERPRETATION
Interval 1	-1.00	0%		-1.00	-0.67	25%	-0.75	-0.59	Rejection of Solution by G/C and T/C
Interval 2	-0.67	25%	-0.75	-0.59	-0.33	25%	-0.42	-0.25	Approval of Solution by T/C, Rejection by G/C
Interval 3	-0.33	25%	-0.42	-0.25	0.00	25%	-0.08	0.08	Approval of Solution by G/C, Rejection by T/C
Interval 4	0.00	25%	-0.08	0.08	0.33	25%	0.25	0.41	Approval of Solution by G/C and T/C but not by G
Interval 5	0.33	25%	0.25	0.41	0.67	25%	0.59	0.76	In principle solution in the context of the Plan fin
Interval 6	0.67	25%	0.59	0.76	1.00	0%	1.00		The Issue is resolved following the referenda on b

Figure 4.18: A concept associated with a number of linguistic variables

Each interval is then given a name, corresponding to a certain linguistic variable as shown in Figure 4.18 and is subsequently stored in a Fuzzy Knowledge Base (FKB) in order to be used in the defuzzification process. Building a FKB is the second step of the fuzzification process [13]. The linguistic sample is encoded directly in a numerical matrix using an uncertainty fuzzy distribution and is subsequently reduced to a scalar form. As shown in Figure 4.19 this linguistic matrix reflects the quantization levels of the input and output spaces, and the number of fuzzy set values assumed by the fuzzy variables.



	A	B	C	D	E	F	G
1	C1	SOLUTION OF THE CYPRUS ISSUE	-1.00	-1.00	-0.73	-0.60	Rejection of Solution by G/C and T/C
2	C1	SOLUTION OF THE CYPRUS ISSUE	-0.73	-0.60	-0.40	-0.27	Approval of Solution by T/C, Rejection by G/C
3	C1	SOLUTION OF THE CYPRUS ISSUE	-0.40	-0.27	-0.07	0.07	Approval of Solution by G/C, Rejection by T/C
4	C1	SOLUTION OF THE CYPRUS ISSUE	-0.07	0.07	0.27	0.40	Approval of Solution by G/C and T/C but not by Greece and Turkey
5	C1	SOLUTION OF THE CYPRUS ISSUE	0.27	0.40	0.60	0.73	In principle solution in the context of the Plan finalized after May 1, 2004
6	C1	SOLUTION OF THE CYPRUS ISSUE	0.60	0.73	1.00	1.00	The Issue is resolved following the referenda on both sides
7	C2	CLIMATE OF TENSION ON THE ISLAND	-1.00	-1.00	-0.73	-0.60	Stability on the island and approval of Plan by both sides
8	C2	CLIMATE OF TENSION ON THE ISLAND	-0.73	-0.60	-0.40	-0.27	Actions intending to reduce tension following referendum
9	C2	CLIMATE OF TENSION ON THE ISLAND	-0.40	-0.27	-0.07	0.07	Statements intending to reduce tension before referendum
10	C2	CLIMATE OF TENSION ON THE ISLAND	-0.07	0.07	0.27	0.40	Violence incidents following rejection of the Plan by T/C
11	C2	CLIMATE OF TENSION ON THE ISLAND	0.27	0.40	0.60	0.73	Violence incidents following rejection of the Plan by G/C
12	C2	CLIMATE OF TENSION ON THE ISLAND	0.60	0.73	1.00	1.00	Tension escalation. Violence incidents before referendum
13	C3	PLATFORM SOLUTION OF THE CYPRUS ISSUE	-1.00	-1.00	-0.73	-0.60	Rejected by both sides
14	C3	PLATFORM SOLUTION OF THE CYPRUS ISSUE	-0.73	-0.60	-0.40	-0.27	Rejected by T/C, approved by G/C
15	C3	PLATFORM SOLUTION OF THE CYPRUS ISSUE	-0.40	-0.27	-0.07	0.07	Rejected by G/C, approved by T/C
16	C3	PLATFORM SOLUTION OF THE CYPRUS ISSUE	-0.07	0.07	0.27	0.40	Marginally approved only by G/C
17	C3	PLATFORM SOLUTION OF THE CYPRUS ISSUE	0.27	0.40	0.60	0.73	Approved only by G/C
18	C3	PLATFORM SOLUTION OF THE CYPRUS ISSUE	0.60	0.73	1.00	1.00	Approved by both sides
19	C4	T/C REACTION TO THE FINAL ANNAN PLAN	-1.00	-1.00	-0.73	-0.60	Unanimous rejection
20	C4	T/C REACTION TO THE FINAL ANNAN PLAN	-0.73	-0.60	-0.40	-0.27	Rejected by Denktash and a number of parties
21	C4	T/C REACTION TO THE FINAL ANNAN PLAN	-0.40	-0.27	-0.07	0.07	Marginal rejection of the Plan
22	C4	T/C REACTION TO THE FINAL ANNAN PLAN	-0.07	0.07	0.27	0.40	Marginal approval of the Plan

Figure 4.19: Linguistic Fuzzy knowledge Base

4.6.3.2 Defuzzification Process

As we have already pointed out, the defuzzification process is more complicated than the fuzzification one and consists of four basic iterative stages [116]. These steps are described in this section, while examples of the results of defuzzification process are shown in Figure 4.19 and Table 4.20.

Stage 1. Iteration

Determination of the initial activation levels for each concept of the FCM. Calculation of the final (baseline) activation levels by running the model for a certain number of iterations and subsequent evaluation of the results derived.

Following one hundred iterations, the results are stored in an *m-by-n* matrix *K* where *m* is the number of concepts and *n* is the number of iterations remaining after the final iteration. We consider that the model is stabilized after one hundred iterations.

Stage 2. Max-Min and Mean Computation

The next step uses matrix *K* to match the appropriate values according to the membership functions of each concept. There are several methods for matching the estimated values, with the main ones being *Max-Min* and *Average*.

Running the model may lead to three possible outcomes: Equilibrium, limit cycle or chaos [112]. A concept is considered to reach equilibrium if the absolute difference of *Max-Min* (peak to peak) value is *0.01* or lower. A concept is classified as a limit cycle in cases in which the absolute difference of *Max-Min* value lies between 0.01 and 0.75.

Stage 3. Categorization

The average, Maximum and Minimum values of the oscillations of the limit cycle are matched depending on the interval these three parameters fall into as a result of the fuzzification process. In cases of equilibrium and limit cycle, if the average value of the concept falls in just one interval then the concept has a confidence rate of 100% and the final level is assigned the meaning of that interval. Whenever the average value falls within two adjacent intervals, the algorithm retains the interval with the highest confidence rate, with the meaning of that interval assigned to the final level. In the case of chaos, by contrast, no meaning can be given to the final level.

Stage 4. Realization-Inference

This last stage involves the implementation of a number of hypothetical scenaria with target values set for each activation level and the GE-FCM used to drive the activation of the concept of interest to the desired level. If the target is attained then the Fuzzy Knowledge Base is employed to determine the context in which the target activation level is realized.

Table 4.20: Defuzzification analysis results

ID	MIN.	MAX.	AVER.	FINAL	CONF.	ANALYSIS RESULT
C1	-0,57	-0,57	-0,57	-0,57	100,00	Approval of Solution by T/C, Rejection by G/C
C2	-0,01	-0,01	-0,01	-0,01	57,60	Statements reducing tension before referendum
C3	-0,79	-0,79	-0,79	-0,79	100,00	Rejected by both sides
C4	0,41	0,41	0,41	0,41	100,00	Approved by the majority of the parties
C5	0,43	0,43	0,43	0,43	100,00	Approved by the majority of the parties
C6	-0,68	-0,68	-0,68	-0,68	58,83	Rejection by both sides/ Greece and Turkey
C7	-0,79	-0,79	-0,79	-0,79	100,00	Unanimous rejection
C8	-0,87	-0,87	-0,87	-0,87	100,00	Unanimous rejection by all parties
C9	0,39	0,39	0,39	0,39	93,36	Pressure on the T/C and the Turkish
C10	-0,70	-0,70	-0,70	-0,70	78,32	Full membership of Cyprus freezes
C11	-0,54	-0,54	-0,54	-0,54	100,00	No support to Turkish full membership
C13	0,72	0,72	0,72	0,72	92,72	Support of the full membership of Turkey

4.7 Automatic drawing of FCM (Simplification)

After all expert level and weight matrices have been included in the model [119], what is left is to normalise the matrices based on the ranking of each expert. Since the expert levels and weights form the basic inputs of the FCM and GE-FCM algorithms it is essential that all levels and weights be represented in one single matrix in each case. In order to avoid complicated calculations, a tool which was designed to serve this capability automatically calculates the normalised values followed by the automatic drawing of the Fuzzy Cognitive Map. Following the fuzzification process, the methodology is improved to offer the ability to construct the model map diagrammatically so that the decision-maker can visually observe the problem at its current state. The map is drawn using nodes and edges, where each concept is symbolised by a node with a unique colour in order to be easily identified (Figure 4.20). Similarly, each weight is symbolised by an arrow leading from the cause concept to the effect concept taking the colour that is equivalent to that of the cause concept. However, if a certain layout is unsatisfactory, there is an option to redraw the map until an improved layout is decided upon. Other actions the tool allows include printing and saving the map in the workspace, while the user is given the ability to right-click on the map draw additional information on concept levels and weights with the aid of dialog boxes.

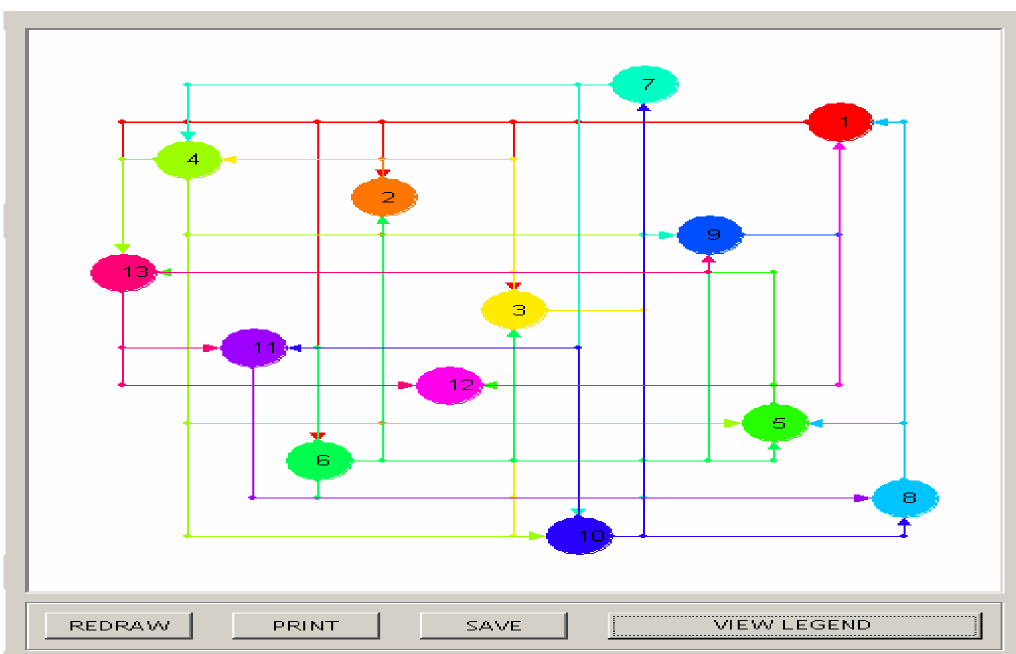


Figure 4.20: Map depiction via the tool

4.8 The limit cycle phenomenon

As previously mentioned, a GE-FCM can reach equilibrium at fixed points in a direct way with the activation levels being decimals in the interval [-1, 1]. It can also exhibit limit cycle behaviour where the system falls in a specific-period loop, reaching the same state after a certain number of steps [71]. A limit cycle phenomenon is encountered in cases where a dynamic system falls into periodic oscillations, failing to ever reach equilibrium. Such oscillations can occur in neural systems due to properties of single neurons [112] and properties of synaptic connectivity among neurons.

The equations that are applied at equilibrium points can be calculated by means of equation (4.11). The equilibrium state is described as:

$$A_i^{t+1} = A_i^t, \quad for \quad i = 1 \ldots n \tag{4.11}$$

This is true only when A_i^t and S_i^t are of the same sign. The equilibrium point is reached on the basis of either the first or the second rule expressed by equations 4.12 and 4.13 respectively. When both A_i^t and S_i^t take positive values, we can calculate the equilibrium value as follows:

$$\begin{aligned}
&\text{If } A_i^t > 0 \text{ and } S_i^t \text{ then} \\
&A_i^{t+1} = A_i^t \Rightarrow A_i^t + S_i^t(1 - A_i^t) - d_i A_i^t = A_i^t \\
&\Rightarrow S_i^t - S_i^t A_i^t - d_i A_i^t = 0 \\
&\Rightarrow A_i^t(d_i + S_i^t) = S_i^t \\
&\Rightarrow A_i^t = \frac{S_i^t}{(d_i + S_i^t)}
\end{aligned} \tag{4.12}$$

$$\begin{aligned}
&\text{If } A_i^t < 0 \text{ and } S_i^t < 0 \text{ then} \\
&A_i^{t+1} = A_i^t \Rightarrow A_i^t + S_i^t(1 + A_i^t) - d_i A_i^t = A_i^t \\
&\Rightarrow S_i^t + S_i^t A_i^t - d_i A_i^t = 0 \\
&\Rightarrow A_i^t (d_i - S_i^t) = S_i^t \\
&\Rightarrow A_i^t = \frac{S_i^t}{(d_i - S_i^t)}
\end{aligned} \qquad 4.13$$

In case that A_i^t and S_i^t are of opposite signs, we can conclude that $A_i^{t+1} = A_i^t$ cannot be satisfied.

$$\begin{aligned}
&A_i^t > 0,\ S_i^t < 0 \Rightarrow f_M(A_i^t, S_i^t) < A_i^t \\
&\Rightarrow f_M(A_i^t, S_i^t) - d_i A_i^t < A_i^t \Rightarrow A_i^{t+1} < A_i^t
\end{aligned} \qquad 4.14$$

$$\begin{aligned}
&A_i^t < 0,\ S_i^t > 0 \Rightarrow f_M(A_i^t, S_i^t) > A_i^t \\
&\Rightarrow f_M(A_i^t, S_i^t) - d_i A_i^t > A_i^t \Rightarrow A_i^{t+1} > A_i^t
\end{aligned} \qquad 4.15$$

In this case the system enters into limit cycle behaviour and the values assumed by the various concept activation levels change periodically, something that reveals the existence of strong interactions between the concepts.

4.8.1 Handling limit cycles: Improving the inference procedure

During the execution phase of the FCM algorithm, all values computed for iterations after processing this limit cycle bound are stored in a matrix, with a minimum, maximum and average value computed for each concept (i.e. each row in the matrix). Under these circumstances there are three possible outcomes: A concept is considered at equilibrium if its minimum and maximum values have an absolute difference of 0.01 or lower. The behaviour of a concept is classified as a limit cycle if the absolute difference between its minimum and maximum values lies between 0.01 and 1.50 (75% of the range of values). Finally, a concept is treated as presenting chaotic behaviour if the absolute difference between its minimum and maximum values exceeds 1.50. In cases of equilibrium and limit cycle, the inference procedure may be applied, while in the case of chaos [180] no linguistic variable can be assigned to the final level and the results can not be considered reliable enough to be used for inference purposes [15].

With respect to limit cycle the proposed inference process for a certain activation level under limit cycle consists of two basic steps:

The first step involves classifying the activation level with respect to its minimum and maximum values as “Bounded limit cycle”, or “Unbounded limit cycle- Possible chaos”. Since the range of values for the activation levels in our case is [-1, 1] the *Baseline Size* of the interval is 2. This value is used as reference figure with respect to which the difference between maximum and minimum values (peak to peak) of each *AL* is calculated in percentage terms. If this difference is lower or equal to the 75% of the *Baseline Size* then the oscillation of the activation level is characterized as “Bounded limit cycle”, and inference is possible through the *Mean* value which is then matched to the appropriate fuzzy interval and defuzzified. In cases in which this difference is greater than [0.75*Baseline Size] the oscillation is characterized as “Unbounded limit cycle- Possible chaos”. In this case the oscillation spans all the available space in the range [*Minimum, Maximum*] and thus the *Mean* value cannot be matched to a single fuzzy interval with confidence, meaning that inference is not possible due to the low degree of reliability of the resulting *Mean* value.

The second step is followed only in the case of a “Bounded limit cycle”. The *Mean* value of the specific activation level presenting limit cycle is matched with a certain fuzzy set interval according to the analysis given for the specific concept. There are two possibilities in this case:

- The *Mean* value falls in one interval only, and thus the confidence level of this fuzzy set is 100%.
- The *Mean* value belongs to two overlapping fuzzy intervals, thus corresponding to two confidence levels, one for each interval. In this case, the value indicating the actual confidence level is assumed by the membership function of the *Mean* value for each of the overlapping fuzzy intervals. The interval chosen for inference purposes is the one for which the *Mean* assumes the highest membership value, or, equivalently, the highest confidence level.

Figure 4.21 demonstrates the proposed smoothening method: The system is run for a total of 250 iterations presenting limit-cycle behaviour while the smoothening process has been applied after the first 100 iterations. Following the computation of the *Mean* value for every activation level presenting limit cycle, the system investigated the type each oscillation something that led to all limit cycles being classified as "BOUNDED". Given that smoothening was considered reliable, for the next 150 iterations the system stabilizes and reaches equilibrium at the fixed points of the smoothened values.

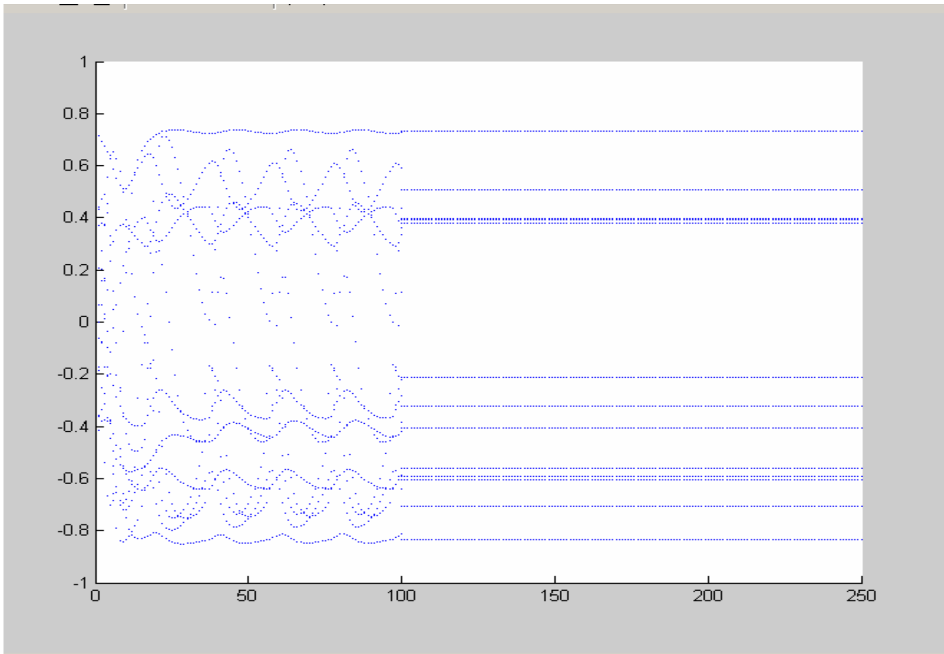


Figure 4.21: Smoothened Limit cycle

The weakness introduced by the limit cycle phenomenon in such systems is an open issue offering ample room for further research in the topic. As described above, when a GE-FCM hybrid system enters a limit cycle phase the experts cannot identify the external influences that drive the system to this behaviour, as in the case of the simple FCM, due to the fact that these influences are controlled automatically by the optimisation process of the Genetic Algorithm [59]. Therefore, the only alternative is to turn to a method that will attempt to eliminate the limit cycle observed and lead to a stable and reliable model.

4.8.2 Methodology for elimination of limit cycles in FCM

The presence of a limit cycle reached by a weight matrix-individual ("seek" individual) causes many problems to the hybrid system. The algorithm we will propose here avoids the persistence of a limit cycle by tracing the weight(s) that caused the limit cycle and modifying its (their) value(s). More specifically, following the modification of a weight matrix-individual using recombination or mutation, our algorithm checks the values of certain activation levels for a given number of iterations.

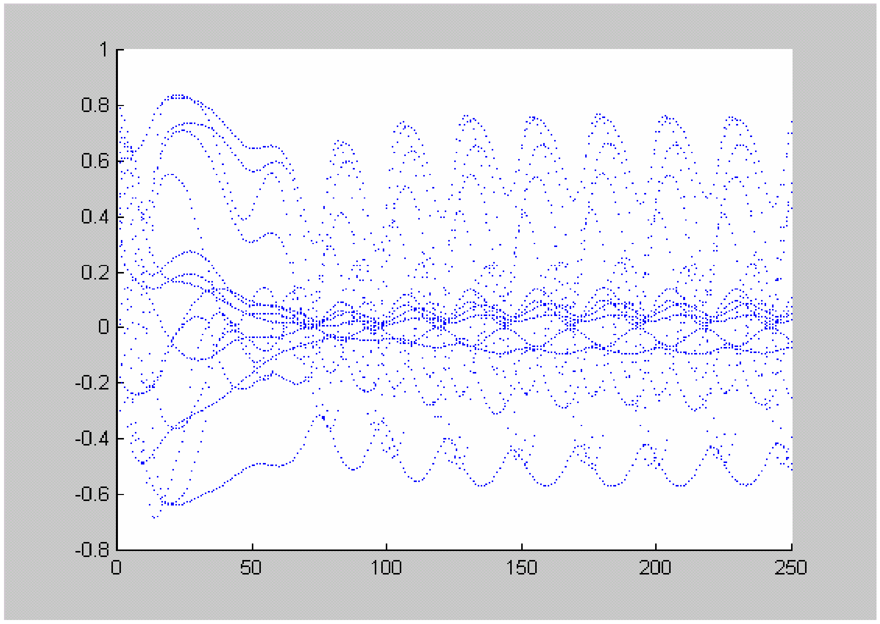


Figure 4.22: Limit cycle

If a difference is observed, then this case is classified as "limit cycle". The weights are then examined one-by-one until those causing the limit cycle (newly modified weights) are located. The values of these weights are repeatedly changed in a random way and the map is run until the limit cycle is removed.

This GA-based methodology to eliminate the limit cycle consists of two main steps described in the subsections below:

4.8.2.1 Checking for limit cycles

Before applying the elimination technique the structure of a limit cycle must be first investigated [72]. The functioning of an oscillation is characterized by three parameters: (i) frequency, (ii) phase and (iii) amplitude. Equilibrium can be described as the case in which all oscillatory units of an ensemble stabilise their frequency to a constant value and their phase and amplitude difference to a constant point within the interval [–1, 1]. Consequently, the stability of an equilibrium oscillation can be described as follows:

$$
\begin{aligned}
&F_k(t) \to Fconst,\ \text{for } t \to \infty \\
&\left|P_k(t) - P_{k+1}(t)\right| \to 0,\ \text{for } t \to \infty \\
&\text{for } k = 1, 2, \ldots, n-1
\end{aligned}
\qquad 4.16
$$

Where, F_k(t) is the frequency of the k^{th} oscillator, at time t in the ensemble of n oscillators, and P_k(t) is its phase at time t. In our case the oscillation is not continuous, as in the case of a sinus wave; it emerges in discrete steps as the activation levels are computed for a certain number of iterative steps.

The objective of the proposed methodology is to eliminate the phenomenon by adjusting the weight matrix which is responsible for the creation of the limit cycle phenomenon. The system first checks whether the system exhibits a limit cycle or chaotic behaviour; if so it searches in the weight matrix table to identify which weight or group of weights created the limit cycle.

4.8.2.2 Genetic optimization to eliminate the phenomenon of limit cycles

The purpose of the proposed methodology for eliminating the limit cycle phenomenon is first to define a new weight matrix W that will lead to equilibrium and second to specify the importance of each node in achieving the goal state. The relative importance of each node is encoded in a weight matrix. Thus, the objective is to identify the weight or group of weights that cause the limit cycle behaviour, using a new algorithm named Genetically Evolved Limit Cycle Elimination (GE-LCE) which is proposed and described in this section [123].

According to the pseudo code of Table 4.21, the first step is to create the FCM model and run it according to the weights and initial activation levels defined by the experts. Next, the FCM algorithm is executed and the final state of the map is checked to see whether it presents limit cycle(s). If so, we turn to the experts once again for manual correction of the weights so as to avoid the cycles. If not, we move to executing the GE-

FCM algorithm which takes a target activation level value and attempts to evolve an optimal weight matrix with which the map reaches the target value.

Table 4.21: Pseudo code of the algorithm that eliminates limit cycles.

```
Procedure create_FCM
  READ Activation List
  READ Weight Matrix
  RUN CNFCM algorithm
  IF model is in Equilibrium THEN
     RUN GECNFCM algorithm
  ELSE
     Go back to the experts and revise the Weight Matrix
  ENDIF
  EXECUTE GECNFCM algorithm
  READ new Weight Matrix (optimized)
  RUN CNFCM algorithm
  IF model is in Equilibrium THEN
     CALL Defuzzification Process
  ELSE
     CALL Limit_Cycle_Elimination Procedure
  ENDIF
End Procedure create_FCM

Procedure Limit_Cycle_Elimination
  FOR  j = 1 to number of weights
      {Crossover}
      Select two individuals (weight matrices) according to fitness
      Select Crossover Point cp
      Exchange j weights from point cp to the left {Mutation }
      Select one individual (weight matrix) according to fitness
      Select randomly a weight and mutate it (+/- 0.1)
      Evaluate individuals and calculate their fitness
      RUN CNFCM algorithm
      IF model is in Equilibrium
         CALL Defuzzification process
         BREAK (stop)
      ENDIF
  ENDFOR
End Procedure Limit_Cycle_Elimination
```

Once the evolutionary process is completed we check for limit cycles by using the optimal weight matrix produced by the genetic algorithm of the GE-FCM and executing the simple FCM. If one or more limit cycles are traced we run the limit cycle elimination procedure, otherwise we proceed with the defuzzification of the numerical values calculated for the ALs. The elimination procedure attempts to evolve the weights so as to stabilize all activation levels in steady states. To do so the algorithm starts evolving the weight matrices by basing the application of genetic operations (crossover, mutation) on *n* weights each time, with *n* starting from 1 and reaching to the total number of weights (if necessary).

In the GE-LCE algorithm a dedicated fitness function is used to define the appropriateness of the weight matrices participating in the optimization process [53]. The evaluation of each individual weight matrix WM_i is performed using the following fitness function:

$$fitness(WM_i) = \frac{1}{1+\sum_{j=1}^{n} ds_j} \qquad 4.17$$

where $ds_j=|max\text{-}min|50$ values represents the maximum distance between the highest and lowest activation level value of concept *i* measured over the last 50 out of a total of *n* iterations, while *n* is the total number of activation levels (i.e the participating concepts). This distance should be zero in case of equilibrium, otherwise the larger its value the higher the amplitude of the limit cycle and hence the less fit the individual weight matrix.

The computational procedure of the GA starts with the random selection of the initial individuals (weight matrices). One of the main characteristics of the FCM is its strong dependence on the values of specific weights, thus a random change of such a weight resulting from a crossover or mutation may cause an increase or a decrease of the fitness value of the specific individual [73]. More specifically, each individual (chromosome) represents a specific weight matrix used by the FCM to provide the final activation values of the participating concepts in equilibrium state. For every pair of weight matrices selected on a fitness basis (the more fit the individuals the more frequent the selection) the values of the specific weights lying to the left of the crossover point randomly produced, are switched between the two parents thus producing two offspring. As regards the mutation operator, on the other hand, it involves taking a fit individual and randomly selecting a weight to which it adds, or, from which it subtracts the value of 0.1

thus producing an offspring. The algorithm described thus far executes for a number of iterations and terminates when a predetermined condition is met (i.e. all limit cycles are successfully eliminated) or when a maximum number of iterations (epochs) is reached.

4.9 Genetically Evolved Fuzzy Cognitive Maps as the basis for developing Computational Intelligent Decision Support Systems

The next section contains a summary of the methodology and a case study verifying its appropriateness as a means to develop Computational Intelligent Decision Support Systems [115]. For completeness purposes, some parts that have already been described may be repeated in the following subsections.

4.9.1 Identification and formulation of domain variables: A cognitive approach

One of the most important requirements of the CI-DSS is the identification of the problem variables using experts' knowledge, a task that heavily depends, to a large extent, on the effectiveness of the methods used (questionnaires, formal consultations, texts etc.) [153]. The importance of this task is high given that it provides a descriptive overview of the system. Once this has been established, these variables and the causal relationships among them which participate in the GE-FCM methodology will be treated as concepts (nodes) and directed arcs respectively.

The contribution of a CI-DSS in determining assumption abstracting reality is the selection of the appropriate variables required and their transformation to candidate concepts of a GE-FCM model [14]. After the concepts have been identified they can be partitioned into fuzzy sets with each set assigned a linguistic value.

4.9.2 Linguistic Fuzzy Sets encoding

The advantage of using fuzzy sets is that they provide a basis for a systematic way of manipulating vague and imprecise concepts and as such they are often treated as representing linguistic variables. The first interval begins at -1 and the last ends at +1. Each of the intervals is given a name, corresponding to a certain linguistic variable and is subsequently stored in a fuzzy knowledge base in order to be used during the defuzzification process. The fuzzy set encoding is a key step in our framework because it is used to build up the most important element of the CI-DSS, namely the Fuzzy Knowledge Base [147].

4.9.3 Fuzzy Knowledge Base representation

The integration of a Fuzzy Knowledge Base (FKB) to GEFCM attempts to overcome the difficulty of transforming linguistic variables into mathematical forms by encoding the experts' assessment [13]. Once the concepts have been defined and the FKB has been built, the experts are ready to provide their estimates of the activation levels and weight values that aim at defining the initial state reflected by the model at a given time period.

The first input requirement is the activation levels, the values of which are assigned by the experts when determining the role that each concept plays in the environment of the problem under consideration. The higher the level, the stronger the influence of a specific concept, with levels taking any real value between –1 and +1. The experts must also assess the causal relationships between these concepts (weight values) ranging again between –1 and +1, with a zero value denoting complete weight absence.

Thus, the linguistic sample is encoded directly into a numerical matrix using an uncertainty fuzzy distribution and is subsequently reduced to a scalar form [116]. This linguistic matrix provided by the fuzzy encoding procedure reflects the quantization levels of the input and output spaces, and the number of fuzzy set values assumed by the fuzzy variables.

4.9.4 Simulations

The GE-FCM proposed uses a simulation technique that facilitates the forecasting and inference process developed as follows:

Step 1: FCM Modelling

This step involves the computation of the normalised level and the weight matrix at the normalisation stage. Then, the FCM algorithm is executed up to a certain number of iterations, following which it calculates the final activation levels (baseline).

Step 2: Application of the GE-FCM

This step introduces different strategies by tracing the near to optimal weight matrix corresponding to a desired activation level for a given concept as computed by the simple FCM model. The results are obtained in the form of graphical representations of the near to optimal weight values and used as input in the next step.

Step 3: Performance of the Post-GEFCM Algorithm

This appears as a variation of the FCM, and uses the optimal weight matrix as computed by the GEFCM as well as the normalised levels matrix to run the FCM algorithm. The results derived by each simulation assume a format similar to that of the FCM algorithm, and are used to perform the inference procedure.

The contribution of GE-FCM in decision-making is their capacity to make inferences. This is a task which justifies the intelligent nature of this model in the sense that it indicates not only how to apply the linguistic variables involved, but in addition, the order in which these variables should be applied to solve a specific problem. To do this, the proposed Intelligent DSS uses an inference engine, that is, a program that makes use of the linguistic variables in the Fuzzy Knowledge Base, in order to draw conclusions on the measures required; thus, one can work on various hypothetical scenaria that aim at studying the variables influencing the model concepts in each case and at selecting the appropriate measures.

4.10 Application of a GEFCM Intelligent DSS: The case of the Annan plan

The international literature includes some significant studies and applications that have been performed in the area of politics and crisis management during the last 25 years [10]. Fuzzy Cognitive Map models were widely used for political analysis [170] and decision making in international relations but a wide variety of difficulties when it comes to modelling complex, real world problems due to the absence of a robust and comprehensive methodology that can handle the unexpected behaviour of such a model in a large-scale, uncertain environment [121].

Our case study on the Cyprus Issue under the Annan Plan, to the best of our knowledge, is the first comprehensive and complete application in this field. This case study uses a novel software tool for decision-making, specially designed and implemented to facilitate the development of intelligent DSS based on Genetically Evolved Fuzzy Cognitive Maps. The proposed software tool provides the policy maker with a graphical user interface designed for the input of data provided by field experts in the form of activation levels and weight values, as well as for the presentation of the FCM simulation results obtained. It also assists decision-makers to reach to conclusions regarding future actions to be taken according to the situation being modelled. The tool incorporates three basic functions: Creation of the model workspace, construction of the model including expert data entry and simulation of the FCM and GE-FCM algorithms. Each basic function is supported by its own graphical interface, adequately user friendly to support the needs of decision-makers that are not familiar with complicated algorithms. All simulations conducted have been based on the following constant values for the variables involved: The population size has been set equal to 100 and the number of generations equal to 400. The weight values were randomly initialized in the range [-1, 1], while the probability of applying the genetic operator of crossover was set to 0.25 and that of mutation to 0.01.

4.10.1 Environment description

The Cyprus issue has been a source of friction between Greece and Turkey for several decades. The latest version of the Annan Plan, which has been advertised as the last chance for settling the matter by retaining a delicate balance between the Greek-Cypriot (G/C) state and the Turkish-Cypriot (T/C) community, has become a very controversial issue following its rejection by the former and its approval by the latter during the April 2004 referendum. The attitude of the two sides, however, was quite different versus an earlier version of the Plan, put forward just one month before the Copenhagen Summit conference at the end of 2002. The Plan had been then considered as an acceptable solution platform, approved by the Cypriot government in view of the full EU membership of the island, while the T/C community had rejected it. In any case, the decision taken during the Copenhagen Summit conference declared that Cyprus was to become a full EU member, a decision not linked to the possibility of a solution to the Cyprus issue. Concerning the North of the island, the aquis communautaire would become applicable once the Cyprus issue had been resolved. Unfortunately, the fact that all subsequent versions of the Annan Plan, were increasingly adverse concerning the G/C interests, led to a failure of the Lucerne talks, at the end of March, 2004, despite the strong pressure exercised on the G/C side mainly by the US/UK as well as the EU. It seems, therefore, that the April 2004 referendum results came as a direct and inevitable reaction to this political pressure, which, however, culminated in Brussels at the end of 2004 leading to the decision to open the door for a full EU membership to Turkey in October, 2005. It remains to be seen to what extent this decision pointed to the right direction for the interests of the international community. For the time being it has been given a first taste of what is to follow once Turkey declared its intension to sign the customs union protocol with the EU member states without, however, acknowledging one of these member states, i.e. Cyprus, a demand in which it insist up today.

4.10.2 Identification and formulation of domain variables

The purpose of the model used is twofold: It has been built to describe the political status on the island following the Cyprus EU full membership in anticipation of the April 2004 referendum results. Using this structure as background information we can then proceed with simulating the extent to which a number of possible political and strategic developments may contribute to solving the Cyprus issue. These developments will mainly refer to the reaction of both the Greek (G/C) and the Turkish Cypriots (T/C) versus the Annan Plan, as well as that of the various governments involved either directly or indirectly with the Cyprus issue. In technical terms these developments were introduced by changing the various activation levels of the concepts involved in the model.

The model was constructed by introducing the various key variables or concepts that outline the Cyprus issue while, in parallel, determining the causal relationships and the weights involved, i.e. the degree to which these concepts influence each other. To do so, we have used a scale that ranges between minus and plus seven, in order to indicate the direction and intensity of the causal relationships between concepts. The weight values of the normalised weight matrix and the initial Activation Level are given in Table 4.22 and 4.23 respectively.

Table 4.22: Activation levels (A_i): Initial dynamic simulation

C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
-0.57	-0.01	-0.78	0.40	0.43	-0.67	-0.57
C8	**C9**	**C10**	**C11**	**C12**	**C13**	
-0.57	0.39	-0.70	-0.54	0.19	0.72	

The interpretation of the simulation results requires that the reader consults Table 4.24 for the various bracket intervals and their corresponding states. It is to be borne in mind that the model described is different than the previous ones given in this section.

Table 4.23: Causal relationships and normalized weights matrix

W1	**W2**	**W3**	**W4**	**W5**	**W6**
C2→C1 -0,35	C4→C1 -0,5	C3→C1 0,6	C6→C1 0,9	C10→C1 0,3	C13→C1 -0,3
W7	**W8**	**W9**	**W10**	**W11**	**W12**
C1→C9 0,1	C1→C12 0,35	C1→C8 0,5	C2→C6 0,3	C4→C2 0,2	C5→C2 -0,1
W13	**W14**	**W15**	**W16**	**W17**	**W18**
C9→C2 0,15	C3→C6 0,8	C10→C3 0,3	C8→C3 0,4	C7→C3 0,85	C4→C3 0,75
W19	**W20**	**W21**	**W22**	**W23**	**W24**
C13→C3 -0,35	C9→C4 0,25	C13→C4 0,25	C5→C4 0,9	C10→C4 0,35	C12→C5 0,1
W25	**W26**	**W27**	**W28**	**W29**	**W30**
C5→C6 -0,28	C11→C5 -0,2	C13→C5 0,35	C6→C10 -0,5	C8→C6 0,4	C7→C6 0,75
W31	**W32**	**W33**	**W34**	**W35**	**W36**
C9→C6 -0,3	C10→C7 0,4	C9→C7 0,55	C4→C7 -0,5	C8→C7 0,75	C8→C10 0,1
W37	**W38**	**W39**	**W40**	**W41**	**W42**
C5→C8 0,3	C9→C13 0,4	C11→C10 0,4	C8→C11 0,8	C11→C13 -0,2	C12→C13 0,2

It involves consulting with experts in order to identify the concepts outlining a given situation, in this case the possibility of settling the Cyprus Issue as a result of the Annan Plan. Thirteen concepts, shown in Table 4.22, were introduced; each is assigned an identification number which is used when drawing the model map (Figure 4.23), or computing the results of the defuzzification procedure.

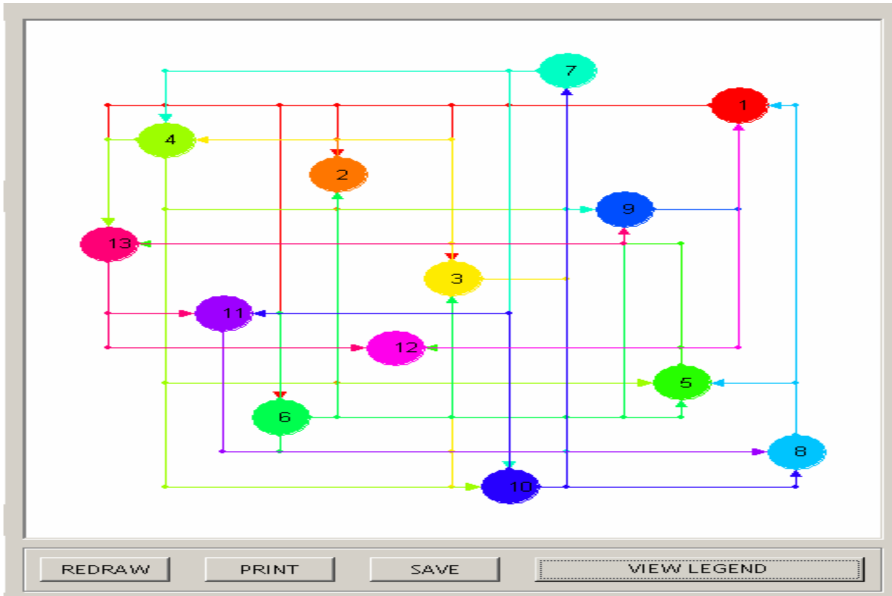
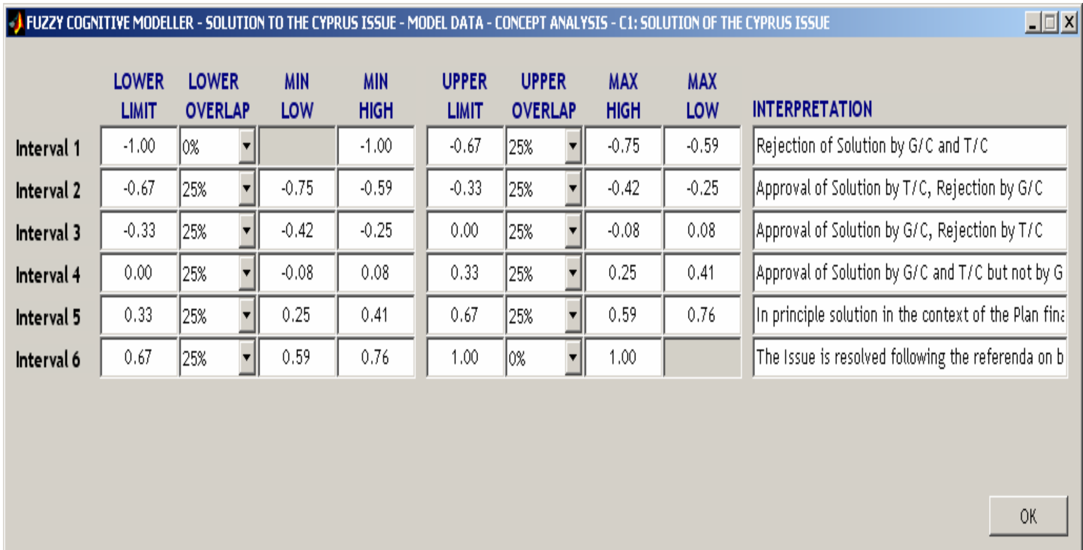


Figure 4.23: Fuzzy Cognitive Maps graphical representation

4.10.3 Linguistic Fuzzy Sets encoding

The tool [119] handles the fuzzification process, a very challenging task indeed, given the extent to supportive software which it involves vagueness and abstraction, in a number of ways. To begin with, it allows a variable number of fuzzy sets assigned to each concept, which means that it does not require all concepts to be partitioned with the same number of fuzzy sets. It also permits the decision-maker to impose specific limits for each fuzzy set in the Fuzzy Knowledge Base, which means that the sets do not necessarily have to have equal widths. This allows an activation level to fall in a fuzzy set the range of which is more (with a greater width) or less (with a smaller width) significant compared to other sets of the same concept.



FUZZY COGNITIVE MODELLER - SOLUTION TO THE CYPRUS ISSUE - MODEL DATA - CONCEPT ANALYSIS - C1: SOLUTION OF THE CYPRUS ISSUE

	LOWER LIMIT	LOWER OVERLAP	MIN LOW	MIN HIGH	UPPER LIMIT	UPPER OVERLAP	MAX HIGH	MAX LOW	INTERPRETATION
Interval 1	-1.00	0%		-1.00	-0.67	25%	-0.75	-0.59	Rejection of Solution by G/C and T/C
Interval 2	-0.67	25%	-0.75	-0.59	-0.33	25%	-0.42	-0.25	Approval of Solution by T/C, Rejection by G/C
Interval 3	-0.33	25%	-0.42	-0.25	0.00	25%	-0.08	0.08	Approval of Solution by G/C, Rejection by T/C
Interval 4	0.00	25%	-0.08	0.08	0.33	25%	0.25	0.41	Approval of Solution by G/C and T/C but not by G
Interval 5	0.33	25%	0.25	0.41	0.67	25%	0.59	0.76	In principle solution in the context of the Plan fin
Interval 6	0.67	25%	0.59	0.76	1.00	0%	1.00		The Issue is resolved following the referenda on b

OK

Figure 4.24: A concept associated with a given name corresponding to a linguistic variable and its fuzzy set partitions

The calculation of the "fuzziness" between adjacent sets based upon a user-selected percentage of overlap indicates that fuzzy sets can overlap with each other at different rates, enabling a greater or smaller overlapping slope between them. Figure 4.24 presents an example of fuzzy sets classification of concept C1, described as the Solution of Cyprus Issue, through the use of the dedicated software tool for developing CI-DSS.

4.10.4 Building the Fuzzy Knowledge Base

Once the concepts have been included in the model, and partitioned into fuzzy sets the software tool provides for a Fuzzy Knowledge Base (FKB) formulation. The domain experts are ready to provide the model with their estimate of the activation levels and weight values that describe the initial state at a given time period.

After all expert levels and weights have been introduced in the model, the two resulting matrices, one for each input category, are normalised based on the ranking of each expert. The resulting normalised level and weight matrices are stored individually as spreadsheet files in the workspace.

Table 4.24: Fuzzy Knowledge Base and model analysis

	Concept C1 : Solution of the Cyprus Issue
0.60 to 1	The Issue is resolved following the referenda on both sides
0.27 to 0.72	In principle solution in the context of the Plan finalized after May 2004.
-0.06 to 0.39	Approval of Solution by G/C and T/C but not by Greece and Turkey
–0.39 to 0.06	Approval of Solution by G/C, Rejection by T/C
-0.27 to -0.72	Approval of Solution by T/C, Rejection by G/C
-0.60 to -1	Rejection of Solution by G/C and T/C
	Concept C2 : Climate of Tension on the Island
0.60 to 1	Tension escalation. Violence incidents before referendum.
0.27 to 0.72	Violence incidents following rejection of the Plan by G/C.
-0.06 to 0.39	Violence incidents following rejection of the Plan by T/C.
–0.39 to 0.06	Statements intending to reduce tension before referendum.
-0.27 to -0.72	Actions intending to reduce tension following referendum.
-0.66 to -1	Stability on the island and approval of Plan by both sides.
	Concept C3 : Platform Solution of the Cyprus Issue
0.60 to 1	Approved by both sides.
0.27 to 0.72	Approved only by G/C.
-0.06 to 0.39	Marginally approved only by G/C.
–0.39 to 0.06	Rejected by G/C, approved by T/C.
-0.27 to -0.72	Rejected by T/C, approved by G/C.
-0.60 to -1	Rejected by both sides.
	Concept C4 : T/C Reaction to the Final Annan Plan
0.60 to 1	Unanimous approval.
0.27 to 0.72	Approved by the majority of the parties.
-0.06 to 0.39	Marginal approval of the Plan.
–0.39 to 0.06	Marginal rejection of the Plan.
-0.27 to -0.72	Rejected by Denktash and a number of parties.
-0.60 to -1	Unanimous rejection.
	Concept C5 : Turkish Government Reaction to the Final Annan Plan
0.60 to 1	Unanimous approval by the government and the military.
0.27 to 0.72	Approved by the majority of the parties.
-0.06 to 0.39	Marginal approval by the parties.
–0.39 to 0.06	Marginal rejection by the parties.
-0.27 to -0.72	Rejected by the government and all political parties.
-0.60 to –1	Unanimous rejection by all sides and the military.
	Concept C6 : Referendum Concerning the Acceptance of the Annan Plan
0.60 to 1	Approval by both sides as well as by Greece and Turkey.
0.27 to 0.72	Approval by both sides as well as by Greece.
-0.06 to 0.39	Approval by G/C, rejection by T/C supported by Turkey.
–0.39 to 0.06	Approval by T/C, rejection by G/C supported by Greece.
-0.27 to -0.72	Rejection by G/C, acceptance by T/C supported by Turkey.

-0.60 to -1	Rejection by both sides as well as by Greece and Turkey.
	Concept C7 : G/C Government Reaction to the Final Annan Plan
0.60 to 1	Unanimous approval.
0.27 to 0.72	Approved by the majority of the parties.
-0.06 to 0.39	Marginal approval by the parties.
–0.39 to 0.06	Marginal rejection by the parties.
-0.27 to -0.72	Rejected by the majority of the parties.
-0.60 to -1	Unanimous rejection.
	Concept C8 : Greek Politicians Reaction to the Final Annan Plan
0.60 to 1	Unanimous approval by the government and the parties.
0.27 to 0.72	Approved by the majority of the parties.
-0.06 to 0.39	Marginal approval by the parties.
–0.39 to 0.06	Marginal rejection by the parties.
-0.27 to -0.72	Rejected by the government.
-0.60 to -1	Unanimous rejection by all parties.
	Concept C9: US / UK Reaction to the Final Annan Plan
0.60 to 1	Pressure on both sides to approve.
0.27 to 0.72	Pressure on the T/C and the Turkish side to approve.
-0.06 to 0.39	Pressure on the G/C and the Greek side to approve.
–0.39 to 0.06	Warning about the consequences of a rejection to both sides.
-0.27 to -0.72	Warning about the consequences of a rejection to the G/C and the Greek side.
-0.60 to -1	Action to Upgrade the Status of the Occupied North in Cyprus.
	Concept C10 : EU Reaction to the Final Annan Plan
0.60 to 1	Full membership of Cyprus with the issue resolved based on the Annan Plan and in full accordance with the acquis communautaire.
0.27 to 0.72	Full membership of Cyprus with the issue resolved based on the Annan Plan with minor deviations from the acquis communautaire.
-0.06 to 0.39	Full membership of Cyprus with the issue resolved based on the Annan Plan with major deviations from the acquis communautaire.
–0.39 to 0.06	Full membership of Cyprus without solution following a rejection from the part of Turkey.
-0.27 to -0.72	Full membership of Cyprus without solution under certain reservations following a rejection by either side
-0.60 to -1	Full membership of Cyprus freezes due to rejection from the part of the G/C.
	Concept C11 : Greek Position with Reference to Turkish EU Membership
0.60 to 1	Support of the full membership of Turkey based on an agreed schedule.
0.27 to 0.72	Agree by the end of 2004 to determine the date that marks the beginning of the full membership negotiations.
-0.06 to 0.39	Vague support to Turkish full membership.
–0.39 to 0.06	Neutral position concerning Turkish full membership.
-0.27 to -0.72	No support to Turkish full membership.
-0.60 to -1	Rejection of Turkish full membership.

	Concept C12 : EU Position with Reference to Turkish EU Membership
0.60 to 1	Support of the full membership of Turkey based on an agreed schedule.
0.27 to 0.72	Agree by the end of 2004 to determine the date that begins full membership negotiations.
-0.06 to 0.39	Vague support to Turkish full membership.
–0.39 to 0.06	Neutral position concerning Turkish full membership.
-0.27 to -0.72	Discourage Turkish full membership.
-0.60 to -1	Rejection of Turkish full membership.
	Concept C13 : US / UK Position with Reference to Turkish EU Membership
0.60 to 1	Support of the full membership of Turkey based on an agreed schedule.
0.27 to 0.72	Agree by the end of 2004 to determine the date that begins full membership negotiations.
-0.06 to 0.39	Vague support to Turkish full membership.
–0.39 to 0.06	Neutral position concerning Turkish full membership.
-0.27 to -0.72	Discourage Turkish full membership.
-0.60 to -1	Rejection of Turkish full membership.

4.10.5 Scenario-Based simulations – Experimental results

The final part of this exercise deals with the performance of the FCM and GE-FCM algorithms using scenario analysis methodology. This yields the final activation levels and the optimal weight matrix computed by the FCM and the GE-FCM respectively. Needless to point out that the analyst's interest focuses on the defuzzification results that are automatically computed by the software tool. In fact, the FCM execution process takes the normalized initial levels and a weight matrix computed at the normalization stage, and runs the FCM algorithm calculating the final baseline activation levels.

4.10.5.1 Initial position outline

The dynamic simulation of the model turned out to be rather promising since the resulting output provided an outline of the Cyprus issue that reflected the climate on the island as it prevailed a few weeks before the referenda. Thus, the dynamic simulation results, as shown in Table 4.25 and Figure 4.25**,** point to the direction of a rejection of the Annan Plan by the Greek Cypriots (G/C) despite international pressure exercised, unlike the Turkish Cypriots (T/C) that seem to decide for a "yes" (A_1 =- 0.57).

Table 4.25: Activation levels (A_i): Initial Dynamic Simulation

C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
-0.57	-0.01	-0.78	0.40	0.43	-0.67	-0.57
C8	**C9**	**C10**	**C11**	**C12**	**C13**	
-0.57	0.39	-0.70	-0.54	0.19	0.72	

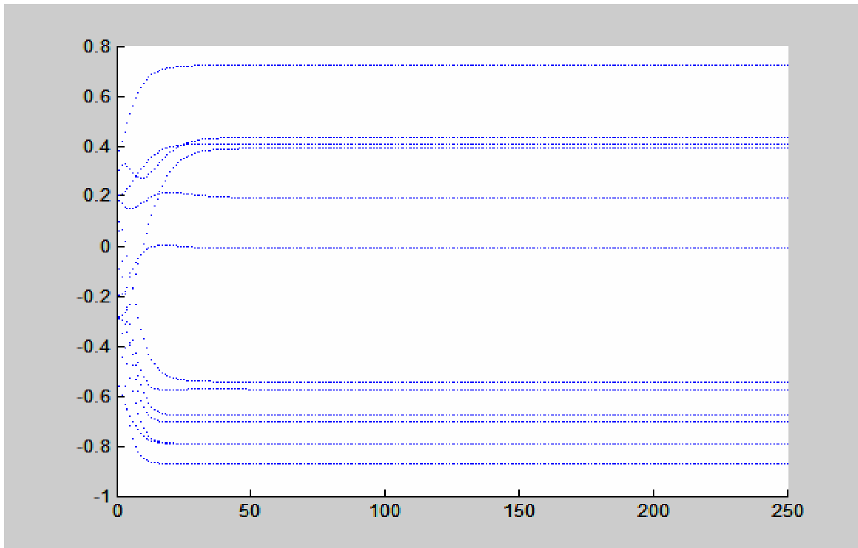


Figure 4.25: Stabilization of the FCM model in Equilibrium

The controversy between the "yes" and "no" followers, in any case, did not seem to create any form of serious friction or tension (A_2 = -0.01), with the possible exception of the North, but the model suggested the likelihood of tension in the future, especially during the period immediately following the referendum, thus subjecting the bilateral relations of the Cypriot government coalition parties to a test. Concerning the Annan Plan, it has not been considered by G/C as an acceptable solution platform (A_3 = -0.78), something which has been pointed out by the majority of the G/C parties (A_7 = -0.57) unlike the case of the T/C political parties, the majority of which have been shown to support the Plan (A_4 = 0.40). As a consequence, the model predicted that the Annan Plan would face a rejection from the G/C (A_6 =-0.67) side while the possibility of a rejection from the part of the T/C side was shown to be very remote with the support of the Turkish government (A_5 = 0.43). The Greek government, on the other hand, is predicted to reject the final version of the Annan Plan (A_8 = -0.57) something, which has only been one of the various meanings attributed to the Prime Minister's masterly diplomatic statement on the subject. This hesitant attitude concerning both the viability and applicability of the Annan Plan may have led the EU to stick to its initial position concerning the Cyprus full membership regardless the attainment of a solution, asking, however, for a number of restrictions (A_{10} = -0.70). The inflexibility of Turkey on the Cyprus issue, seems to point to the direction of a trade-off involving the full membership of Turkey, something which may be the source of bitter feelings at least as regards the Greek position (A_{11} = -0.54), unlike that of the EU and the US/UK which reveal a vague support (A_{12} = 0.19) and a warm backing (A_{13} = 0.72) respectively. The latter are shown to have exercised considerable pressure on both sides towards an approval of the Plan (A_9 = 0.39).

4.10.5.2 Inference through scenario analysis

Following the initial dynamic simulation phase, the tool considers, in addition to the number of epochs (generations), the selected concept, its desired activation level and the probability of crossover and mutation, both in the interval [-1, +1]. Running the model with the normalised levels matrix and a randomly initialised weight matrix produces various graphical representations of the fitness functions, as well as an optimal weight matrix that can be used in the next step. This matrix is stored in the workspace together with a log file of the GE-FCM simulation. The first scenario results for the FCM algorithm are shown in Figure 4.26.

The GE-FCM algorithm is a variation of the FCM algorithm. As previously mentioned, if the simulation attains the target activation level, then the decision maker uses the Fuzzy Knowledge Base to determine the environment in which this target has been realized, then interpret the results with the aid of the FKB at a linguistic level, and finally use this information to make strategic and tactical concept modifications according to the final activation levels as the model has suggested.

4.10.5.3 First Policy Scenario: Rejection of the Annan plan by the G/C and acceptance by T/C. Failure to reach a solution

This scenario actually verifies the initial situation by assigning a value of -0.5 to concept C1 indicating a failure to reach a solution of the Cyprus issue following a rejection of the Annan Plan by the G/C side and acceptance by the T/C side. The simulation stabilised the system for a value of A_1 =-0.61 thus ensuring the rejection by the G/C side, an outcome supported by the value assumed by A_3=-0.002. The results of this simulation, as shown in Table 4.26 and Figure 4.26, may be outlined as follows:

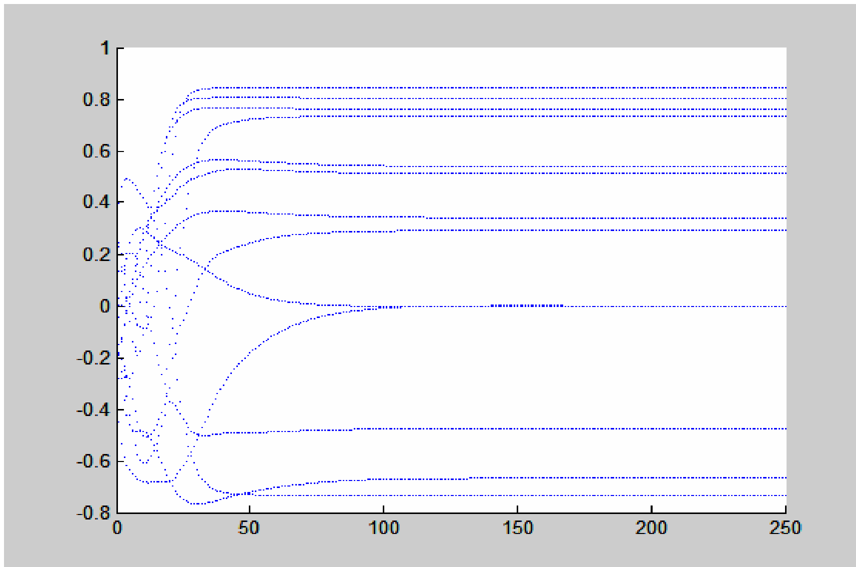


Figure 4.26: First Scenario: Equilibrium

Table 4.26: First Scenario : Plan Rejection by G/C and acceptance by T/C

C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
-0.61	0,54	-0.002	- 0.70	0,86	- 0.34	-0.75
C8	**C9**	**C10**	**C11**	**C12**	**C13**	
0.37	-0.003	- 0.70	0.51	0.80	0.84	

The April 24 referendum results have been forecasted to suggest a rejection of the Plan by the G/C side unlike the T/C side that has been taken to accept it (A_6 =-0.34). The rejection of the Annan Plan by the G/C side has been considered to lead to a possibility of a rising tension and a number of violence incidents or provocative actions (A_2= 0.54). The Plan approval by the T/C has not been exactly what one may consider as unanimous, this being largely a result of pressure exercised by Denktash, the T/C leader during that time, to reject the Plan (A_4 = -0.70).

As it concerns official and government reactions, the majority of the G/C parties have been assumed to reject the Plan (A_7=-0.75) unlike the reaction of the Greek parties that have been shown to offer their marginal, certainly not wholehearted, approval

(A_8=0.37). In fact this has been the case, with only one party expressing its full support to the Plan while most of the remaining ones asking for a postponement of the referndum which would give the Cypriots the time required to be informed on the Plan provisions. The majority of the Turkish political parties have been considered to more or less favour the Plan (A_5=0.86), while the pressure exercised by the US/UK side has been taken to restrict itself to just warning statements (A_9=-0.003). Finally, the EU has been thought as favouring the full membership under a number of restrictions following the Plan rejection by the G/C (A_{10} = -0.70).

The model shows that the outlook of a Turkish EU full membership may be rather promising since the Greek government has already agreed on the issue of the Turkish full EU membership (A_{11}=0.51), while both the EU (A_{12}=0.80) and the US/UK (A_{13}=0.84) seem to offer their strong support.

4.10.5.4 Second Policy Scenario: Excessive pressure exercised by the US/UK

This scenario has been designed to investigate the extent to which the US/UK pressure can affect the environment and consequently the decision-making process on the Cyprus issue. To this end we have assigned the relevant concept an extreme value, (A_9=0.8) indicating that the US/UK side exerts considerable pressure on both sides to accept the Annan Plan.

Table 4.27: Second Scenario: A: Excessive pressure exercised by the US/UK

C1	C2	C3	C4	C5	C6	C7
-0.75	- 0.78	-0.72	0.46	0.44	-0.39	0.39
C8	**C9**	**C10**	**C11**	**C12**	**C13**	
0.71	0.41	0.65	0.65	0.49	0.44	

As shown in Table 4.27 and Figure 4.27, it seems that this pressure can lead to exactly the opposite result, namely a rejection by both sides (A_1=-0.75), probably as a result of a defensive reaction to the pressure exercised. It is interesting to see, in fact, that in this case the US/UK pressure activation level (A_9 = 0.41) reaches its maximum value allowed by the model, despite its much higher initial input required by this scenario (A_9=0.8). The moderate value assumed by the model in this scenario is probably close to its ceiling value and suggests that part of the US/UK pressure should probably focus on the Turkish and the T/C side rather than the G/C and the Greek one. The ceiling value imposed in this case indicates, in addition, the limits that such forms of exogenous pressure may be allowed to reach in order to become convincingly fruitful.

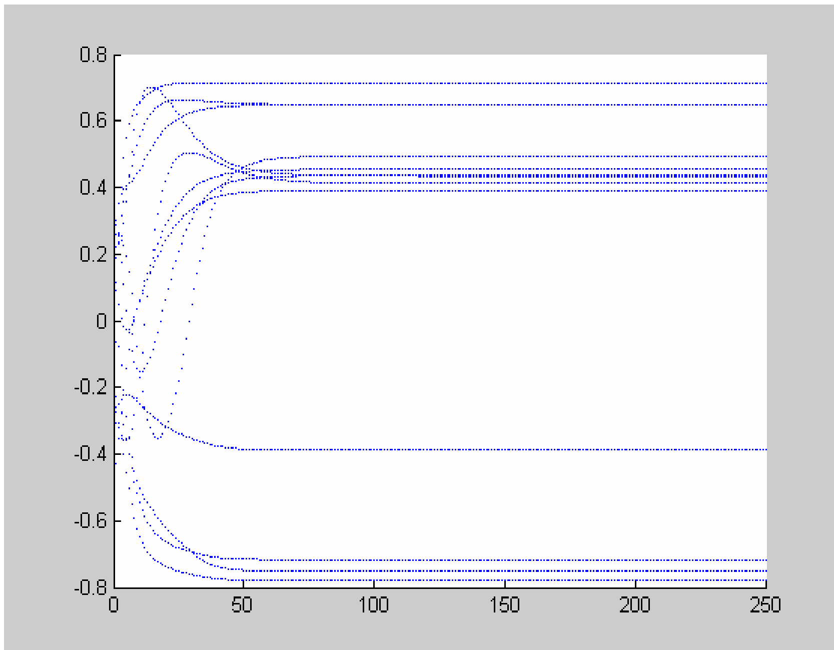


Figure 4.27: Second Scenario: Equilibrium

Concerning the remaining model concepts, the stability and tension reduction on the island (A_2=-0.78) indicates the rapprochement of both sides urged by their willingness to cooperate, a fact that shows that the mistrust between the two sides may not be as widespread as it is believed to be. The Annan Plan, in this case, does not seem to be regarded as an acceptable platform solution by either the G/C or the T/C (A_3 =-0.72) something that contradicts the approval of the Plan by the majority of the T/C parties (A_4=0.46), a result that holds for the majority of the Turkish political parties (A_5=0.44). Unlike the referendum results (A_6 =-0.39) that indicate a G/C rejection of the Plan and a T/C approval, the majority of the G/C parties (A_7=0.39) and the Greek political powers (A_8=0.71) are shown to approve the Plan. Regarding the EU, it seems to decide that Cyprus is a full member with the issue resolved based on the Annan Plan, which may not, however, suffer from major deviations from the aquis communautaire (A_{10}=0.65). Finally all EU members including Greece, as well as the US/UK sides agree on a date given before the end of 2004 to Turkey to start full membership negotiations (A_{11}=0.65, A_1 =0.49, A_{13} =0.44).

4.11 Discussion

This section will present two major issues in the form of discussion. The first one lies with investigating whether there is another similar method used in political and crisis management problems for comparison. The second issue is related to timing aspects during the execution process of FCM. Some results will be presented and a comparison of the simple FCM and the genetically evolved FCM with respect to time will be given.

4.11.1 FCM and Bayesian-based methods applied in political decision making

Forecasting in political decision making is a key issue for strategic analysis, decision making and policy planning. Several methods have been proposed for forecasting based primarily on game theory and modeling strategies [51]. The main obstacle in modeling political situations and developing effecting tools is the absence of numerical data in the decision process. Understanding such a model requires a manipulation of data relying on natural language arguments. Fuzzy logic and particularly Fuzzy Cognitive Maps is an alternative methodology to political decision models that merges mathematical values with a linguistic approach in decision making. This approach makes possible the manipulation of words without the necessity of pre-existing data. The experts' assessment is encoded in a linguistic fuzzy knowledge base and each numerical value is associated with a fuzzy set, representing a linguistic meaning. Comparing FCM with similar technologies [3] applied in political decision making, like expert systems and neural networks, the FCM has certain advantages over them, the main one being that it is relatively easy to represent knowledge and inferences can be computed by numerical matrix operations instead of IF/THEN rules. FCM avoid several problems arising from the hierarchical structure of the rule-based systems from which the knowledge is extracted through a decision tree [77]. The disadvantages of the latter are that it is impossible to use rule-based systems in large scale problems and that these systems are not flexible enough for modifications.

Instead of a fuzzy approach in political decision making probabilistic reasoning employed by Bayesian methods may be used as a decision making, tool. Bayesian methods use probabilistic approximate reasoning, while fuzzy logic reasoning uses fuzziness as the concept of approximation [82]. Bayesian refers to statistical data analysis telling us how to update prior beliefs about parameters or hypotheses in light of data arriving at posterior beliefs and how to learn about parameters from data based on the probability laws. The mathematics behind the Bayesian theorem was simplified via an algorithm called Markov Chain Monte Carlo (MCMC) [80, 65] which increases its computational power and applicability. The main distinction between probabilistic reasoning and fuzziness is that the former is basically a methodology that uses statistics to make inference. More precisely, observations or new information are used to update or support a hypothesis from an expert [89]. On the other hand, in the world of fuzziness, the decision is made when a particular concept belongs to a given fuzzy set in which the classification is a matter of perception. This classification is very close to the human thinking and behavior (reasoning) and it is more accurate and understandable to decision makers.

4.11.1.1 Bayesian Belief Networks

Bayesian Belief Networks (BBN) are a graphical representation model that combines the theory of probability with directed graphs to show the variables as nodes and the probabilistic dependences as arcs [113]. For example, the relationship between infection and symptoms is given by the description of the symptoms and then a BBN can compute the probability of the presence of the infection. BBN combine the causal relation and probabilities thus making their models very efficient in the representation of prior knowledge.

The result of a Bayesian network is the posterior probability of the hypotheses given the identified indicators [166]. In BBN the nodes represent variables and the arcs causal links between variables. This sort of networks takes into consideration the probabilistic relationship between variables using historical information about their relationships. What is interesting in BBN is their ability to model probabilistic reasoning and that they are very useful for modeling situations where information is inexact. The Bayesian statistical methods and the Bayesian network models are used for avoiding overfeeding of data in a system [109].

BBN offer consistent semantics for representing uncertainty and graphical representation of the nodes and causal links between various concepts. They can also be seen as an effective method for modeling uncertain situations which may be described in the form of cause and effect. Variables in the BBN are represented by nodes that can be viewed as a switch which is *on* or *off* [28]. The weather could be *cloudy* or *sunny*, the engine is *on* or *off*, the enemy is *near* or *far*, the symptoms are *present* or *not*. The above description seems to have many similarities with FCM in terms of nodes and arcs but the description of the nodes in BBN is bivalent, while fuzzy theory follows a fuzzy set classification [54].

In the example of Figure 4.28, a small model of BBN is presented describing the possibility of the grass to be *wet* which is either a result of *cloudy* and *rainy* weather, or a sprinkler is *on*. The state of the first node gives the likelihood of the sky if it is *sunny* or *cloudy*. This possibility affects the node *rain* in the child node. In the second child node named sprinkler, the likelihood can be *on* or *off*, and the grass can be *wet* or *dry*. The causality is that if the weather is *rainy* then the grass will be *wet* directly or if the weather is *sunny* then the grass is *wet* only if the sprinkler is *on*. A BBN represents possible states of a given domain also containing probabilistic relationships among some of the states of the domain [44]. In those cases probabilities are introduced in BBN that can be used to answer questions like, how likely is it to have water on the grass on a cloudy day?, or, similarly, what is the probability to have water on the grass in the summer time? This question, without current evidence, can be answered using conditional probability tables. This table is built using prior information about the relationships among nodes indicating that the likelihood of a node in one state is dependent on another node's state. Prior information between nodes indicates the likelihood that the node in one state or another is dependent on another node's state.

The construction of Bayesian networks follows a hierarchical tree structure with the higher node directly influencing the lower node [43]. When two nodes are connected by an edge then the causal node is called parent node. The nodes take bivalent values called states in the form of something that will or will not happen.

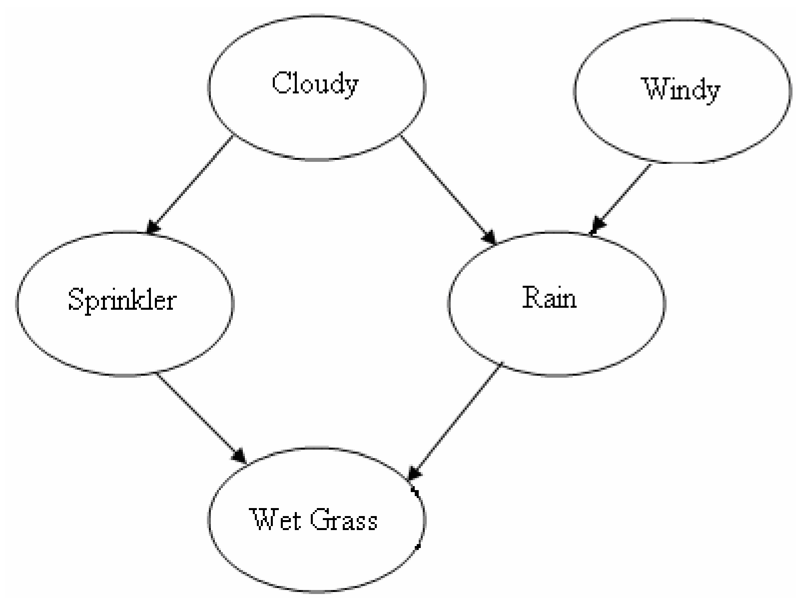


Figure 4.28: A BBN model: The possibility of raining

4.11.1.2 Bayesian and political decision making

A Bayesian method can represent knowledge in an uncertain environment using probability theory to represent this uncertainty. However, in this method some limitations are present in obtaining reliable results that may lead to computational ambiguity. This is mainly due to the assumption that all factors in a system are equal and assigned the same binary value. This inability of the Bayesian approach limits the use of the method in real-world political problems [79]. Another reason why Bayesian Belief Networks have not been widely used in political decision making is that the posterior expected value requires integrating the posterior distribution, the analysis of which is very difficult and almost impossible**.** Encoding political judgment is a difficult task requiring special tools for the mathematical manipulation of this encoding. Bayesian methods provide limited ability to formally include this type of information given by experts using statistical analysis through the use of prior information [166].

An example of the use of comparative politics is given in Jackman's study [79] describing the escalation of a crisis between two nations. The Bayesian approach can compare a number of independent variables to examine whether it is appropriate to assume that the error terms are correlated [127]. The escalation of a crisis between two nations can occur in different cases, taking into consideration many parameters. This method is suitable for comparison analysis using two actors at a time. This limitation of the Bayesian approach is very important and in cases of real crises or political problems in which a lot of parameters are involved the method can not be applied. The reason is that the Bayesian theorem does not support multivariate computation and the aggregation of many parameters into a single variable is difficult and problematic.

4.11.1.3 Comparison between BBN and FCM

The Bayesian approach was selected for comparison with FCM because both are using a similar symbolic notation and modelling stand for the encoding of a given problem. More precisely, the structure of a BBN has many common aspects with FCM; both use nodes to represent concepts and arcs to indicate their causal link. BNN follow a single parameter and associate it with another parameter in a hierarchical tree structure. This form of structure limits the applicability of BBN in complex real world problems like political decision making. For example, this structure lowers the computational ability of BBN [183] because it uses a linear multiplication function with pairs of concepts, unlike FCM which use matrix computation. [163]. The linear computation of BBN suffers from feedback causal influence which is a necessary feature for dynamic systems [155]. The way that FCM are built and the iteration process satisfy the needs of dynamical systems.

A FCM represents knowledge in a symbolic manner and relates state activation function, causal effect and input/output events in a Fuzzy Knowledge Base (FKB). Expert knowledge is encoded in this FKB giving FCM the ability to handle incomplete information via a linguistic form. The FCM is built with the help of experts and it is used as an inference mechanism. The FKB is the bridge between the natural meaning of a node or concept and its mathematical interpretation. In FCM, approximate reasoning is also possible, with qualitative and linguistic knowledge.

In BBN the knowledge is represented through a probabilistic table using prior information. This table is built with the aid of existing statistical data and most of the times this data is bivalent (*ON* and *OFF*) [6]. This method is subjective and fixed; the current situation of a given problem in BBN is not known as it is not possible to gather all possibilities in the conditional probability table and associated these with a probability figure to be used for prediction. In FCM the current situation of a given problem is known, thanks to experts' assessment and matrix computational formulation which, after the first execution of the algorithm, gives the current modelling status of a given problem. A FCM using GA is a goal oriented optimization technique which sets the target value of a concept to reflect a certain political situation. In the Bayesian approach the target value is the estimation of the posterior value related to the prior value delivering an error [151]. This linearity in the Bayesian method allows comparison of two concepts at a time while in FCM all concepts are involved in the forecasting procedure.

The objective of finding the initial state among a large number of possible concepts that the FCM represents is a search problem that can be optimized. The initial condition, with the help of genetic algorithms, is used as the basis in the forecasting process. For example, uncertainty is statistical inexactness due to random future behaviour of events. In FCM the decision is made when a particular object belongs to a given set and the result is a matter of perception which can be subjective. Another important difference is that in uncertainty there is a degree of probability associated with the occurrence of conditions. In fuzziness the membership function of the condition is not defined under a crisp value. Summarizing the above, we can conclude that the BBN approach and FCM are two approaches that despite the fact that they share some similarities, they also have fundamental conceptual differences. It is clear, therefore, that the two approaches are not comparable due to their different structure, computational methodology and nature of applicability to political decision making. Any further comparison of the two approaches will provide nothing more than biased and misleading results.

4.11.2 FCM time performance – Computational burden

4.11.2.1 Introduction

Execution time determines the duration of execution of a program to complete a certain task and therefore the steadiness of a system with respect to time. The experiments for the purpose of time performance analysis were conducted on an Intel® Pentium (M) Processor with 1.50GHz speed and RAM capacity of 512MB with an access time of 40Hz on a Windows® XP® operating system. The tool was implemented using Matlab® 2007b. The objective of this execution time analysis is to designate the performance of the FCM methodology with respect to the quantity of concepts and weights in a model. A total of ten different models were used with varying numbers of concepts and weights.

4.11.2.2 Simple FCM execution time

The simple FCM model was tested in full-scale starting with a small-sized FCM model consisting of 3 concepts and 5 weights, with a gradual increase in the number of concepts and weights resulting in a large-sized FCM model consisting of 35 concepts and 377 weights. Table 4.28 and Figure 4.29 and Figure 30 displays the concepts and weights characteristics of each simple FCM model tested along with its execution time (in seconds), which varies from 1.39s to 6.31s. The average increase in execution time of the ten samples is 18.45% as can also be seen in Table 4.28.

Table 4:28: Time performance of simple FCM algorithm

Simple FCM Model	Number of Concepts	Number of Weights	Execution time (s)	Increase (%)
Model 1	3	5	1.39	-
Model 2	6	15	1.63	17.27
Model 3	8	25	2.10	28.83
Model 4	10	25	2.49	18.57
Model 5	13	46	2.87	15.26
Model 6	15	61	3.27	13.94
Model 7	18	92	3.90	19.27
Model 8	25	192	4.96	27.18
Model 9	30	265	5.80	16.94
Model 10	35	377	6.31	8.79

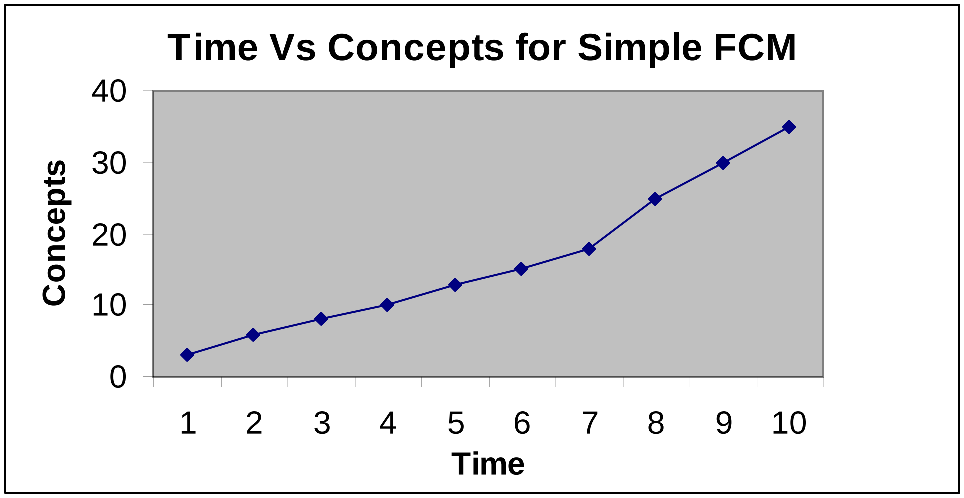


Figure 4.29: Graphical representation of time performance with respect to concepts for the simple FCM

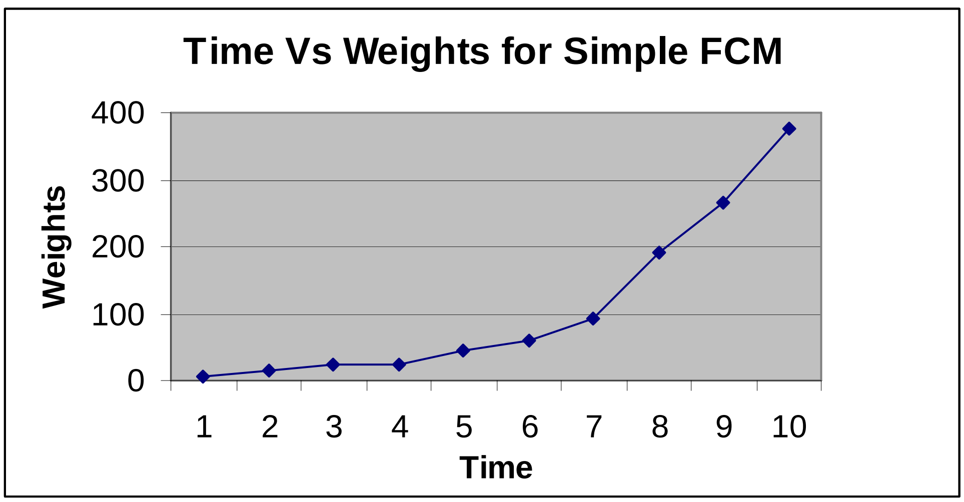


Figure 4.30: Graphical representation of time performance with respect to weights for the simple FCM

4.11.2.3 Evolutionary FCM execution time

The execution time was also measured for Genetically Evolved FCM models. The same models used in the simple FCM were used but furthermore they were evolved using the GECNFCM algorithm. For the simulation of the algorithm, a population size of 100 individuals was used and evolved for a total of 400 generations. The weight values were randomly initialized in the range [-1, 1], while the probability of applying the genetic operator of crossover was set to 25% and that of mutation to 1%. Table 4.29 and Figures 4.31 and 4.32 illustrate the performance of the models by comparing the time performance against concepts and weights.

The execution time for the smallest FCM was found to be 7.2 seconds while for the largest model (comprising 35 concepts and 377 weights) was computed at 197.66 seconds. The average increase rate of the execution times is 46.96% largely due to the fact that from the first model to the second a 110.42% increase occurs. Otherwise an average of 39% is observed. It appears that the increase rate follows that of simple FCM. Clearly, the time needed for the execution of simple FCM models compared to genetically evolved FCM models is due to the fact that the execution time for identification of the new weight matrix performing genetic operations on population of chromosomes becomes the more significant part of the total execution time. This is a clear indication that the number of weights evolved during the optimization process affects the execution time of the genetically evolved FCM algorithm.

Table 4.29: Time performance of evolutionary FCM Algorithm

Evolutionary FCM Model	Number of Concepts	Number of Weights	Execution time (s)	Increase (%)
Model 1	3	5	7.2	-
Model 2	6	15	15.15	110.42
Model 3	8	25	18.59	22.71
Model 4	10	25	24.42	31.36
Model 5	13	46	41.38	69.45
Model 6	15	61	48.60	17.45
Model 7	18	92	64.73	33.19
Model 8	25	192	109.89	69.77
Model 9	30	265	149.58	36.12
Model 10	35	377	197.66	32.14

The execution time for the evolutionary algorithm with respect to absolute numbers is reasonable for such demanding type of computation. Thanks to the evolution of technology situation has greatly improved as the time needed for the largest FCM (with 35 concepts and 377 weights) in the genetic environment is less than 3 minutes and may therefore be considered as acceptable.

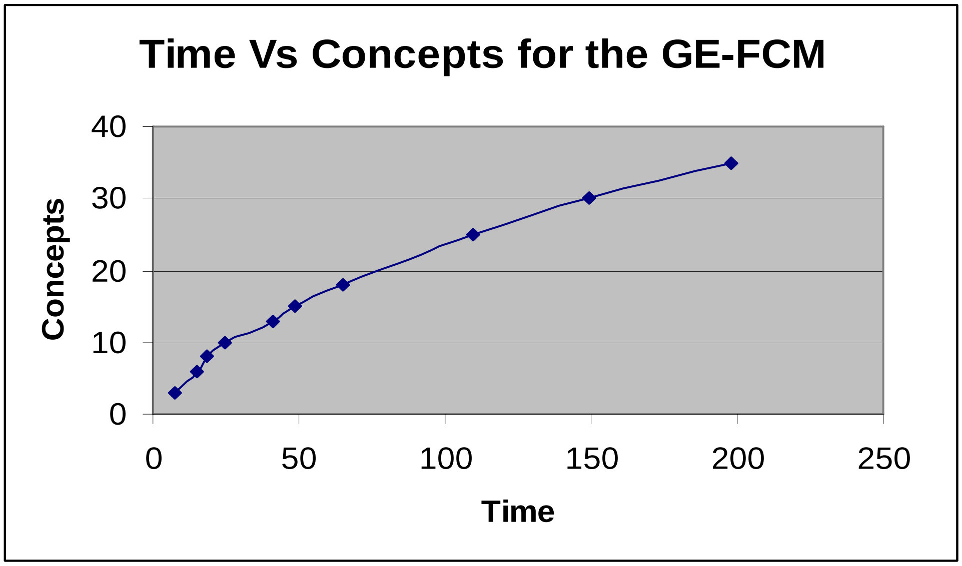


Figure 4.31: Graphical representation of time performance with respect to concepts for the GE-FCM

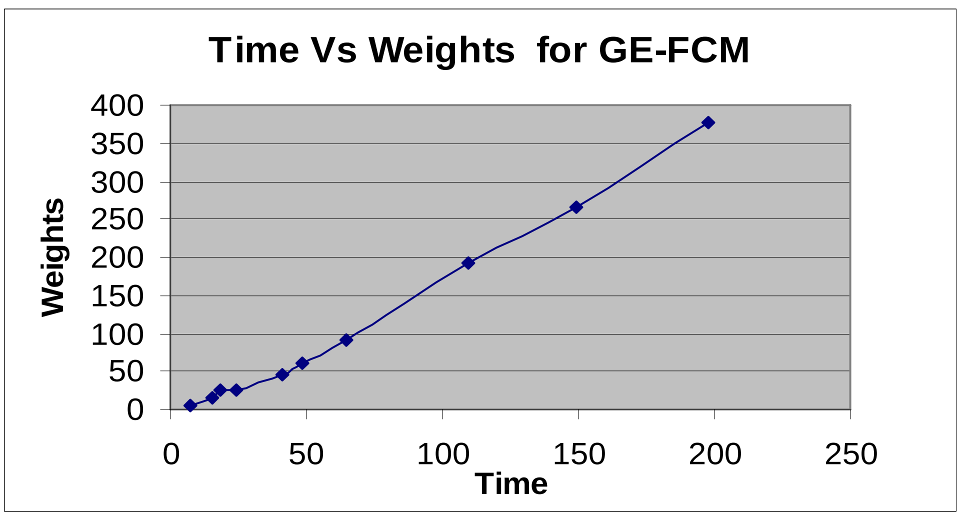


Figure 4.32: Graphical representation of time performance with respect to weights for the GE-FCM

Comparing the results obtained from the above tests, the clear conclusion as expected is that as the number of concepts and weights increases, the execution time, both in simple and in genetically evolved FCM algorithms progressively increases. It is also important to notice that in Genetically Evolved FCM the time follows more closely the increase of weights instead of concepts increase. On the contrary, in simple FCM the number of concepts and weights does not affect significantly the increase of time.

Chapter 5: Multi-Layer Fuzzy Cognitive Maps (ML-FCM)

5.1 Introduction
5.2 Building and running a Multi-Layer FCM
5.3 Multi-layer FCM Algorithm: How it works
5.4 Limitation of ML FCM and proposition of a new algorithm.
The Enhanced ML-FCM
5.5 Case study using the Multi-Layer approach.

5.1 Introduction

Multi-Layer Fuzzy Cognitive Maps (ML-FCM) is a new approach developed to improve the decision-making process in large scale problems which are modeled using Fuzzy Cognitive Maps [96]. The main issue here is the decomposition of complex parameters into smaller, more manageable quantities organized in a hierarchical structure. This structure forms a model, which consists of subsystems working together and supporting a central objective. The latter is related to the model structure of a particular system and is represented by a main, central FCM, with distinct FCM sub-models (layers) linked together in a hierarchical structure [4]. The sub-models represent and implement (in computational terms) the decomposed parameters and variables of the system, thus facilitating the focus on and the study of the critical parts of the system under consideration [145].

Recall that an FCM is a figure composed of nodes and edges, the former introducing the qualitative concepts of the analysis while the latter indicating the various causal relationships. This diagrammatical notation offering a graphical view, allows the decision maker to visualize the problem at its current state [92]. The activation level of each of the nodes describing the system and the weighted arrows are set to a specific value based on input provided by expert knowledge on the subject. Such input must be very carefully considered given that some concepts can be more important than others, being sometimes composed of a wide variety of variables that influence their activation levels. This applies for most of the concepts in an FCM, especially if the problem under study is highly complicated. For example, if the problem consists of sixty concepts, it becomes very difficult or even impossible to create a single map and identify each interaction between each concept. This is exactly what the present chapter aspires to tackle by proposing a new methodology for constructing Multi-Layer Fuzzy Cognitive Maps [121], thus targeting to handle the complexity of such problems. The essence of the methodology lays with grouping a number of concepts in such a way that each group may be associated with a specific concept of interest in the upper level, which corresponds to a crucial, complex variable of the system. The group of concepts sums up to a "local" FCM, which is linked to the concept of interest properly expanded for further analysis. This grouping may be repeated for a number of concepts of interest and may decompose a concept using a stepwise approach. Each step gives birth to a new discrete level, which includes in its turn a new FCM corresponding to an expanded form of the central concept in the previous level.

The execution of the computational part starts with those FCMs that lie at the lowest levels and continues with transferring the computed activation level of the concept in focus to the next upper layer. This makes sure that the main variables influencing the concept in focus are analyzed and assessed "locally" (i.e. focusing only on this specific concept of interest thus reducing complexity by sharing it evenly between layers. An additional advantage of this algorithm is that it contributes to the efficiency of decision making by allowing the simulation of the selected scenarios separately in each layer. More specifically, the algorithm, named ML-FCM, designs layered Fuzzy Cognitive Maps in a hierarchical structure, in order to compute the activation levels of the children FCMs in each layer and update the Activation List of the decomposed father FCMs in the upper layer. What this algorithm offers, in addition, is the capability to perform scenarios facilitating the forecasting procedure.

The Genetic Algorithms implemented in the ML-FCM may be considered as a powerful and successful enhancement able to handle large complicated problem-solving. It is interesting to point out that the proposed evolutionary multilayered approach (described later on) is reflected both in the implementation of the GA as well as in the methodology applied for solving large-scale problems [126]. In fact, the reasoning behind the use of this hybrid system is to obtain the optimal solution to the weight values corresponding to an FCM in any layer. This is very useful for the simulation process and helps the decision-maker to develop scenarios with the involvement of more than one concept in any place of the ML-FCM. The basic principle of the methodology requires the initial building of the hierarchical structure forming the ML-FCMs. Subsequently, the GA can be applied to the central FCM or any sub-FCM generating a new, near to optimal set of weight values for that particular FCM. Ultimately, the FCMs are run using the recalculated weights beginning from the lowest-level FCMs upwards to the root FCM.

An additional advantage of using GAs here is that genetic optimization can be applied to a concept that expands to a sub-model, thus being common to two FCMs (parent- and child-FCM). As a result, the concept's final level computed in the child FCM will be the initial level of the parent FCM, both of which are predetermined by the user. Therefore, any scenario analysis becomes quite flexible and allows for different experiments at some or all of the levels of interacting FCMs. The final step involves the execution of the FCM. Two algorithms are used during the execution process of the Multi-Layer FCM: The simple FCM, which is used for the creation of the baseline of the model, and the Genetically Evolved ML-FCM, which is used when scenario analysis is required. However, before an FCM is executed if it is marked for genetic optimization then what actually runs is the Genetically Evolved ML-FCM (GEML-FCM) algorithm. The resulting weight matrices of each such experiment are then fed as input to the FCM algorithm for completing the scenario analysis. The proposed algorithm (which integrates genetic optimisation with ML-FCMs) runs following a bottom-up sequence so that any newly-computed final activation level of a concept in a child FCM is used as the initial activation level of its parent FCM after it has been calculated on the basis of the optimised weight matrix of the child GEML-FCM algorithm [126].

5.2. Building and executing a Multi-Layer FCM

The first part of the procedure to follow has already been described in the previous chapters and involves the identification of the main concepts participating in a given problem, the sort of input provided by experts in the relevant field. Once all concepts have been identified they are partitioned in fuzzy sets, each assigned a linguistic variable. This encoding of experts' knowledge is stored in a fuzzy knowledge base, which is an essential part of the fuzzification and defuzzification processes [116]. The second part is the creation of the Multi-Layer FCM, in which the concepts are grouped together in smaller sub-systems called sub-FCMs, formatted in a hierarchical structure. The advantage of this structure is the creation of small and more easily manageable sub-FCM models, which interact to support the main FCM. For the main FCM and each of the sub-FCM models the domain experts provide their estimate concerning activation levels and weight values. It is important to point out that there may be cases of concepts in which the activation level (AL) value is not estimated directly. Instead, a sub-FCM model is created, which is used for calculating this AL for this specific concept. Each such sub-FCM model participates in the defuzzification process following which a report for each of these sub-FCM models is issued to explain and justify the calculated activation level for the corresponding concept of interest. More specifically, the steps followed by the proposed ML-FCM methodology are the following:

Step 1: Acquiring Expert Knowledge

When developing a model for a certain problem the first step involves consulting with domain experts in order to identify the concepts playing the role of the leading variables in the problem under consideration. In the ML-FCM environment, the experts are asked to decompose (describe) concepts in higher levels to various concepts forming smaller FCMs at a lower level. The concepts are related to each other and are grouped around a central concept for each FCM, which is the link of the particular FCM to the upper layer of the model.

Step 2: Building the Fuzzy Knowledge Base

Once all concepts have been identified and grouped together, they are partitioned into fuzzy sets, each set assigned a linguistic value thanks to the integration of a FKB to each FCM, which allows the analyst to encode the domain experts' assessment concerning a given real-world problem and represent this knowledge in a graphical representation language. To do so, the linguistic sample is encoded directly in a numerical matrix using an uncertainty fuzzy distribution and is subsequently reduced to a scalar form. This linguistic matrix reflects the quantisation levels of the input and output spaces, and the number of fuzzy set values assumed by the fuzzy variables. The ML-FCM methodology uses a single Fuzzy Knowledge Base in which all concepts and their analysis is stored. Once all concepts have been defined and the FKB has been built, the domain experts provide their estimate of the activation levels and weight values defining the initial state of the main FCM that contains the selected concepts participating in the first layer (n^{th}) of the model. Finally, the experts select the concepts that they consider to be the most important for further analysis without, however, estimating their Activation Level values. The fuzzy knowledge related to the case study described in this chapter is given in Appendix A.

Step 3: Defining the structure of the Multi-Layer Fuzzy Cognitive Map

The AL values for each concept that intentionally were left without estimation by the experts will be computed by the new sub-FCMs, designed specifically for this purpose. The new sub-FCMs are children of the main FCM and consist of a number of concepts related to the concept in focus which is the central concept of the new sub-FCM. Each sub-FCM gives birth to a new discrete level, which includes, in its turn, a new FCM corresponding to an expanded form of the central concept in the previous level, with the central concept of each sub-FCM being the direct link between the father FCM and the child FCM. Given the complication of this analysis section 5.3 provides a detailed description of the design and implementation of the Multi-Layer FCM.

The same process is repeated for the new sub-FCMs provided that they also include concepts which can be further analyzed to include new sub-FCMs. For example, if we consider the first layer of expansion of the main FCM (layer *n-1*), for each sub-FCM participating in this layer we can identify concepts that need to be broken down to more components. The decomposition of such concepts results in the creation of new sub-FCMs in another layer at a lower level (layer *n-2*). In case that a FCM consists of only leaf nodes, meaning that none of its concepts requires further analysis decomposition, the particular FCM is ready for executing the computational part of a simulation scenario**.** The expansion dimensions of the Multi-Layer FCM depend on the complexity of the problem and the number of the participating concepts. The decomposition of the problem structure takes place via the expansion of certain nodes to different layers until one reaches the leaf nodes which represent the final level of the FCM's decomposition into elementary pieces of information (cognitive states).

Step 4: Simulation Results - Inference

As previously mentioned, the Multi-Layer FCM follows a hierarchical structure [77], meaning that we need to identify the order in which the FCMs will run and execute the computational part of a simulation. The methodology used for this purpose is similar to the Depth-First Search (DFS) [157]. DFS is used to go all the way down branch by branch reaching the leaf nodes at the bottom of the structure before trying the next branch over. The first run takes place when the lower level of a branch is visited. After running each FCM we backtrack to the father FCM for updating its activation level list, in which case the specific FCM having its activation level list completed is "removed" from the list (stack). The search continues until the next leaf node is reached to continue the process of execution, backtracking and updating until another leaf node in another branch at the bottom of the ML structure is found. After all FCMs that are linked together in this hierarchical form have been executed one-by-one, the final step involves the execution of the main FCM at top most layer *n*. Each layer uses the Fuzzy Knowledge Base to determine the context in which the activation level of interest is realized, while the inference engine directs the search through the knowledge base as soon as each layer is completed. This process provides the necessary information for every FCM which participates in each layer. The advantage of this method is that the concepts in the upper layer can be deeply analysed in their internal parameters. Taking into consideration the lower levels of the FCM model, the decision-maker retrieves the results, interprets them with the aid of the FKB at a descriptive, linguistic level, and uses this information to make strategic and tactical movements towards further analyzing a concept in a certain layer.

5.3. Multi-Layer FCM Algorithm: How it works

5.3.1 Search spaces and the multilayer algorithm

The Multi-Layer Fuzzy Cognitive Map (ML-FCM) methodology conceives the process of developing and traversing such a map as being a space problem [157], with the term "space" used to refer to a search algorithm employed to find and execute a sub-FCM, as will be described later on.

Search spaces are often depicted graphically by drawing the initial state and the states that result from the application of certain domain operators, as shown in Figure 5.1. The initial state is placed at the top of a ML-Structure, while the resulting states are grouped in layers.

It is important to point out, however, that search spaces [2], even in cases of very simple problems, may contain an enormous number of states. The possible number of states *(k)* at a total level *(n)* is i^{n-1}, where i is the number of operators being applied on each state of each layer, while the total number T_n of states including level n is

$$T_n = \sum_{k=1}^{n} i^{n-1} \tag{5.1}$$

Taking into consideration equation 5.1 and supposing that only two operators *(i=2)* are applied to each level in the search space the resulting number of states *(k)* after applying the operators to a state in the previous layer is two (Figure 5.1) which raises the total number of states in the space to 3. At a second round, each of these 2 states may yield two additional ones, which means that there will be 4 states at the next layer, yielding a total of 7 states. Accordingly, the next level will result in 8 new states, yielding a total of 15 and so forth.

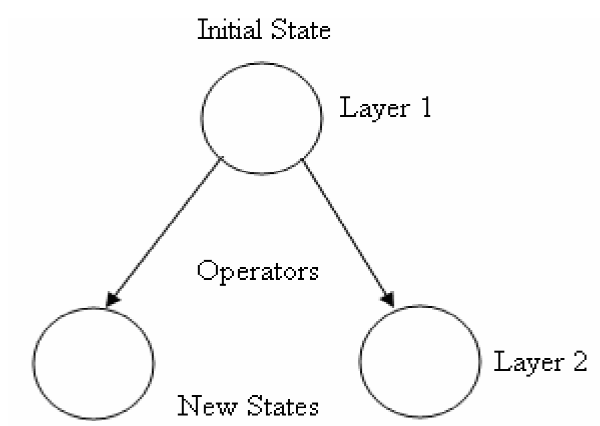


Figure 5.1: Search space diagram

Therefore, we decided to base our search algorithms on the notions of a search space problem due to the fact that the Multi-Layer FCM is expanded like a tree structure the branches of which are linked together in a hierarchical form [4]. Of course in our case an FCM is not expanded strictly in accordance to equation 5.1 due to the different level of complexity of each problem which essentially determines the way new states are introduced in the model. By partially applying the above equation we have the flexibility to build a FCM structure more freely in order for the model under study to reflect the real condition of a problem [77]. For example, in Figure 5.3 the first, second and third layers follow the rules of equation 5.1 while layer four has only two FCMs (operators). A detailed example of how the Multi-Layer FCM structure is developed in practice is given in the next subsection.

5.3.2 Multi-Layer FCM

The problem of expanding the Multi-Layer FCM can be implemented using the so-called partially expanded trees. In most of the problems there is an indication or criterion as to which action must be taken at each stage (i.e. expand or not). We can consider the ML-FCM structure as a partially expanded tree, in which the basic concept of a ML-structure FCM, in our case the Main or Initial node (sub-map), which we will call Main FCM, is placed at the top of the ML-FCM. Then, an arrow is drawn downwards to represent each possible sub-node or sub-FCM. At the end of each arrow an appropriate new FCM is placed. The reasoning behind placing a sub-FCM in a lower layer branch from the need to conduct a deeper and more extensive analysis of a certain concept and to form smaller groups of concepts due to the limitations observed in the classical FCMs to handle problems with a large number of concepts. In fact, expanding a specific sub-FCM is required in the case in which the execution of a parent FCM misses an activation level from its AL list, which is thus calculated by the child FCM at the lower layer. In the event that the list is complete no expansion is required.

5.3.3 Genetically Evolved Multi-Layered Fuzzy Cognitive Maps (GEML-FCM)

The integration of evolutionary computing with Multi-Layer Fuzzy Cognitive Maps, [121] (ML-FCMs) aims at resulting in a promising and reliable methodology used for modelling complicated, large-scale problems. One of the main challenges faced hereafter, is the design of scenarios that describe specific problems in a multilayered environment and the determination of the optimal solution, if any, to such problems. In fact, the main goal is not just the implementation of such a situation using ML-FCMs, but, in addition, the calculation of the AL values which represent the solution to our problem.

A new algorithm named GEML-FCM, the pseudo code of which is presented in Figure 5.2, is designed to serve the above evolutionary methodology. As previously mentioned, the essence of the proposed methodology is the decomposition of a large-scale, complex problem into smaller and more manageable groups of parameters [124] that can be modelled by means of FCMs to produce a layered hierarchical structure, the ML-FCM. The algorithm for the methodology can be decomposed into three segments: The first segment involves the determination of the ML-FCM hierarchy, the second establishes the initial condition, and the third segment selects the FCMs used for genetic optimization and the simulation process [107].

```
Create main FCM
Check the AL_List
 For each missing activation level in the AL_List
 Create child FCM in n+1 layer
 If  FCM is a leaf node (AL_List is complete)
       Run CNFCM algorithm
       Update parent FCM AL_List
 Else repeat from 3 until all AL_Lists are complete
       Select FCMs for scenario analysis
 Endif
 Select concepts for GA and identify its target level
 For each FCM in the multilayered structure starting from the lowest level
   If FCM requires genetic optimization
      Run GECNFCM
      Run CNFCM algorithm (with new weight matrix where applicable)
      Update the parent AL_List
   Endif
Endfor
```

Figure 5.2: Pseudo code of the GEML-FCM algorithm

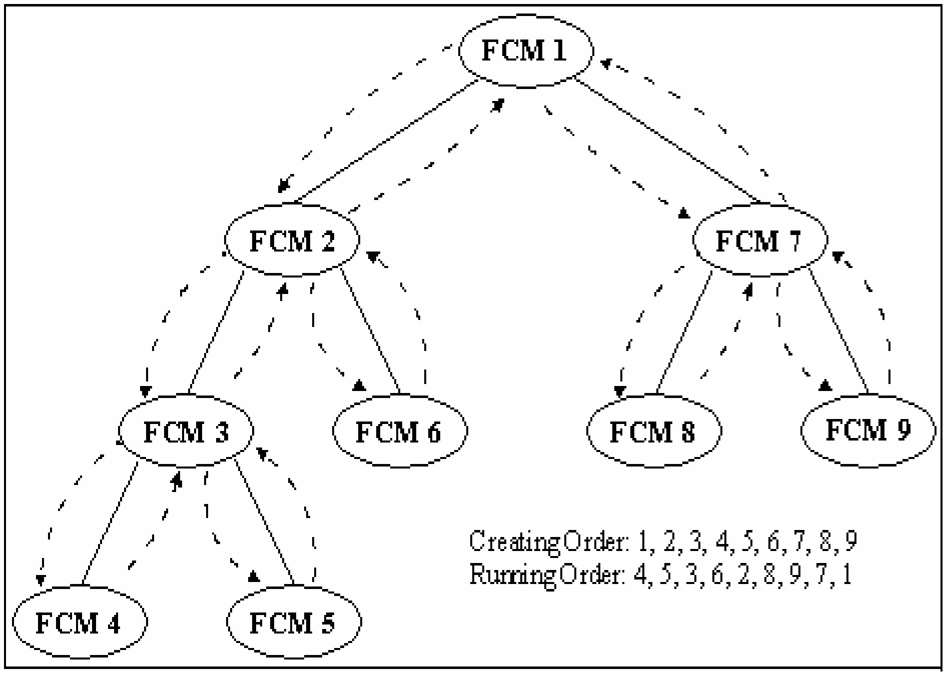


Figure 5.3: An example of a ML-FCM

The main idea is to create new FCMs and continue the procedure until we reach a leaf FCM, i.e., a map without children, which does not require any further expansion. Once we reach a node of the ML-FCM where the activation level list of the specific FCM is complete, then the algorithm backtracks to its parent in order to see whether or not another concept with a missing activation level exists and if so, to create another child FCM. Figure 5.3 illustrates how an ML-FCM structure is built. The creation sequence is as follows: FCM1, being the main map, is created first. The first missing value from FCM1's activation level list triggers the creation of FCM2, followed by the creation of FCM3 is created, as it corresponds to the first missing value from FCM2's activation list. The next map to be created is FCM4, a leaf node, followed by FCM5, with the creation of FCM5 following the FCM4 execution. Subsequent to the backtracking, FCM3 is revisited in order to update its activation level list and to check if it is complete. In this case it is not complete, thus the algorithm creates and runs FCM5 which is also a leaf node, followed by FCM3. The latter becomes a leaf node itself, after the execution of FCM4 and FCM5. Further backtracking to FCM2 shows that its activation level list is incomplete which requires the creation of FCM6. Once FCM6 is run it is followed by a run of the FCM2, which is a leaf node after the execution of FCM6. It is important to remember that this sequence refers to the first branch of the main node (FCM1) while the second branch includes FCM7, this being first in order with regard to this particular branch and seventh taking into account the entire structure. FCM8 followed by FCM 9, complete the creation sequence of the example of Figure 5.3.

Once the ML-FCM structure is completed the second stage of the algorithm establishes the initial condition of the system. The execution process takes the activation levels and the weights given by the experts for the particular FCM and runs the FCM algorithm for a selected number of iterations. During the iterative process the model is left to interact, with each concept's level being revised. After all iterations have been completed the results are fed into the defuzzification process in order to justify the requested value for the concept of interest. Therefore, an updating procedure is required to accomplish the activation level value for the concept for which the new FCM was build. As soon as the updating procedure is completed, backtracking checks if the parent's activation level list is complete.

The third stage of the algorithm allows genetic optimization to be carried out on selected FCMs. For each FCM of interest, a concept belonging to that FCM is assigned a target final activation level. The genetic optimization carried out in the next phase will compute a new weight matrix that will bring the target concept to its target final level. The algorithm allows for the selection of concepts from any or all FCMs. Hence, even though only a number of FCMs may be selected for genetic optimization, the methodology will ultimately perform the FCM algorithm on all FCMs using a bottom-up approach. This property that allows for the application of genetic optimization on more than one FCM is very useful, especially when genetic optimization is applied to a concept that expands a particular node. Since the concept is common in two FCMs, genetic optimization is carried out twice, once in the child FCM and once in the parent FCM. As a result, the concept's final level computed in the child FCM will at the same time be the initial level of the parent FCM, both of which have been predefined for a specific scenario analysis. This means, therefore, that such a scenario analysis can be very flexible allowing for different experimentations either at all or at some of the points of interacting FCMs.

The simulation process that completes the methodology involves the execution of the FCM and GE-FCM algorithms as explained in previous paragraphs. The proposed methodology executes these algorithms on the ML-FCM structure based on a bottom-up approach, so that any newly-computed final level of a concept (of a child FCM) may be used as the initial activation level of its parent FCM after it has been calculated using the optimized weight matrix of the child GE-FCM. More specifically, the simulation begins on the FCMs that are located in the bottom of the structure and the GE-FCM algorithm is executed on those specific FCMs while the resulting weight matrix is then fed to the FCM algorithm to complete the scenario analysis.

Following the execution of the FCM algorithm, the value of the central concept's final level is passed to its parent FCM node in order to update the parent's initial activation level list. The backtracking procedure continues until the root FCM node is reached and its activation list is complete. At this stage, the last run of the main FCM algorithm is carried out and the results of all iterations are inputted in the defuzzification process so as to transform the numerical values of the final levels of the concepts to their linguistic equivalents.

5.4 Limitation of the ML-FCM and proposition of a new algorithm: The Enhanced ML-FCM algorithm

As previously mentioned regarding the execution order, the ML-FCM algorithm starts with those FCMs that lie at the lowest levels and continues with transferring the computed activation level of the concept in focus to its above layer. This makes sure that the main variables influencing the concept in focus are analysed and assessed "locally" (i.e., focusing only on this specific concept of interest), thus reducing complexity by sharing it evenly between layers. An additional advantage of this algorithm is that it contributes to the efficiency of decision-making by allowing the simulation of the selected scenarios separately in each layer. More specifically, the ML-FCM algorithm forms layered Fuzzy Cognitive Maps in a hierarchical structure, in order to compute the activation levels of child FCMs in each layer and update the activation levels of the decomposed parent FCMs in the upper layers.

The major weakness of the ML-FCM algorithm is the time lack between the layers. More specifically, the different FCMs work individually in each layer and the value of the intermediate outcome is transferred to the upper layer. The estimation time of this transformation, that is, the time corresponding to the actual events being modelled, cannot be determined exactly. The time estimation in FCM is a general problem discussed during the last years [3], thus to address it we attempted to improve the ML-FCM algorithm by minimizing the time lag between layers using a new advanced algorithm named Enhanced Multi-Layer Fuzzy Cognitive Map (EML-FCM) [126]. More specifically the main idea of the ML-FCM algorithm is that each FCM is executed once for a number of iterations and only after all of the concepts resigning in it achieve an activation level. However, what is not taken into account is the fact that at each iteration the values of the levels change and as such these new values must somehow be fed back to the parent FCM during the same iteration. Therefore, we proposed an enhancement to the multilayered algorithm which takes into consideration this change in values of levels during each iteration.

5.4.1 Description of the EML–FCM algorithm

The purpose of this new enhanced algorithm is to offer an alternative type of layer traversal in the map and computation of the activation levels of the nodes. In particular, the activation levels of all concepts in each layer starting from top to bottom are computed for each iteration and not after fully completing the execution process of a certain layer. This is performed depending on the position of a node (i.e., the layer it belongs to) and the status of each concept (whether it is a central, complex concept described in lower levels by a number of other parameters or not). Each iterative calculation taking place at a layer is fed back to the parent FCM and the last computed activation level value is used in the next iteration. This modification to the ML-FCM algorithm is very important because now the execution process takes into consideration the detailed, small-step information produced within iterations in the form of intermediate activation level values as opposed to the former algorithmic approach which, although Multi-Layered in structure, practically worked as a single map using a depth search mechanism [167]. Just as the original multilayered algorithm, the new algorithm begins by creating the Multilayer FCM structure. However, when a leaf node is reached (i.e., the FCM has no children) the FCM is executed for one iteration only. The change in the corresponding value of the central concept of the leaf FCM (in other words, the concept with a missing activation level in the parent FCM) is fed back to the parent FCM which then continues to either execute for one iteration (if no more levels are missing) or to create a new child FCM that will have as a central concept the corresponding concept of the parent FCM with a missing activation level.

```
Create and execute process
1.      create main FCM
2.      check the FCM's AL list if it is complete
3.      for each missing AL in the FCM's AL list
4.              create child FCM in (n+1)th layer
5.              If child FCM's AL list is complete
6.                      run CNFCM algorithm for one iteration
7.                      update parent FCM's AL list
8.                      repeat from step 2
9.              else repeat from step 3
10              endif
11          endfor

Updating function
1.      current FCM ← root FCM
2.      for each iteration
3.              while current FCM has children
4.                      for each child
5.                              parent FCM ← current FCM
6.                              current FCM ← child FCM
7.                              update current FCM's AL list based on the
                                        values of its parent FCM's AL list
8                         endfor
9                       run current FCM for one iteration
10        endfor
11.             update the parent's AL list based on the result on
12                      the current FCM's execution
```

Figure 5.4: Pseudo code describing the Enhanced ML-FCM Algorithm

This process repeats until the root node is reached, keeping in mind that FCMs are run for one iteration. Once at the root, the root FCM executes, again only once, and passes down to its child FCMs the levels of those concepts that were once missing in order for the children to execute. If the children also have child FCMs then they will halt their execution and pass down the value of the activation level that was also initially missing. As a result, execution of an FCM only takes place whilst moving in a bottom-up direction, and never while moving downwards. The process followed by the EML-FCM algorithm for creating and executing different FCMs in various layers of the modelling structure is presented in Figure 5.4 in pseudo code form.

5.4.2 Mathematical formulation of Multi-Layer structure

Another challenge in the Multilayer FCM is the time relationship (or time lag) involved before a change in activation level of node *Ci* having an effect on node *Cj*. The problem is increased in Multilayer FCM due to the fact that an updating procedure is introduced in which the AL value of the central concept of an FCM is transformed to the upper Layer. This procedure introduces some aspects of time in the Multilayer structure. During the updating procedure, each concept node can be seen as a memory cell that is activated (positively or negatively) and can be influenced by a cell belonging to a lower layer of the multilayer structure (child FCM). The behaviour of this cell is such that it looses some of its activation when there is no stimulation to maintain the activation. The activation level of a concept that has no other influence from other concepts gradually, as time passes decays towards zero. A time decay (T_d) is introduced aiming that the activation level of a concept in each FCM layer will not be drawn only by the local FCM final state but also from its previous value and transition stage from one layer to another. It can take values within the interval of [0,1] and the maximum it is, the faster the cell becomes inactive when it receives no stimulation.

The following formula is proposed so as to serve the multilayer structure of a FCM. The main characteristic of this formula is the utilization of pointers *l* and *k* which indicates at each execution step the layer and sub FCM respectively to which the formula is applied.

$$A_{i(l,k)}^{t+1} = f\left(\sum_{\substack{j(l,k)=1 \\ j(l,k)\neq i}}^{n(l,k)} A_{j,(l,k)}^{t} . W_{i,j(l,k)}^{t} \right) - T_{d\,(l,k)} A_{i(l,k)}^{t} \qquad 5.2$$

where, $A_{i(l,k))}^{t+1}$ is the activation level of concept C_i at time $t+1$ at layer l in FCM k, $A_{j(l,k))}^{t}$ is the activation level of concept C_j at time t in the same layer and same FCM. f is a threshold function that specifies the way the influences from the other concepts affect the current activation level to produce its new value. This function takes also into consideration the updating function of the ML-FCM algorithm. So the new state vector $A_{i(l,k))}^{t+1}$, which is computed by multiplying the previous state vector by the edge matrix $W_{i,j(l,k)}^{t}$, shows the effect of the change in the activation level of one concept on the other concepts for a particular FCM k in layer l. Finally, T_d is the decay factor which subtracts a percentage of the previous activation level to weaken its effect on the current activation value.

5.5. Case study using the Multi-Layer approach

5.5.1 The solution of the Cyprus Issue through the provisions of the Annan Plan

We have decided to extent the use the “Cyprus Issue” as a typical political and strategic issue in the environment of which we shall demonstrate the efficacy of the proposed ML-FCM algorithm. The model had been built to describe the political, institutional and economic environment in the eve of the April 2004 referendum on the island and consider the extent to which a number of possible political and strategic developments may contribute to solving the Cyprus issue.

The model identifies fifty six concepts as indicated in Appendix A grouped in seven sub-FCMs as shown in Figure 5.5. Each sub-FCM consists of a number of concepts which describe one central concept of interest. FCM 1 is the main FCM of the model consisting of 13 concepts as shown in Table 5.1, with C1 “ Solution of the Cyprus Issue” being the central concept of this map. Two main concepts of interest have been selected for further analysis, namely C3 “Platform Solution of the Cyprus Issue” and C6 “Referendum concerning the acceptance of the Annan Plan”. The two concepts have been indicated by the experts for further analysis because of their importance. The experts were looking for the parameters influencing the Platform of the Solution of the Cyprus issue in respect to the acceptance of the Annan Plan during the referendum of the 24th of

April 2004. Table 5.1 indicates the 13 concepts that constitute FCM1. Figure 5.6 depicts FCM1, while the interconnection weights and activation level values are shown in Appendix A.

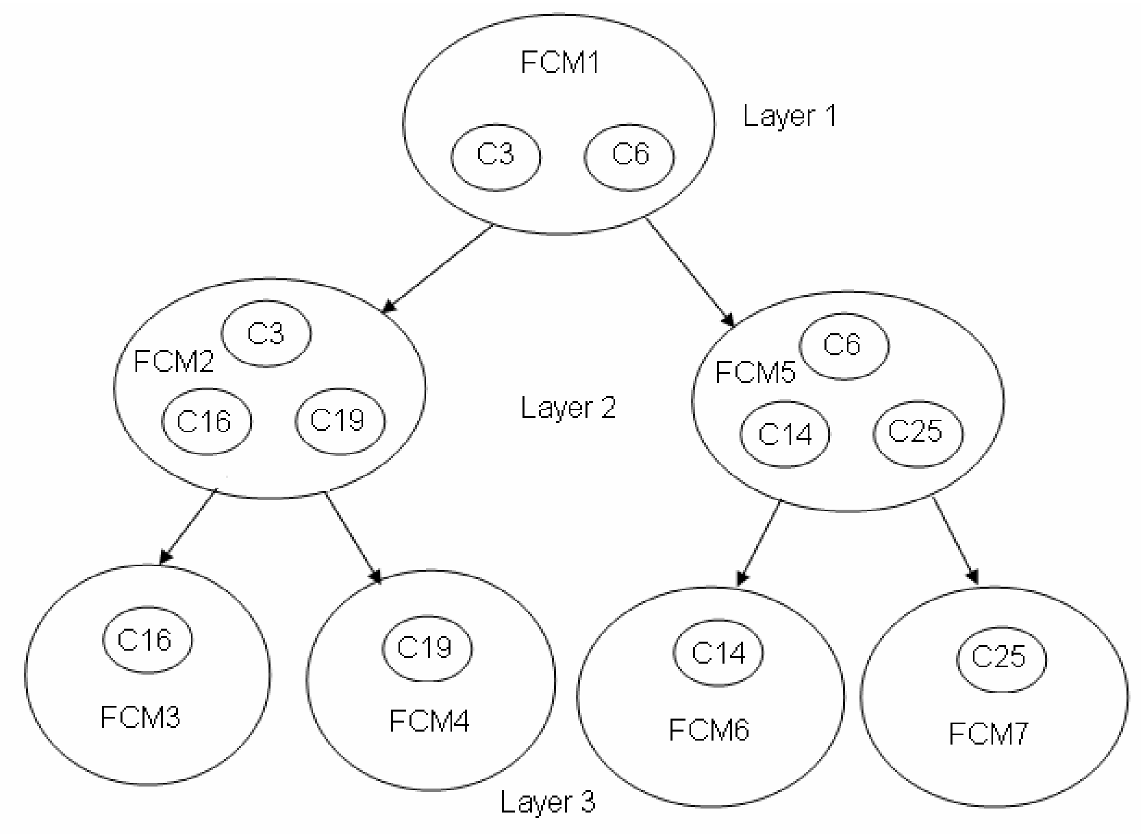
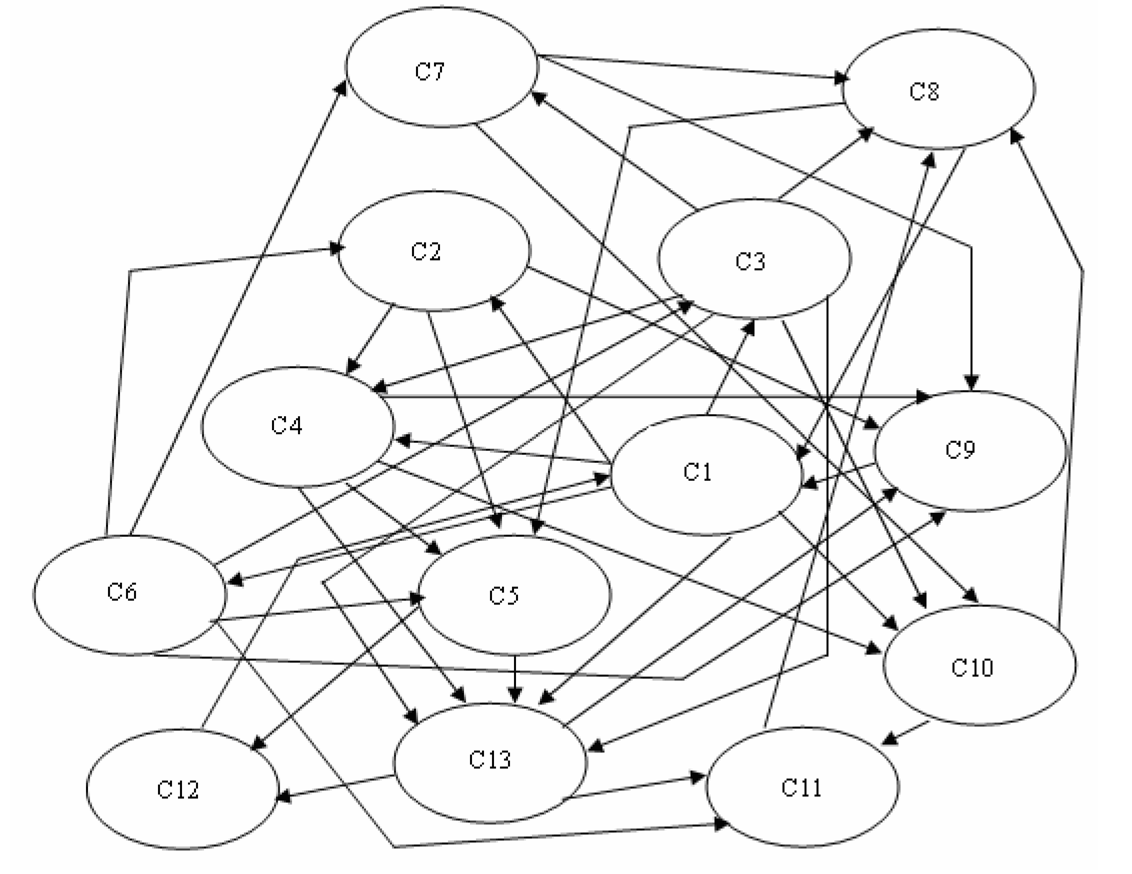


Figure 5.5: Multilayer representation of the Annan plan

Table 5.1: FCM1 concepts

C1	Solution of the Cyprus Issue
C2	Climate of Tension on the Island
C3	Platform Solution of the Cyprus Issue
C4	T/C Reaction to the final Annan Plan
C5	Turkish Government reaction to Annan Plan
C6	Referendum concerning the acceptance of the Annan Plan
C7	G/C Government reaction to the final Plan
C8	Greek politicians reaction to the final Plan
C9	US / UK reaction to the final Annan Plan
C10	Greek position with reference to Turkish EU Membership
C11	Cyprus position with reference to Turkish EU Membership
C12	EU Position with reference to Turkish EU Membership
C13	US/UK position with reference to Turkish EU Membership




```
C1 --> C2: -0.35
C1 --> C3: 0.70
C1 --> C4: -0.50
C1 --> C6: 0.70
C1 --> C10: -0.40
C1 --> C13: -0.30
C2 --> C4: 0.40
C2 --> C5: -0.40
C2 --> C9: 0.15
C3 --> C4: 0.60
C3 --> C7: 0.70
C3 --> C8: 0.40
C3 --> C10: 0.30
C3 --> C13: -0.35
C4 --> C5: 0.90
C4 --> C9: 0.40
C4 --> C10: 0.35
C4 --> C13: 0.20
C5 --> C12: -0.20
C5 --> C13: 0.35
C6 --> C2: 0.40
C6 --> C3: 0.80
C6 --> C5: -0.35
C6 --> C7: 0.75
C6 --> C8: 0.40
C6 --> C9: -0.30
C6 --> C11: 0.20
C7 --> C4: -0.50
C7 --> C8: 0.70
C7 --> C9: -0.50
C7 --> C10: -0.10
C8 --> C1: 0.30
C8 --> C5: -0.20
C9 --> C1: 0.30
C10 --> C8: 0.10
C10 --> C11: 0.40
C11 --> C8: -0.60
C12 --> C1: 0.20
C13 --> C9: 0.60
C13 --> C11: -0.20
C13 --> C12: -0.20
```

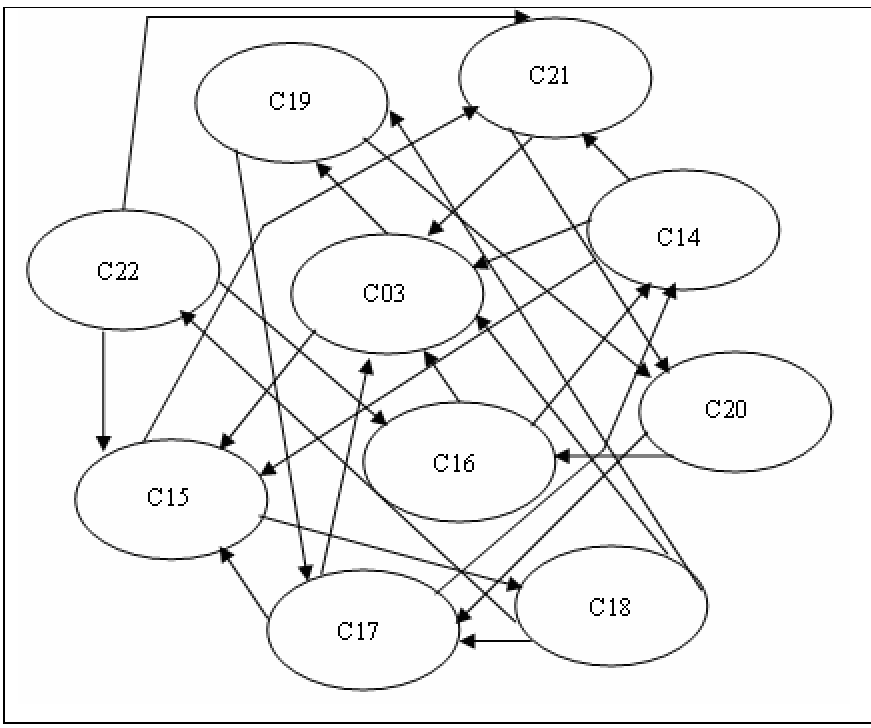
Figure 5.6: FCM1 map representation

FCM2 is a child node of FCM1 and represents the decomposition of concept C3 participating in FCM1 which is a key concept for resolving the Cyprus Issue. Thus, concept C3 is the central concept of FCM2. FCM2 as shown in Table 5.2 consists of ten concepts. From FCM2, two important concepts have been selected for further analysis

C16 “Security” and C19 “Legislative”. Figure 5.7 depicts FCM2 expanded, while the interconnection weights and activation level values are shown in Appendix A. Due to the complexity of this model its detailed explanation will be skipped. All information regarding the model is given in Appendix A. Only few indicative values will be given to demonstrate some examples and used as reference for comparison purposes of the two multilayer algorithms, ML-FCM and EML-FCM.

Table 5.2: FCM2 concepts

C3	Platform solution of the Cyprus issue
C14	Territorial
C15	Property
C16	Security
C17	Freedoms (freedom of movement of goods and services)
C18	Constitutional
C19	Legislative
C20	Executive power
C21	Economy
C22	Guarantees



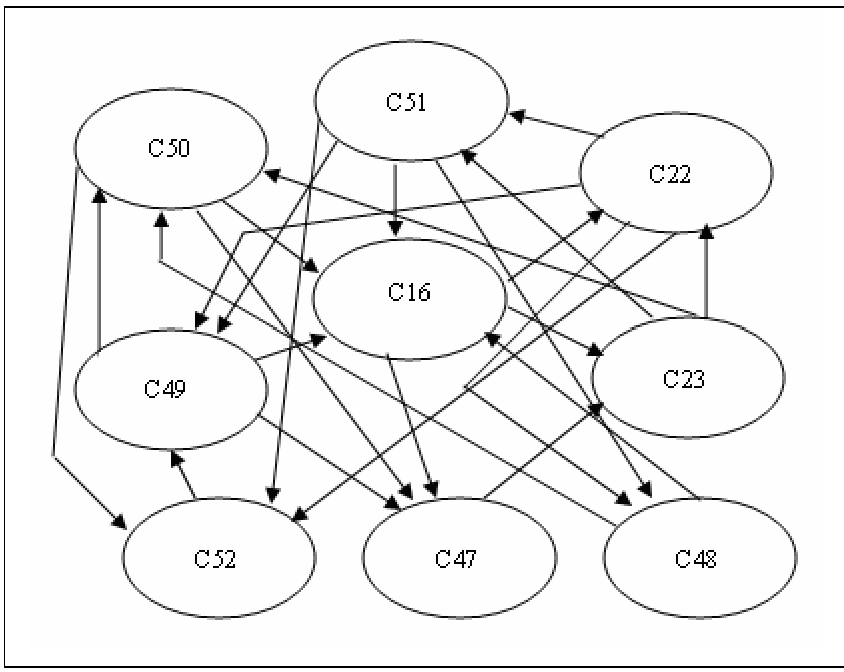

```
C3 --> C15: -0.60
C3 --> C19: 0.50
C14 --> C3: 0.70
C14 --> C15: 0.70
C14 --> C21: -0.20
C15 --> C18: 0.10
C15 --> C21: 0.20
C16 --> C3: 0.60
C16 --> C14: 0.20
C17 --> C3: 0.30
C17 --> C14: 0.10
C17 --> C15: 0.40
C18 --> C3: 0.30
C18 --> C17: 0.60
C18 --> C19: 0.80
C18 --> C22: 0.40
C19 --> C17: 0.30
C19 --> C20: 0.60
C20 --> C16: 0.40
C20 --> C17: 0.30
C21 --> C3: 0.30
C21 --> C20: 0.20
C22 --> C15: 0.30
C22 --> C16: 0.60
C22 --> C21: 0.20
```

Figure 5.7: FCM2 expanded representation

Following the creation/execution steps of the proposed ML-FCM, it is noted that so far neither FCM1 nor FCM2 can be executed due to the fact that their activation level lists are incomplete. Such a list is left intentionally incomplete in order to instruct the system that an FCM in the lower layer is needed for the computation of the AL of the relevant concept. Continuing, FCM3 is created as a child of FCM2 in layer 3, with its central concept being C16. Note that FCM3 consists of nine concepts as shown in Table 5.3, given that FCM3 is a leaf node, that is, its activation lists are complete and is, therefore, readily executable. Figure 5.8 depicts FCM3 while the interconnection weights activation level values and results are shown in Appendix A**.**

Table 5.3: FCM3 concepts

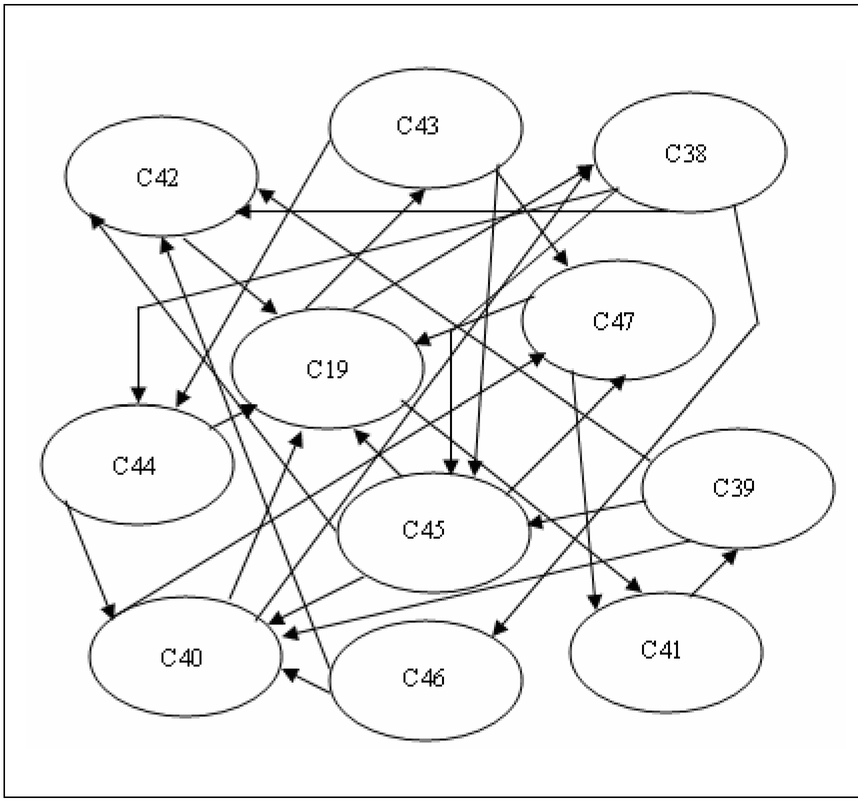
C16	Security
C22	Guarantees
C23	EU acquis
C47	International personality of state
C48	Demilitarization
C49	Intervention rights
C50	Remaining of military forces
C51	European guarantees
C52	Guarantee forces




```
C16 --> C22: -0.30
C16 --> C23: -0.30
C16 --> C47: -0.20
C22 --> C48: 0.10
C22 --> C49: 0.60
C22 --> C51: 0.50
C22 --> C52: -0.40
C23 --> C22: 0.20
C23 --> C50: 0.40
C23 --> C51: 0.60
C47 --> C23: 0.30
C48 --> C16: 0.50
C48 --> C50: 0.60
C49 --> C16: -0.50
C49 --> C47: 0.10
C49 --> C50: -0.30
C50 --> C16: -0.50
C50 --> C47: -0.50
C50 --> C52: 0.40
C51 --> C16: 0.50
C51 --> C48: 0.40
C51 --> C49: 0.40
C51 --> C52: 0.30
C52 --> C49: 0.60
```

Figure 5.8: FCM3 expanded representation

The execution of the FCM algorithm on FCM3 results in the calculations of the activations of the value of concept C16 (A_{16}=-0.69) which is then transferred to its parent map FCM2; the activation-level list of which is thus updated. Given that C16 represents the concept of “Security”, which is the central concept of FCM3, its negative value represents the Greek-Cypriots’ skepticism concerning the security provisions of the Annan Plan. Meanwhile, since the FCM2 activation level list is still incomplete computing the missing activation level requires the creation of FCM4 as a leaf node of FCM2 consisting of eleven concepts. As indicated in Table 5.4. Figure 5.9 depicts graphically FCM4 while the interconnection weights and activation level values are shown in Appendix A.




```
C19 --> C38: 0.40
C19 --> C41: 0.50
C19 --> C43: 0.30
C38 --> C42: 0.40
C38 --> C44: 0.50
C38 --> C45: 0.10
C38 --> C46: 0.70
C39 --> C40: -0.30
C39 --> C42: 0.30
C39 --> C45: 0.60
C40 --> C19: 0.50
C40 --> C38: 0.40
C40 --> C47: -0.50
C41 --> C39: 0.30
C41 --> C47: -0.30
C42 --> C19: 0.60
C43 --> C44: 0.60
C43 --> C45: 0.40
C43 --> C47: -0.50
C44 --> C19: 0.40
C44 --> C40: -0.35
C45 --> C19: -0.40
C45 --> C40: -0.35
C45 --> C42: 0.70
C45 --> C47: 0.40
C46 --> C40: 0.50
C46 --> C42: -0.30
C47 --> C19: 0.50
C47 --> C41: 0.40
```

Figure 5.9: FCM4 expanded representation

Concept C19 “Legislation” is the central concept of FCM4 which, being a leaf node, is readily executable. The CNFCM algorithm applied on FCM4 yields a value of A_{19}=-0.77.

This value according to the Fuzzy Knowledge Base of Appendix A is pointing to an inapplicable legislative framework.

Table 5.4: FCM4 concepts

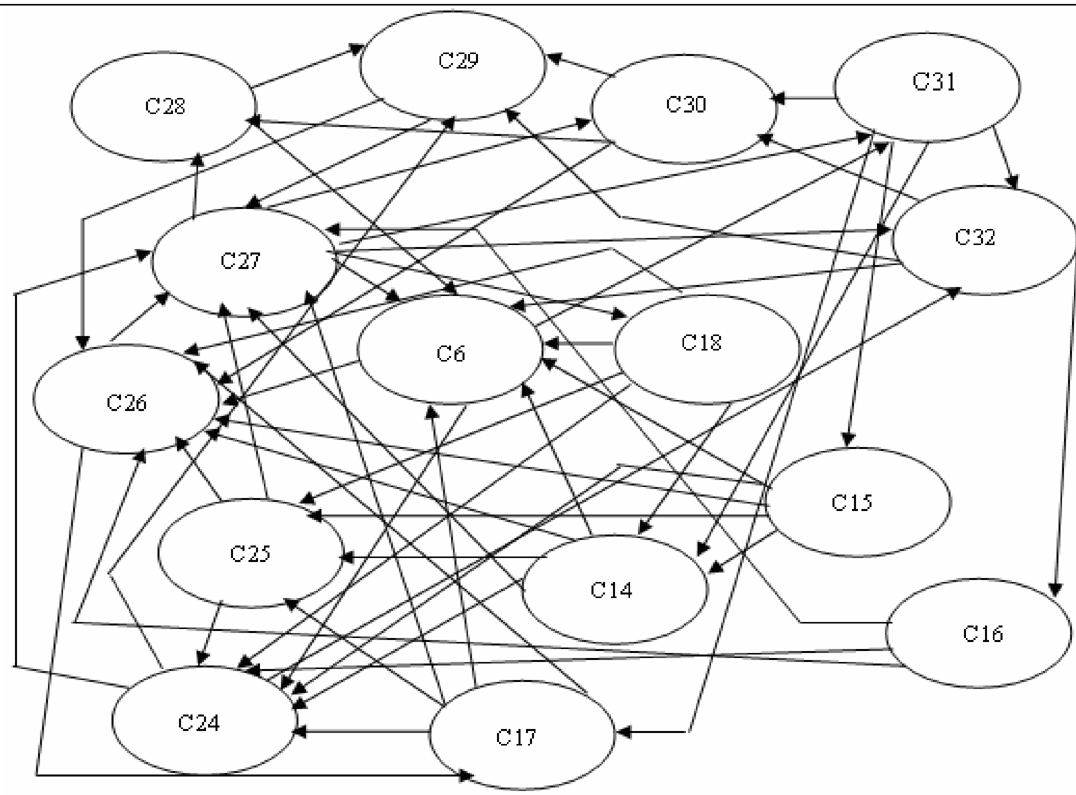
C19	Legislative
C38	Supreme court
C39	Legislative power
C40	Mechanism for settling disputes
C41	Executive power – Composition
C42	Executive power – Decision-making
C43	Concept 43 Senate/Parliament – Representation
C44	Senate/Parliament – decision-making
C45	Presidential council
C46	Judicial power
C47	International personality of state

This value is fed back to FCM2 to complete its activation level list and thus turns it to a leaf node which allows for its execution process to start. The value of its central concept "Platform of the Cyprus issue" (A_3=-0.70) indicates that the platform solution of the Cyprus issue (i.e. the Annan Plan) is rejected by the Greek-Cypriots. This value is transferred to the main FCM1 in the first layer in order to update its activation level list. At this point, our periodic ALs FCM1 list check indicates that concept C6 has not yet assumed a value, something which requires the creation of FCM5 for its computation.

Table 5.5: FCM5 concepts

C06	Referendum concerning the acceptance of a new Annan plan
C14	Territorial
C15	Property
C16	Security
C17	Freedoms (freedom of movement of goods and services)
C18	Constitutional
C24	Perception for Annan plan
C25	Cost of the solution – Help from international community
C26	Changes in the Annan plan- New Plan
C27	Future acceptance of a new plan from the Greek Cypriots
C28	Future acceptance of a new plan from the Greece
C29	Anglo-American position for a new plan
C30	Future acceptance of a new plan from the Turkish Cypriots
C31	Future acceptance of a new plan from the Turkey
C32	EU position for a new plan

FCM5 represents the decomposition of concept C6 which is its central concept and consists of sixteen concepts in total, as shown in Table 5.5. FCM5 is a not leaf node, and its two concepts that have been selected for further analysis are C14 and C25. Figure 5.10 depicts graphically FCM5 while the interconnection weights and activation level values are shown in Appendix A.



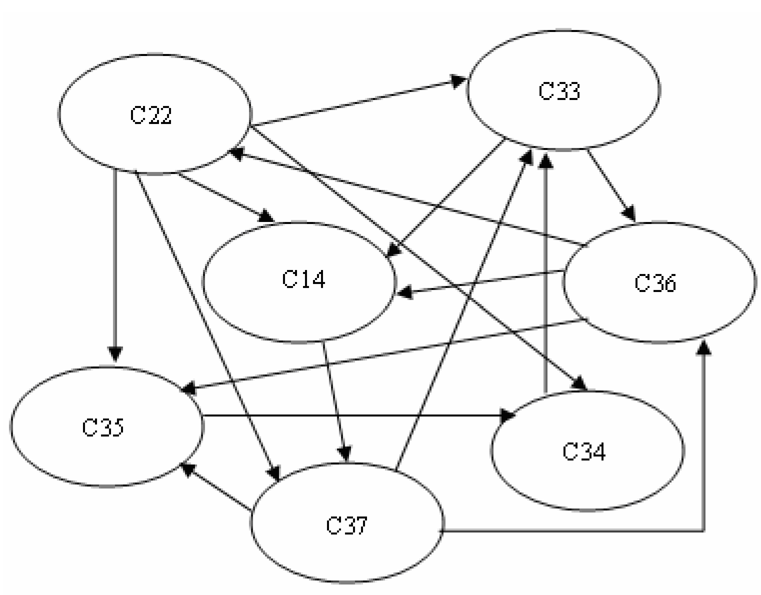
C6 --> C24: 0.20	C17 --> C6: 0.30	C26 --> C16: 0.50	C30 --> C29: -0.40
C6 --> C26: 0.30	C17 --> C24: 0.50	C26 --> C17: 0.50	C31 --> C6: 0.40
C6 --> C31: 0.60	C17 --> C25: 0.30	C26 --> C27: 0.40	C31 --> C14: 0.30
C14 --> C6: -0.30	C17 --> C26: 0.70	C27 --> C6: -0.10	C31 --> C15: 0.20
C14 --> C24: 0.50	C17 --> C27: 0.50	C27 --> C18: 0.40	C31 --> C17: 0.20
C14 --> C25: 0.30	C18 --> C6: 0.40	C27 --> C28: -0.70	C31 --> C30: -0.50
C14 --> C26: 0.70	C18 --> C14: 0.50	C27 --> C30: -0.50	C31 --> C32: 0.30
C14 --> C27: 0.50	C18 --> C24: 0.40	C27 --> C31: 0.30	C32 --> C6: 0.30
C15 --> C6: 0.20	C18 --> C25: 0.30	C27 --> C32: 0.40	C32 --> C16: -0.40
C15 --> C14: 0.20	C18 --> C26: 0.40	C28 --> C6: 0.30	C32 --> C29: 0.30
C15 --> C24: 0.40	C24 --> C27: 0.70	C28 --> C29: -0.10	C32 --> C30: 0.20
C15 --> C25: 0.30	C24 --> C29: 0.40	C28 --> C31: 0.30	
C15 --> C26: 0.40	C24 --> C32: 0.30	C29 --> C26: -0.30	
C16 --> C24: 0.30	C25 --> C24: 0.40	C29 --> C27: 0.60	
C16 --> C26: 0.50	C25 --> C26: 0.20	C30 --> C26: 0.50	
C16 --> C27: 0.40	C25 --> C27: 0.40	C30 --> C28: 0.50	

Figure 5.10: FCM5 expanded representation

The next step is the creation and execution of FCM6 which is a leaf node and describes the decomposition of C14 as shown in Table 5.6 into seven concepts. The execution of FCM6 yields A_{14}=-0.86 meaning that the territory returned under the Greek-Cypriot control is not adequate. This activation level is transferred to FCM5.

Table 5.6: FCM6 concepts

C14	Territorial2
C22	Guarantees
C33	Free settlement
C34	Free movement
C35	Property rights
C36	Return of territories of the Greek Cypriot refugees
C37	Remaining of settlers



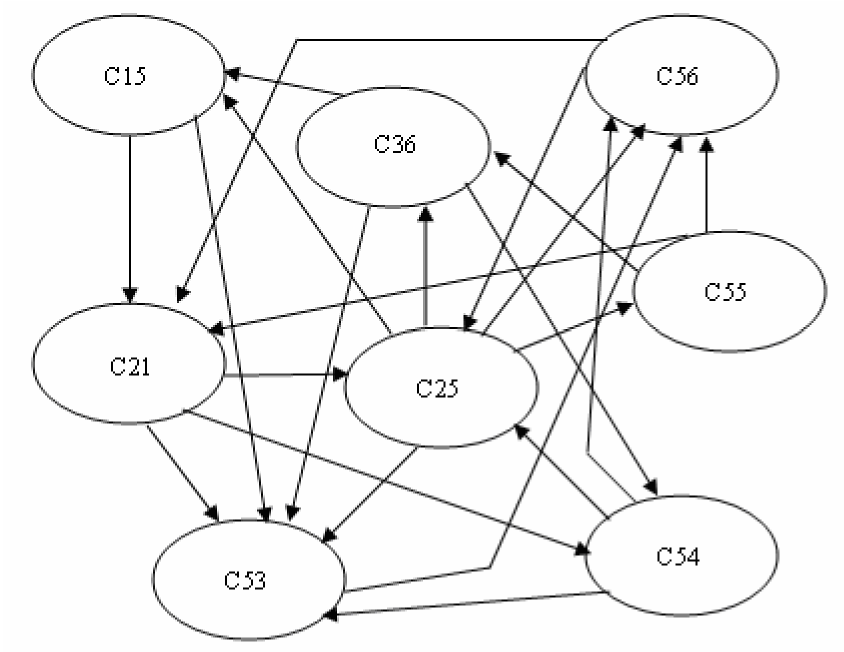

```
C14 --> C37: -0.50
C22 --> C14: -0.10
C22 --> C33: 0.30
C22 --> C34: 0.50
C22 --> C35: 0.50
C22 --> C37: 0.20
C33 --> C14: 0.10
C33 --> C36: 0.10
C34 --> C14: -0.20
C34 --> C33: 0.30
C35 --> C33: 0.70
C35 --> C34: 0.40
C36 --> C14: 0.30
C36 --> C22: 0.20
C36 --> C35: 0.20
C37 --> C33: -0.30
C37 --> C35: -0.30
C37 --> C36: -0.30
```

Figure 5.11: FCM6 expanded representation

The next task is the formulation of FCM7 consisting of eight concepts (Table 5.7) and involving the parameters describing concept C25. After the execution of the map the activation level is calculated (A_{25}=-0.66) and transferred to its parent FCM5 which subsequently becomes a leaf node. It is then executed, and the activation level value of concept C6 is computed (A_6=-0.81) and transferred to the main map, FCM1.

Table 5.7: FCM7 concepts

C15	Property
C21	Economy
C25	Cost of the solution – Help from international community
C36	Return of territories of the Greek Cypriot refugees
C53	Functional cost of the unified state
C54	Economical Contribution towards unified state
C55	Compensation – External Aid
C56	Eurozone Criteria




```
C15 --> C21: 0.30
C15 --> C55: 0.40
C21 --> C25: 0.30
C21 --> C53: 0.60
C21 --> C54: 0.30
C25 --> C15: -0.40
C25 --> C36: 0.20
C25 --> C53: 0.40
C25 --> C55: 0.30
C25 --> C56: 0.30
C36 --> C15: 0.60
C36 --> C53: 0.20
C36 --> C54: 0.20
C53 --> C15: -0.20
C53 --> C36: 0.20
C53 --> C56: 0.20
C54 --> C25: -0.10
C54 --> C53: 0.60
C54 --> C56: 0.30
C55 --> C21: 0.30
C55 --> C36: 0.30
C55 --> C56: 0.20
C56 --> C21: 0.20
C56 --> C25: 0.20
```

Figure 5.12: FCM7 expanded representation

5.5.2 Comparison of the two algorithms

In the second branch of Figure 5.13, FCM5 represents the decomposition of concept C6. A new FCM is created to indicate the factors influencing concept C6. As the central concept of FCM5, C6 consists of sixteen concepts in total, as shown in Table 5.8. FCM5 is not a leaf node; hence two of its main concepts, C14 and C25 have been selected for further analysis.

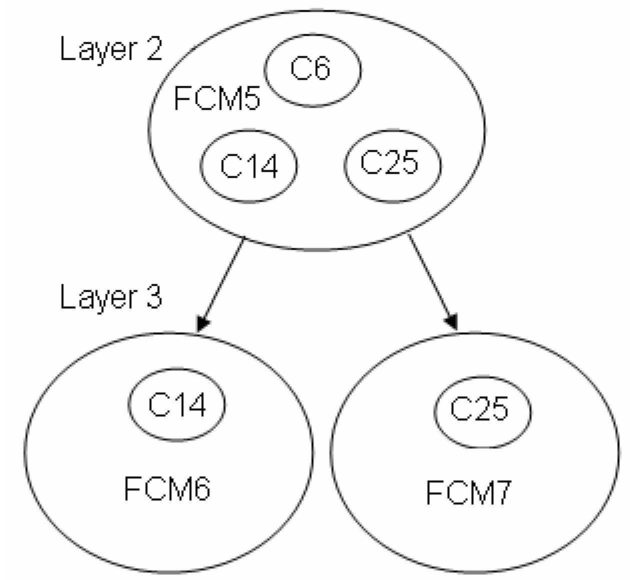


Fig. 5.13: Second Branch of the multilayered model

FCM5 was executed and the results are summarised in Table 5.8. The initial values of the experts are shown in the first column, the results obtained from the execution of the ML-FCM in the second column and the results of the EML-FCM in the third.

As can be observed from the last two columns of Table 5.8, there are some differences in the final results produced by the execution of the two algorithms. We consider this as a normal outcome since the algorithms follow a different execution process as regards the propagation of the central concepts from the two child FCMs (C14 and C25) to their parent. These results were evaluated by the experts who justified that the results of the EML-FCM reflected more accurately the parameters of the Cyprus issue at that time period of the referendum. More specifically, the results differ in the values of the final AL of concepts C6 and C31, while the values for the rest of the concepts remain within the same fuzzy sets. The evaluation of our results indicates that the outcome of the EML-algorithm reflects more accurately the political situation at that period of time. From the graphs of Figures 5.14 and 5.15 that represent the results of the execution of FCM5 with both algorithms, it is noticed that while the exact values of each concept (except C6 and C31) are almost the same, the graphical representation of EML-FCM algorithm reveals bounded limited cycles. This phenomenon will be investigated further to identify the origin of the limit cycles.

Table 5.8: FCM5 summarised results

Concept	Initial Value	ML-FCM Algorithm	EML-FCM Algorithm
C6	-0.30	-0.45	-0.30
C14	-0.46	-0.54	-0.42
C15	0.20	-0.16	-0.00
C16	-0.30	-0.22	-0.19
C17	-0.30	-0.55	-0.47
C18	-0.60	-0.55	-0.54
C24	-0.30	-0.78	-0.73
C25	-0.68	-0.61	-0.61
C26	-0.60	-0.72	-0.62
C27	-0.60	-0.86	-0.85
C28	-0.40	0.72	0.70
C29	0.40	-0.70	-0.68
C30	-0.30	0.57	0.42
C31	0.40	-0.34	0.33
C32	0.20	-0.66	-0.59

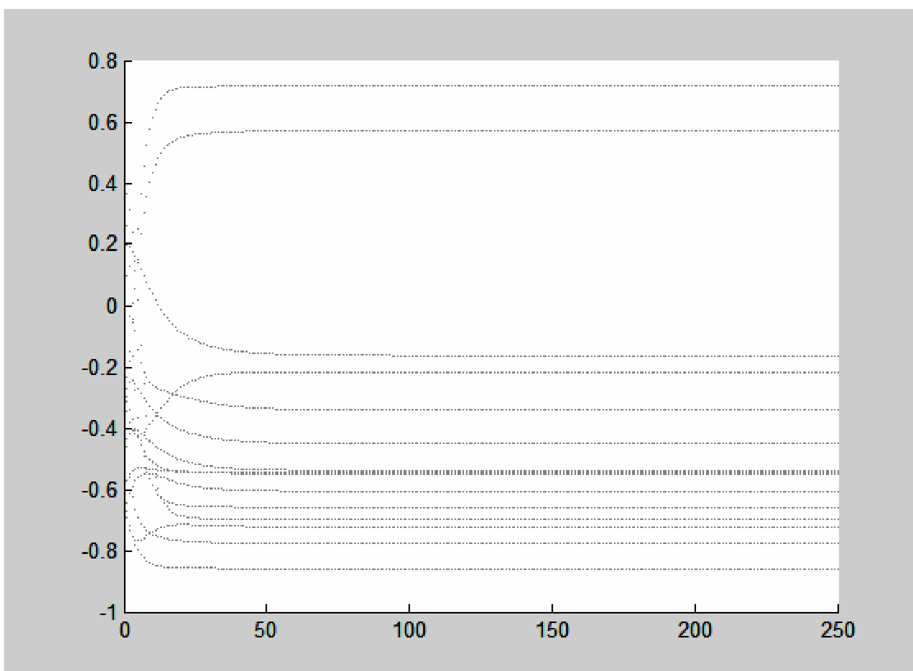


Figure 5.14: ML-FCM execution results for FCM5

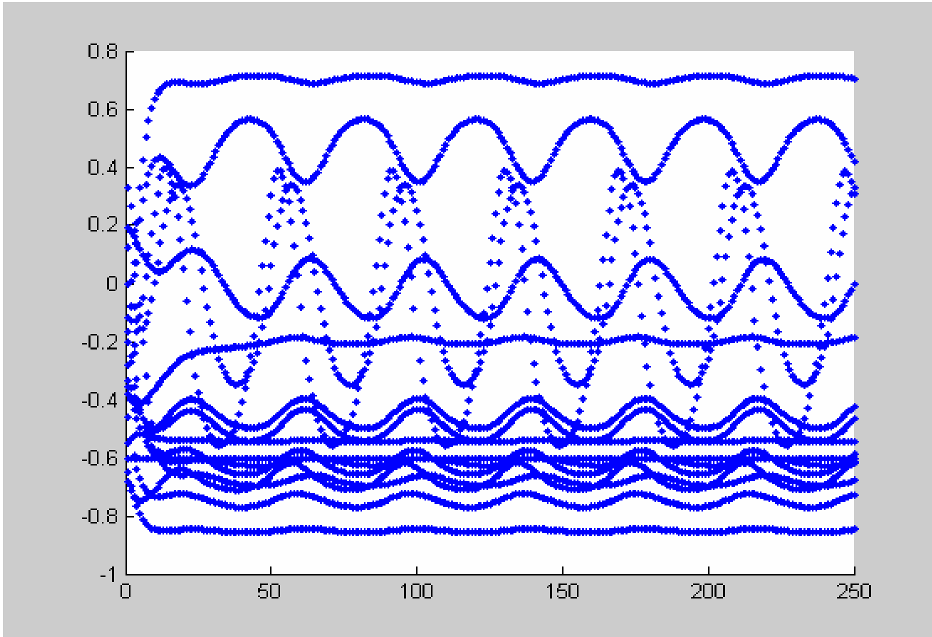


Figure 5.15: EML-FCM execution results for FCM5

The next step is the formulation and execution of FCM6 and FCM7 which are leaf nodes of FCM5. FCM6 consists of six concepts, the descriptions of which are given in Table 5.9 and the descriptions of FCM7, which consists of seven concepts, are provided in Table 5.10. After the execution of these two maps the activation levels of C14 in FCM6 and C25 in FCM7 are calculated and transferred to their parent FCM5, which subsequently becomes a leaf node of FCM1. The transfer of C14 and C25 activation values follows a different procedure in the two algorithms.

The ML-FCM performs the transfer after completion of 250 iterations, that is, after a full execution of the child FCMs and their stabilisation. On the other hand, the EML-FCM transfers the activation values after every single iteration, that is, the values are passed to the parent FCM 250 times. A careful examination of the results of the two algorithms on FCM6 and FCM7 (Tables 5.9 and 5.10, respectively) shows that the results are almost identical. This is due to the fact that the two FCMs are leaf nodes and they do not receive any influence from other FCMs. The graphical representation (Figures 5.16 and 5.17) of the two FCMs is also quite similar, with the graph representing the EML-algorithm presenting minor fluctuations as well as some pronounced oscillations which can be characterized as limit cycles.

Table 5.9: FCM6 summarised results

Concept	Initial Value	ML-FCM Algorithm	EML-FCM Algorithm
C14	0.40	-0.46	-0.44
C22	0.30	-0.29	-0.59
C33	-0.60	-1.00	-1.00
C34	0.20	-0.86	-0.86
C35	-0.20	-0.86	-0.86
C36	-0.30	-0.72	-0.72
C37	-0.20	0.52	0.52

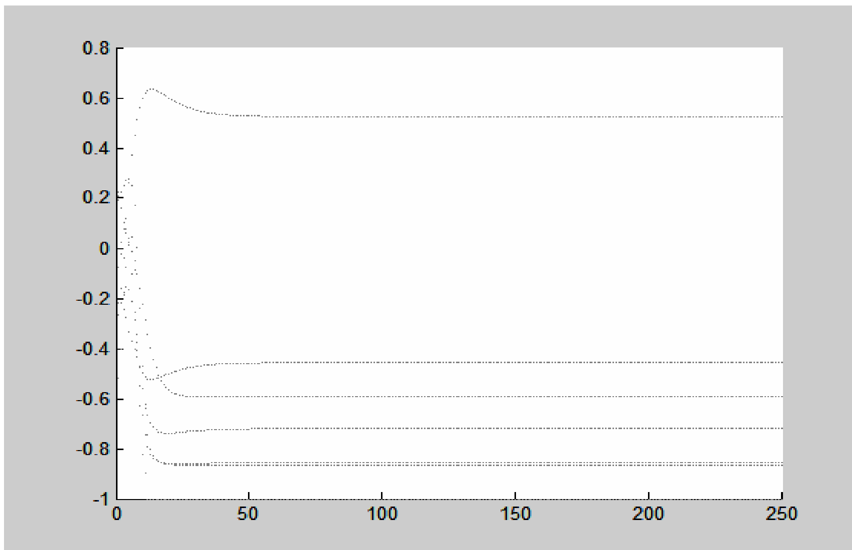


Figure 5.16: ML-FCM execution results for FCM6

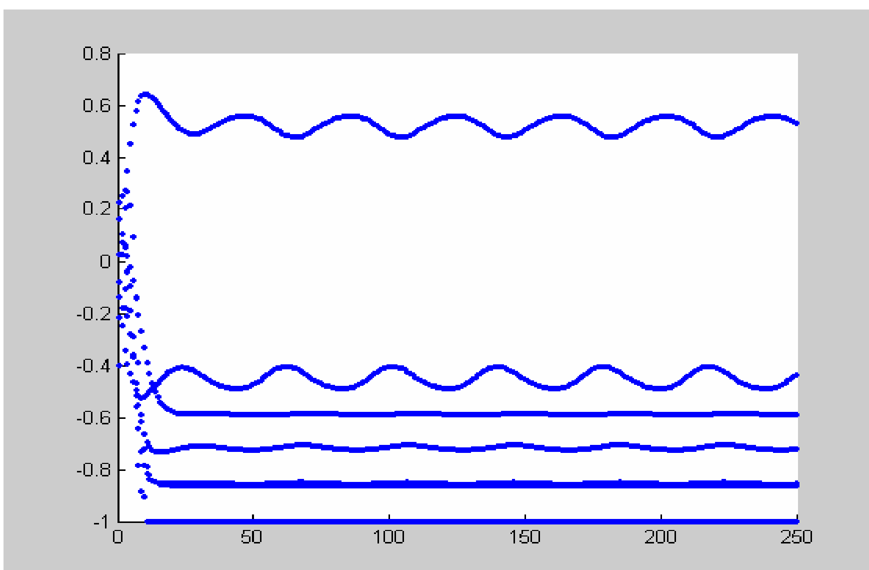


Figure 5.17: EML-FCM execution results for FCM6

Table 5.10: FCM7 summarised results

Concept	Initial Value	ML-FCM Algorithm	EML-FCM Algorithm
C15	-0.50	-0.05	0.08
C21	0.30	-0.61	-0.55
C25	-0.50	-0.58	-0.56
C36	-0.30	-0.68	-0.63
C53	-0.60	-0.85	-0.84
C54	0.20	-0.62	-0.59
C55	0.20	-0.49	-0.40
C56	0.10	-0.79	-0.75

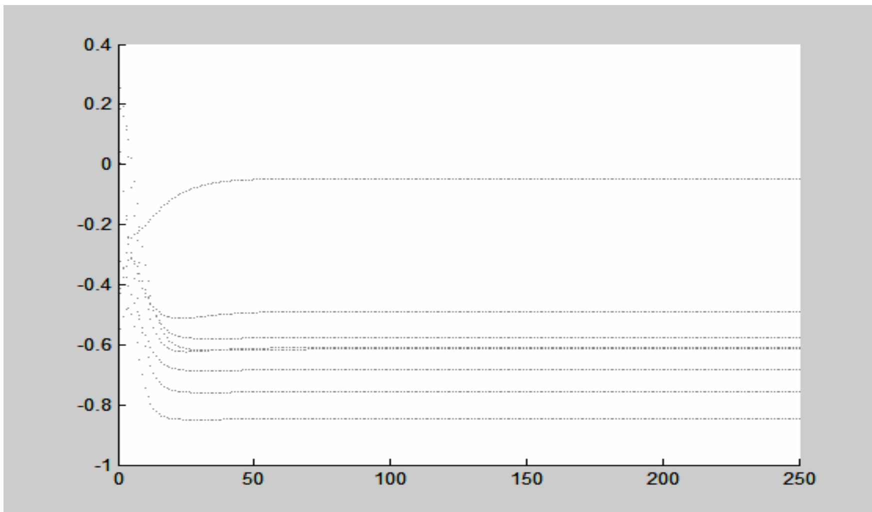


Figure 5.18: ML-FCM execution results for FCM7

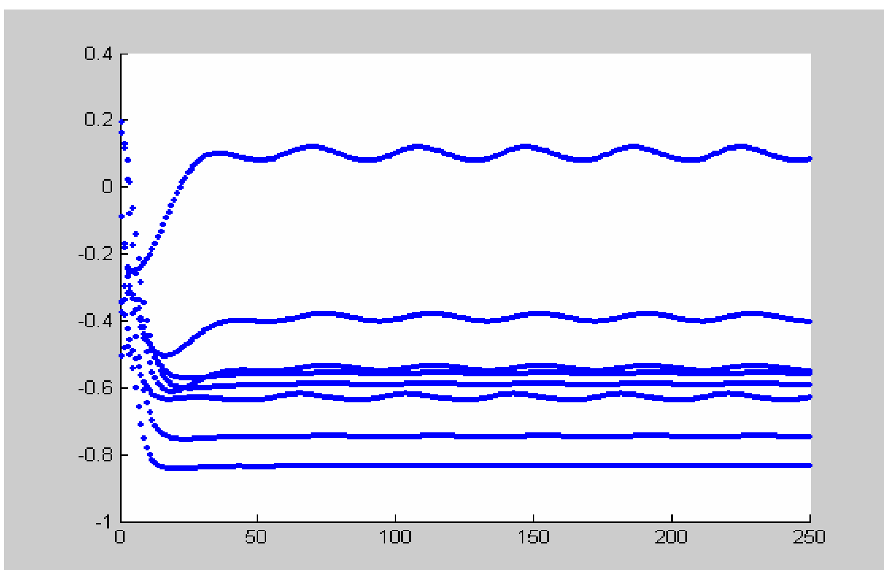


Figure 5.19: EML-FCM execution results for FCM7

5.5.3 Execution time in a multilayered environment

Two algorithms were designed to serve the multilayered methodology. More specifically, the ML-FCM works individually in each layer and the outcome of each FCM is transferred to the upper layer. The limitation of this methodology lies in the estimation of the time needed for an action that takes place in one layer and the time needed for the next action in another layer. The graphical representation of concepts and weights are shown in Figures 5.20 and 5.21 respectively. The execution time for the ML-FCM algorithm is rather short (19.23s) for 56 concepts and 299 weights built in a hierarchical form of three layers and a total of seven FCMs. On the other hand, for the EML-FCM algorithm, the execution times are roughly fourfold slower. Specifically, five models were executed using different number of maps appearing in different layers as displayed in Table 5.11. The first test was performed using two FCMs in two layers with a total number of 23 concepts and 71 weights. The execution time for the ML-FCM algorithm was 5.6s while for the EML-FCM algorithm 20.11s, which is almost 400% increase. The second test used three FCMs in two layers in which an increase of 51% for the ML-FCM and an increase of 56% for the EML-FCM is observed. Almost the same increase occurs in the third test in which four FCMs in three layers were used (20.9% and 24% respectively). As a whole the average increase rate for the ML-FCM algorithm is 36.7s while for the EML-FCM the rate is slightly lower at 33.7s.

Table 5.11: Comparison table for Multilayered FCM algorithms

Number of Concepts	Number of Weights	Number of Layers	Number of FCMs	Execution time (in seconds-s)		Number of Executions	
				ML-FCM	EML-FCM	ML-FCM	EML-FCM
23	71	2	2	5.60	20.11	500	503
38	130	2	3	8.46	31.54	750	754
43	124	3	4	10.23	35.87	1000	1025
58	183	3	5	12.98	48.42	1250	1256
73	225	3	7	19.23	62.60	1750	1724

There is a considerable difference between the execution times of the two algorithms as depicted in Figures 5.22 and 5.23, which shows the EML-FCM around three-and-a-half times slower than the ML-FCM.

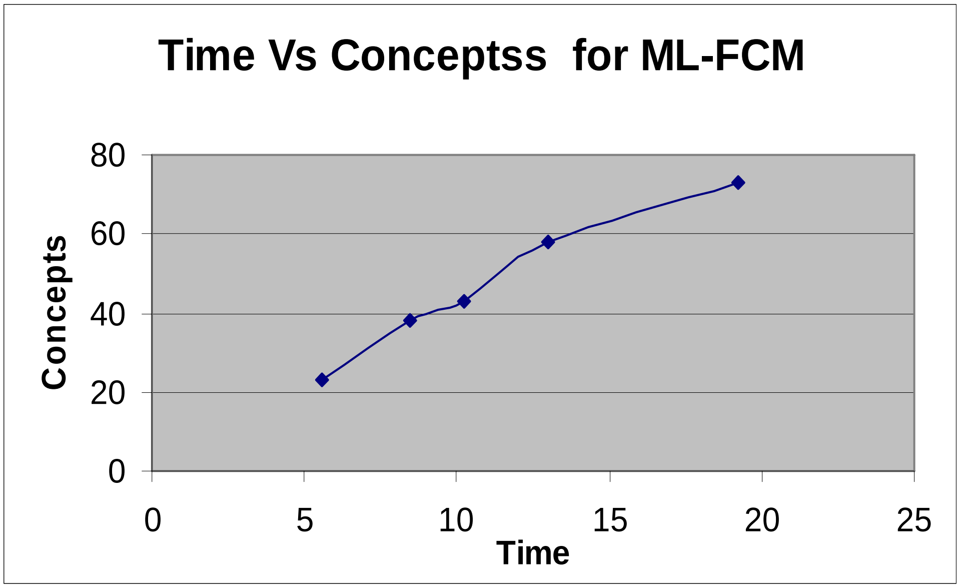


Figure 5.20: Graphical representation of time performance with respect to concepts for the ML-FCM

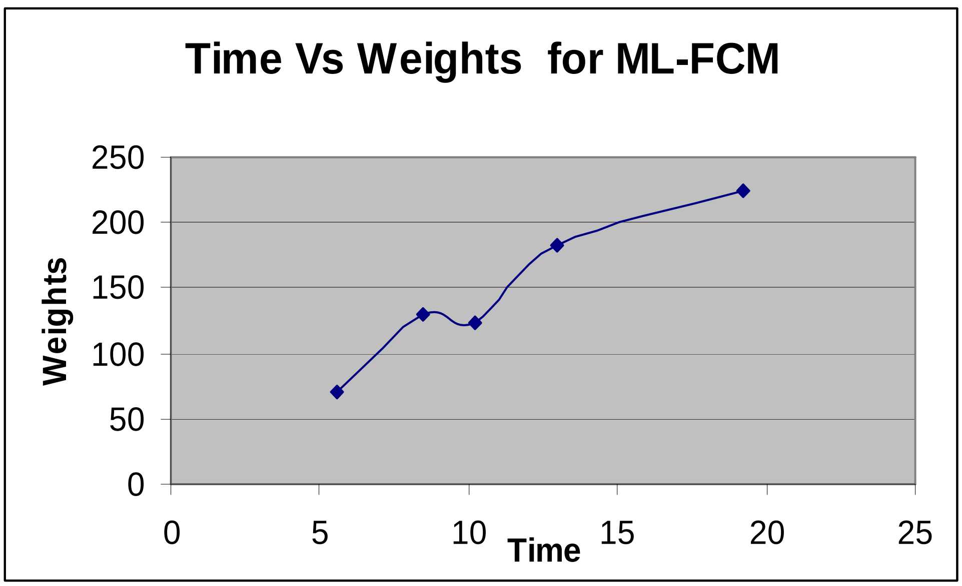


Figure 5.21: Graphical representation of time performance with respect to weights for the ML-FCM

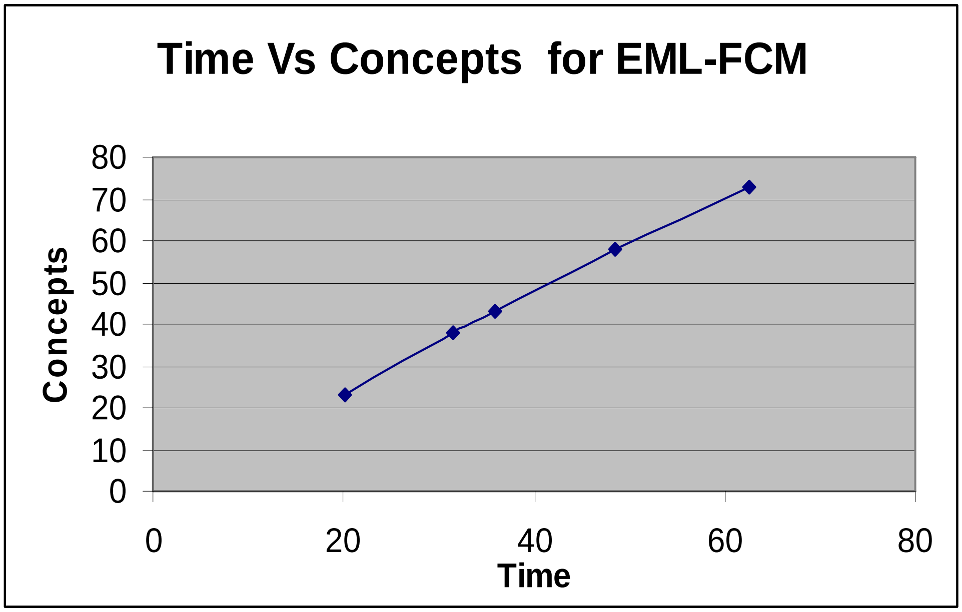


Figure 5.22: Graphical representation of time performance with respect to concepts for the EML-FCM

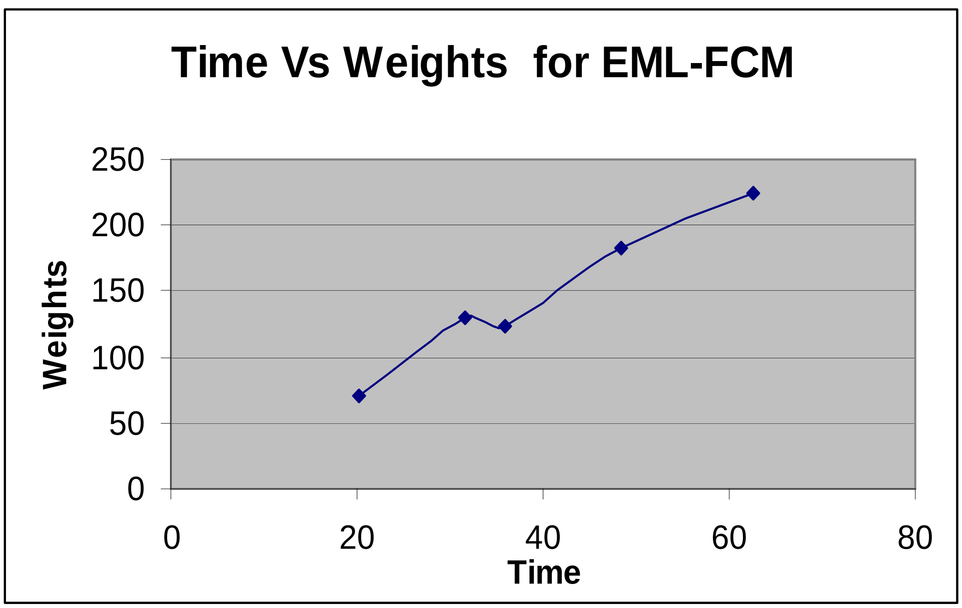


Figure 5.23: Graphical representation of time performance with respect to weights for the EML-FCM

Comparing the execution process of the two algorithms we may point out the following:

i. The ML-FCM algorithm is simple and quick. On the other hand, the EML-FCM algorithm is more complicated and consumes more time to fully execute the maps in the layered structure as it introduces the overhead of passing the intermediate computed AL values to the parent nodes and vice-versa.

ii. The ML-FCM algorithm works stepwise in a bottom-up execution process. The transformation of AL to the upper level is performed only when the lower FCM is fully executed. The EML-FCM algorithm follows a single multilayer process in which for each iteration step the updating of each central concept is performed. This makes the multilayer structure behave as a single map minimizing the time delay between each layer when the updating function is executed.

iii. The execution of each map in the ML-FCM algorithm is performed individually and the propagation of the value to the upper layer (parent FCM) is performed in steps, each step requiring the full cycle execution of an FCM at a lower level. In the EML-FCM algorithm all concepts and all FCMs, irrespectively of where they belong in the Multi-Layer structure, are involved in the execution process in each single iteration.

iv. The ML-FCM algorithm does not take into account the small changes in intermediate values of the activation levels in the different layers, while the EML-FCM does, thus having the advantage of being more aware of what is occurring within the layered structure in the behavioural evolution process of the numerical stabilization.

v. The limit cycle phenomena appearing in the EML-FCM do not seem to affect the results but this is surely something that needs further investigation. The oscillations observed may be the result of the "delayed" update taking place in consecutive processing actions (i.e. from layer to layer). We believe that during the updating procedure, the time needed for a value to be passed to the higher layer distorts possible equilibria that are being formed. Further studies and experiments should be conducted to verify the source of this phenomena and a good way to start this investigation is by varying the value of decay factor in equation 5.2.

At this point we should some up what the current section involves: Two algorithms that serve a multilayer approach developed to expand the capabilities of FCMs were presented. The first algorithm (ML-FCM) was recently proposed to model effectively complicated, large scale problems. The two algorithms were compared and evaluated using a real-world problem from the area of political decision making. The results obtained suggested the superiority of the EML-FCM algorithm and provided the means for a comparative discussion on the strong features and weaknesses of each algorithm. The validation process included also a final consultation round with our experts, which proved that both algorithms constitute reliable tools in the hands of decision makers and that the enhanced Multi-Layer algorithm presents more advantages than the ML-FCM, such as flexibility, ability to handle efficiently the time step between layers, among others. Appendix A gives a complete overview of the simulation of the 56 concepts grouped in five FCMs working together to encode a very complicated problem, that of the Annan plan.

Chapter 6: Conclusions

6.1 Introduction
6.2 Research Contribution
6.3 Future Research Directions

6.1 Introduction

The research of the present thesis focuses on the development of a new Intelligent Decision Support System (IDSS) which is based on a form of Fuzzy Cognitive Map encoding experts' knowledge and assessment. This IDSS enables the creation of models that are very flexible and adaptive, easy to develop and friendly to use.

A cognitive approach using Fuzzy Cognitive Maps (FCM) has been adopted in this research, where trend-projecting forecasting techniques attempt to remove uncertainties by providing one specific forecast at a time. FCM use scenario analysis that faces environmental uncertainties by considering several alternative forecasts. They, thus, aim at influencing the decision makers' reasoning by pointing to a feasible future state of the problem under modeling.

The key issue here is the encoding and assessment of experts' knowledge which is integrated in a Fuzzy Knowledge Base giving the ability of computation with variables in a linguistic form. A new technique is proposed for this encoding, while a fuzzification and defuzzification process is implemented and used to interpret the results along the lines of the human reasoning pattern. This type of defuzzification allows decision-makers to define their strategy in order to promote a future desired state or to plan certain actions to avoid an undesirable state.

During the implementation of the FCM methodology two weak points were identified: The first one involved the invariability of the weights, which leaves only the activation levels to participate in the configuration of a given problem. The second lies with the inability of the method to model a certain situation, by performing all possible computational simulations following the change of a certain weight or group of weights. We addressed these issues by combining FCMs with Genetic Algorithms (GA), thus creating an Evolutionary Fuzzy Cognitive Map hybrid model.

The validation process of our new type DSS's performance through scenario analysis identified another two areas for further improvement: The first one concerned the inability to support multi-objective decision-making; thus, guiding the FCM to more than one desired AL final values was not feasible because the GA could compute an optimal weight matrix only for a single target concept. The second area which the initial methodology did not take into account was the limit-cycle phenomenon, which may occur during the FCM calculation process. The proposed approach was improved so as to overcome these limitations, being based on a new Genetic Algorithm specially designed to support a multi-objective decision-making environment and take into account the limit-cycle phenomenon.

The research conducted in the context of this thesis included also the expansion of the modeling methodology to account for cases in which the problem becomes more complicated or multidimensional. Modelling was enhanced through an innovative methodology, which produces a Multilayer Hybrid System. The introduction of Evolutionary Fuzzy Cognitive Maps and the new structure (Multilayer FCM) gave new potentials and advanced capabilities in the domain of modeling and forecasting complex systems of the real world.

Neural Networks and Fuzzy Logic constitutes the cornerstone of the computational part the present thesis was based on. The factors that contributed to adopting these two approaches, as well some weak points, are briefly addressed below. Neural Networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. This restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. By contrast, the ability of NN to learn by means of examples makes them very flexible and powerful, not requiring the development of an algorithm in order to perform a specific task, which means that there is not even a need for the analyst to understand the internal mechanisms of that task. NN process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem. Given that they learn by using examples, they cannot be programmed to perform a specific task. There are, however, two important points that must be taken into consideration: First, the examples to use must be selected carefully to avoid time wasting or even worse, network incorrect functioning. Second, since the network finds out how to solve the problem by itself, there may be cases in which its operation can be unpredictable.

Fuzzy Logic (FL) is a powerful problem-solving methodology with many applications in embedded control and information processing. FL provides a remarkably simple way to draw definite conclusions from vague, ambiguous or imprecise information. Thus, in a sense, the ability of FL to look for precise solutions based on approximate data provides a close resemblance with human decision-making. Unlike classical logic which requires a deep understanding of a system, exact equations, and precise numerical values, FL incorporates an alternative way of thinking, which allows modelling complex systems using a higher level of abstraction originating from our knowledge and experience. Thus, FL allows expressing this knowledge with subjective concepts such as “very hot”, “bright red”, and “long time” which are mapped into exact numeric ranges.

Neuro-Fuzzy systems combine the strong features of both ANN and FL. Neuro Fuzzy systems can model general nonlinear mappings in a manner similar to feedforward ANN since it is a well-defined function mapping of real-valued inputs to real-valued outputs. All that is needed for their practical application is a means for adjusting the system parameters so that the system output matches the training data. Genetic algorithms can provide such means.

Summing up the chapters of the present thesis, we have already dealt extensively with four key issues concerning new developments in the Fuzzy Cognitive Maps theory. The hybrid FCM was initially indroduced to facilitate the scenario analysis along with the creation of a specific Fuzzy Knowledge Base which was integrated in FCMs to give stronger capabilities to the fuzification and defuzzification processes. Some weak points, like the limit cycle phenomenon and the automatic construction of a FCM, have been successfully handled. The final issue to tackle has been the development of a new structural approach to handle large scale problems using the FCM methodology which has been validated on a case study, namely the possibility of settling the Cyprus issue through the provisions of the Annan Plan, with a number of new algorithms developed to serve this methodology.

The genetically evolved methodology proposed in this research can effectively and efficiently perform tasks without requiring the structure of a sophisticated and complicated Rule Base Knowledge, which is time consuming and inapplicable in complex problems. The methodology is able to emulate the best human expert in building a Fuzzy Knowledge Base, which is considered the core of the hybrid system. In the next section a summary of the main contributions of this research will be presented.

6.2 Research Contribution

The main contribution of this thesis is summarized in the next subsections while the framework and methodology to develop a new type of Computational Intelligent Decision Support Systems is briefly described.

6.2.1 FCM Hybrid Model - Integration of GA to FCM

The methodology employed introduces the Genetically Evolved Fuzzy Cognitive Map which is based on combining the theory of Fuzzy Cognitive Maps and Genetic Algorithms. This combinations leads to the development of a Hybrid Form of FCM used as the basis of a framework for producing a new type of Computational Intelligent DSS (CI-DSS) [115]. The CI-DSS involves the identification and formulation of expert knowledge encoded in a Fuzzy Knowledge Base and expressed in a linguistic form, followed by the simulation process and inference mechanism.

The reasoning behind using GA was to overcome the two main limitations of FCMs: The invariability of the weights, which leaves only the activation levels to participate in the configuration of a problem under study and the inability of the method to model a certain situation by performing all possible computational simulations following the change of a certain weight or group of weights.

It follows, therefore, that the integration of genetic algorithms with fuzzy systems and neural networks satisfied two main goals: It improved the design process of fuzzy systems by developing a unified cognitive model suitable for embedding various linguistic connectives used for handling uncertainties that serve the inference mechanism of the FCMs. The second goal was to improve the performance of FCMs by increasing the flexibility of the forecasting mechanism in the hands of the policy-makers. This performance increase can be interpreted as the accuracy of the control action and the efficiency in terms of time computation. Thus, the hybrid model offers the ability not only to design multi-objective scenarios for specific hypothetical situations, but also to predict the dynamics of a future realization of such scenarios.

The importance of such a model to decision-makers is underlined by the fact that it offers them the luxury to base their decision not only on the experts' evaluation, but also on the optimal weights that lead multiple concepts to be activated to certain predefined degrees. Thus, decision-makers are able to introduce hypothetical cases reflected through the target activation levels for certain concepts in the model and study those corresponding weights and activation levels for the rest of the concepts that are compatible with the predetermined target activation levels. Based on this information, the policy maker is then able to take decisions leading to the desired simulated solution. This hybrid FCM system was tested on a well-known political crisis, the one known as the S-300 missiles crisis, which took place among Turkey, Greece and Cyprus in 1997-1998. The model achieved a successful prediction of the dynamics behind a hypothetical situation leading to some interesting conclusions.

The Genetically Evolved Fuzzy Cognitive Map introduced is supported by a novel software tool. This tool provides the policy maker with a graphical user interface designed to input the data provided by domain experts in the form of activation levels and weight values, construct and execute a FCM model, and present the FCM simulation results.

6.2.2 Improving the inference process of FCM

Aiming at facilitating the FCM encoding of experts knowledge and its integration to the model, the Fuzzification and Defuzzification processes have been reinforced through the development of a specific Fuzzy Knowledge Base (FKB) merging the mathematical output of the system with the linguistic assessments of experts. It was revealed that the fuzzy reasoning system working in numerical environments can be effectively and efficiently implemented by FKB relying on a linguistic variable encoding scheme. The above innovative encoding of experts knowledge in FCMs not only provides useful insight into a deeper understanding of the relationship between the mathematical terms and their meaning but also offers readily available results to the experts and policy makers whose knowledge regarding the inference engine of the model may be inadequate. The inference process was improved even further by taking into consideration the behaviour of the system in cases of a limit cycle and by proposing a defuzzification method to handle such a possibility.

More specifically, a new methodology was developed that is able to emulate the best human expert in order to build a FKB, which is considered the core of the hybrid system. To the best of our knowledge there is currently no systematic way of producing a FKB that could support the modelling framework of FCMs by enabling the transformation of key problem linguistic parameters into numerical and vice versa. The construction of a FKB treats each concept as a fuzzy linguistic variable, the term set of which is decomposed into linguistic values realized in specific numerical ranges via fuzzy sets of certain membership functions. Using the FKB as a guideline, the system allows inference on the level of realization of the different participating cognitive stages, whilst concentrating on various hypothetical scenarios. The decision makers are thus able to retrieve the results of a certain scenario and interpret them with the aid of the FKB at a descriptive linguistic level.

6.2.3 Handling the Limit Cycle phenomenon

An FCM system is expected to either reach equilibrium, or present a limit cycle or even a chaotic state. In cases of equilibrium decision-makers use the information provided by the FKB to make decisions leading to the desired simulated solution. In cases, however, in which the system reaches a limit cycle, decision-making is practically impossible. Two methods were suggested in the present thesis to handle this phenomenon. The first method improves the defuzzification process and is divided into two parts: The first part calculates the mean value of the limit cycle oscillation of every activation level (AL) participating in the conceptual domain. The mean value of each AL is considered as the equilibrium point of the corresponding smoothened limit cycle. The second part examines the structure of a certain limit cycle and attaches a degree of confidence to the output suggesting whether the resulting smoothened AL value is reliable enough to be used in the decision making process. In case the confidence level of the smoothened AL is high, a defuzzification process is utilized to facilitate inference based on the fuzzy intervals defined for the specific concept in focus. In the opposite case involving a low confidence level, inference is not possible, or to be more precise, it is neither reliable nor accurate.

The above handling of limit cycle offers a solution to the outcome of a dynamic system but it does not deal with the origin of the problem. In an attempt to eliminate the phenomenon by examining the origin of the problem, a new algorithm was designed, which constitutes tributes the second method for handling limit cycles. This method is also divided into two parts: The first part investigates the structure of a certain limit cycle and is checking whether a limit cycle or chaotic behaviour of the system exists, while the second avoids the sustenance of a limit cycle by tracing the weight(s) that caused the limit cycle and modifying its (their) value(s). More specifically, after the modification of a weight matrix - individual resulted from crossover or mutation, our algorithm checks the values of certain activation levels for a given number of iterations. If a difference is observed under a certain threshold, then this case is categorized as “limit cycle” and the elimination process is invoked: A genetic algorithm evolves new weight matrices aiming at solving a certain set of weights that will free the map from limit cycles.

6.2.4 Multilayer FCM

The advantages of FCMs lie with their simplicity and adaptability with which they may be utilised in various application domains. However, in large scale complicated problems the FCMs’ simplicity suddenly changes to complexity due to the high increase in cognitive states, concepts and connections, something that makes the work of experts both complicated and inflexible. Having this in mind another major contribution to FCM theory was the development of a new FCM Multi-Layer structure to handle complicated problems which are characterized by a large number of parameters, concepts, variables, nonlinearities and uncertainties that make their analysis and modelling a very difficult task. The objective of the proposed methodology was to provide an alternative approach for dealing with such difficulties, offering a new computational algorithm designed so as to support the creation of layers of parameters and variables describing the system under study, as well as the simulation of its evolution dynamics.

The new algorithm for determining sub-FCMs, named ML FCM, has been built as a hierarchical structure and has been designed in such a way so that it can find the Activation Level (AL) that satisfies a predefined FCM, which is designed specifically to compute the requested AL for a certain concept. In general terms, therefore, the algorithm designs layered Fuzzy Cognitive Maps in a hierarchical structure aiming at computing the ALs of the children FCMs in each layer and updating the Activation List of the decomposed father FCM in the upper layer. It also performs execution of each FCM and reports the results. The proposed methodology provides a robust solution for large-scale problems by grouping the large number of parameters influencing a problem. The advantage of this structure is the creation of small and more easily manageable sub-FCM models, which work together to support the main FCM. Domain experts provide their estimate for the activation levels and weight values of the main FCM and each of the sub-FCM models. Some concepts are decomposed into a number of parameters which affect their AL. Thus these dependent activation level (AL) values are not estimated and instead sub-FCM models are created as to calculate these missing ALs. Each sub-FCM model participates in the defuzzification process and a report for each sub-FCM model is issued. These reports provide explanation and justification of the calculated AL for the concept of interest on which each sub-FCM model is built.

The use of GAs in such a FCM modelling scheme is very appealing since they offer the optimal solution without a problem-solving strategy, once the requirements have been defined. It is interesting to point out that the evolutionary Multi-Layered approach is reflected both in the implementation of the GA as well as in the methodology applied for solving large-scale problems. In fact, the reasoning behind the use of this hybrid system is to obtain the optimal solution to the weight values corresponding to an FCM in any layer. This is very useful for the simulation process and helps the decision-maker to develop scenarios with the involvement of more than one concept in any place of the Multi-Layered FCM. The basic principle of the methodology requires the initial building of the hierarchical structure forming the Multi-Layered FCMs. Subsequently, the GA can be applied to any FCM or sub-FCM generating a new near to optimal set of weight values for that particular FCM. Ultimately, the FCMs are executed using the recalculated weights beginning from the lowest-level FCMs upwards to the root FCM. It is interesting to point out that since genetic optimisation has been applied to a concept that expands to a sub-model, and this makes it common to two FCMs (father- and child-FCM). As a result, the specific concept’s final level computed in the child FCM is treated as the initial level value of the concept in the parent FCM, both of which have been predefined by the user. It is obvious therefore that scenario analysis thus becomes quite flexible and allows for different experimentations at some or all of the levels of interacting FCMs. The final step involves the execution of the FCM algorithm. However, before an FCM is executed, if it is marked for genetic optimisation then the Genetically Evolved (GE) ML-FCM algorithm is executed. The resulting weight matrices of each execution are then fed as input to the FCM algorithm for completion of the scenario analysis. The proposed algorithm (which integrates genetic optimisation with multi-layered FCMs) executes in a bottom-up sequence so that any newly-computed final level of a concept in a child FCM can be used as the initial activation level of its parent FCM after it has been calculated using the optimised weight matrix of the child GE ML-FCM. The integration of evolutionary computing in ML-FCMs has been shown to be a promising and reliable methodology for modelling complicated, large-scale problems through a practical case study conducted. One of the main challenges faced hereafter, was the design of scenarios that describe specific problems in a Multi-Layered environment and the proposal of an optimal solution for each such problem, as this is described by the appropriate values of the ALs involved.

In addition to the advantages described earlier in this section, the new enhanced multilayered algorithm was also proposed to take into consideration the value level changes during each iteration. This is a very important feature bearing in mind that one of the drawbacks of the Multi-Layered algorithm is that each FCM is executed once for a number of iterations and only after all of the concepts resigning in it achieve an activation level, not taking into account that at each iteration the value of the levels change and as such these new values must somehow be fed back to the parent FCM during the same iteration.

The new algorithm begins by creating the ML-FCM stucture, like the original Multi-Layered algorithm does. However, when a leaf node is reached the FCM is executed just for one iteration. The change in the corresponding value of the central concept of the leaf FCM (in other words, the concept with a missing activation level in the parent FCM) is fed back to the parent FCM which then continues to either execute for one iteration (if no more levels are missing) or to create a new child FCM that will have as a central concept the corresponding concept of the parent FCM with a missing AL. This process is repeated until the root node is reached, keeping in mind that FCMs are run for just one iteration. Once at the root, the root FCM executes, again only once, and passes down to its child FCMs the levels of those concepts that were missing during the first iteration in order for the children to execute. If the children also happen to have a child FCM then they halt their execution and pass down the value of the AL that was also once missing. As a result, execution of an FCM only takes place whilst moving in a bottom-up direction, and never while moving downwards.

The two algorithms serve the Multi-Layer approach developed to expand the capabilities of FCMs. The first algorithm (ML-FCM) was proposed to model complicated, large scale problems effectively. The second algorithm (Enhanced Multi-Layer FCM), aims at tackling the weakness of the first algorithm to deal with calculations of the intermediate AL values and the participation of the latter in the evolution of the behaviour of the Multi-Layered structure in terms of numerical stabilization and inference. The two algorithms were compared and evaluated using a real-world problem from the area of political decision making. The results obtained suggested advantage of the EML-FCM algorithm and offered a chance for a comparative discussion on the strengths and weaknesses of each algorithm. The validation process included also a final consultation round with our experts, which strongly suggested that both algorithms constitute reliable tools in the hands of decision makers and that the Enhanced Multilayer algorithm presents more advantages than the ML-FCM, such as flexibility and efficiency in handling the time step between layers.

6.2.5 A Framework for the Development of Computational Intelligent Decision Support Systems

The methodology described thus far is part of a general framework for developing a new category of intelligent decision support systems using evolutionary fuzzy cognitive maps. The principal steps of this framework may be summarized as follows:

- *Identification and Formulation of Domain Variables: A Cognitive Approach*

  One of the most important requirements of the methodology is the identification of the problem variables, using experts' knowledge, a task that heavily depends on the effectiveness of the identification and description methods used (questionnaires, formal consultations, texts etc). The importance of this task is crucial given that it provides a descriptive overview of the system. Once this has been established, these variables and the causal relationships among them are treated as concepts (nodes) and directed arcs participating in the FCM model.

- *Linguistic Fuzzy Sets Encoding*

  Once the names and roles of each concept have been identified, they are partitioned into fuzzy sets and each set is then assigned a linguistic value. The advantage of using fuzzy sets, therefore, is that they provide a basis for a systematic way of manipulating vague and imprecise concepts and as such they are often treated as representing linguistic variables. A linguistic variable can be regarded as a variable with values that appear either as fuzzy numbers or in linguistic forms. The fuzzy set encoding is a key step in our framework because it is used to build up the most important element of the Computational Intelligent DSS (CI-DSS), namely the fuzzy knowledge base.

- *Fuzzy Knowledge Base Representation*

  The construction of a fuzzy knowledge-based system is a very complicated task, requiring occasional adjustment of knowledge, especially in cases of complex applications. The integration of a Fuzzy Knowledge Base (FKB) to our CI-DSS, attempts to overcome this difficulty by encoding the experts' assessment. Once the concepts have been defined and the FKB has been built, the domain experts are ready to provide their estimation of the activation levels and weight values that aim at defining the initial state reflected by the model at a given time period. The linguistic sample is encoded directly into a numerical matrix using an uncertainty fuzzy distribution and is subsequently reduced to a scalar form. This linguistic matrix provided by the fuzzy encoding procedure reflects the quantization levels of the input and output spaces, and the number of fuzzy set values assumed by the fuzzy variables.

- *Evolutionary Strategy Formation*

  An evolutionary strategy represented by a hybrid model (FCM and GAs) is the heart of the framework, enabling forecasting by tracing the degree of the causal relationships between the various concepts, so that it can "force" them to be activated to a certain level. This technique enables simulations that retrieve the final activation levels of the rest of the concepts, as well as the strength of the causal relationships between them. The analyst is thus able to proceed to tactical movements in his decision-making by varying the degree of such relationships in line with the final activation levels the model has suggested. In general, finding a near to optimal weight matrix, which will guide a FCM to desired AL values for a specific concept, is a task which is performed using genetic algorithms.

- *Simulations Execution*

  The CI-DSS proposed in this thesis uses a simulation technique that facilitates a forecasting and inference process. The first step of this process incorporates all previously described notions, including the computation of the normalised level and the weight matrix, at the normalisation stage. After a certain number of iterations, the final activation levels are calculated giving the baseline of the model. In the second step, different strategies are introduced by tracing the optimal weight matrix corresponding to a desired activation level for a given concept. The results are obtained in the form of graphical representations of optimal weight values and used as input in the next step. The third step, performs genetic optimization and different scenarios make the simulation of future situations possible, thus helping in forecasting and interpreting future states of the problem under investigation.

- *Handling Limit Cycles: Improving the Inference Procedure*

  As we have already pointed out, the CI-DSS comprises Fuzzy Cognitive Maps and Genetic Algorithms and its execution converges to equilibrium at a fixed point, or present limit cycle or chaos. The dynamic behaviour of FCMs is addressed and improved in this stage by introducing various methods for handling the Limit Cycle phenomenon in two ways. Firstly, a new fuzzification technique is integrated in the defuzzification process and handles the limit cycle by introducing a confidence rate for each result. The second approach attempts to identify the cause of the limit cycle and to eliminate the phenomenon using again a dedicated evolutionary algorithm to increase the reliability of the method.

- *Multilayer FCM structure*

  The framework is completed by the use of a new structured approach for the development of FCM-based layered models able to handle large-scale, complex systems. Two algorithms serve the multilayer approach for systems which are characterized by a large number of parameters, concepts, variables, nonlinearities and uncertainties. The two algorithms offer a new computational technique designed to support the creation of layers of parameters and variables describing the system under study, as well as the simulation of its evolution dynamics. The main issue here is the decomposition of the parameters into smaller, more manageable quantities organized in a hierarchical structure forming a model, which consists of subsystems working together and supporting a central objective.

The various stages either individual or combined were successfully applied in practice. Several problems of the real-world were modeled using the proposed framework, coming mostly from the fields of crisis management, political decision-making and strategy definition. More specifically, the Cyprus issue was modeled several times following its different stages over the last six years, the 2002 tension in Cyprus due to Turkey's threats as regards Cyprus's bit for full member of EU, the S-300 missiles crises and the Turkish-Cypriots elections in December 2003 were modeled, as well as the settlement of the Cyprus issue through the Anan Plan using a Multi-Layer structure consisting of 56 concepts. The principle of the modeling approach was successfully validated using a well known example from game theory, namely the Prisoner's Dilemma paradigm.

The application of the framework however, is not limited to political or crisis management problems, but can be further extended without any restrictions, to other domains due to its generic nature and simple and straightforward steps. Based on the description of the stages of the framework, the way the CI-DSS performs the modeling process does not rely on any application domain parameters and is not restricted to the characteristics of specific real-world problems under study. On the contrary, these characteristics are critical parts of the modeling process itself. Therefore, it is clear that the proposed methodology is general enough to accommodate the study and modeling of a number of different problems provided that the basic principles of interrelated parameters (concepts) and uncertainty are satisfied.

6.3 Future research directions

It is evident that the role of Evolutionary Fuzzy Cognitive Maps, a combination of Fuzzy Logic, Neural Networks and Genetic Algorithms, in the development of Computational Intelligent Decision Support Systems is very significant. The integration of Fuzzy Cognitive Maps in CI-DSS reported in this thesis has shown some promising and encouraging results, particularly when applied in crisis management and policy making environment. Despite the contribution of this work, there are still areas which offer plenty of room for further research and development in this field of interest.

The boundaries between Decision Support Systems and Experts Systems are becoming pretty fuzzy. New technologies like Neuro-fuzzy processing, data mining, cognitive science and Precitiate Natural language, have emerged and their combination should be investigated in order to build new systems that they will behave as closer as possible to human behavior. The above technologies have common features revolving around human behavior, human knowledge and human thinking. As Lotfi Zadeh says “computing with words and perceptions is likely to emerge as an important direction in science and technology”. The necessity to deal with real world problems dictates that there is much to be gained by exploiting the tolerance for imprecision, uncertainty and partial truth. Developing future Computational Intelligent Decision Support Systems should seriously take into consideration the new Computational theory of Perception [192]. The basic concept of this new theory is computing with words and is expected to change the philosophy and the way current technology moves.

The problem becomes even more complicated in the case of forecasting because the assessment of the results is difficult.

The methodology described in chapter 4 has two major steps, namely the development of a system that reflects a current situation of a given problem and the forecasting process using scenario analysis methodology. The evaluation of the first phase of the methodology is possible and is performed through the experts’ assessments. One additional method that could be implemented is the automatic verification of the system to reflect the known situation of a given problem. The problem of judgment from different experts is always something that needs further analysis in order to eliminate this phenomenon. The way our methodology deals with this problem is by categorizing the experts according to a credibility level and then by applying a formula to achieve a consensus. Further studies on the credibility of the experts and how their assessment is inserted in the system is another area of study which will improve the establishment of a reliable initial state of a given problem. The second step of the methodology, which is dedicated to identifying the future parameters by forming a hypothetical scenario using Genetic Algorithms, is very difficult to control. Evaluating the reliability of the results depends on the accuracy of the fitness function and whether the target criterion is met. These two conditions provide an indication of the reliability of the results. An automatic method that will assess the results is currently not possible and this may be studied further. Future work should consider the evaluation of an FCM model with respect to measurable parameters to determine the effects of the results in the whole process.

One of the main challenges in FCM is the autonomous creation of Fuzzy Cognitive Maps. Some attempts have been executed during the past few years the main one using Genetic Algorithms as a methodology to identify the main principal which may consist a potential FCM. FCM parameter estimation techniques show the way for automatically determining causal strength from state observations, while their success relies heavily on background knowledge about the causal structure of the system, acquired from interviews with domain experts. The development of a FCM usually occurs within a group of experts to improve identification of relevant concepts and causal relationships between concepts. The assumption that the combined and some times incomplete opinions of different experts may be canceled out by the effects of omission, ignorance and prejudice is not always the case. A way of how the experts' opinions are inserted into the system and how causal discovery is performed as fundamental tasks for automated FCM synthesis provide a basis for future work in the area of autonomous creation of FCM.

Another important issue for further analysis is how to improve the performance of a FCM system firstly by improving the correct implementation of a problem and secondly the successful runs giving meaningful results. One of the phenomena that may appear in the FCM methodology is Multicollinearity [63]. The analysis of an FCM reveals the presence of cycles, that is, paths starting and ending at the same node that include more than one node. A cycle is characterized as positive if the number of negative weights on the cycle is zero or even, otherwise it is characterized as negative. A positive cycle tends to increase the activation level of the concept on which it closes, whereas a negative cycle decreases this value. The presence of a large number of cycles in an FCM increases its complexity. Moreover, in the presence of cycles some undesired effects may take place, such as a form of multicollinearity. The latter is realized when a concept is affected by a number of other concepts which are linearly correlated. This correlation may exist in FCM as a result of the kind of modelling followed, that is, if the map is constituted by cognitive factors of the problem under investigation which provide essentially the same part of information to describe a certain, common concept, but, at the same time they are considered too important to leave out of the model.

Multicollinearity in FCM may be regarded as a phenomenon possibly present in any dynamic modeling attempt. One may detect it by investigating cases in which the activation level of a concept is constantly driven towards +1 or -1 due to the fact that the majority of its input weights are positive or negative values respectively. Apart from multicollinearity, one additional undesired effect may be observed in FCMs related to single-fed concepts (i.e. concepts with only one input), where the receiving concept is “forced” through the iterative process to a certain activation level value dictated by the input concept’s AL and the sign of the connection. Finally, a modelling weakness of FCM may also be brought to light regarding the exclusion of factors that, even though they have a role to play in the problem under study, they do not receive influence from other concepts participating in the map. Thus, these factors, although significant, can only take part in the map as external elements, something which requires modifying the structure (definition) of a FCM to allow their inclusion.

The aforementioned modelling problems and weaknesses may be overcome by using a form of bias in the execution process of the map. Some preliminary studies have been proposed in [125] where a bias concept was introduce that behaves like a constant variable in the application domain and normalizes the FCM in order to reflect the real condition of a given problem. Great care should be exercised when using the bias concept, so that parameters that will bring distortion to the model are not inserted. The best criteria to insert or to verify the correctness of using a bias node is the execution of the system and the analysis of the initial condition formed. This phenomenon needs to be examined in more detail and new research activities should be explored.

Another area for further improvement is the elimination of chaotic or limit cycle behaviour of models, which, despite the contributions of the present work, is still an open issue for further investigation mainly for two reasons. First, because the reliability of the system depends on the stability and the reliable execution of the map and second because any further improvement of the FCM modelling process must take the necessary steps so that the resulting system can guarantee stability. A new approach based on the work that has already been performed by Mateou and Andreou [123] which can be characterized as a semi automatic method for identification of limit cycles should be investigated. An automatic process, with the use of intelligent techniques that will automatically identify instability in the system and will suggest possible solutions to overcome the problem is an area for further research.

The question of the functional representation, as well as the computational capabilities of FCM, by means of developing new flexible and more manageable structures, is an area requiring further investigation. Irrespectively of the links offered for further improvement and research, the fact remains that the creation of Multi-Layer FCMs, in which concepts are grouped together, has been found to be essential in facing the limitations encountered in the classical FCM cases when tackling problems with a large number of concepts. Thus, Multi-Layer Fuzzy Cognitive Maps provided robust solutions for large-scale problems on the basis of parameter-grouping, meaning that a new algorithm is required to determine sub-FCMs built as a hierarchical tree structure. Suggestions for future work may concentrate on the development of new algorithms which will face problems with even higher complexity by combining the multilayer formation with some more flexible and ductile FCM structure. For example, the use of neighbouring FCM may give more flexibility and simplicity to FCM structure design. This new structure may overcome the problem of hierarchical level of computation appearing in the Multi-Layer FCM, by obtaining a single map structure working in parallel at the same layer.

Finally the time relationship (or time lag) involved before a change in node C_i has an effect on node C_j may be further investigated. Currently a FCM assumes that all effects take place in one unit of time. Thus, a more realistic map would introduce a time lag corresponding to each effect. However, the time lags are hard to estimate, and there is a trade-off between the generality of the map and the possibility of estimating its time lags in a realistic way. Several methods try to solve the problem of the time behavior of FCM but to the best of our knowledge this success is limited. Further research in this subject may increase the reliability of FCM modeling and thus may enable the study of time effects between the participating concepts as part of the computational procedure.

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Appendix B

The Example of the Prisoner's Dilemma

B.1.1 Introduction
B.1.2 The Prisoner's Dilemma as an example of strategic-form and Fuzzy Cognitive Maps formulation
B.1.3 Prisoner's Dilemma transformation to FCM
B.1.4 The Prisoner's Dilemma strategies and scenaria
B.1.5 Fuzzy Cognitive Maps interpretation of the Prisoner's Dilemma using three concepts.
B.1.6 FCM and evolutionary strategy applied in Prisoner's Dilemma problem
B.1.7 Application of FCM in a Prisoner's Dilemma conflict resolution: The example of 1963 Cuban missile crisis
B.1.8 Fuzzy Cognitive Maps implementation in the Cuban missile crisis
B.1.9 Assessment of the methodology

B.1.1 Introduction

Chapter 4 presented a detailed explanation of the proposed FCM methodology development together with certain politics and crisis management examples to demonstrate its applicability and effectiveness. What Appendix B does is relate the FCM methodology to the Prisoner's Dilemma [56], a well known game theory example [84] aiming at proving that FCM are applicable and reliable to face a wide selection of problems, to the extent that these can be translated as game theory problems instances.

Game theory is a branch of mathematics concerned with decision making [51] in social interactions and applies to situations (games) in which there are two or more sides (called players), each attempting to choose between two alternative strategies. The possible outcomes of a game depend on the choices made by all players, and can be ranked by each player's order of preference.

This part of the thesis focuses on adopting the logic of the Prisoner's dilemma to the FCM methodology in the light of a case study, namely the Cuban missile crisis [62], thus underlining the relationship between strategic-form and extensive-form games.

B.1.2 The Prisoner's Dilemma as an example of strategic-Form and Fuzzy Cognitive Maps Formulation

The Prisoner’s dilemma, in its original version involves two “players”, Prisoner 1 and Prisoner 2, and two strategies, defect or cooperate [56]. Both players aim to obtain maximum personal gain, this depending upon their strategies as outlined in Table B.1.1. The two prisoners are supposed to have committed a crime for which there is no evidence meaning that they can not be proven guilty [149]. So the police catch them and put them in two separate cells trying to use one’s testimony against the other’s. Each Prisoner is given two options, either to confess the crime or to deny it. If Prisoner 1 confesses but Prisoner 2 denies then the first Prisoner’s statement serves as testimony against the other and Prisoner 1 gets no punishment, while Prisoner 2 gets a full 10 years term and vice versa. If both confess, both get 5 years of imprisonment each, as now the police have evidence against both of them, while if both deny the police have evidence against none, this meaning that the two Prisoners get 1 year of imprisonment each [84]. These possibilities are summarised in Table B.1.1.

Table B.1.1: Prisoner’s Dilemma Strategy and Payoffs

I \ II	*Confess*	*Deny*
Confess	5,5	0,10
Deny	10,0	1,1

Each cell of the matrix gives the payoffs to both players for each combination of actions. Prisoner 1's payoff appears as the first number of each pair, Prisoner 2's as the second. So, if both Prisoners confess, each one gets a payoff of 5 year in prison as it is indicated in the upper-left cell. If both deny, they will get one year each it appears in the lower-right cell. If Prisoner 1 confesses and Prisoner 2 denies then Prisoner 1 is allowed to go free while Prisoner 2 gets 10 years in prison. This appears in the upper-right cell. The reverse situation, in which Prisoner 2 confesses and Prisoner 1 denies, appears in the lower-left cell.

B.1.3 Prisoner's Dilemma transformation to FCM

B 1.3.1 Constructing the Prisoner's Dilemma Model

The FCM Prisoner's Dilemma model structure relies, to its largest extent, on the relevant theoretical background, thus minimizing its dependence on expert knowledge, a reliance that constitutes probably the focus of the major criticism against the use of the particular method in crisis management. The required input includes concept descriptions together with expert activation levels and weight values, while it is considered essential to provide the fuzzy set partitioning as well as the assignment of linguistic variables to each concept's fuzzy set. The end result of the whole process is a graphical depiction of the fuzzy cognitive model map at its initial/current state.

B 1.3.2 Identifying the Model Concepts

Developing such a decision–making model first requires identifying the key concepts outlining the model environment. The simplest version of the model in this Prisoner's Dilemma (PD) case involves two concepts, namely, Prisoner 1 and Prisoner 2, as outlined in Figure B.1.1. Each concept is then given an identification number (concept C1 and C2) that will be used as reference for further explanation and analysis. In this context, the decision of Prisoner 1 affects him while it bears a direct impact on the second Prisoner's decisions as well and vice versa for the second Prisoner's decision. In order to simulate this PD problem in a FCM form we need to draw attention to a number of definitions that are useful in analyzing a suitable Fuzzy Cognitive Map.

Node: A point at which a player takes an action

Concept: A node represents a concept, in our case one of the two players (prisoners)

Initial Activation level: The point at which the first action in the game occurs

Final Activation level: The outcome corresponding to each terminal node

Weights: The influence between nodes

Outcome: An assignment of a set of payoffs, one for each player

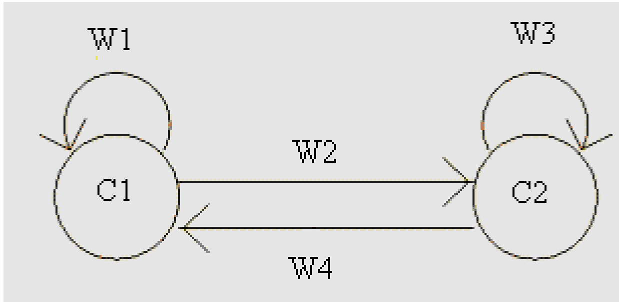

Figure B.1.1: FCM1 Representation

Table B.1.2: Concepts Description

C1	Prisoner 1's Decision
C2	Prisoner 2's Decision

B 1.3.3 Fuzzification of the Prisoner's Dilemma Problem

The fuzzification process consists of two basic steps. During the first step the interval of each concept is analyzed into trapezoidal membership functions, as shown in Figure B.1.2 and Table B.1.2 Since the concept activation levels fall in the range between -1 and +1, the concept intervals themselves must also fall in this range, with the minimum number of intervals in our model being two.

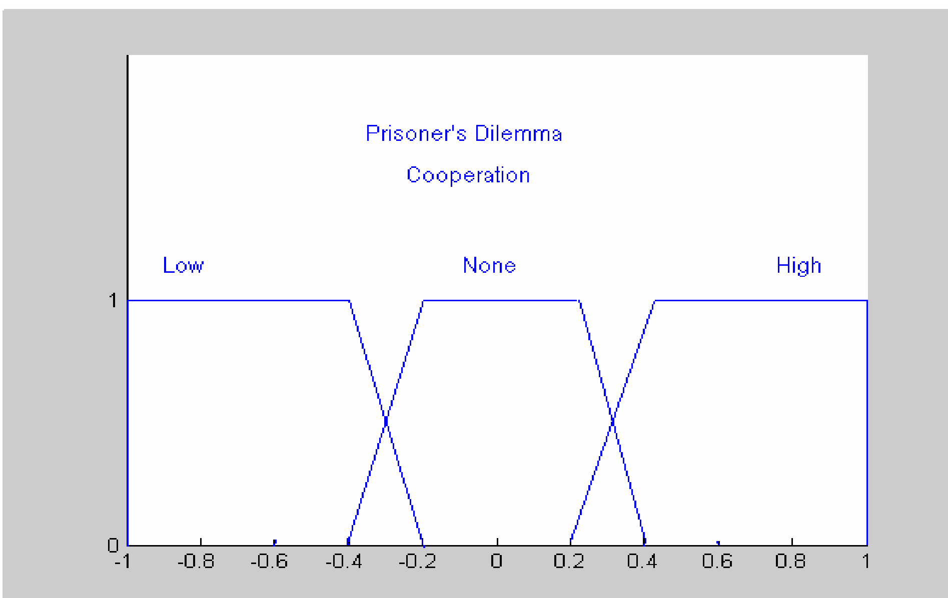

Figure B.1.2: A Concept with 3 Membership Functions, Low, None and High Cooperation

Using the cooperation strategy we can introduce it in the Fuzzy Knowledge Base (FKB) which is designed to serve the methodology. Building a knowledge-based system for the Prisoner's Dilemma problem is a rather straightforward task especially in cases of two concepts. Thus, the linguistic variables of the two concepts are encoded in a numerical matrix using an uncertainty fuzzy distribution as shown in Table B.1.3.

Table B.1.3: Modelling Fuzzy Analysis of the Concepts Participating in the PD Problem

C1	-1	-0.2	Low Cooperation 5, 5 → Five years in prison for both Prisoners
C1	-0.4	+0.4	No Cooperation 10, 0 → Ten years in prison for the first Prisoner and release of the second Prisoner
C1	0.2	1	High Cooperation 1, 1 → The two Prisoners get one year in prison each
C2	-1	-0.2	Low Cooperation 5, 5 → Five years in prison for both Prisoners
C2	-0.4	+0.4	No Cooperation 0, 10 → Ten years in prison for the second Prisoner and release of the first Prisoner
C2	0.2	1	High Cooperation 1, 1 → The two Prisoners get one year in prison each

B 1.3.4 Execution and Defuzzification Processes

The FCM execution process takes the normalised initial levels and a weight matrix computed at the normalisation stage, and runs the FCM algorithm for a selected number of iterations, thus calculating the final activation levels (baseline). During the iterative steps the model is left to interact and after all iterations have been completed, the results are presented to the decision-maker in the form of a graphical representation, followed by the defuzzification of the final activation levels. The defuzzification process in particular, is designed to facilitate the decision-maker reference from the numerical output to the corresponding linguistic interpretation. Thus, it is very important that the final activation levels be matched with their respective linguistic values in order to facilitate the decision maker's effort to focus on the most efficient solution.

B.1.4 The Prisoner's Dilemma strategies and scenaria

The problem is specified in terms of the following hypotheses: The two Prisoners are detained in separate rooms unable to communicate with each other and the police visit each of them and offer a deal: the one who provides evidence, i.e. testifies against the other, will be set free. If none of them accepts the offer, they are in fact cooperating against the police, and both of them will either suffer the punishment provided by the law, in case that they both confess or just a moderate term of imprisonment due to lack of evidence. However, if one of them provides evidence against the other, then that one can walk free while the other one who denied will receive the full punishment, since there is enough evidence against him. If they both plea guilty, they will be both punished, however the punishment will be less severe compared to the one each of them would face if he had denied while the other one confessed. The difficulty of the dilemma rests, therefore, with the fact that each Prisoner has a choice between only two options, but cannot take the decision with the highest personal payoff without knowing the choice of the other Prisoner.

B 1.4.1 Both Prisoners Deny

Let's take the possibility that they both deny. The fact remains that Prisoner 1 doesn't know if Prisoner 2 is going to confess or deny, but he nevertheless wants to minimise his punishment. So he considers two cases.

a) Prisoner 2 (P2) confesses

In this case confessing means at least a five–year imprisonment for Prisoner 1 (P1) So it's better for P1 to confess.

b) Prisoner 2 denies

In this case confessing gives P1 his freedom while denying gives them both one year in prison. So it's better for P1 to confess in this case too.

The conclusion therefore is that the best option for P1 is to confess no matter what P2 does and mutatis mutandis the same thing applies for P2.

This environment can be modelled through Fuzzy Cognitive Maps in the first run with the activation levels and weights representing the deny situation shown in Table B.1.4. The model reaches equilibrium described by a Deny-Deny result which is a win-win situation for both Prisoners (Figure B.1.3).

Table B.1.4 represents a summary of the Deny-Deny configuration. The first and second column shows the weights and the initial activation level respectively, while the third column presents the final activation levels of concepts C1 and C2. The fourth column presents the defuzzification of concepts C1 and C2 using Table B.1.3. The model successfully demonstrates the Deny-Deny configuration confirming the one year in prison. The rest of the tables follow the same structure summarizing the different scenarios.

Table B.1.4: Deny – Deny Configuration

Weights	Initial AL	Final AL	Defuzzification
W1=0.9 W2= 0.9 W3=0.9 W4=0.9	C1, AL=0.9 C2, AL=0.9	C1, AL=0.9 C2, AL=0.9	Prisoner 1 - High Cooperation: Deny The two prisoners get 1 year each Prisoner 2 - High Cooperation : Deny The two prisoners get 1 year each

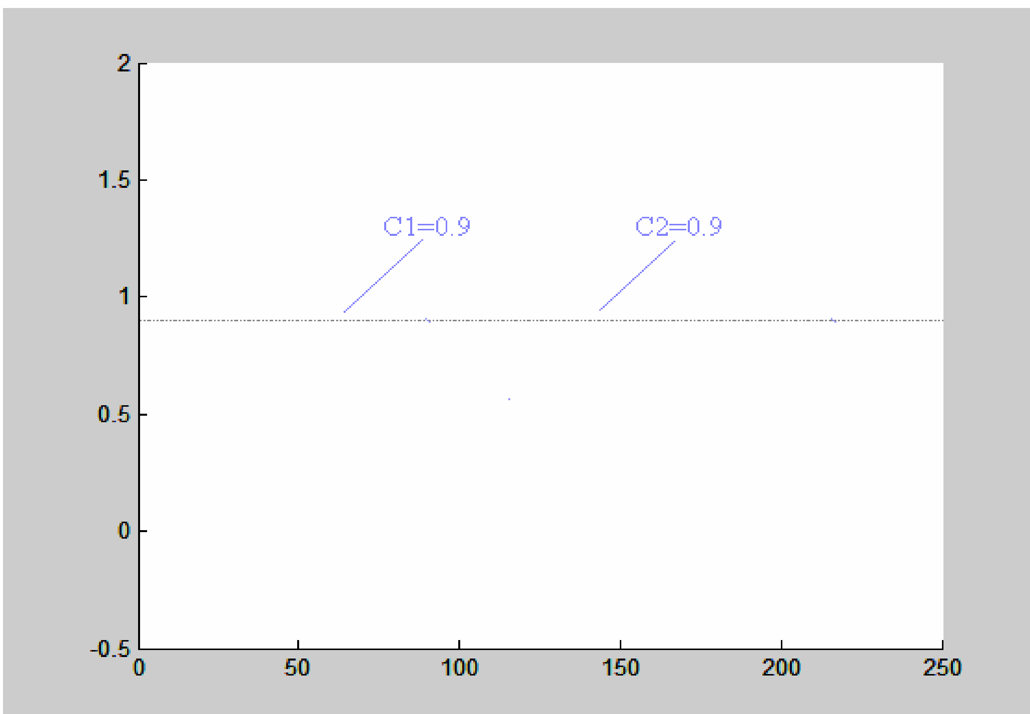

Figure B.1.3: High Cooperation -Deny – Deny Equilibrium

B 1.4.2 Both prisoners confess

Even though the best outcome for both Prisoners is the Deny-Deny scenario, for modelling purposes the two other strategies will be also examined. P1 compares the two possible outcomes by considering which of the P2 actions are preferable for every possible action by P1 prisoner and chooses using the following reasoning: If P2 confesses then P1 gets a payoff of 5 years by confessing and a payoff of 10 years by denying. If P2 denies, P1 gets a payoff of 0 by confessing and a payoff of 1 by denying. Therefore, P1 is better off by confessing regardless of what P2 does. P2, meanwhile, evaluates P1's actions by comparing P2's payoffs down each row, and P2 comes to exactly the same conclusion that P1 did. Wherever one action for a player is superior to P2 other actions for each possible action by the opponent, we say that the first action strictly dominates the second one. In the PD, then, confessing strictly dominates denying for both players. Both prisoners know this about each other, thus entirely eliminating any temptation to depart from the strictly dominated path. Thus both prisoners will confess, and both will go to prison for 5 years. Table B.1.2 and Figure B.1.4 show that the model reaches equilibrium described by a Confess – Confess result which is a compromise for both Prisoners.

Table B.1.5: Confess- Confess Configuration

Weights	Initial AL	Final AL	Defuzzification
W1=0.9 W2= 0.9 W3=0.9 W4=0.9	C1 AL=-0.9 C2 AL=-0.9	C1 AL=-0.9 C2 AL=-0.9	Prisoner 1 - Low Cooperation: Confess, 5 years in prison for both Prisoners Prisoner 2 - Low Cooperation: Confess, 5 years in prison for both Prisoners

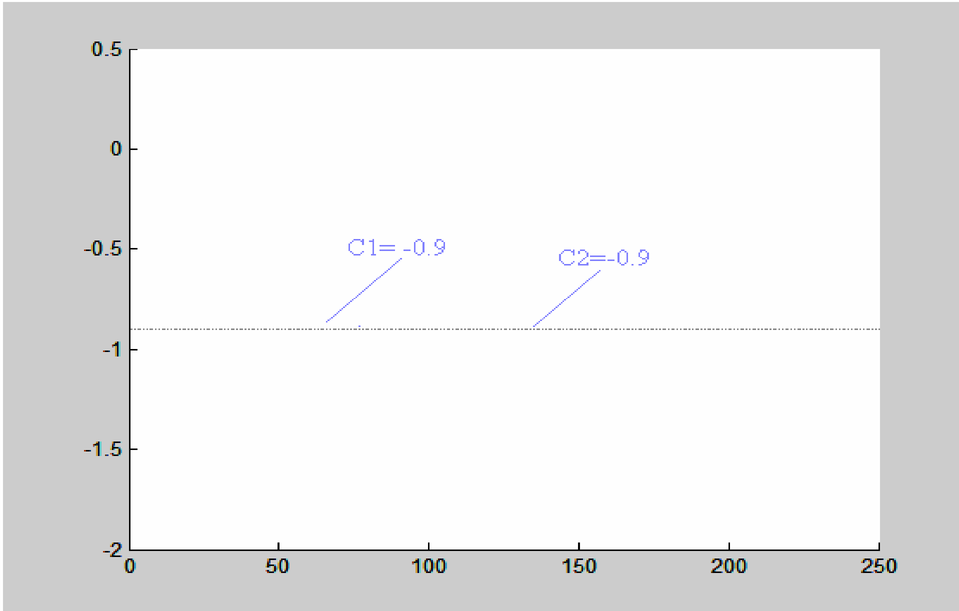

Figure B.1.4: Confeess-Confess Equilibrium

B 1.4.3 The first prisoner confesses and the second one denies

When we represent the PD as a strategic-form game, we implicitly assume that the Prisoners can't attempt collusive agreement since they choose their actions simultaneously. In this case, agreement before the fact can't help. If P1 is convinced that P2 will stick to the bargain then P1can seize the opportunity to go free by confessing. Of course, P1 realizes that the same temptation will occur to P2; but in that case P1 again wants to make sure P2 confesses, as this is P1's only means of avoiding the worst outcome. But now suppose that P1 does not move simultaneously. That is, suppose that one of the prisoners can choose after observing the other's action. This is the sort of situation that the two prisoners will choose a different strategy and not cooperate for their own maximum benefit. This situation does not give equilibrium but limit cycle. (Figure B.1.5 and Table B.1.6)

Table B.1.6: Deny-Confess Configuration

Weights	Initial AL	Final AL	Defuzzification
W1=0.9 W2= -0.9 W3=0.8 W4=0.8	C1 AL=-0.9 C2 AL=0.9	C1 AL=0.29 C2 AL=-0.86	Prisoner 1 - Low Cooperation: Deny, The two Prisoners get one year each Prisoner 2- Low Cooperation: Confess, Five years in prison for both Prisoners

The experiments undertaken thus far point to a satisfactory performance of the model with the results derived being self explanatory in terms of a Nash equilibrium logic. It appears, however, that in this particular case the option of cooperation between the two players may provide results which are preferable compared to those suggested by the Nash recipe, indicating that the environment described by the specific model is a lot more complicated than what it seems at first sight. What we propose to do, therefore, is to introduce an additional concept (C3) named “Results,” which will separate the strategy option from the results and then apply the fuzzy knowledge reasoning to proceed with analysing the concepts involved.

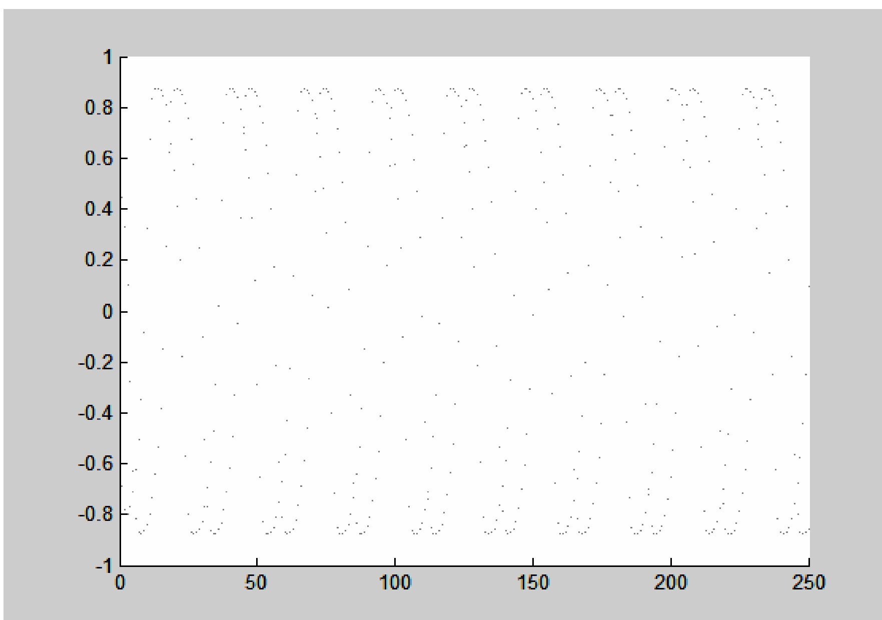

Figure B.1.5: P1 Denies and P2 Confesses. Case: Limit Cycle

B.1.5 Fuzzy Cognitive Maps interpretation of the Prisoner's Dilemma using three concepts.

The new model as described in Table B.1.7 consists of three concepts, Concepts 1 and 2 representing Prisoner 1 and Prisoner 2 respectively and Concept 3 standing for the results of the chosen strategies from the two players. The advantage of this model is that by introducing a new concept, the decision of each prisoner is technically separated from the outcome of the model. In this way all outcomes are considered as possible and therefore potentially leading to an equilibrium state. The fuzzification of the three concepts is listed in Table B.1.8. Three fuzzy sets were identified for concept C1 and C2. The fuzzy classification follows the order High Cooperation, Low Cooperation and No Cooperation, associated by the expectation results from the prisoners which decide to Cooperate or not. The reasoning behind creating concept C3 and the fuzzification philosophy it is that using it we can verify the end results as these are formulated after the two prisoners have made their decisions while participating actively in the forecasting procedure which is our main objective.

Table B.1.7: Analysis of PD example with three concepts

C1	Prisoner 1
C2	Prisoner 2
C3	Result

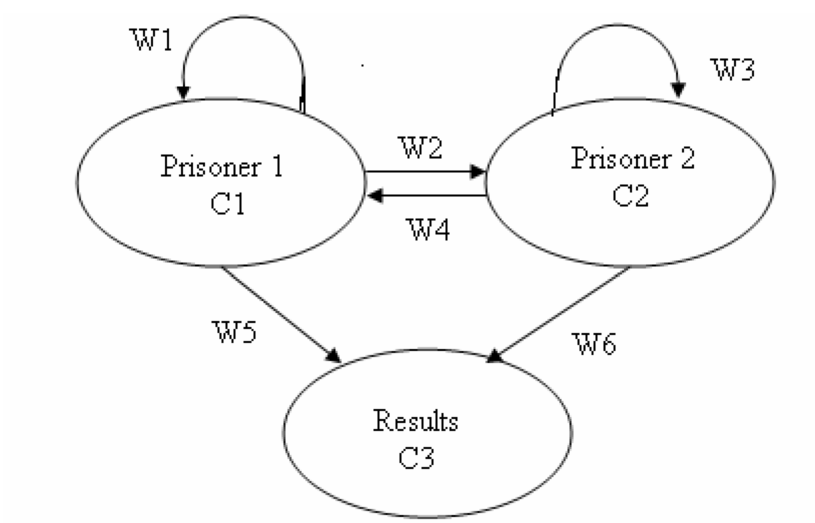

Figure B.1.6: Three-State Fuzzy Cognitive Representation of PD

Table B.1.8: Fuzzy Analysis of PD using three concepts

C1	-1	-0.2	Low Cooperation 5, 5 Five years in prison for both Prisoners
C1	-0.4	+0.4	No Cooperation 10, 0 Ten Years in prisons for the first Prisoner and release the second Prisoner
C1	0.2	1	High Cooperation 1, 1 The two Prisoners get one year each
C2	-1	-0.2	Low Cooperation 5, 5 Five years in prison for both Prisoners
C2	-0.4	+0.4	No Cooperation 10, 0 Ten Years in prisons for the second Prisoner and release of the first Prisoner
C2	0.6	1	High Cooperation 1, 1 The two Prisoners get one year each
C3	-1	-0.4	5, 5 Five years in prison for both Prisoners
C3	-0.5	0.1	10, 0 Ten Years in prison for the first Prisoner and release the second Prisoner
C3	-0.1	0.5	0, 10 Ten Years in prison for the second Prisoner and release the first Prisoner
C3	0.4	1	1, 1 The two Prisoners get one year each

B 1.5.1 High Cooperation Scenario: Both Prisoners Deny

As shown in Table B.1.9 and Figure B.1.7 the results are identical to those derived using the two–concept model with the only difference being that the option of High Cooperation leads to the best possible outcome according to which both prisoners are released.

Table B.1.9: High Cooperation (Deny configuration)

Weights	Initial AL	Final AL	Defuzzification
W1=0.9 W2= 0.9 W3=0.9 W4=0.9 W5=0.9 W6=0.9	C1 AL=0.9 C2 AL=0.9 C3 AL=0.9	C1 AL=-0.9 C2 AL=0.9 C3 AL=0.9	**C01: Player 1** High Cooperation The two Prisoners get 1 year each **C02: Player 2** High Cooperation The two Prisoners get 1 year each **C03: Result** The two Prisoners get 1 year each

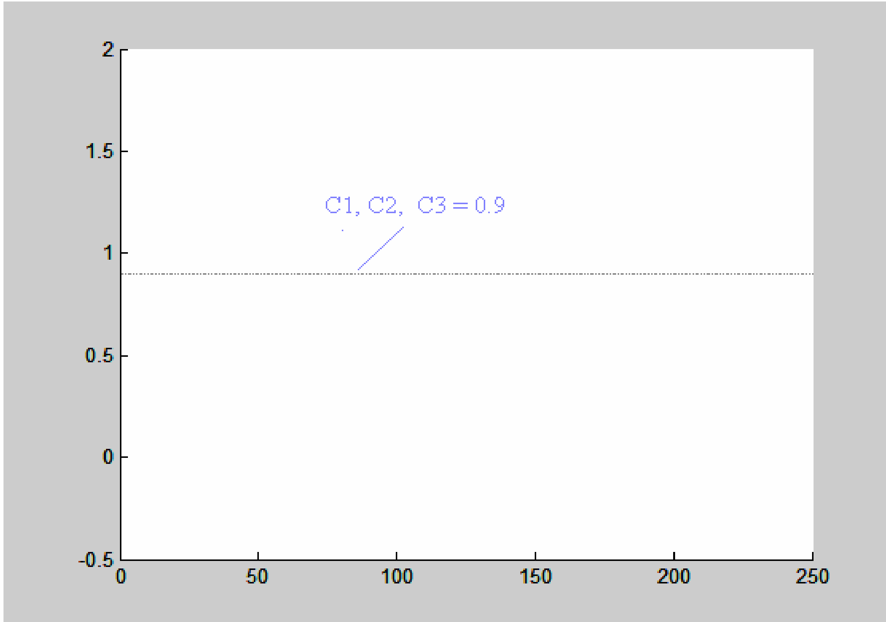

Figure B.1.7: High Cooperation: Both Prisoners Deny

B 1.5.2 Low Cooperation Scenario: Five Years in Prison for both

In this strategy the system also verifies the possibility of Low cooperation meaning that the two Prisoners confess leading to minimum punishment which is five years in prison for both of them. The results shown in Table B.1.10 and Figure B.1.8 are similar to those of the previous model with the two concepts.

Table B.1.10: Low Cooperation (Confess)

Weights	Initial AL	Final AL	Defuzzification
W1=-0.9 W2= 0.9 W3=0.9 W4=0.9 W5=0.9 W6=0.9	C1 AL=-0.9 C2 AL=-0.9 C3 AL=0.9	C1 AL=-0.9 C2 AL=-0.9 C3 AL=-0.9	**C1: Player 1** Low Cooperation 5 years in prison for both Prisoners **C2: Player 2** Low Cooperation 5 years in prison for both Prisoners **C3: Result** 5 years in prison for both Prisoners

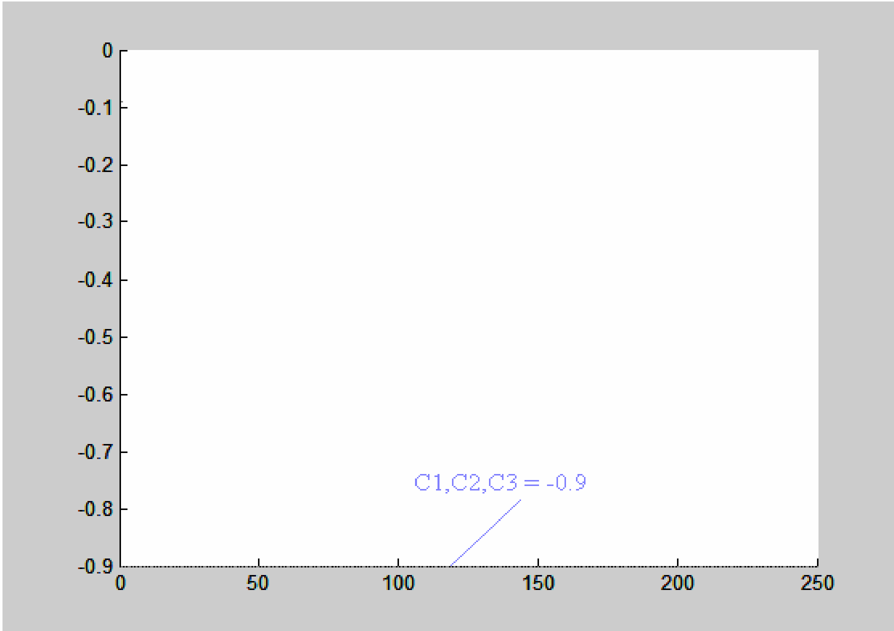

Figure B.1.8: Low Cooperation: Both Prisoners Deny

B 1.5.3 No Cooperation Scenario: Low-High Cooperation

In this case the first Prisoner confesses, hoping that his partner will confess too and thus suffer the minimum punishment which is five years in prison for both, while the second Prisoner denies, expecting his partner to do the same. The end result is that the first Prisoner suffers minimum punishment walking free, while the second one gets 10 years which is the maximum penalty. This is the worst case scenario with the same results applying, mutatis mutandis, when the first prisoner denies and the second confesses. (Table B.1.11 and Figure B.1.9)

Table B.1.11: Low to High Cooperation (Deny and confess configuration)

Weights	Initial AL	Final AL	Defuzzification
W1=0.9 W2=- 0.9 W3=0.9 W4=-0.9 W5=0.9 W6=0.9	C1 AL=-0.50 C2 AL=0.50 C3 AL=0.50	C1 AL=-0.9 C2 AL=0.9 C3 AL=-0.01	**C1: Player 1** Low Cooperation: 5 years in prison for both prisoners **C2: Player 2** High Cooperation: The two prisoners get 1 year each **C3: Result** 10 years in prison for the first Prisoner and release the second Prisoner

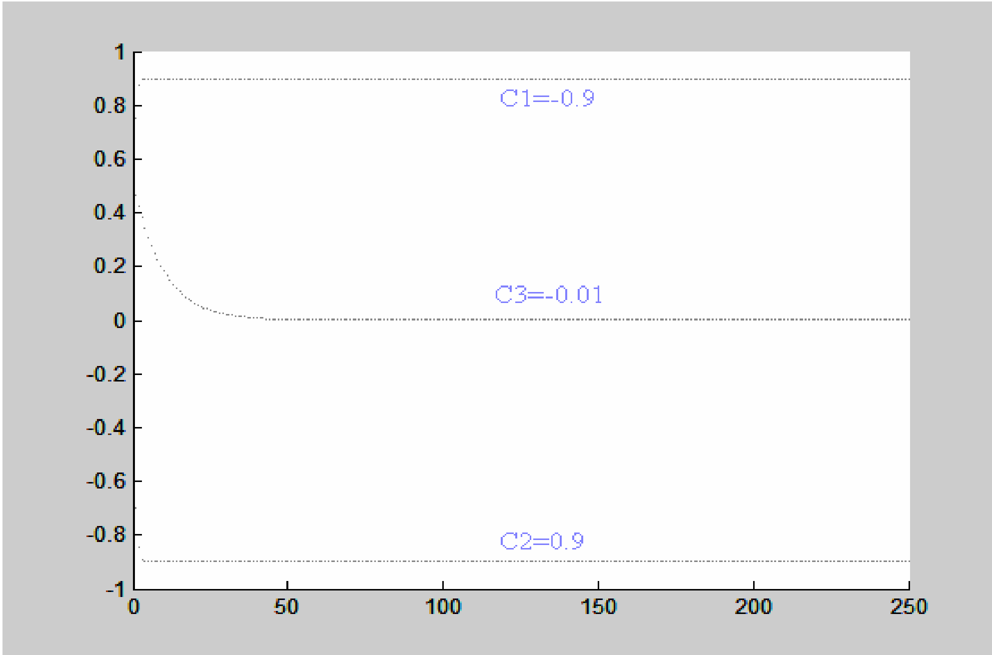

Figure B.1.9: Low and High Cooperation

B 1.5.4 No Cooperation Scenario: High Low Cooperation

Table B.1.12: Deny Configuration

Weights	Initial AL	Final AL	Defuzzification
W1=0.9 W2=-0.9 W3=0.9 W4=-0.9 W5=0.9 W6=0.9	C1 AL=.50 C2 AL=-0.50 C3 AL=0.50	C1 AL= 0.9 C2 AL=-0.9 C3 AL=-0.01	**C1: Player 1** High Cooperation: The two prisoners get 1 year **C2: Player 2** Low Cooperation: 5 years in prison for both prisoners **C3: Result** 10 years in prison for the second Prisoner and release the first Prisoner

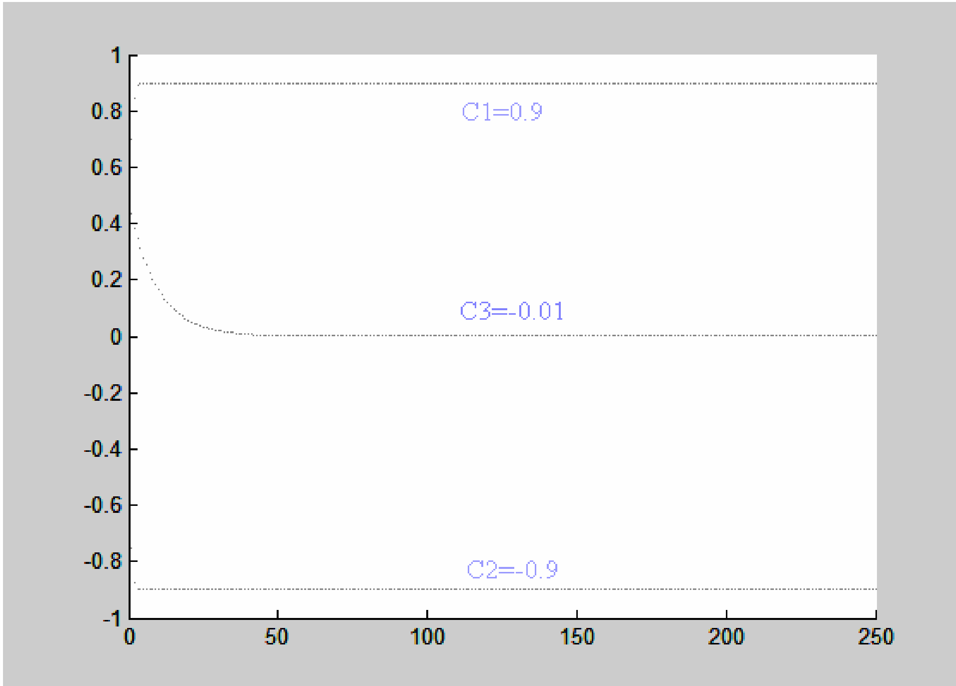

Figure B.1.10: Low and High Cooperation

B.1.6 FCM and evolutionary strategy applied in Prisoner's Dilemma problem

It became obvious from the previous paragraph that, that the Prisoner's Dilemma problem can be well modelled using Fuzzy Cognitive Maps with the three concept version providing increased flexibility and for more efficient strategies. What is very interesting to see next is the forecasting behaviour of the model with the help of Genetic Algorithms**.**

Evolutionary game theory is a popular subject across diverse disciplines of social and natural sciences. It provides a framework for studying the evolution of different strategies under various conditions that are modelled by the rules of games to which players must conform, like in the case of the Prisoner's dilemma game. In this specific case, however, which is known as an Evolutionary Prisoners Dilemma, the most active area of research concerns perhaps the evolutionary strategy when success requires doing well with other successful strategies, rather than doing well with a wide range of strategies. Three scenarios will be implemented here to verify the hybrid methodology in PDs.

B 1.6.1 Strategy 1: Starting from No Cooperation asking for Low Cooperation

Starting from the situation of No Cooperation A_1=0.5 and A_2=-0.5 the first one confesses and the other denies. We apply evolutionary strategy and ask the model to provide for a Low Cooperative strategy A_3 =-0.7. As shown in Table B.1.13 and Figure B.1.11, the model reaches equilibrium giving negative low cooperation results, A_1=-0.72, A_2 =-0.89, A_3 =-0.42. The meaning of these results is shown in column four of Table B.1.13. This strategy indicates that when the two Prisoners do not cooperate the methodology through the evolutionary FCM can alter the No Cooperation strategy to Low Cooperation.

Table B.1.13: Strategy 1- From No Cooperation to Low Cooperation (A_3 = - 0,7)

Weights	Initial AL	Final AL	Defuzzification
W1=0.09 W2=-0.64 W3=0.76 W4=0.38 W5=0.9 W6=-0.49	C1 AL=0.50 C2 AL=-0.50 C3 AL=0.50	C1 AL= -0.72 C2 AL=-0.89 C3 AL=-0.42	**C1: Player 1** Low Cooperation: 5 years in prison for both prisoners **C2: Player 2** Low Cooperation: 5 years in prison for both prisoners **C3: Result** 5 years in prison for both prisoners

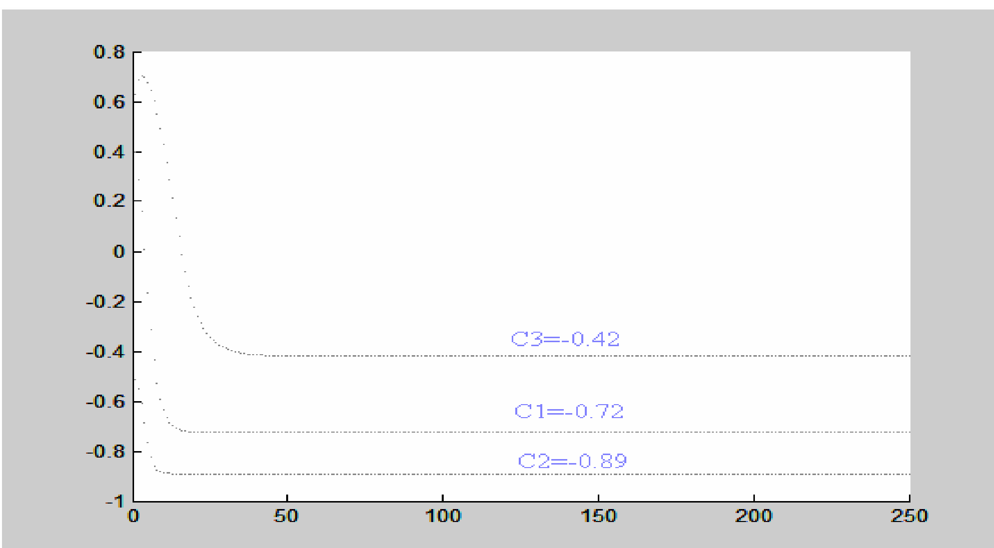

Figure B.1.11: Strategy 1- From No Cooperation to High Cooperation

B 1.6.2 Strategy 2: From No Cooperation (Low-High) to High Cooperation

Starting from the situation of no cooperation A_1=0.5 (High for P1) , A_2=-0.5 (Low for P2), we apply a strategy evolution asking the model to give a High Cooperative scenery denoted by A_3= 0.90. As shown in Table B.1.14 and Figure B.1.12 the model reaches equilibrium giving positive high cooperation results. A_1= 0.67, A_2= 0.66 and A_3= 0.87. The meaning of these results is shown in column four of Table B.1.14 more precisely the evolutionary mechanism of FCM successfully indicates that the No Cooperation can alter to High Cooperation.

Table B.1.14: Strategy 2-From Low-High Cooperation to High Cooperation (A_3= 0.90)

Weights	Initial AL	Final AL	Defuzzification
W1= 0.56 W2=-0.92 W3= 0.59 W4=-0.31 W5=-0.69 W6= 0.27	C1 AL= 0.50 C2 AL=-0.50 C3 AL= 0.50	C1 AL= 0.67 C2 AL= 0.66 C3 AL= 0.87	**C1: Player 1** High Cooperation: The two prisoners get 1 year each **C2: Player 2** High Cooperation: The two prisoners are released **C3: Result** The two prisoners get 1 year

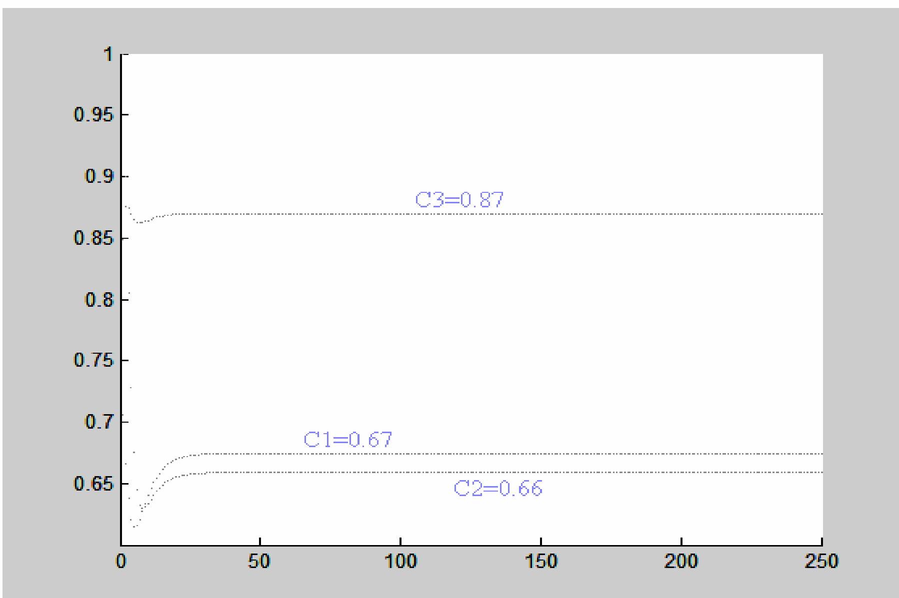

Figure B.1.12: Strategy 2 - From No Cooperation to High Cooperation (C3=0.9)

B 1.6.3 Strategy 3: From Low-Low Cooperation to High Cooperation

Another scenario to verify the applicability of Evolutionary FCM to Game theory is the following: Starting from the situation Low-Low cooperation A_1=-0.9 and Low Cooperation for A_2=-0.9, we apply evolutionary strategy and ask the model to give a High Cooperative strategy A_3= 0.90. As shown in Table B.1.15 and Figure B.1.13 the model reaches equilibrium giving positive high cooperation results with A_1= 0.9, A_2= 0.9 and A_3= 0.9.

Table B.1.15: Strategy 3- From Low-Low Cooperation to High Cooperation (A_3= 0.90)

Weights	Initial AL	Final AL	Defuzzification
W1=0.90 W2=0.90 W3=0.90 W4=0.90 W5=0.90 W6=0.90	C1 AL=-0.90 C2 AL=-0.90 C3 AL=0.90	C1 AL=0.90 C2 AL=0.90 C3 AL=0.90	**C1: Player 1** High Cooperation: The two prisoners get 1 year each **C2: Player 2** High Cooperation: The two prisoners are released **C3: Result** The two prisoners get one year

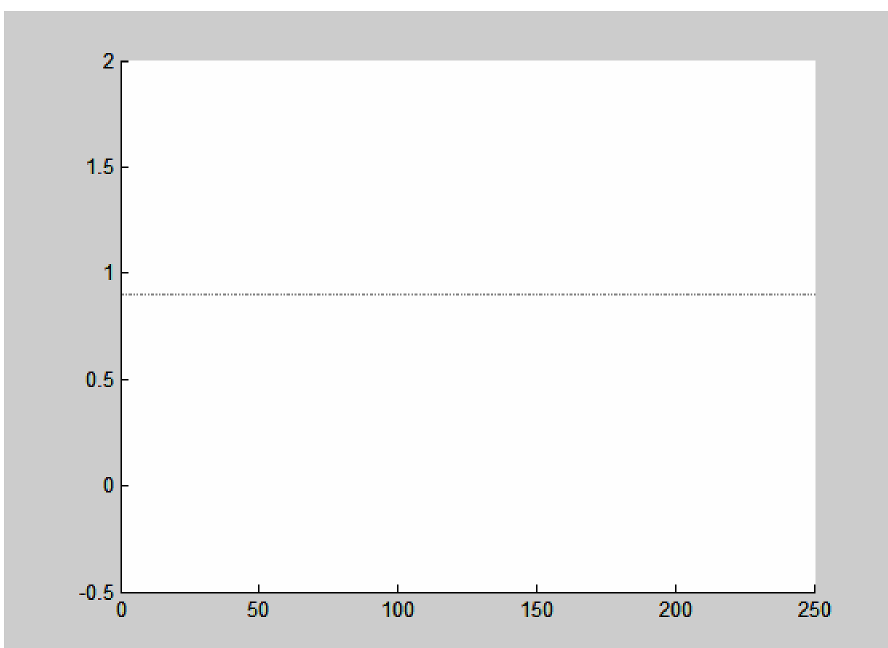

Figure B.1.13: Strategy 3 -From Low-Low Cooperation to High Cooperation (C3=0.90)

The main objectives of the analysis have been the followings: (a) To establish enough evidence indicating that FCMs can contribute to modelling game theory problems like the PD one with the analyst being able to consider a wide selection of strategies using Genetic Algorithm methodology integrated to FCM. (b) To extent the argument and provide evidence that the FCM methodology is efficient and robust and that it may be seen as a solid promising technique for modelling problem of the real-world that present a substantial level of uncertainty.

B.1.7 Application of FCM in a Prisoner's Dilemma conflict resolution: The example of 1963 Cuban missile crisis

B 1.7.1 Introduction

The environment created by a model such as that of the "Prisoners' Dilemma" has been considered particularly suitable to reflect the conditions prevailing due to the absence of communication between the parties involved in the Cuban crisis [62]. This is a rather common feature in an environment of conflicting interests given that, at least in their crisis initial phase, such models exclude the possibility of any form of "rapprochement" between the sides involved. It is often the case, however, that a period of increased tensions precedes a conflict incident [131]. In such a case there can be two possible reactions from the part of the sides involved in the conflict in their effort to evacuate the crisis. First, to prevent the outbreak of hostility as it has been the case with the Cuban Missile Crisis during which a small number of communication channels were used in an attempt of a peaceful resolution of the crisis. The second possibility, however, is that communication channels between the parties involved may degrade during the crisis, increasing the likelihood of further escalation and violence. In both cases, however, there will definitely be a serious attempt to increase communication between the sides involved in the crisis. There is always a possibility, however, that the parties involved will ignore all available channels of communication, or withhold information, or even use increasingly divisive forms of communication, in which case any form of compromise will be eliminated.

B 1.7.2 The Cuban missile crisis

The Cuban missile crisis was triggered by a Soviet attempt in October 1962 to install medium-range ballistic missiles in Cuba, a weapon that would constitute a conventional, or even a nuclear threat against the United States. The United States demanded their immediate removal and considered two strategies to achieve this end with an equal number of options given to the USSR side to respond. In such a case it is convenient to distinguish between “sustain” and “compromise” for both sides, the first one revealing an intention to “maintain” one’s position, while “compromise” is translated as an intention to withdraw. This distinction is quite clear cut to describe the USSR position on the subject. For the USA, though, things are different: We need to subdivide the two main categories (sustain and withdraw) as follows: The “sustain” option can be broken down to three alternatives, namely, “attack” (describing a massive attack), “strike” (meaning a surgical air strike focusing on eliminating the missile bases) or “blockade” (which was what actually happened). The “compromise” option, in its turn, can be allowed to include choices like “complete withdrawal”, “petition” to the international court and “bargain”. All these alternatives for each of the two options, namely the “sustain-deny” and the “compromise-confess” ones are introduced in the Fuzzy Knowledge Base listed in Table B.1.16 and in the analysis in the form of activation levels ranging between -1 and 1 depending on the reaction of each side, combined, of course, with the appropriate weighting scheme.

It is important to point out in this case that the options given by the system in the form of a solution to the crisis can often involve the so-called “shadow solutions”. In this specific case, for example, most people believe that the US reaction that led to the final solution was the “blockade” choice. What has been behind the actual solution, however, was a form of a hard “bargain” as the USSR agreed to withdraw the missiles provided that the US would remove its own missiles from Turkey. This is in fact a “shadow” solution and yet it reveals much more than what meets the eye. It will be very interesting, therefore, to see if the FCM used in this case points to just the actual solution, or instead, is in a position to reveal the shadow solution as well.

Table B.1.16: Cuban missile Crisis modeled using the PD paradigm

			USSR- Soviet Union
		Withdraw (W)	**Retain (R)**
United States of America (U.S.A)	**Blockade (B)**	Compromise (3,3)	Soviet victory, U.S. defeat (1,4)
	Air strike (A)	U.S. victory, Soviet defeat (4,1)	Nuclear war (1,1)

The strategies can be thought of as alternative courses of action that the two sides or "players" can choose. They lead to four possible outcomes, which the players are assumed to rank as follows: 4=best; 3=next best; 2=next worst; and l=worst. Thus, the higher the number, the greater the payoff; it is important to be borne in mind, however, that the payoffs are only *ordinal*, that is, they only indicate an ordering of outcomes from best to worst, and by no means denote a cardinal measurement of the benefit incurred. The first number in the ordered pairs for each outcome is the payoff to the row player (United States), the second number the payoff to the column player (Soviet Union).

B.1.8 Fuzzy Cognitive Maps Implementation in the Cuban missile crisis

Following the fuzzification principle of the Prisoner's Dilemma the three concepts involved in the Cuban Missile crisis are indicated in Table B.1.17. C1 corresponds to the USA position in this crisis which distinguishes between three options, namely a direct massive military attack, a surgical air strike focusing on eliminating the missile bases and a blockade with the threat of direct military attack. C2 refers to the Soviet Union position which was either to retain or withdraw the missiles. The third concept is the outcome of the different strategies namely a result concept which incorporates the outcome of the different combinations of strategies. The fuzzification is indicated in Table B.1.18

Table B.1.17: Cuban missile crisis concept description

C1	USA Position
C2	Soviet Union Position
C3	Result

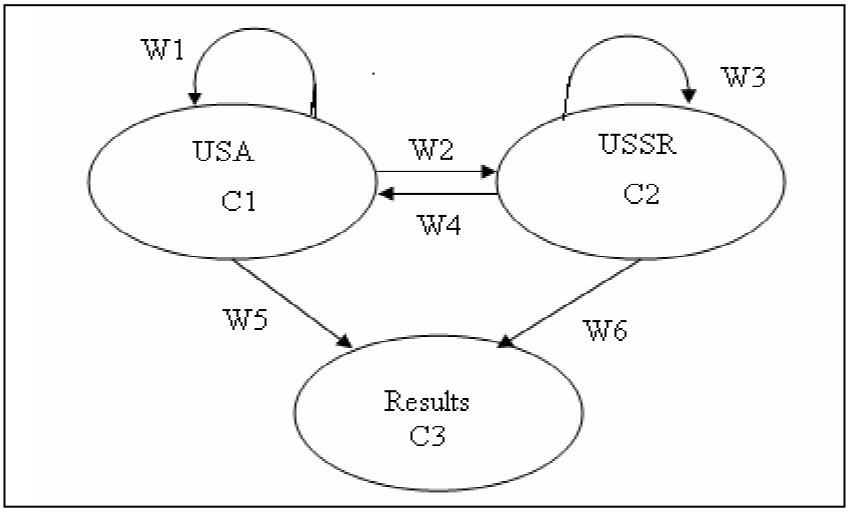

Figure B.1.14: FCM Diagram for Cuban Missile Crisis

Table B.1.18: Fuzzy Knowledge base for Cuban Missiles Crisis

C1	-1	-0.2	Direct massive military attack (Air strike /invention to Cuban (A))
C1	-0.4	+0.4	Surgical air strike focusing on eliminating the missile bases
C1	0.2	1	Blockade with the threat of direct military attack (B)
C2	-1	-0.2	Retain (R)
C2	-0.4	+0.4	Partially Retain the Missile (R)
C2	0.2	1	Withdraw the Missiles and Proceed to Shadow Agreement (W)
C3	-1	-0.4	An air strike that partially destroys the missiles is the worst case for both. The outcome of (1,1), may lead to a nuclear war
C3	-0.5	0.1	An air strike that destroys the missiles is the best outcome for USA that thwarts the Soviets which is the worst outcome for them (4,1).
C3	-0.1	0.5	In the face of a U.S. blockade, Soviet maintenance of their missiles leads to a Soviet victory which is their best outcome and U.S. capitulation is the worst outcome for them (1,4).
C3	0.4	1	The choice of blockade by the United States and withdrawal by the Soviet Union is the compromise solution for both players (3,3).

B 1.8.1 Scenario 1: The Pessimistic Case. Both sides Deny, Possible Nuclear War

The initial AL for C1 and C2 were set to -0.7, meaning that the US will take direct measures like an air strike that will partially destroy the missiles and the Soviet Union will take action attacking American cities using Cuban bases. The model simulates this scenario successfully indicating that (A_3=-0.87) an air strike will lead to nuclear war with unpredictable consequences for the two countries and their allies (Table B.1.19 and Figure B.1.15).

Table B.1.19: Strategy 1- The Pessimistic Case: Both Players Deny

Weights	Initial AL	Final AL	Defuzzification
W1=0.80 W2=0.70 W3=0.50 W4=0.60 W5=0.70 W6=0.50	C1 AL=-0.70 C2 AL=-0.70 C3 AL=0.50	C1 AL= -0.90 C2 AL=-0.90 C3 AL=-0.87	**C1: USA** Air strike (A) **C2: USSR** Maintenance (M) **C3: Result** An air strike that partially destroys the missiles is mutually the worst case. The outcome of, may leads to a nuclear war

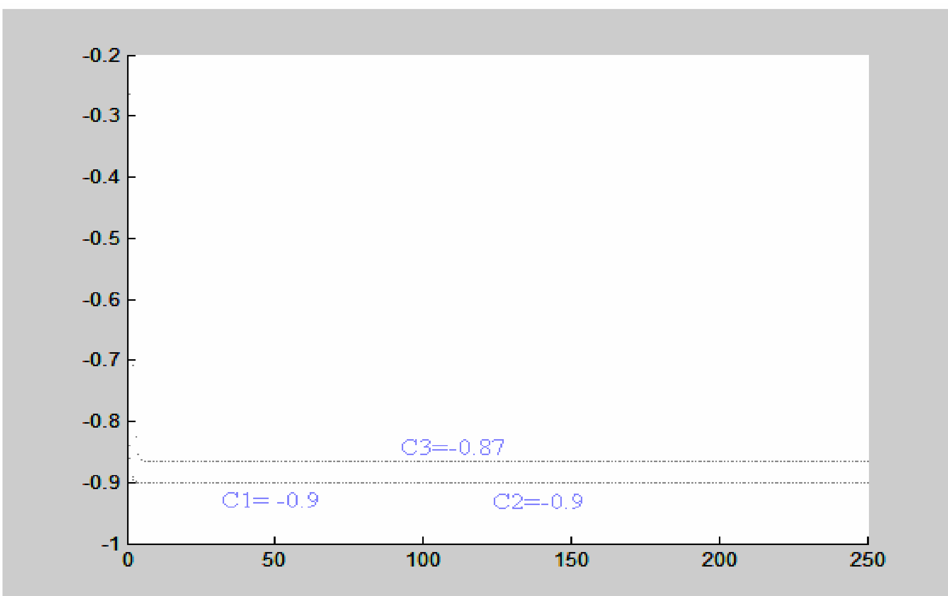

Figure B.1.15: The Pessimistic Scenario: Both Players Deny

Table B.1.19 simulates the negative and pessimistic case where no communication and no cooperation between the two countries exist. The model successfully demonstrates this negative scenario giving as final output of A_1=-0.9, A_2=0.9 and A_3=-0.87. The defuzzification process in column four indicates that in case of Air strike from the USA provided that the Soviets will maintain the missiles the end result would be a possible nuclear world.

B 1.8.2 Scenario 2: The Optimistic case: Both sides compromise, End of Crisis

This second scenario attempts to simulate the optimistic scenario leading to the compromised solution. In this case, the U.S.A strategy was to blockade Cuba (A_1= 0.7) sending a clear message to USSR that it will attack in case that the missiles do not withdraw. On the other hand the USSR after hard negotiations and following a possible secret agreement decides to withdraw its missiles (A_2= 0.7). The summary results of Table B.1.20 and Figure B.1.16 indicate that the model simulates this scenario successfully achieving a (A_3= 0.87) which represents a compromised position.

Table B.1.20: Strategy 2- The Optimistic Scenario: Both Sides Compromise (A_3= 0.90)

Weights	Initial AL	Final AL	Defuzzification
W1=0.80 W2=0.70 W3=0.50 W4=0.60 W5=0.70 W6=0.50	C1 AL=0.70 C2 AL=0.70 C3 AL=0.50	C1 AL= 0.90 C2 AL=0.90 C3 AL=0.87	**C1: USA** Blockade (B) **C2: USSR** Withdrawal (W) **C3: Result** The choice of blockade by the United States and withdrawal by the Soviet Union remains the compromise for both players

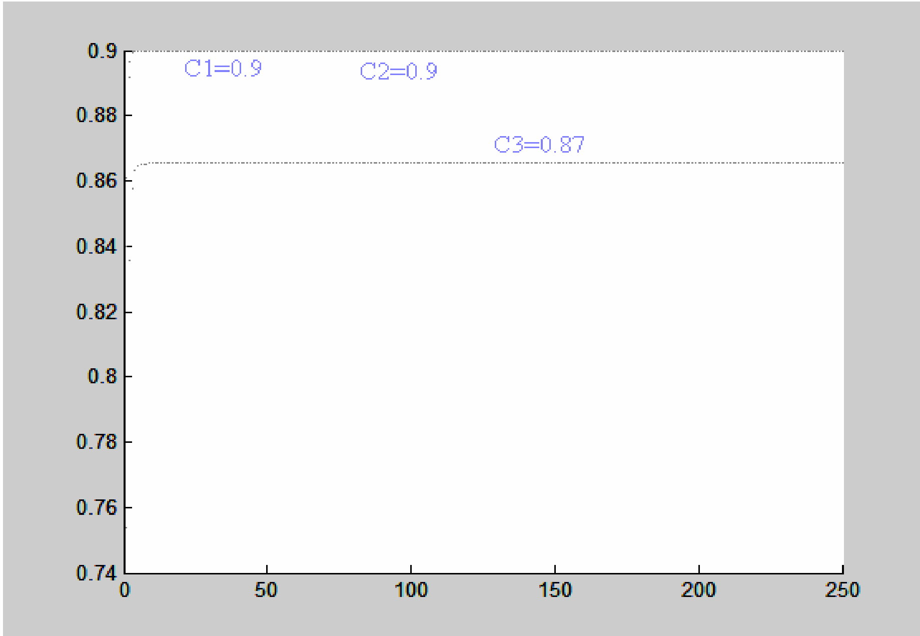

Figure B.1.16: The Optimistic Scenario.

B 1.8.3 Scenario 3: The USA Denies and the USSR Withdraws

This scenario reflects the USA Joint Chiefs of Staff view of a full-scale attack and invasion to Cuba as the only solution (A_1= 0.70), insisting that the Soviets would not act to stop the US from conquering Cuba (A_2=-0.70). This option was eventually turned down by President Kennedy. Supposing, however, that the Soviets would not take any action in this case, then the model is shown to describe the scenario successfully leading to A_3= -0.20, this being the best outcome for the USA. Table B.1.21 simulates the best outcome for USA where a successful air strike with Russian to retreats from Cuba. The defuzzification process in column four of the same table indicates that an air strike that destroys the missiles is the best outcome for USA that thwarts the Soviets which is the worst outcome for them.

Table B.1.21: Strategy 3- The USA Denies and the USSR Withdraws

Weights	Initial AL	Final AL	Defuzzification
W1=-0.80 W2=0.80 W3=0.50 W4=0.80 W5=-0.70 W6=0.50	C1 AL=0.70 C2 AL=-0.70 C3 AL=0.50	C1 AL= -0.02 C2 AL=-0.02 C3 AL=-0.20	**C1: USA** Air strike (A) **C2: USSR** Maintenance (M) **C3: Result** An air strike that destroys the missiles is the best outcome for USA, that thwarts the Soviets which is the worst outcome for them

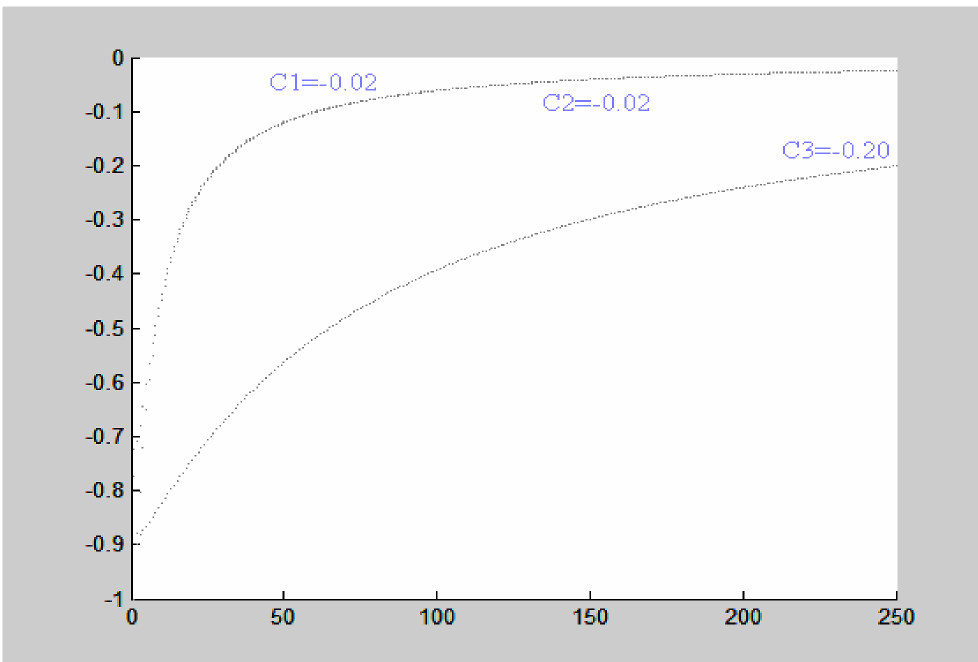

Figure B.1.17. The USA Denies and the USSR Withdraws

B.1.9 Assessment of the methodology

The FCM methodology was tested on a game-theory environment, namely the well known Prisoner's Dilemma, showing that such a method can be very reliable in terms of implementation and results. The framework proposed in chapter 4, validated with various problems related to the settlement of the Cyprus issue was also verified using a general well-known problem the Prisoner's dilemma. This dilemma has provoked various challenges to game theory and decision making. The methodology was validated using a two concept configuration of indicating that when the two prisoners are not in agreement (one selects Deny and the other Confess) the system gives limit cycle. The inability of the methodology to implement in full scale this problem led us to propose a three state configuration which was successfully implemented proving the efficiency of the methodology. The FCM hybrid methodology was also tested with equally promising and reliable results. As a concrete example, the well-known Prisoner's dilemma was examined exactly because this dilemma has provoked various problems in decision theory due to its complicacy. The application of the PD reasoning to a case study, namely the 1963 missile crisis between USA and USSR, highlights the usefulness of the FCMs application in facing intricate crisis environments and pointing to the appropriate solutions. The objective of this Appendix was primarily to apply the FCM approach to a general and widely known problem, and thus show that our approach is generalized in the sense that it is well suited in application in complicated and real world problems. The outcome of this implementation was successful and the results verified the political actions of that time.