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MARIA PAPAIOANNOU

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ΠΕΡΙΛΗΨΗ

Ο κύριος άξονας της έρευνας που διεξήχθη στα πλαίσια αυτής της διδακτορικής διατριβής είναι η εξερεύνηση διαφόρων λύσεων σε θέματα που αφορούν τον σχεδιασμό, την κατασκευή και την λειτουργικότητα των Ασαφών Γνωστικών Χαρτών (ΑΓΧ). Η συνεισφορά αυτού του έργου μπορεί να αναλυθεί σε τρία επίπεδα. Το πρώτο επίπεδο αφορά στην πρόταση μιας μεθοδολογίας κατασκευής ΑΓΧ για προβλήματα τα οποία δεν περιγράφονται από σύνολα δεδομένων και η μόνη πηγή πληροφόρησης για την κατασκευή τους προέρχεται από μια ομάδα ειδικών στον τομέα του προβλήματος. Τέτοια προβλήματα βρίσκονται στον κοινωνικό, πολιτικό κι οικονομικό τομέα. Στα πλαίσια αυτής της δουλειάς, προτάθηκε επίσης μια συνάρτηση ενεργοποίησης με σκοπό την καλύτερη αναπαράσταση του τρόπου που διαχέεται η αιτιώδης πληροφορία δυναμικά στο σύστημα.

Το δεύτερο επίπεδο αφορά στην κατασκευή ΑΓΧ όταν υπάρχουν σύνολα δεδομένων που περιγράφουν το σύστημα όσο αφορά τις παραμέτρους του και τις διασυνδέσεις μεταξύ τους. Σε αυτόν τον τομέα υπάρχει δύο κατηγορίες. Η πρώτη κατηγορία ασχολείται με προβλήματα για τα οποία υπάρχουν σύνολα δεδομένων σε αριθμητική μορφή τα οποία όμως δεν μπορούν να αξιοποιηθούν για την κατασκευή ασαφών συστημάτων. Ως εκ τούτου, μια μεθοδολογία μεταμόρφωσης των αριθμητικών συνόλων δεδομένων σε ασαφή προτάθηκε και χρησιμοποιήθηκε σε συνδυασμό με τις Εξελικτικές Στρατηγικές για την δημιουργία ενός ΑΓΧ. Η συμμετοχή των ειδικών στην όλη διαδικασία είναι απαραίτητη καθώς δίνουν την δική τους οπτική για το πώς ερμηνεύουν διάφορες αριθμητικές τιμές των παραμέτρων. Η δεύτερη κατηγορία επικεντρώνεται στις περιπτώσεις για τις οποίες υπάρχει μεν διαθέσιμο σύνολο δεδομένων προς αξιοποίηση, δεν καθίσταται παρόλα αυτά δυνατή η εύρεση ή η επικοινωνία με ειδικούς που να γνωρίζουν το πρόβλημα. Παράλληλα, είναι διαθέσιμη μια πλούσια βιβλιογραφία μέσα στην οποία μπορεί κανείς να βρει πληροφορίες για διάφορα θέματα που αφορούν στην δομή και στην αναπαράσταση του προβλήματος. Ορμώμενοι από αυτή την παρατήρηση, προτείνουμε μια μεθοδολογία αναγνώρισης σημαντικών παραγόντων μέσα από την μελέτη σχετικής βιβλιογραφίας με το πρόβλημα προς μοντελοποίηση. Έπειτα, οι παράγοντες ορίζονται και αρχικοποιούνται βάσει πιθανοτικών μοντέλων που εξάγονται από την ανάλυση του διαθέσιμου συνόλου δεδομένων.

Το τρίτο επίπεδο αυτής της δουλειάς εισάγει μια ιεραρχική αρχιτεκτονική των ΑΓΧ η οποία εκφράζεται μέσα από την χρήση δυναμικών βαρών. Διαφορετικοί συνδυασμοί αρχικών καταστάσεων κόμβων που θεωρούνται «πιο σημαντικής αξίας» οδηγούν σε

διαφορετικές τιμές βαρών που έχει ως αποτέλεσμα την ενδυνάμωση ή την αποδυνάμωση μιας σχέσης. Αυτό το σχήμα προτάθηκε ως ένας μηχανισμός ελέγχου διαφόρων δυνατών συνεργιών που μπορεί να εμφανιστούν στο σύστημα κάτω από διαφορετικές συνθήκες.

Όλες οι προαναφερθείσες μεθοδολογίες και μηχανισμοί υλοποιήθηκαν και δοκιμάστηκαν σε πραγματικά προβλήματα. Το πρώτο πρόβλημα προέρχεται από την κυπριακή πραγματικότητα των τελευταίων ετών και σχετίζεται με την οικονομική κρίση στην Κύπρο κι Ελλάδα. Το δεύτερο πρόβλημα προέρχεται από τον ιατρικό χώρο και πιο συγκεκριμένα τον διαγνωστικό και αφορά στην διάγνωση της Τρισωμίας 21 που είναι πιο γνωστή ως σύνδρομο Down.

Η δομή της διατριβής χωρίζεται σε τέσσερα βασικά μέρη. Το πρώτο μέρος είναι εισαγωγικό στο θέμα που καταπιάνεται η διατριβή. Το δεύτερο μέρος είναι μια βιβλιογραφική ανασκόπηση σε θέματα που άπτονται του ενδιαφέροντος της εργασίας αυτής. Το τρίτο μέρος αποτελείται από τρία κεφάλαια και περιγράφει τα προτεινόμενα σχήματα των ΑΓΧ. Επιπλέον παρουσιάζονται τα αποτελέσματα που επιτεύχθηκαν από την υλοποίηση τους. Στο τέλος, το τέταρτο μέρος περιέχει τα συμπεράσματα που εξήχθησαν από την εργασία αυτή όπως επίσης και κάποιες μελλοντικές κατευθύνσεις εργασίας.

ABSTRACT

The main goal of this research is to explore new methodologies regarding the design, building and functionality of Fuzzy Cognitive Maps (FCM). The contributions derived from this thesis can be analyzed into three main dimensions. The first is about presenting a specific methodology of building FCM models for problems for which datasets are absent and the only source of information for building a FCM model is a group of experts in the problem's domain. Such systems lie in the social, political and economic fields. In the context of this work, a new activation function is also proposed as a try to represent in a more realistic way the way causal dynamics are expressed in such problems.

The second dimension of this work is about constructing FCMs when datasets do exist and useful information about the problem's factors and their interrelations can be extracted. The work done in this field can be further analyzed into two categories. The first deals with the cases a dataset describing several problems' factors exist in crisp form making it useless for developing a fuzzy system. To solve this problem, a methodology for transforming the crisp dataset into fuzzy is proposed and then actually used in combination with Evolutionary Strategies to build a FCM. Experts participate in this process giving their insight on how they interpret the crisp values of each parameter. The second category is more concerned about the cases were datasets do exist but experts in the problem's domain are absent or there is a lack of communication with them making it difficult to exploit their knowledge and experience to build a FCM. At the same time, a rich bibliography describing different problem's aspects is published and available. Hence, a methodology of identifying the concepts through published bibliography is proposed. Then, the concepts are defined and initialized by probabilistic models which are derived by proper analysis of the existing dataset.

The third and last dimension of this work introduces a hierarchical architecture of FCMs which is essentially expressed in the use of dynamic weights of the network's relations. Different combinations of the "higher in significance" concept states can lead to different weight values by strengthening of weakening the relation. This schema was proposed as a mechanism of handling potential synergies that might appear in a system under different conditions.

All of the proposed FCM methodologies and mechanisms were implemented and tested on real problems. The first chosen problem was drawn from Cypriot reality of the last years

related to economic crisis and the second problem was a medical diagnostic one related to the diagnosis of Trisomy 21.

The structure of the thesis is divided into four main parts. The first is introductory to the thesis' subject. The second is a literature review in aspects related to the thesis main subjects. The third part presents in detail the proposed schemas about FCMs and the results derived from their implementation followed by the fourth part which includes the conclusions and future directions of this work.

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ABREVIATIONS

AHL	Active Hebbian Learning
ANN	Artificial Neural Networks
AUC	Area Under the Curve
b-hCG	Maternal Serum free ß-human Chorionic Gonadotropin
BDA	Balanced Differential Algorithm
BIC	Bayesian Information Criterion
cfDNA	maternal cell-free DNA
CI	Computational Intelligence
CM	Cognitive Maps
CRL	Crown Rump Length
DDNHL	Data-Driven Nonlinear Hebbian Learning
DDSS	Diagnostic Decision Support System
delta NT	Delta Nuchal Translucency
DHL	Differential Hebbian Learning
DST	Dempster-Shafer Theory
DV	Ductus Venosus Flow
EM	Expectation-Maximization Algorithm
ES	Evolutionary Strategies
FCM	Fuzzy Cognitive Map
FMF	Fetal Medicine Foundation
FL	Fuzzy Logic
FN	False Negative
FP	False Positive
MCC	Matthews Correlation Coefficient
MLP	Multilayer Perceptron
MoG	Mixture of Gaussians
MoM	Multiple of the Median
NB	Nasal Bone
NT	Nuchal Translucency

PAPP-A	Pregnancy-Associated Plasma Protein-A
PSO	Particle Swarm Optimization
PSI	Private Sector Involvement
RBFCM	Rule-Based FCM
RCGA	Real Coded GA
SEM	Structural Equation Modeling
SRCGA	Sparse Real-Coded Genetic Algorithm
T21	Trisomy 21
TF	Tricuspid Flow
tFCM	Temporal FCMs
TN	True Negative
TP	True Positive

1. Introduction

The memories of the 20th century rather have a bitter taste since this time period counts two World Wars with mass deaths and extensive destructions, transnational local wars, genocides, civil wars and dictatorships. This destructive character of this century, however, is only the dark side; because, on the bright side, there was an unbridled growth and technological progress! Through pain and suffer, humanity managed to understand, create, invent and discover ideas, mechanisms and technologies that could throw light on problems regarding different aspects of human life. As a result, the idea of European Union arose, Biology was enriched by the discovery of the building block of life (DNA double helix structure), Physics bloomed in the theory of relativity, Astronomy confirmed Galileo Galilei theories through satellites, preventive Medicine was enhanced with the introduction of vaccinations and Information technology flourished through the establishment of specific algorithms and data structures needed to satisfy the exponentially increasing human needs.

Computer Science is a field where algorithmic processes, methods and techniques describing, transforming and generally utilizing information are created to satisfy different human needs. Humans have to deal with a variety of complex problems in different domains as Medicine, Engineering, Ecology, Biology and so on. In parallel, humans have aggregated through years vast databases of a plethora kind of information. The need to search, identify structures and distributions and overall take an advantage on all this information along with the simultaneous development of computer machines (in terms of hardware level) led humans in inventing different ways on how to handle information for their own benefit. Computational Intelligence lies under the general umbrella of Computer Science and hence encloses algorithms/ methods/ techniques of utilizing and manipulating data/information.

1.1 Computational Intelligence

One of the most important findings worldwide was to discover how organized and structural thinking arises from a bunch of individual processing units, which co-function and interact in harmony under no specific organized supervision of a super unit. In other words humanity shed a light on how the brain works. The appearance of computers and the outstanding evolution of their computational capabilities enhanced even more the human need in exploring how human brain works by modeling single neurons or group of interconnected neurons and run simulations over them. That meant the first generation of the well-known Artificial Neural Networks (ANN). Through time scientists have made more observations on how human and nature works. Behavioral concepts of individuals or organizations of individuals, psychological aspects, biological and genetic findings have contributed into computerized methods which firstly went down the algorithms class of "Artificial Intelligence" but later on created a novel category of algorithms, the "Computational Intelligence"(CI).

As indicated by the name of this area, CI methods aim in incorporating some features of human and nature intelligence in handling information through computations. Although there is no strict definition of intelligence, approximately one could say that intelligence is the ability of an individual to, efficiently and effectively, adapt to a new environment, altering from its present state to something new. In other words, being able under certain circumstances to take the correct decisions about the next action. In order to accomplish something like that certain intelligence features must exist like learning through experience, using language in communications, spatial and environmental cognition, invention, generalization, inference, applying calculations based on common logic and so on. It is clear that humans are the only beings in this world gathering all the intelligent features.

However computers are more able to take a big amount of effort into solving a specific and explicitly defined by humans, problem, taking an advantage on a vast amount of available data. CI technologies are offered in mimicking intelligence properties found in humans and nature and use these properties effectively and efficiently in a method/algorithm body and eventually bringing better results faster than other conventional mathematical or CS methods in the same problem domain.

The main objective of CI research is the understanding of the fashion in which natural systems function and work. CI combines different elements of adaptation, learning, evolution, fuzzy logic, distributed and parallel processing, and generally, CI offers models which employ intelligent (to a degree) functions. CI research is not competitive to other classic mathematical methods which act in the same domains, rather it comprises an alternative technique in problem solving where the employment of conventional methods is not feasible.

Some of the application areas of CI are medical diagnostics, economics, physics, time scheduling, robotics, control systems, natural language processing, and many others. The growing needs in all these areas and their application in humans' everyday life intensified CI research.

The three main sub-areas of CI are Artificial Neural Networks, Evolutionary Computation and Fuzzy Logic. Artificial Neural Network models are inspired by brain processes and structures. There are various configurations of ANN topologies and training algorithms like the Multilayer Perceptron (MLP), Kohonen and Support Vector Machines. ANN are applicable in a plethora of areas like general classification, regression, pattern recognition, optimisation, control, function approximation, time series prediction, data mining and so on.

Evolutionary Computation essentially draws ideas from natural evolution as first stated by Darwin. Evolutionary Computation methods are focused in optimization problems. Potential solutions to such problems are created and evolved through discrete iterations (named generations) under selection, crossover and mutation operators. The solutions are encoded into strings (or trees) which act analogously to biological chromosomes. In these algorithms, the parameters comprising a problem are represented either as genotypes (which are evolved based on inheritance) or phenotypes (which are evolved based on environment interaction aspects). The EC area can be analyzed into four directions: Evolutionary Strategies, Evolutionary Programming, Genetic Programming and finally Genetic Algorithms. All these EC subcategories differ in the solution representation and on the genetic operators they use. Fields where EC has been successfully applied are telecommunications, scheduling, engineering design, ANN architectures and structural optimisation, control optimization, classification and clustering, function approximation and time series modeling, regression and so on.

The third main domain of CI addresses Fuzzy Logic elements and aspects. Coming from the Fuzzy Logic inventor himself, Dr. Zadeh, the word "fuzzy" indicates blurred, unclear or confused states or situations. He even stated that the choice of the word "fuzzy" for describing his theory could had been wrong. However, what essentially Fuzzy Logic tries to give is a theoretical schema on how humans think and reason. Fuzzy Logic allows computers to handle information as humans do, described in linguistic terms, not precisely defined yet being able to apply inference on data and make correct conclusions. Fuzzy Logic has been applied in a wide range of fields as control, decision support, information systems and in a lot of industrial products as cameras, washing machines, air-conditions, optimized timetables etc.

1.2 Fuzzy Cognitive Maps

To deal with the growing interest in utilizing fuzzy logic theory in solving different kind of problems, novel CI methodologies have been proposed. Fuzzy Cognitive Maps (FCMs), proposed in 1986 by Bart Kosko, has been one of them. FCMs can be seen as an extension of Cognitive Maps (CMs), a model given by Robert Axelord in 1976 which was mainly used to describe social systems in a graphical way. The nodes of a CM represented specific concepts of a system where the interconnections between the nodes represented the causal interrelations amongst the corresponding concepts. FCMs kept the graphical representation of such causal systems and additionally:

1. Used fuzzy logic in representing the state of the concepts and the strength of their interconnections.
2. Introduced a method of creating scenarios for the modeled system by simulating how causality runs through the parameters of the system.

Hence, FCMs manage to represent human knowledge and experience, in a certain system's domain, into a weighted directed graph model and apply inference presenting potential behaviors of the model under specific circumstances. Causal systems can be significantly aided by simulating hypothetical scenarios in decision making. However, it is true that many of such systems miss the existence of related data describing somehow the behavior of the system for different cases. That is why one of the most attractive features of FCMs is the fact that they can be used to adequately describe and handle fuzzy and not precisely defined knowledge, since their construction can be implemented based on knowledge extracted from experts on the modeled system. The experts are called to define the number of the concepts and then describe each one of them using linguistic/fuzzy terms. Additionally they have to define the causal relationships between the concepts and describe their type (direct or inverse) as well as their strength. Nevertheless, through the last years, some algorithms of the FCM's weight adaptation and optimization have been also proposed. Such algorithms are needed to be used in cases where available data describing the system behavior is feasible and experts are not in position in describing the system adequately or completely.

The main features of FCMs are their simplicity in use and their flexibility in designing, modeling and inferring complex and big-sized systems. These features attracted the writer of this work to examine different sides of FCMs and propose specific ways of extending their use on realistic systems.

1.3 Motivation

Most humans have a common natural characteristic: the need of being valuable contributors to the greater good. To achieve that, people have to marry their physical and mental abilities with their education to give feasible and planet friendly solutions in real problems of this world. These problems are multi-domain (including areas such as Medicine, Mechanics, Environment, Politics, Economics, Agriculture, Education, Industry, etc.) and described by high complexity.

Computational Intelligence (CI) opens the door for the generation of new solutions to such problems requiring a minimum economic cost and having the number of side effects on the real system eliminated. The charming ability of CI methods to use existing data and human knowledge to exploit and reveal hidden data patterns and relations amongst the parameters of a problem is its strongest tool.

All above, along with the pure need of becoming a valuable contributor and her Computer Science background, motivated the writer of this work, in studying some certain CI methods in depth and then use them to develop applications trying to deal with real problems.

Some of the existing problems are related to systems whose parameters are hard to be quantified in real numbers. For example, it is easier to evaluate a nation's economy as "poor" / "rich" or "problematic" / "excellent" rather than using a real number (e.g. a percentage). This applies for all complex and multivariate parameters which depend on non-palpable metric factors. However, humans have the ability to describe such complicated parameters using their experience and professional instinct or, what people often call, "based on their feeling".

The problem comes when humans need the computer to do some high level calculations on such non-numerically quantified systems. How can computers get that "feeling" about the state of the parameters and use it during a simulation of the modeled system? Fuzzy Logic, a subdomain of CI which immerged back in 1965 by Lofti A. Zadeh (Zadeh, 1965), offers a new way of linguistic representation of the data in a rather approximate fashion. Essentially, what FL does, is to represent human way of thinking in mathematical terms.

The potentiality of Fuzzy Logic inspired Bart Kosko to evolve Cognitive Maps into Fuzzy Cognitive Maps (Kosko, 1986). The ancestor model of Fuzzy Cognitive Maps (FCM) named Cognitive Maps (CM) was first proposed by Robert Axelrod (Axelrod, 1976; Zadeh, 1965) in 1976 and constitutes a symbolic representation of social scientific knowledge. As implied by its name, FCM introduced some kind of fuzzification in the two core components of the model, the set of concepts of the system and the set of their interconnections. Although CM were mainly used in social science disciplines for decision making problems, FCMs have been widely used in a larger variety of areas as Medicine, Engineering, Agriculture, Politics, Economics and Social systems. The main purpose of using FCMs is to explore the modeled system's behaviour under a certain set of circumstances. The reason why this model became popular during the last years is that they can inform the user about the potential behaviour of the modeled real system without causing any undesired or irreversible repercussions on the actual real system.

The ability of the Fuzzy Cognitive Maps model in examining systems' behaviour in multivariate areas motivated the writer of this work to get involved with the subject. More specifically this work aims at creating an enhanced version of FCM in terms of building methodologies and functionality allowing the incorporation or collaboration of other CI and intelligent system methodologies. In order to satisfy the need of contributing to the greater good, the enhanced model of FCM will be applied and tested on real life problems, preferably drawn from Cypriot reality. To achieve that a generic tool of FCM has been also developed during this project.

1.4 Problems, Questions and Hypotheses

From the day a human can articulate basic words there is one underlying question in his mind, which acts as a foundation stone for his findings of greater or lesser importance; "Why?". This question can be driven by an observation we made, a fact, a situation, a certain behaviour, a change, etc. We can group all above under the category with the label "effects". Each effect is generated by one or more causes. It is true that answering what causes what effects has been fundamental through the ages even before Plato's Phaedo or Aristotle's Four Causes theory (Frede, 1980).

One way to study the mystery behind the relations amongst causes and effects, is to implement experiments. There is a long list of different kind of experiments one can do, to appropriately explore different experimental settings. Such experiments rely on a common basis: If we wish to explore whether A is a cause of B, we will need to establish whether deliberate and purposive variations in A result in changes in B. (Ducheyne, 2006).

Systems from Engineering, Ecosystem, Physics, Biology, Medicine, Economy, Society and Politics tend to have causal interrelations. Many times exploring the behaviours of these systems through their causal relations may lead to better decision making about the systems. The main problem, though, with experimenting with such systems, is the requirement for real intervention in their inner parameters and interconnections. If that intervention takes place in the actual real system the danger of applying a bad decision lurks. As a result some undesired irreversible consequences on the real system may happen. Hence, real experimenting with such systems can be categorized as high risk experiments with increased human, economic, social and political cost.

Computational modeling of cause-effect systems is a methodology which offers a safe, valid, low cost environment for testing and understanding causality in real systems. The model of Fuzzy Cognitive Map comprises a Computational Intelligence (CI) methodology which offers an alternative approach of testing how causality works in real systems in order to understand their behaviour under certain circumstances. The most important features of FCM modeling is their capability of representing graphically complex systems, involving fuzzy representation of their parameters and interrelations and allowing causal propagation, in particular forward and backward chaining (Stylios & Groumpos, 1998).

FCM methodology might give solutions in investigating causal system's behaviours where no sufficient data describing the system is available making it hard for other CI methods to capture the structure and dynamics of the system. On the contrary, FCMs take an advantage on the human knowledge and expertise about a real system to build the modeled system. For example, a political/social system incorporating parameters like "people's knowledge about history", "people's trust in voting system", "quality level of mass media", etc., is hard to be quantified with real numbers yet much easier to be described in words using linguistic terms like "fair", "big", "average" by someone with deep knowledge in the subject.

The fuzzy character of the model is expressed through the use of linguistic terms when describing the system. The fact that the experts use a natural language to define parameters allows them to better understand what they are supposed to do during the FCM construction phase.

Additionally, given that the simulations of a FCM model cause no effects on the real system, the implementation of all the possible scenarios regarding the modeled system is feasible.

Therefore, the general frame of this work is the improvement of the FCMs in terms of the model construction and problem representation as needed to make the FCM model a suitable, useful and user friendly tool for multi-domain cause-effect systems.

To address the research problem of this work an extensive study of bibliography related to classical Computational Intelligent methods, FCMs modeling general area and other relevant fuzzy modeling methodologies, has been done. The above search was proven to be a very helpful procedure for the formulation of the hypothesis of this project:

During FCM simulations an update function is used to calculate the next iteration concept state values aggregating the effects caused by its causal neighbours. In FCM bibliography, it is called activation function and it exhibits a weakness in limiting the new concept states values in the interval of [0, 1], which this is semantically significant in the context of FCM model (Glykas, 2010). To deal with this squashing functions, also reported as transformation functions (Napoles, Bello, & Vanhoof, 2013; Papageorgiou, 2013), are used to keep new concept state values into the desired range of [0, 1] (Bueno & Salmeron, 2009). It is clear, taken from many studies (Bueno & Salmeron, 2009; Kreinovich & Stylios, 2015; Lee & Kwon, 2010; Tsadiras, 2008), that the choice of different transformation functions might lead to different steady states of the same system. However, although the FCM is a model whose functionality is based on semantics of causality in systems as interpreted by human logic, the choice of the transformation function cannot be semantically justified. Hence was interesting to investigate new activation functions that will have no need of squashing functions.

FCMs are basically a man-trained network. Although, many times it has been criticized exactly for that reason, it still comprises a great solution for those systems that humans need to model, yet there is no enough or qualitative data available describing the parameters of the system. Therefore, for many FCM applications, the whole FCM building phase is fully depended on experts' knowledge and experience. Sometimes though, in spite the fact that the experts themselves might indeed have a strong knowledge background in the modeled system's domain, a lack of communication between the FCM handler and the experts might emerge a serious problem. For that reason, another hypothesis was the establishment of a FCM building methodology which will guide the experts on how to extract their knowledge aiming at minimizing the miscommunication mistakes between the two sides.

When attempting to examine the behaviour of a dynamic system under some specific circumstances someone has to keep in mind that certain synergies might appear in the network. A synergy in causality systems, involves a set of concepts of the system and when they are all activated in a certain way, their total effect (synergic effect) is more or less than their aggregated individual effects. Accordingly, FCMs should be able to capture different synergies describing the modeled system behaviour. An attempt of capturing synergies in FCMs has been illustrated in (Koulouriotis, Diakoulakis, Emris, Antonidakins,

& Kaliakatsos, 2003) by using simple arithmetic rules. The incorporation of a functional way of representing synergies in the model was another hypothesis of this project.

Medical prognosis problems have a powerful advantage; there usually exists a database, relevant to the problem, including quantitative characteristics of a large set of medical cases. There are already many CI methodologies for representing knowledge extracted from databases and using it towards medical prediction problems. The model of Fuzzy Cognitive Maps has also been very popular in medical applications (Amirkhani, Mosavi, Shokouhi, & Mohammadizadeh, 2012; Anninou & Groumpos, 2014; Bourgani, Stylios, Manis, & Georgopoulos, 2014; Froelich, Papageorgiou, Samarinas, & Skriapas, 2012; Georgopoulos, Malandraki, & Stylios, 2003; Georgopoulos & Stylios, 2015; Lee, Kim, & Cho, 2012; Papageorgiou, 2011) since causal relations connect different factors which lead to a certain disorder or illness. The early identification of chromosomally abnormal foetuses has been an issue for the majority of pregnant women. Following a non-invasive method for successful screening of foetuses has been proposed (Neocleous, Nicolaides, & Schizas, 2016) using Artificial Neural Network based on a vast database describing pregnancy cases in the context of chromosomal abnormalities. However, the pregnancy characteristics recorded in this database are part of an examination procedure done only by specialized sonographers. It would be interesting, though, to examine whether linguistic observations made by common gynaecologists about the same pregnancy characteristics can be introduced to a computationally intelligent model and get satisfactory results on predicting chromosomal abnormalities. Hence the question here was if we could get qualitative results by using FCMs in prognosis of chromosomal abnormalities using fuzzy definition of the core concepts.

Based on the same observation, that medical problems are many times described by large datasets along with the fact that medical health providers and clinicians often describe in detail medical problems in relative bibliography and literature arose the question whether these two can be combined to provide the main information basis on which a diagnostic FCM can be built. The relative to the medical problem’s bibliography can be used to extract information about the structure of the network whereas the datasets can be used to derive probabilistic models describing the factors of the problem.

Additionally, a final task of this project was the development of a generic tool which would encompass all the FCM functionalities as described above. In first place, the tool would help to the implementation of the tests needed to answer all aforementioned hypotheses. Yet, by the end of this work, the tool will be available for anyone who wishes to model a real causal system and make certain experiments on its behaviour, mostly focused on decision making problems.

1.5 Outline

Chapter 2 reviews the literature on the FCMs regarding four main axes: (1) Activation Functions, (2) FCM construction methodologies and (3) Medical Decision Making using FCMs (4) Time in FCMs. Specifically, the most popular activation functions used to simulate FCMs are reviewed along with a selection of transformation function used to squash the output state of each concept to a specific interval. Additionally, different proposed expert-based methodologies for building FCMs are presented including intelligent or optimization algorithms which are used either to substitute the experts or to complement them. Finally, the application of FCMs in Medical Decision problems is investigated and reviewed.

Chapter 3 presents the proposal of this work for a FCM building methodology especially for social – political – economical systems. Such systems are highly complex, multi-dimensional and hard to be described by any kind of data. Experts' in such domains often comprise the one and only source of information regarding these systems. The proposed methodology which is oriented in FCM handler – experts' communication is presented step by step. Additionally, an activation function which can be used for such systems, avoiding the use of squashing functions with its adverse effects is designed. The combination of the proposed building methodology and the activation function is tested on a real system drawn from Cypriot financial-socio-political reality.

Chapter 4 presents a methodology of "transforming" a crisp medical dataset into fuzzy. The methodology calls for medical experts in the problem's domain to participate. The goal is to transfer their way of thinking when interpreting crisp values of different medical parameters into the formulation of membership functions. The proposed methodology has been applied on a real medical dataset which described various medical factors of the Trisomy 21 disorder. The participant medical experts were two gynaecologists who selected the medical parameters they preferred to fuzzify. The resulting fuzzified dataset was then used to train and test a diagnostic FCM. The network's weights were set by Evolutionary Strategies (ES). The structure of the network, the way ES were employed and the results are described in detail in this chapter.

In Chapter 5 the steps followed to construct and define a diagnostic FCM based on relative bibliography and statistical analysis of a relative dataset are given. The chapter explicitely describes how medical datasets can be used to make statistical observations like the distributions underlying each parameter, the correlations amongst them, calculate likelihood ratios and use all this information to contribute in diagnostics. This statistical information is then used to build fuzzy cognitive maps towards constructing a medical diagnostic FCM. Another dimension of this work is the modeling of the synergies happening to a medical system. This is implemented using dynamic weights which are allowed to change under different system initial states. The proposed methods under this unit will be tested on a real medical system and the results are presented and discussed.

Finally, Chapter 6 overviews the entire work of this thesis by summarizing what has been implemented reaching to specific conclusions. A list with the contributions of this work is also presented along with some directions about future work.

2. Literature Review

During the last twenty years FCMs have gained a big growth in different research studies and applications (Papageorgiou & Salmeron, 2013). Therefore, contributing in FCMs area requires from the researcher to study and understand what has already been done and also use this information for further study. To address this need, an extended literature review in FCMs has been done. In this chapter, a subset of this work will be presented. The pieces of work which are selected are the ones mostly related to the main axes of this thesis.

Before proceeding into further details about related work, a description of the basic elements comprising a FCM is given. Fuzzy Cognitive Maps (FCMs) constitute a powerful soft computing modeling method that emerged from the combination of Fuzzy Logic and Neural Networks. FCMs were introduced first by Kosko (Kosko, 1986) and since then a wide range of applications in modeling complex dynamic systems have been reported such as medical, environmental, supervisory and political systems. Essentially, a Fuzzy Cognitive Map is developed by integrating the existing experience and knowledge regarding a cause – effect system. Kosko presented FCM as an extension of Cognitive Maps (Kosko, 1992). CMs where firstly introduced as a decision making modeling tool for political and social systems (Axelrod, 1976). Such systems can be analyzed into two fundamental elements, the set of concepts (parameters of a system) and interrelationships or causalities amongst them. They are graphically represented as nodes and signed directed edges respectively of a signed digraph. The concepts which behave as causal variables are positioned at the origin of the arrows which always show to the effect variables. Each edge can be either positive (+1) representing positive causality or negative (-1) representing negative causality. However according to Kosko, causality tends to be fuzzy and it is usually expressed or described in vague degrees (a little, highly, always, etc.) where in CMs each node simply makes its decision based on the number of positive impacts and the number of negative impacts.

Essentially, FCM modeling constitutes an alternative way of building intelligent systems providing to the users the availability of predicting the final states of the system caused by a change on initial concept states to a degree. Since the introduction of fuzzy sets was the upgrade step done by Kosko on simple cognitive maps, a review on the basic principles of fuzzy logic is firstly presented.

2.1 Background

"Fuzzy logic is a tool for embedding structured human knowledge into workable algorithms" (Kecman, 2001). The way that humans think is rather approximate than exact. As result expressions like "a little", "not so much", "too many", "so and so", etc. are used in all languages to express the fuzziness which characterizes human reasoning and thinking. Such expressions don't give precise information or quantity about what they refer to but they still comprise an adequate description of it, giving the necessary information to "get the feeling". Real life concepts are not binary; rather their description is graduated from absolute false to absolute true. Therefore, there are not just beautiful or ugly people, good or bad; the weather is not just absolutely sunny or absolutely raining, the food is not tasteful or tasteless, etc. In most of the times there is an intermediate state for every concept in human understanding which classic set theory is unable to handle. This observation led to the emergence of Fuzzy Logic theory the scientist Lofti A. Zadeh, back in 1965.

Fuzzy logic (FL) is about encoding human reasoning providing a mathematical model representation of the linguistic knowledge. FL achieves that by introducing fuzzy set of classes which are not independent or disjoint and their boundaries are fuzzy and indistinct, diverging from classical set theory. In contrast to crisp sets, there are no strict, precise or exact criteria defining whether an object belongs or not to a fuzzy set. Consequently, an object belongs to a class (represented by a fuzzy set) to some grade.

In notation, a classical set can be defined by:

1. A list of elements

   $S_{colours}$ = {red, orange, green, blue, yellow, purple}

2. Specifying some property

   $S_A = \{x \in S_{colours} \mid x == red\}$

   $S_B = \{x \in S_{colours} \mid x == blue\}$

   $S_C = \{x \in S_{colours} \mid x == yellow\}$

3. A membership function

   $$\mu_{SA}(x) = \begin{cases} 1 & , if\ x \in S_A \\ 0 & , if\ x \notin S_A \end{cases}$$

The membership function of a classical set satisfies the principle of bivalence since it returns only true (1) or false (0) excluding any other truth value. Contrarily, fuzzy membership functions may return real values other than zero and one, escaping the divalent constraint. Hence, if an object x $\in X$ then essentially the membership function d =

$\mu_S(x)$ is a mapping between X and the integral [0, 1]. Membership functions of fuzzy sets assign an object to a fuzzy set, with a truth value between [0, 1] describing the degree of belonging. Zero degree totally excludes the object from the set and full degree (one) means that the object is outright a member of the specific set.

Considering the example given in Figure 2.1, there are three sets, each describing objects of a particular colour. More specifically, the classes of red, blue and yellow comprise the universe of discourse. The task is to assign an orange, purple and green object to a colour class. Using the classical set theory (the representation on the left) the three new objects are rejected, as their membership function returns zero for all three fixed colour sets. However, in reality, orange is given by mixing red and yellow, green by blue and yellow and purple is red and blue. So, orange contains a little red and a little yellow and so on. If colour classes are modeled with fuzzy sets then orange, green and purple belong to a combination of the colour sets, to a specific degree, given by the membership function of each colour set. Note than none of the three membership functions will ever return 1 for any of the three new coloured objects, since they are not totally red, neither totally blue nor yellow.

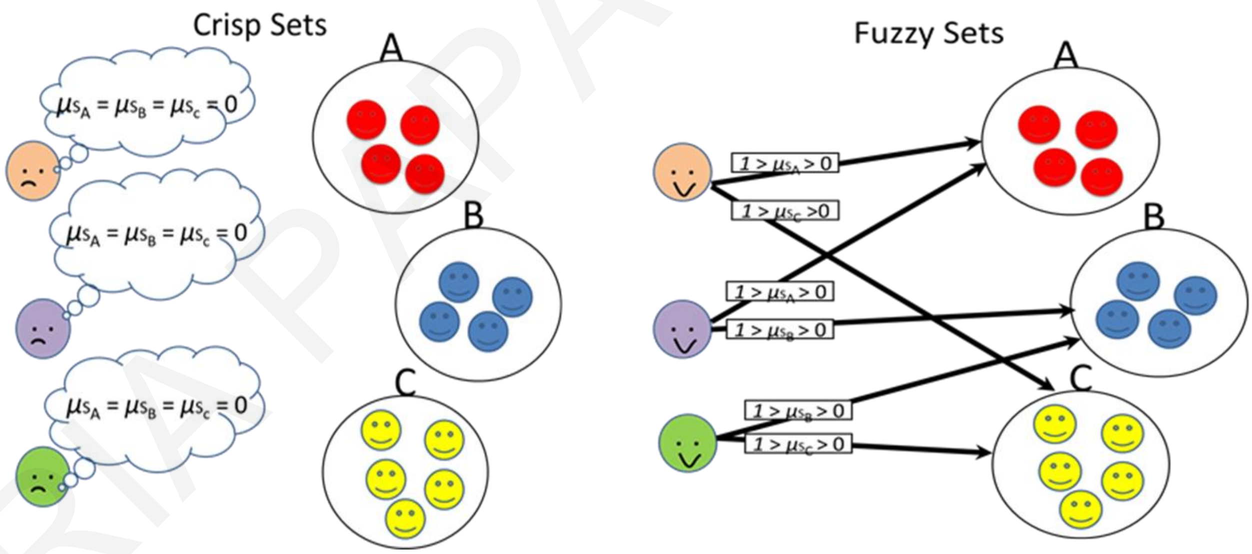

Figure 2. 1: A, B and C represent three colour sets, red, blue and yellow class respectively. Using crisp set logic, orange, purple and green objects cannot become members to any of these sets whereas using fuzzy logic all three different colours can become members

As in crisp sets, the universe of discourse is a set *X*. This set may contain either discrete or continuous valued elements which participate to the modeled problem/system. In Fuzzy Logic a linguistic variable, which is just a label, is also used to describe the general domain of the members included in the set *X* (e.g. age, weight, distance, etc.). The linguistic variable is then quantified into a collection of linguistic values. A linguistic value is a label describing a state/situation/ characteristic of the concept defined by the linguistic variable (e.g. young, heavy, long, etc). Each linguistic value is defined by a fuzzy set. A fuzzy set is a collection of ordered pairs whose first element is an object of the universe of discourse and the second element is the object's degree of belonging to the particular fuzzy set given by the predefined membership function. Therefore a basic notation of a fuzzy set is:

$$S = \{(x,\mu_s(x)) \mid \mu_s(x) \text{ definition}\} \qquad \text{Equation 2. 1}$$

where x is an object of universe of discourse and $\mu_s(x)$ is the membership function which characterizes the set S. An example of the aforementioned concepts is presented on the right side of Figure 2.2 (weight example). As stated already, fuzzy logic is used to express in a formal way, human reasoning. In real life human reasoning is used to reflect the content of a specific problem/discussion/model etc. However many times vague terms are used to describe an aspect of any concept concerning either the physical or spiritual world. That is why each statement should be interpreted in the frame of the problem/system which is discussed. For example consider a man P whose height is 1.80 meters. The statement "P is short" sounds incorrect since an ordinary man who has 1.80 meters height is generally considered tall. However if the discussion is about professional basketball players then the exact same statement sounds reasonable and valid. Therefore each statement of human reasoning strongly depends on the context of a discussion. Consequently, linguistic values are innately context dependent. Similarly, they strongly depend on the system and on whom or what the system refers to. They depend on the system's character. Even using the same universe of discourse and the same linguistic variable, the linguistic values might take a totally different scaling if the main subject of the system is different.

Furthermore, Fuzzy Logic allows to an element to belong to two or even more fuzzy sets (to a different degree) whereas in classical set theory an element can be a member only of one set. Hence, an object might be a little more member of fuzzy set A and at the same time little less member of fuzzy set B. Going back to example given in Figure 2.1, if the colour of a new object is deep purple then it is a little more blue and a little less red, but still is considered a member of both colour sets!

Assuredly, the membership function is the identity characteristic of each fuzzy set. Each linguistic value of a linguistic variable is assigned to a membership function. Human reasoning, as stated above, is subjective and though different membership functions may be produced by different persons for the same linguistic value of a common linguistic variable.

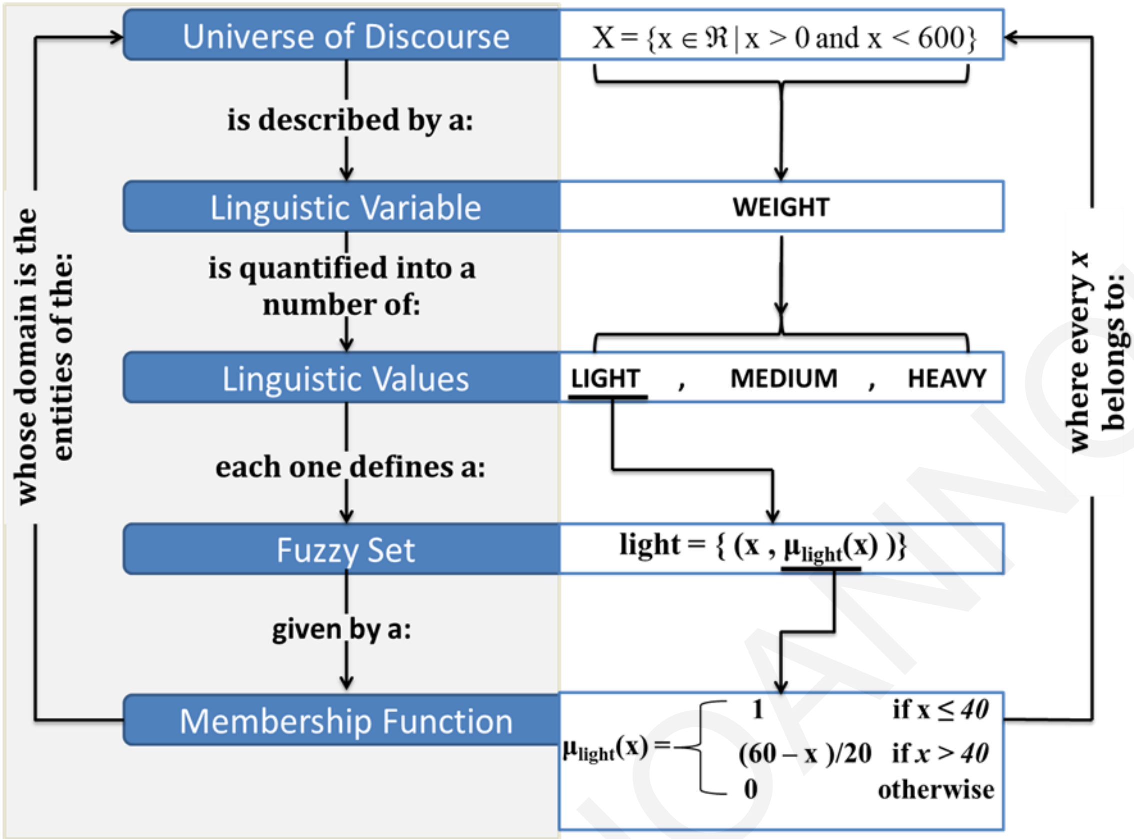

Figure 2. 2: The left part describes the relationship between some concepts of Fuzzy Logic. The right part of the figure builds a simple example based on the theory of the left side.

Hence the criteria of choosing a function to be a membership function are problem dependant. The shape of each function changes along with the criteria set for a problem and therefore there is a big range of functions which can be used to define a linguistic value. However, it is difficult to build from scratch your own membership function since there is a big risk of modeling arbitrary functions with arbitrary shapes. That is why most of the times some specific types of functions, which have preponderated in bibliography of fuzzy modeling, are commonly chosen and adjusted to new datasets. Some classical examples of such membership functions are the trapezoids, triangular, Gaussian bell and singleton functions.

As shown in Figure 2.3, trapezoid, triangular and Gaussian bell functions can be used to model membership functions of continuous valued elements. Contrarily, singleton function is more about modeling discrete data where each case must be individually assigned to a certain membership grade (hence the parameter *a* of the singleton function represents an element of the data).

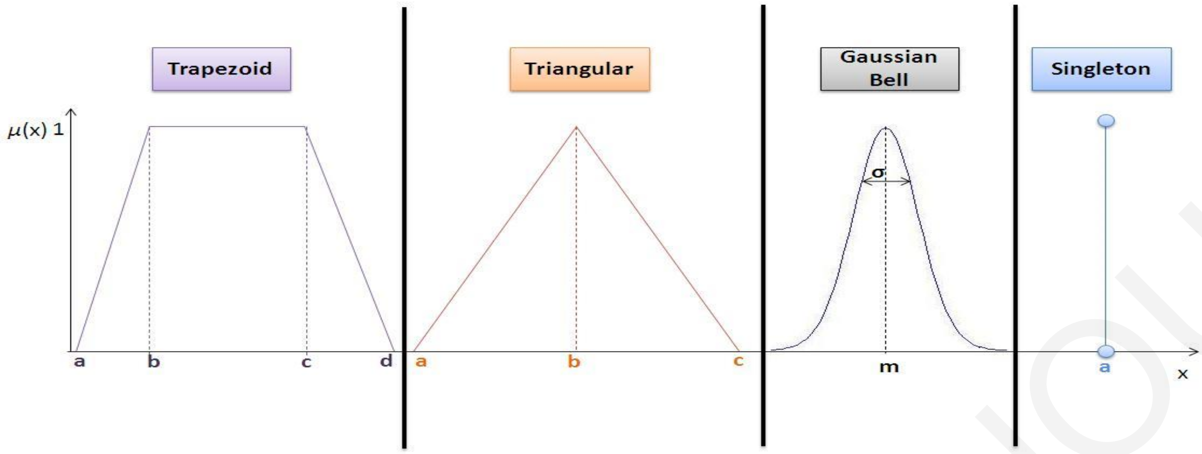

Figure 2. 3: Trapezoid, triangular and Gaussian bell and singleton membership functions.

Building a trapezoid function requires the definition of four parameters [a, b, c, d]. The elements of the universe of discourse which fall between the interval (a, b) and (c, d) are partially members of the defined fuzzy set while the elements included in the range [b, c] are fully members of the set. Triangular function can be regarded as a special case of trapezoid function taking parameters [a, b, b, c]. The substantial difference between the two of them is that the trapezoid allows a range of elements to be assigned to full membership grade while triangular allows only one. Gaussian bell function differs from other two continuous functions since the parameters needed to define the function is a pair of [σ, m]. The first parameter is the standard deviation of the function describing the width of the function. The function is symmetrical about the second parameter m, which is the mean of the function, and though the element which will equal to mean will be the only one to be assigned to a membership grade of one. Another difference between the Gaussian and the rest functions is that, the derivative of the former exists at each point of its domain while this is not applied for the other two (for elements at a or b or c or d). Hence for applications which demand the usage of mathematical optimization algorithms (e.g. gradient descent) over fuzzy variables, Gaussian is more preferable membership function than others.

Nevertheless, there are some common concepts which are used to describe all classical membership functions presented in Figure 2.4. The function's *support* is a set which contains all those elements which are assigned to non-zero membership degrees while the members of the *core* set have degree of membership equal to one. The variable *a* is a specific defined membership function degree. All the elements which have a membership degree bigger or equal to *a* are included to the *a-cut* set. Therefore when *a* is equal to zero the resulting *a-cut* set is the initial domain of the specific membership function. Finally the variable *height* is about the maximum membership degree for the specific function's domain. In Figure 2.4 these basic concepts are presented for a trapezoid function but they can easily be adjusted to any other type of classical fuzzy membership functions.

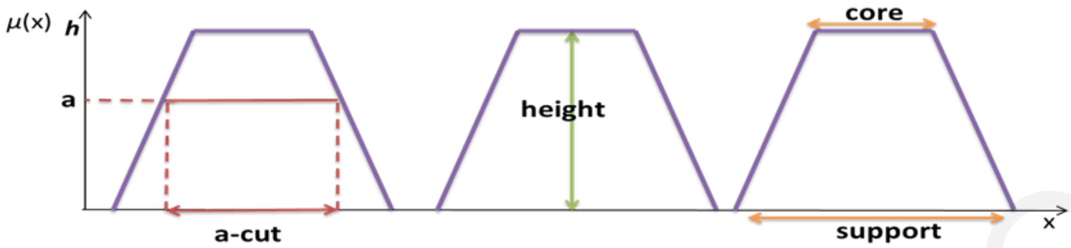

Figure 2. 4: The concepts of support, core, a-cut and height describing a fuzzy membership function.

Additionally, a fuzzy set A is considered convex if and only if the inequality in equation 2.2 is satisfied for every pair x_i and x_j where $x_i, x_j \in$ A and every $\lambda \in [0, 1]$.

$$\mu_A(\lambda x_i + (1-\lambda)x_j) \geq \min\{\mu_A(x_i), \mu_A(x_j)\} \qquad \text{Equation 2. 2}$$

Furthermore the cardinality of a fuzzy set A is defined as:

$$|A| = \int \mu_A(x)\, dx \qquad \text{Equation 2. 3}$$

If the support set of the fuzzy set is discrete, including N elements then the cardinality can be calculated as:

$$|A| = \sum_{i=1}^{N} \mu_A(x_i) \qquad \text{Equation 2. 4}$$

2.1.1 Basic fuzzy set operators

The basic classical set operations of conjunction, disjunction and negation are defined for fuzzy sets as well. Actually, there are multiple operators which model the conjunction and disjunction of fuzzy sets. The simplest though, is the min-max operators as well as the algebraic product and sum which are presented in Table 2.1 as well as in Figure 2.5 and Figure 2.6 respectively.

Any fuzzy set operation will result a new fuzzy set. So, since a fuzzy set is defined by its membership function, the operations are applied on membership functions and the result is a new membership function on the universe of discourse.

There is a plethora of other operators which can be used to model conjunction and disjunction on fuzzy sets. In Fuzzy Logic conjunction operators are labelled as *T-norms* and disjunction operators as *S-norms*. Each one of them gives a new membership function with different shape but still reflecting the concepts of intersection and union of two fuzzy sets. For example algebraic product gives a smoother conjunction membership function (Figure 2.6) that min operator (Figure 2.5 (b)). The choice an operation norm depends on the problem and generally on the model that the user wishes to produce.

Table 2. 1: Two different operators for conjunction, disjunction on two fuzzy sets A and B. The negation operation has the same form for both operators.

	Min/Max Operators	Algebraic Product/Sum Operators
Conjunction	$\mu_{A \wedge B} = \min\{\mu_A, \mu_B\}$	$\mu_{A \wedge B} = \mu_A \cdot \mu_B$
Disjunction	$\mu_{A \vee B} = \max\{\mu_A, \mu_B\}$	$\mu_{A \vee B} = \mu_A + \mu_B - \mu_A \cdot \mu_B$
Negation	$\mu_{A^c} = 1 - \mu_A$	$\mu_{A^c} = 1 - \mu_A$

Finally, there are two substantial differences between the crisp set logical operators and fuzzy set. Starting with crisp logic, it is well known that the intersection between a set and its complement results an empty set. Contrariwise, the union of a set and its complement gives the universe of discourse. The corresponding operators on fuzzy sets will result a fuzzy set other than empty or universe of discourse set respectively. Hence for a fuzzy set A:

$$\mu_{A \wedge A^c} \neq 0 \qquad \text{Equation 2. 5}$$

$$\mu_{A \vee A^c} \neq 1 \qquad \text{Equation 2. 6}$$

These two interesting side effects are presented in Figure 2.7.

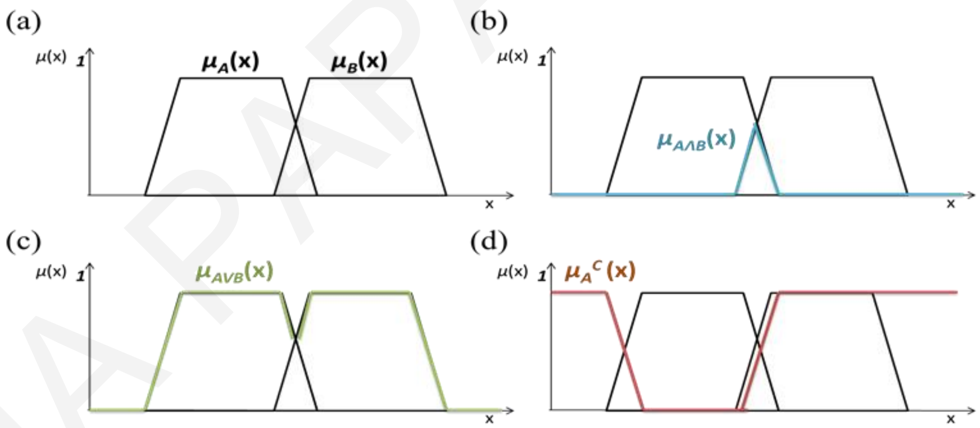

Figure 2. 5: (a) The membership functions of two fuzzy sets named A and B (b) The membership function (m. f.) of the conjunction of A and B using min norm (c) The m. f. of the disjunction of A and B using max norm (d) the m. f. describing the negation of A (complement of A)

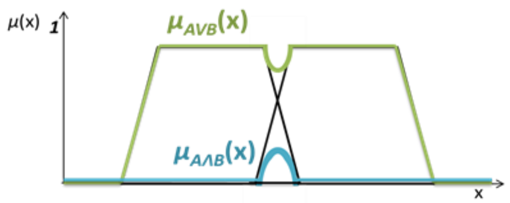

Figure 2. 6: The membership functions of the conjunction and the disjunction of A and B using algebraic product and algebraic sum respectively

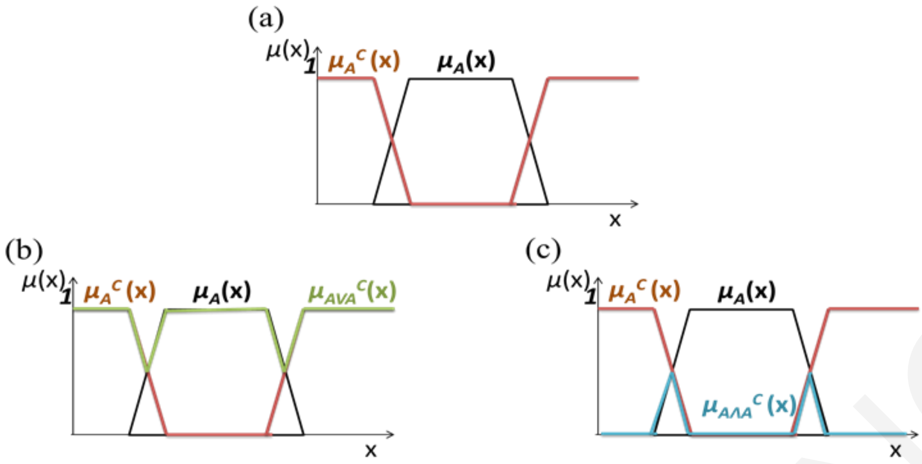

Figure 2. 7: (a) The m. f. of a fuzzy set A and its compliment (b) Their conjunction m. f. (c) Their disjunction m. f.

2.2 FCM technical background

2.2.1 FCM structure

In a graphical form, the FCMs are represented by a signed fuzzy weighted graph, usually involving feedbacks, consisting of nodes and directed links connecting them. The nodes represent descriptive behavioural concepts of the system and the links represent cause-effect relations between the concepts.

2.2.2 Concepts

A system is characterized and defined by a set of parameters associated with the system. These parameters might be facts, actions, trends, restrictions, measurements, etc. depending on the system's utility, goals and nature. Since the type of FCM parameters varies they are all described as different concepts of the system.

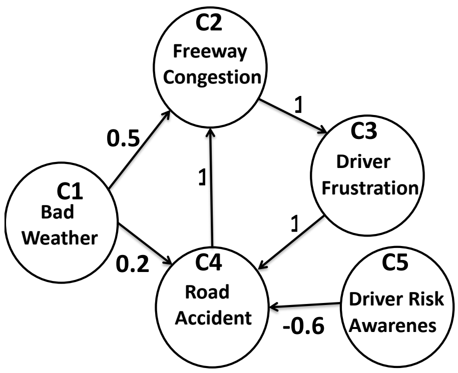

Figure 2. 8: A simple FCM modeling freeway conditions at rush hour (Khan & Chong, 2003)

More precisely, each concept is represented by a fuzzy variable. Taken from Fuzzy Set theory, each fuzzy (or linguistic) variable can be described with different linguistic values. For example a fuzzy variable named "Height" might be described with the linguistic values {"Short", "Normal", "Tall"}. Each linguistic value is described by a fuzzy set. A fuzzy set is shaped through a membership function. Hence, each crisp value from the modeled parameter domain belongs to each fuzzy set to a certain degree. This membership degree is defined by the fuzzy set's membership function. The membership function returns zero if the crisp value cannot be described by the corresponding fuzzy set in no possible way. On the other hand, if the crisp value is fully described and justified by the corresponding fuzzy expression (set) then the membership degree will be 1. Therefore, a human with height of 2.50 m will "participate" to the fuzzy set "Tall" with a membership degree of *1* and a membership degree of *0* would be the answer of the membership function of the fuzzy set "Short".

Graphically, every concept is represented by a node in a FCM. A node is characterized by an activation state value, A_i where for most of the FCM applications $A_i \in [0, 1]$. A zero activation value shows that the concept is fully disabled in the system and therefore is not allowed to have any influence on other concepts. On the contrary, a concept that has an activation value equal to 1 is a fully enabled concept in the system which can have the maximum impact on his connected neighbours.

A FCM which describes a system of N variables manipulates the set of the activation state values with a $1 \times N$ vector A where N is the number of concepts. The "Freeway conditions" FCM presented in Figure 2.8 includes five concepts (C1 – C5). In this case the experts should define the activation state values (or activation levels) of each concept to reflect the real conditions of a specific freeway. Therefore if they suggest the initial activation level vector A_0 to be:

$$A_0 = [0.2, 0.9, 0.7, 0, 1]$$

then we can infer that the conditions of the freeway are:

- The weather is fairly good. (C1 = 0.2)
- There is a big congestion in the freeway. The cars are moving with relatively slow speed for some time. (C2 = 0.9)
- The drivers are quite frustrated. (C3 = 0.7)
- There no accident in the freeway. (C4 = 0)
- The drivers are fully aware of the risk they run in the freeway.(C5 = 1)

2.2.3 Weights (Sensitivities)

In FCM context, weights or sensitivities are the links connecting two nodes. They are directional and they are also characterized by a numerical value and a sign. Generally a weight describes the cause-effect relationship between two concepts. The causal relations (weights) can be positive or negative. A positive weight expresses a direct influence relation whereas a negative one defines an inverse relation between two concepts. Thence, if two concepts C_i and C_j are related to a degree defined by the weight W_{ij} and:

- $\boldsymbol{W_{ij} > 0}$ then if the activation levels A_i (of the concept C_i) increases, A_j (of the concept C_j) will also increase. On the other hand, if A_i decreases, A_j of the influenced concept will decrease.
- $\boldsymbol{W_{ij} < 0}$ then if the activation levels A_i are increased, then A_j of the influenced concept will be decreased and vice versa.
- $\boldsymbol{W_{ij} = 0}$ then there is no causal relation between the concepts.

FCM models use graded causality. A concept can be designed to affect another concept to a degree. So FCM escapes the drawback of bivalent causality, from which CMs suffer. FCM causal relations are fuzzy and hence they belong to a fuzzy set. Each of them is assigned to a real, numerical value expressing the degree of the influence a concept accepts from another concept. In other words the weight shows how strong and intensive the causal relation is. The value of a weight lies in the interval [-1, 1]. If the weight is -1 then the causal relation is totally negative (or inverse) and if it is +1 then it is and totally positive (or direct). Anything between zero and -1 or zero and +1 correspond to various fuzzy degrees of causality. The closer a weight is to zero the weaker the relation is. As the weight increases to one the causal concept affects more intensively the effect concept whereas as the weight approaches -1 the causal concept affects more intensively the effect concept in an inverse way.

A FCM which models a system with N variables utilizes the relationships amongst them with a matrix W (weight matrix) with size $N \times N$. The element W_{ij} represents the weight of the relation between the concepts C_i and C_j.

Therefore the weights of the example in Figure 2.8 would be represented in a matrix:

W	C1	C2	C3	C4	C5
C1	0.0	0.5	0.0	0.2	0.0
C2	0.0	0.0	1.0	0.0	0.0
C3	0.0	0.0	0.0	1.0	0.0
C4	0.0	1.0	0.0	0.0	0.0
C5	0.0	0.0	0.0	-0.6	0.0

Figure 2. 9: The weight matrix of the "Freeway Congestion" example as given in Figure 2.1

The weight matrix presented in Figure 2.2 can be interpreted by the following statements:

- $\boldsymbol{W_{12} = 0.5}$: Bad weather conditions (C1) contribute to the cause of congestion in the freeway (C2)

- ***W_{14} = 0.2***: Bad weather conditions (C1) contribute to a small degree the creation of an accident in the road (C4)
- ***W_{23} = 1***: When there exist congestion in the freeway (C2) then surely the drivers will become more frustrated (C3)
- ***W_{34} = 1***: When the drivers are frustrated (C3) then there will be certainly an accident (C4)
- ***W_{42} =1***: If an accident happens in the freeway (C4) then congestion follows for sure (C2)
- ***W_{54} = -0.6***: The fact that drivers have risk awareness (C5) decreases in an adequate degree the chances of an accident in the freeway (C4)

All the rest weights are zero and they show the absence of any kind of causal relation between the concepts.

FCM use membership functions as a communication channel between the linguistic description of the influence level between two concepts and the corresponding numerical value of their relation (weight) which will be entered in the matrix. The name of the linguistic variable describing a weight is "Influence". The linguistic values express different levels of "Influence" (e.g. low, medium, high) and they are defined by the designers of the system. Each linguistic value comprises a fuzzy set whose membership function is defined over the domain [-1, 1].

For example, the designers of the system presented in Figure 2.10 (Papageorgiou & Groumpos, 2004) defined nine linguistic values for the linguistic variable "Influence". Therefore a weight can be {negative very strong, negative strong, negative medium, negative weak, zero, positive weak, positive medium, positive strong, positive very strong} and their corresponding membership functions are: μ_{nvs}, μ_{ns}, μ_{nm}, μ_{nw}, μ_{z}, μ_{pw}, μ_{pm}, μ_{ps}, and μ_{pvs}.

After defining the fuzzy sets of the "Influence" amongst the concepts, the experts are called to use the specific fuzzy expressions to linguistically describe each weight of the system. Thereafter, each weight is deffuzified (e.g. by using centre of gravity method) resulting a weight degree in the interval of [-1, 1].

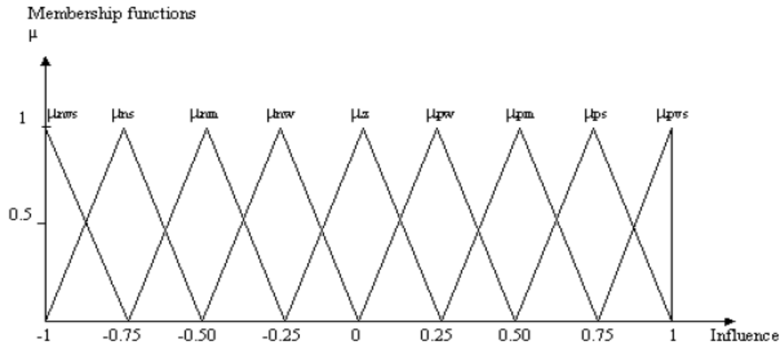

Figure 2. 10: Membership functions describing the linguistic variable "Influence"

2.1.4 Simulating a FCM

FCM is widely used as a dynamical tool analysis of certain scenarios (involving the parameters of the system) through time (discrete iterations). Inference in FCM is expressed by allowing feedbacks through the weighted causal edges. Given the weight matrix along with the initial activation levels vector A^0, FCM "runs" through certain steps until converge to the final activation levels vector A^{final} including the final stable states of the concepts. Finally, by analyzing the final state vector one can retrieve important information about potential effects caused by a change on the system's parameters.

The FCM inference algorithm is:

BEGIN

STEP 1: Read the initial state vector A^0, t=0

STEP 2: Read the weight matrix W

STEP 3: $t = t + 1$

STEP 4: For every concept C_i calculate the new activation levels (A_i^t) by (or some other activation function):

:

$$A_i^t = \sum_{j=1}^{N}(A_j^{t-1} W_{ji}) \qquad \text{Equation 2. 7}$$

STEP 5: Apply a transformation function to the present activation levels vector

$$A^t = f(A^t) \qquad \text{Equation 2. 8}$$

STEP 6: If $A^t == A^{t-1}$ or $t ==$ *maximum_iterations* or other terminal conditions

Set $A^{final} = A^t$

STOP

Else

Go to STEP 3

END

In the above algorithm the variable t enumerates the iterations needed until the FCM model reaches a certain behaviour which could be either steady point attractor, limit cycle or chaotic attractor. The vector A^t includes the activation levels of the concepts at t^{th} iteration.

FCM allows the concepts to interact with each other to a certain degree specified by the weight connecting them. The new state value of each concept strongly depends on the state values of the concepts affecting it. The whole update process of the activation levels can be described as a simple vector – matrix multiplication:

$$A^t = f(A^{t-1}W) \qquad \text{Equation 2. 9}$$

The algorithm terminates when one of the following three FCM behaviours is identified:

1. ***Steady point attractor***: The FCM concepts stabilize their state to a specific value which implies that the activation levels vector is not altered through iterations.

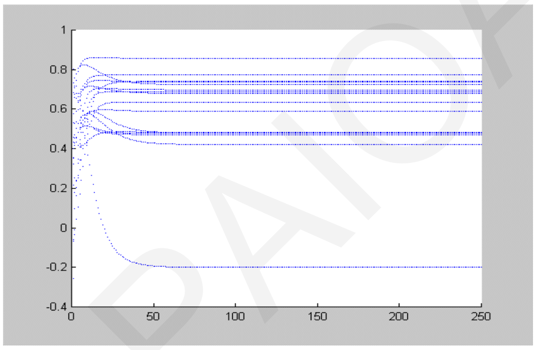

Figure 2. 11: Steady point attractor. The X-axis represents the iterations number and the Y-axis presents the values of each concept state

2. ***Limit Cycle***: In this case the FCM model falls into a loop of activation level vectors which repeatedly appear in a certain number of iterations in the same sequence.

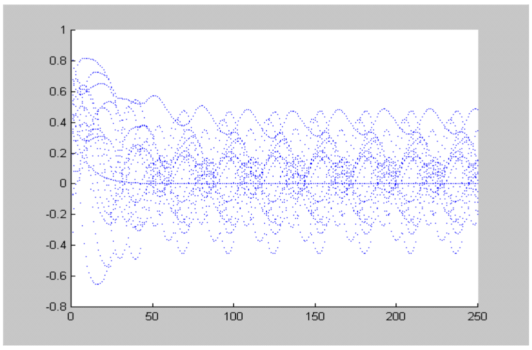

Figure 2. 12: Limit Cycle behaviour

3. ***Chaotic attractor***: The activation levels are continuously changing through iterations with a totally random, non-deterministic way, leading the FCM model to present unsteadiness.

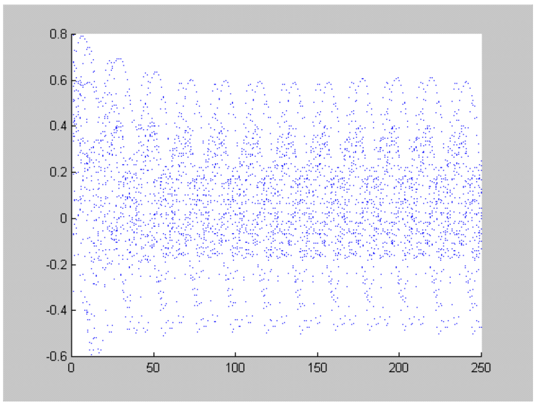

Figure 2. 13: Chaotic attractor

FCM model can be used to answer "WHAT-IF" questions about how a change to a subset of parameters can affect the whole system. Therefore FCM modeling provides a scenario development framework for retrieving hidden relations between the concepts of a system. To run a scenario a particular sequence of steps must be taken. The first step is to define the initial activation levels of the concepts and the weight matrix and then introduce them to the FCM model. The FCM model will run through a number of iterations allowing the interaction among the concepts and therefore changing their activation levels according to FCM inference algorithm. The inference process ends when the FCM convergences to a steady point attractor (any other behaviour at this point implies that the modeled system suffers from designing problems). The final activation levels vector exposes the *present* dynamics of the system based on the system's designers' experience and knowledge. More precisely, the resulting activation levels vector can be used as the base vector for development of various scenarios examining the system's responses on different changes.

To build a scenario, a "WHAT-IF" question is defined and the activation levels of the parameters which compose the premise of the question are locked to the desired values. The inference process is then initiated, again, yet this time the activation values of the "locked" concepts will not be updated through the iterations. The FCM inference algorithm will terminate when the FCM model presents one of the three aforementioned system behaviours. However, in this case the final activation levels vector presents the *future* dynamics of the system after applying the changes to its parameters. Further analysis of the results may lead to various conclusions about the modeled system's future progress under certain conditions (defined by the "locked" valued concepts).

2.3 Activation Functions in FCMs

The selection of the functions used to calculate the new concept states during a simulation of FCM system is very fundamental for FCM proper use. The activation function models the flow of causality happening in the system after changing one or more concept states in the system. The final behaviour of a FCM system should be interpreted according to the way the weights have been defined and to the structure of the used activation function. Although, as we will see, the structure of all the proposed activation functions is quite similar, their application gives totally different results.

To start with, let’s see how an activation function is used in the context of FCM theory. During each simulation cycle, a concept updates its own state based on the changes made to the system during the previous simulation cycle. To do so, the concept must somehow aggregate the incoming effects from its own neighbours (the other concepts with which it is connected). This is the basic philosophy behind the design of an activation function. Based on this, Kosko first proposed as a FCM activation function the one presented in Equation 2.10. By using this function, each concept updates its state only with the integrated effects from its neighbours.

Table 2. 2: The activation functions proposed for FCM

Allows self-causation	Function		
No	$A_i^t = \sum_{j \neq i}^{N} A_j^{t-1} * w_{ji}$	(Kosko, 1986)	Equation 2. 10
	$A_i^t = \sum_{j \neq i}^{N} (2A_i^{t-1} - 1) * w_{ji}$	(Papageorgiou & Froelich, 2010)	Equation 2. 11
Yes	$A_i^t = A_i^{t-1} + \sum_{j \neq i}^{N} A_j^{t-1} * w_{ji}$	(Stylios & Groumpos, 1999)	Equation 2. 12
	$A_i^t = 2A_i^{t-1} - 1 + \sum_{j \neq i}^{N} \left(2A_j^{t-1} - 1\right) * w_{ji}$	(Papageorgiou, 2011b)	Equation 2. 13
	$A_i^t = k1 * A_i^{t-1} + k2 * \sum_{j \neq i}^{N} A_j^{t-1} * w_{ji}$	(Glykas, 2013)	Equation 2. 14

Table 2.2 presents the activation functions that have been proposed for simulating FCMs during the last 20 years where A_i^t represents the activation levels of the concept C_i at iteration t, N is the number of the concepts, W_{ji} is the weight value between the concepts C_j and C_i, and finally k_1 and k_2 are the coefficients which regulate in what degree the new state value of a concept will be affected by its own present activation levels value and in what degree it will be affected by the activation levels of its neighbouring concepts respectively.

The rest of the suggested activation functions are variants of these methods except the RBFCM which are further explained in a following section of this chapter. In general, the update functions can be divided into two main categories: the ones that allow the concepts to affect themselves (e.g. see equations 2.13 - 2.15) and the rest that prohibit self-causation (e.g. see equations 2.11 & 2.12). Although the use of a specific activation function plays a vital role in the interpretation of the final results, almost none (if none at all) of the authors justifies why the selection of a specific activation function is appropriate for the modeled problem and how they use this information when "reading" the final system behaviour. A discussion on what the right structure of an activation function should be for a FCM has been initiated by Joao Paulo Carvalho (Carvalho, 2013) only few years ago without, however, getting any response from other researchers. What Carvalho argues about, is that a FCM should not allow the concepts to influence themselves since it is commonly accepted that *"causality is not reflexive"*. On the other side, Stylios et al suggested the activation function presented in equation 2.13 which allows the concepts to add the integrated effects accepted from their neighbours to their existing concept value. This is equivalent to allowing self-feedback with a weight equal to one. The authors state that by doing so, they manage to add a kind of memory to the concept, regarding the influence it accepted in previous simulations (Stylios & Groumpos, 1999).

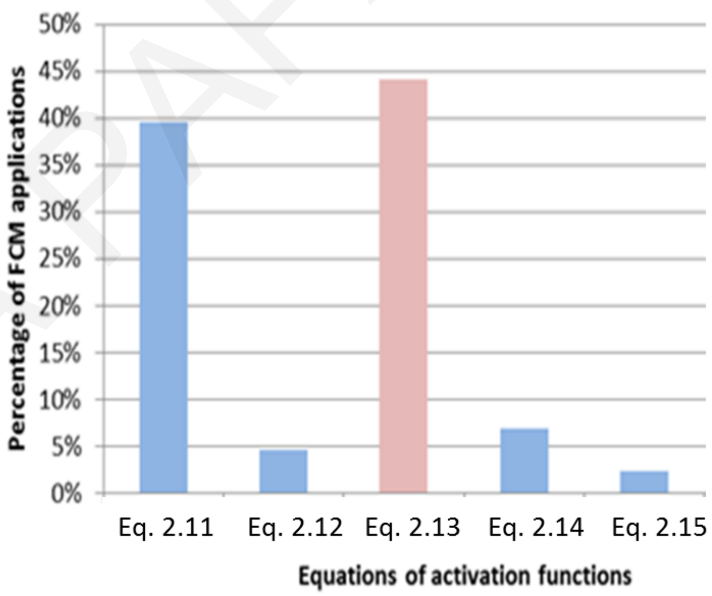

Figure 2. 14: The percentage of the FCM applications per each activation function taken from reviewed journal papers from 2010 - 2016

Although there is not extensive research work on the use of different activation functions and their impact on the final results, the frequency of each update function in real FCM applications can shed some light on what suits the most FCM handlers when building a real FCM system. So, as we can see in Figure 2.14, the most preferable activation function for the FCM applications is Equation 2.13, with an almost 45% preference percentage, where the original FCM update function (Equation 2.11) comes second in preference with an approximately 40%. Considering the fact that the two "oldest" activation functions are running neck and neck in FCM handlers' preferences (holding together approximately the 85% of the total applications) and the fact that almost none of the authors justifies adequately the reasoning behind the selection of the one or the another update function, one can assume that their choice could be even made in a random way, based mostly on the function's popularity rather than their actual contribution to the proper modeling of the FCM system. Nevertheless, since the interpretation of the results should be made based on this selection, this issue must be addressed.

Additionally, by looking to the proposed activation functions in Table 2.2, it is obvious that under some conditions the activation levels of a concept might exceed the desired interval of [0, 1] (or [-1, 1]) at some iteration during the inference phase (e.g. if a concept accepts impact from neighbours through strong positive causal weights). However in the context of FCM theory, it is important to have concepts states varying from 0 to 1 (or -1 to 1) since there is a specific semantic interpretation for this interval of states. To deal with this phenomenon, FCM researchers have proposed the use of a transformation function which can be any squashing function which results values given in the desired interval. The squashing functions which are more widely used by FCM authors are presented in Table 2.3. Substantially, the transformation functions are divided in two categories: the ones which map an arithmetic value in the interval [0, 1] (namely the sigmoid function and the bivalent) and the others which result a value in the interval of [-1, 1] (the hyperbolic tangent and the trivalent). Therefore, depending on what is the pre-defined interval of states a concept is allowed to take (defined by the experts in cooperation with the FCM handler) the FCM handler is amongst two choices. The most popular transformation function is the sigmoid one since most of the authors choose to represent the concept states in the interval of [0, 1]. The impact of each selection on the final inference results was examined by different authors.

Some argue that the selection of a sigmoid function (Equation 2.15) is the most proper (amongst the other proposed options) (Bueno & Salmeron, 2009; Kreinovich & Stylios, 2015; Lee & Kwon, 2010; Tsadiras, 2008).

As stated in (Tsadiras, 2008) sigmoid function is the most suitable for systems which need representation of a degree of increase / decrease or stability of a concept under the design of strategic planning scenarios.

Table 2. 3: Most used transformation functions for FCMs

Range	Function	
[0 , 1]	$f(x) = \dfrac{1}{1+\ e^{-\lambda x}}$	Equation 2. 15
	$f(x) = \begin{cases} 0, & x \le 0 \\ 1, & x > 0 \end{cases}$	Equation 2. 16
[-1, 1]	$f(x) = \dfrac{e^{2x}-1}{e^{2x}+1}$	Equation 2. 17
	$f(x) = \begin{cases} -1, & x \le \alpha \\ 0, & \alpha < x \le \beta \\ 1, & x > \beta \end{cases}$	Equation 2. 18

Using sigmoid function increases the complexity of a FCM model since the handler must experiment with different values of the coefficient λ to get somehow more realistic FCM results. To deal with this issue, a mathematical way to adapt the value of this coefficient to a specific FCM model was proposed in (Lee & Kwon, 2010), the model of Particle Swarm Optimization was called forth to optimize the specific coefficient in (Napoles et al., 2013) where in (Bueno & Salmeron, 2009) the authors suggest that by setting $\lambda = 5$ will probably give a good degree of normalization for most of the FCM models.

However, the use of a sigmoid function exhibits a spurious behaviour considering some specific state values of the concepts. For simplicity reasons, let's take a pair of a concept C_j which is only connected with C_i in such a way that C_i influences the state of C_j. Suppose that the influencing concept is totally inactive which means $C_i = 0$. Accordingly, during FCM simulation C_j is expected to retain its previous state since it does not accept any effect from its neighbour. However, this will not be the case if the activation levels of the system pass through the sigmoid transformation function. Particularly, C_i will increase its state value by 0.5 (by using Equation 2.11 and sigmoid function with λ=5). If we consider that the concept states are bounded to take values from 0 to 1 and the actual change for the influenced concept should be 0, a change by 0.5 is far away from reality and could lead to misleading results for the system's behaviour! This problem was addressed by the proposal of the two activation functions presented in Equation 2.12 and 2.14. Essentially by using these activation functions the concept states are mapped, through a linear relation, to the interval [-1, 1]. As a result, the spurious impact emerging from inactive concepts during FCM simulation when using the sigmoid function is remarkably decreased. While this new FCM scheme addresses the aforementioned serious limitation of the sigmoid function, there are still some arguments against the use of it during FCM simulations. In (Lee et al., 2012) the author makes the determination that the sigmoid function is not used to model the natural process of interaction between the parameters of the system, but it is used as a last resort for normalization. Not only that, but it is also argued that the unequal slope of the sigmoid function for different values, that a FCM concept can take, renders the use of sigmoid function for normalization purposes insufficient. Nevertheless, some other authors insist on the use of sigmoid function for FCM by setting the argument that FCMs were inspired by Artificial Neural Networks (ANN) which also use the sigmoid function for neurons' activations. Following their statement, FCMs were first inspired by the structure of ANN (in combination of the knowledge representation given by Fuzzy Logic). Therefore, they conclude that FCM concepts should interfere in a similar manner as neurons in ANN (Kreinovich & Stylios, 2015). However, this statement comes in contradiction with the semantic nature of FCMs. Nodes in FCMs represent actual concepts of a real system. Therefore, they have an identity, a meaning and they play a specific role in the modeled system. The same applies for the interrelations between the concepts. They can be interpreted and explained and be used to achieve knowledge representation. Hence, the inference process which takes place in FCM models has nothing to do with the way ANNs work. ANNs are comprised by nodes organized in different layers. The ANN handler can identify the input and the output layer. The rest of the nodes have no identity and cannot be interpreted. They can be seen as individual process units with no specific role and meaning but when combined to work together they manage to carry out certain tasks in a non-interpretable way. There is no connection between the structure of a ANN model and the nature of the problem being modeled, justifying thus their title as "black box". Consequently, besides the fact that both ANNs and FCMs are both networks with connected nodes and the fact that both of these models somehow allow their nodes to aggregate the input they accept from other nodes, the reasoning theory behind them is totally different and should not be compared. The semantic nature of FCMs can lead us to the formalization of an activation function which will realistically model the way causation is excited and applied amongst connected concepts of a system.

2.4 Building a FCM

FCM development is traditionally based on human experience and knowledge. Therefore, it is very important for a FCM designer to extract qualitative information from experts in the system's domain and transform this information into an FCM structure. In any other case the system may not be adequately modeled and the results might be invalid. Hence a group of humans with proper expertise in the scientific or industrial area of the system to be modeled is required for building an FCM. The experts group is responsible to define the number and the type of the concepts which will be represented by the FCM model. An expert is able to identify and distinguish the concepts which compose the environment of a system and which affect its behaviour. Due to their experience and interaction with similar kind of systems, each expert has a specific map of the system's relations between the concepts. Each of them has a notion about which concepts affect other concepts and whether this influence relationship amongst them is positive or negative. They can also describe linguistically the degree of influence between the concepts. FCM development methodologies exploit expertise about the system's function and representation to create an FCM.

2.4.1 Linguistic Description of weights

This FCM development methodology is based on the linguistic description of the graded levels of the causal system's interconnections (Stylios & Groumpos, 2000). According to this methodology, the expert/experts along with the FCM designer must define the desired linguistic values of the linguistic variable "Influence" which describe at the best the causal relations of the system. More precisely, they must define the linguistic terms expressing the grading of the influence (e.g. weak, medium, strong) and then assign to each of them a membership function on the domain [-1, 1]. Right afterwards, the experts must spend some time in thinking and describing the present causal relationships between every pair of concepts. As a first step they define the sign of the cause-effect connection (positive or negative). Then they must linguistically evaluate the influence degree of the relation using one predefined linguistic value. Each causal relation is expressed by an IF-THEN rule and therefore every expert must define *N* number of IF-THEN rules where *N* is the number of the existing system's interconnections. An IF-THEN rule describing a causal relation has the form:

"IF the concept C_i takes the value of A THEN the value of the concept C_j changes to the value of B. Conclusion (about the weight value) → The influence of C_i upon C_j is D."

The terms *A*, *B*, and *D* are linguistic values (*A* and *B* describe the states of two different concepts and *D* describes linguistically the influence level). Each expert works individually. Hence, if the number of the experts is *E* then there are *E* linguistic terms describing a specific weight which are aggregated using the SUM method (or any other S-norm method). Finally, the real value of each weight is computed by using a deffuzificaton method (e.g. centre of area method) on the resulting aggregated membership function.

2.4.2 Group decision support using fuzzy cognitive maps

This method of FCM development strongly requires a group of several experts because more than one experts increases the credibility of the resulting FCM model. The creator of FCMs was the first to suggest a method of combining different FCM structures into one (Kosko, 1988). During the following years, many other researchers proposed variations or alternatives to this method (Despi, Song, & Chakrabarty, 2011; Iakovidis & Papageorgiou, 2011; Khan & Quaddus, 2004; Salmeron, 2009; Stylios & Groumpos, 2004). The target is always the same; to take a number of individual FCM weight matrices, which are separately created by a number of experts and aggregate them concluding with a unique weight matrix which will be used to simulate the modeled system.

For the most of the proposed methods, the experts do not predefine the number of the participating concepts, rather each expert works on his own, from the very beginning of the development process, defining the number and the type of the concepts and describing their causal interconnections with real numbers in the range [-1, 1]. Therefore each expert "builds" his own FCM which basically reflects his own mental believes about the modeled system. Then, all the suggested FCM models (by the experts) are merged to create the preliminary version of the final FCM. The structuring function of the merging process is relatively easy since the proposed weight matrices are averaged to give the final resulting matrix. The augmented weight matrix is calculated by Equation 2.19 where *E* is the number of involved experts and W_{ij}^{e} is the weight estimation of the e^{th} expert for the interconnection between the concepts C_i and C_j.

$$W_{ij} = \frac{\sum_{e=1}^{E} W_{ij}^{e}}{E} \qquad \text{Equation 2. 19}$$

Apparently, the aforementioned methodology of combining different expert mental models allows the experts to contribute to the formation of the final weight matrix equally. Some variations of this method, though, suggest the penalization of the experts who give weight estimations which are highly different from others. To do so they introduce the term *credibility* which is assigned to each expert. When an expert is regarded to make a mistake in his suggestion, his credibility is reduced. The first to discuss the notion of credibility in building FCMs is found to be in (Taber, 1991) and from there many others got involved with this matter. The studies mainly differ in the way they judge a weight estimation coming from an expert to be insufficient and the way they penalize the expert. To make it clearer, a simple example is given below taken from (Stylios & Groumpos, 2004). All the experts are assigned to a credibility factor $p \in [0,1]$. Initially, all the experts are evaluated as totally credible and thus they all have a unit credibility factor. The weight estimations are given in linguistic terms (e.g. very positive influence). To proceed to the aggregation of the weights for one interconnection, the 1/3 of the experts must fully agree on the same linguistic value otherwise the experts must re-estimate the particular weight. Otherwise, if there is an expert who suggests a linguistic term which has no overlapping (in terms of fuzzy sets) with the suggestions of the rest experts, this expert must be penalized. The problematic weight suggestion is disregarded and the corresponding expert's credibility is reduced by a specific degree. The final weight degree of each interconnection in a FCM system is calculated, as shown in Equation 2.20, by weighting each expert's estimation by his credibility factor.

$$W_{ij} = \frac{\sum_{e=1}^{E} p^e W_{ij}^e}{\sum_{e=1}^{E} p^e} \qquad \text{Equation 2. 20}$$

An alternative approach of evaluating the credibility of the experts is presented in (Papageorgiou & Iakovidis, 2013; Iakovidis & Papageorgiou, 2011). The novelty of this work lies in the fact that the experts themselves have to evaluate how confident they feel about every weight estimation they make by expressing a hesitancy degree. The philosophy of this methodology is based in intuitionistic fuzzy sets (Atanassov, 1986) which essentially introduce the notion of *non-membership degree* allowing each element of a fuzzy set to have two characteristics, the membership degree to the specific fuzzy set and the corresponding non-membership-degree. According to the proposed model of intuitionistic Fuzzy Cognitive Maps, during the FCMs construction process the experts are called to describe the cause-effect relations of the model using fuzzy terms and, at the same time, specify the degree to which they hesitate to express each weight estimation they make. The hesitance degree is used to calculate the non-membership degree of each relation to a specific influence level and though the intuitionistic fuzzy sets are formed for each causal relation of the network. During the simulation of the intuitionistic FCMs, the intensity of the weights is decreased according to the hesitancy degree which accompanies each relation. Only in the case where the averaged hesitancy degree is zero the weights are retained as expressed by the experts during the construction phase.

2.4.3 Learning and Optimization of FCM

Two crucial structural elements one should consider when building a FCM model is the right identification of the concepts and the successful description of the type and the intense of their interrelations. The first aspect is important to adequately represent the actual structure of the system as it is in the real world, where the second aspect regulates the behavior of the system in terms of causality. So far in this work, a disclosure of methods requiring experts to define both of these aspects was given. While the identification of the participating concepts indeed requires always the involvement of experts, the same does not apply for the second issue since several attempts were made to define the influence levels amongst the concepts using learning and optimization.

In FCM context, learning and optimization mainly refer to methods which are used to adapt the weights (of FCM interconnections) so that to achieve more precise and credible representation of the modeled system. All FCM learning algorithms take for granted that the number and the type of the concepts is known and given. One of the motivations behind the use of such methods is to facilitate FCM handlers to overcome potential conflicts among a group of experts about one or more weight evaluations. Furthermore, such methods enable the construction of FCM models in the absence of experts relative to the modeled system. Yet, the basic argument used to justify the need of developing such methods is that human knowledge is subjective by nature (Yesil, Ozturk, Dodurka, & Sakalli, 2013; Hengjie, Chunyan, & Zhiqi, 2007; Papageorgiou, Stylios, & Groumpos, 2004; Stach, Kurgan, Pedrycz, & Reformat, 2005) and, thus, data-driven FCM methodologies can enhance the accuracy and the operation of the FCMs.

During the last decades, this particular FCM research area has flourished, yielding a big number of different intelligent adaptation methods of a FCM. An overview of the most popular and used models will be described in the following sections. The learning and optimization techniques that were proposed to build the FMC weight matrix can be divided in generalized categories, the unsupervised, the supervised and the population-based methods.

2.4.3.1 Unsupervised and Supervised Learning

Unsupervised training of FCMs mainly comprises Hebbian – based methodologies. All of them involve the definition of an initial weight matrix (as suggested by the experts). Based on the initial weight matrix and by applying iterative methods, which are alternations of the Hebbian law, they converge to the final weight matrix which is considered to be optimally adjusted to the modeled decision making and prediction problem.

Differential Hebbian Learning (DHL) was the first proposed learning method for FCM (Dickerson & Kosko, 1994). DHL tries to identify pairs of concepts whose values (activation levels) are positively or negatively correlated (e.g. if the value of the cause concept increases then the value of the effect concept increases as well). The algorithm increases the weight value of the edge connecting such pairs of concepts. If the modification of two connected concepts is not correlated then the algorithm decreases their weight. For every discrete iteration *t* the algorithm assigns the following value to each weight connecting the concept C_i to C_j:

$$\mathrm{W}_{\mathrm{ij}}^{\mathrm{t+1}} = \begin{cases} \mathrm{W}_{\mathrm{ij}}^{\mathrm{t}} + \mathrm{c}^{\mathrm{t}}\left(\Delta\mathrm{A}_{\mathrm{i}}^{\mathrm{t}}\Delta\mathrm{A}_{\mathrm{j}}^{\mathrm{t}} - \mathrm{W}_{\mathrm{ij}}^{\mathrm{t}}\right) & \text{if } \Delta\mathrm{A}_{\mathrm{i}}^{\mathrm{t}} \neq 0 \\ \mathrm{W}_{\mathrm{ij}}^{\mathrm{t}} & \text{if } \Delta\mathrm{A}_{\mathrm{i}}^{\mathrm{t}} = 0 \end{cases} \quad \text{Equation 2. 21}$$

$$\Delta\mathrm{A}_{\mathrm{i}}^{\mathrm{t}} = \mathrm{A}_{\mathrm{i}}^{\mathrm{t}} - \mathrm{A}_{\mathrm{i}}^{\mathrm{t-1}} \quad \text{Equation 2. 22}$$

$$\mathrm{c}^{\mathrm{t}} = 0.1\left[1 - \frac{\mathrm{t}}{1.1\mathrm{q}}\right] \text{ where } \mathrm{q} \in \mathbb{N} \quad \text{Equation 2. 23}$$

where $\mathrm{A}_{\mathrm{i}}^{\mathrm{t}}$ represents the activation levels of the concept C_i in t^{th} iteration and $\Delta\mathrm{A}_{\mathrm{i}}^{\mathrm{t}}$ is the difference of its activation levels values between the present iteration and the previous (t-1). The learning coefficient c^t is slowly decreased through iterations and should ensure that the updated weights will lie in the interval [-1, 1]. The term $\Delta\mathrm{A}_{\mathrm{i}}^{\mathrm{t}}\Delta\mathrm{A}_{\mathrm{j}}^{\mathrm{t}}$ simply indicates whether the changes in the activation levels of the two concepts move to the same or opposite direction. The weights are updated in every iteration until converge.

Following to this learning approach, a weight is updated based only on the changes of the two participating (to that causal relationship) concepts. However the effect concept (of the specific relationship) might be also affected by other concepts and thus accepting aggregated influence from many sources. This serious drawback was pointed out by Huerga who presented the Balanced Differential Algorithm (BDA), which is an extension of the DHL (Huerga, 2002). DHL defines that each weight update will depend on the changes occurring to other concepts which also affect the particular effect concept at that certain time instance. Therefore the weight connecting concepts C_i and C_j is updated as a normalized value of the change in their activation levels to the changes (to the same direction) occurring in all concepts which affect C_j at the same iteration. Compared to DHL this approach presented better results but it was only applied to binary FCM models (using bivalent activation function).

Another FCM optimization method which utilizes a modified version of Hebbian law is Active Hebbian Learning (AHL) algorithm, which also requires from experts to set the initial weights representation and then allows the modification of the weights under the main principles of the Hebbian law at every single iteration. The concepts are activated at every iteration by obeying to a pre-determined activation sequence defined by experts. The whole procedure is terminated under specific criteria defined by the experts. Nevertheless, the same author proposed another edition of Hebbian-based learning algorithms which is considered as one of the most popular weight adaptation algorithms for FCMs named the Nonlinear Hebbian Learning (Papageorgiou, Stylios, & Groumpos, 2003; Sheng-Jun Li & Rui-Min Shen, 2004). This method needs four requirements to be fulfilled in order to be applied. The initial weight matrix (which the algorithm optimizes) should be defined by the experts, the concepts should be divided into two categories input and output, the intervals in which concept's state value is supposed to lie should be specified as well as the desired sign of each weight. Obviously, only the enabled initial weights ($W \neq 0$) are updated through the running of this algorithm while the rest remain disabled. The algorithm updates the weights iteratively until the satisfaction of a termination criterion which can be either reaching the maximum number of iterations or the minimization of the difference of output concepts state value (after presenting steady state) between two sequential iterations. Note that the concepts which are characterized as output are more important concepts for the system than other (according to the experts) and hence they deserve more attention on behalf of the designer (Anninou & Groumpos, 2014; Kannappan, Tamilarasi, & Papageorgiou, 2011; Paz-Ortiz & Gay-Garcia, 2014).

Another unsupervised learning algorithm proposed for FCM is the Adaptive Random FCM (Aguilar, 2002) which is based on the same learning principle as the Random Neural Networks (Gelenbe, 1989). RNNs generally use the probabilities that a signal leaving from a neuron to another is positive or negative so that to calculate whether the neuron which accepts the signals will "fire" or not. To fire it needs the aggregated signals it accepts to be positive. Based on this idea, ARFCM divides every FCM weight W_{ij} into two components, a positive component W_{+ij} and a negative W_{-ij}. Therefore whenever the weight between two concepts is positive then $W_{+ij} > 0$ and $W_{-ij} = 0$ while if the weight is negative then $W_{+ij} = 0$ and $W_{-ij} > 0$. Otherwise, $W_{+ij} = W_{-ij} = 0$. Each effect concepts is characterized by a probability of activation q_j which is calculated based on the positive and negative influence accepting from the cause concepts and their activation probabilities. At each learning step the weights are updated as:

$$W_{ij}^{t} = W_{ij}^{t-1} + \eta\left(\Delta q_i^t \Delta q_j^t\right) \qquad \text{Equation 2. 24}$$

The algorithm terminates whenever the system converges to the activation levels of the concepts as defined by the experts.

The aforementioned unsupervised algorithm *NHL* was extended to perform supervised learning by the proposal of Data-Driven NHL (DDNHL) which essentially allows the weight adaptation on historical data (Stach, Kurgan, & Pedrycz, 2008). Historical data include the initial state values of the concepts and their corresponding "caused" steady state values. The algorithm updates the weights, allows the FCM to run with the new weights drawing the initial activation levels from the data base and then compares the system's final output state values with the correct ones.

2.4.3.2 - Population-based Algorithms

There is a plethora of population-based algorithms proposed for optimizing FCMs especially the last ten years. Most of them share the same learning goal of finding the optimum weight matrix which best represents the causal paths of the modeled system. Additionally the representation structure of the individuals (either chromosomes or particles) is approximately identical with very small variations (e.g. some do not include the zero weights in the representation). The basic steps of encoding, decoding and evaluating individuals which represent FCMs are presented in Figure 2.15.

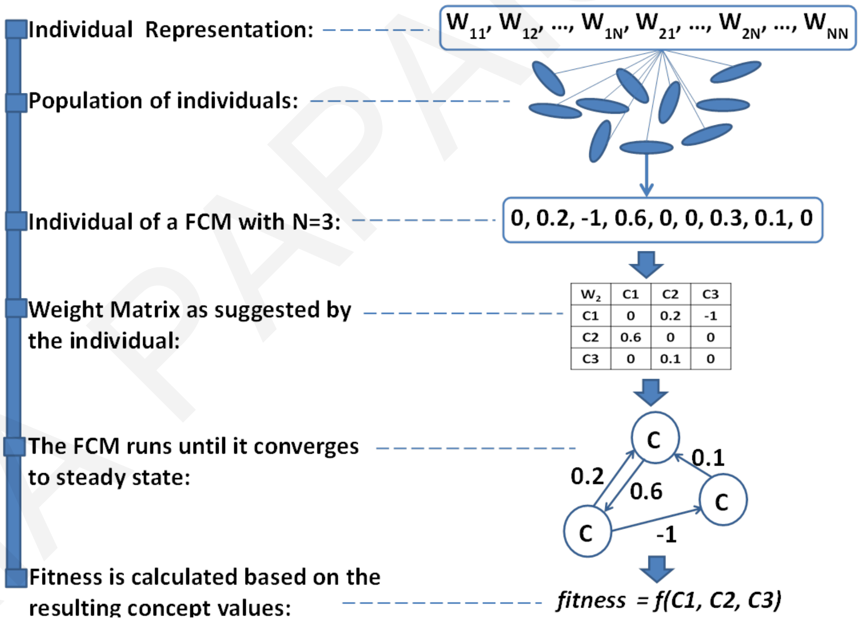

Figure 2. 15: General FCM solution representation for individuals participating in population-based algorithms

The first population-based algorithm for FCM optimization was used is Evolution Strategies (Koulouriotis, Diakoulakis, & Emiris, 2001). Each chromosome suggests a different connectivity of the modeled FCM system. The algorithm requires that the domain experts of the system have defined the output concepts which gain the main interest about how they evolve in the system under any scenario. Additionally, the algorithm uses historical paired input/output data points. Input data are the initial states of the concepts and output data are the final steady state concept values. The fitness function of the algorithm simply calculates the distance between each output concept's real steady state value and the desired one for every pair of data points. The algorithm terminates if the maximum number of generations is reached or if the fitness of the best fitness individual is less than a very small positive number.

Genetically Evolved FCM comprises an alternative evolutionary approach of mutli-objective decision making in terms of satisfying more than one desired concept values at the same time (Mateou & Andreou, 2008). In the context of a specific desired scenario, the concepts of the main interest are characterized as output and their desired activation levels are defined. Then a population of randomly initialized chromosomes is evolved in order to find the weight matrix which generates, through FCM dynamic analysis, the desired output values. The distance between the generated activation levels of the output concepts and the corresponding desired values is calculated and aggregated. The fitness value of a chromosome is then inversely proportional to the sum of these distances. The writers also state that by using this algorithm they also manage to handle limit cycle phenomenon. The FCM which is suggested by a certain chromosome, generated by crossover or mutation, runs and if for a number of iterations the same activation levels (among the output concepts) keep repeating it is categorized as a limit cycle case. After the identification of a limit cycle case, the weights of the specific FCM are examined one by one until the detection of the one/ones which are responsible for the limit cycle phenomenon. As soon as they are identified, the weight/weights are iteratively changed randomly until the FCM converges to steady state behaviour.

Another genetic algorithm named Real Coded GA (RCGA) was proposed which also utilizes historical data to achieve optimized weight adaptation (Stach, Kurgan, Pedrycz, & Reformat, 2005). The dataset is built as follows: For each system example, the initial values and the final (steady state) values of the concepts are given as well as all the intermediate state values per iteration (of a FCM model). The form of a dataset describing the desired evolution of the concept values through FCM inference is shown in Figure 2.16 (left part). In order to evaluate each chromosome, the dataset is divided in pairs of cause and effect concept values. Therefore if $\hat{C}$ denotes the set with the correct activation levels of a system per each iteration, the new dataset will be $\{\hat{C}^t, \hat{C}^{t+1}\}$ = {initial concept values, final concept values} so that $\hat{C}^t \rightarrow \hat{C}^{t+1}$. Hence for every candidate FCM (represented by chromosomes) a set of initial values $\hat{C}^t$ will be presented and the resulting concept values will be compared with the correct final concept values ($\hat{C}^{t+1}$). In other words, if the dataset includes the concept values for K iterations, the K-1 initial values will be presented to the candidate FCM and K-1 comparisons between the generated final values and the correct ones will occur. The fitness of a chromosome is then evaluated by aggregating the K-1 distances between the candidate model's steady state values and the corresponding desired ones.

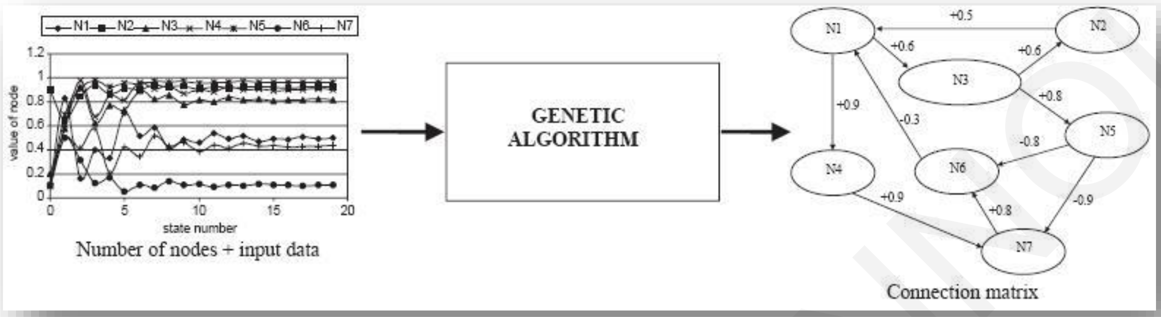

Figure 2. 16: The activation levels per each iteration, of a system consisted of seven nodes, are presented in the first part of the figure. The RCGA is then called to optimize a random weight. The optimum FCM, suggested by the fittest chromosome, "runs"

The algorithm terminates if the fitness best fit chromosomes reaches a specific threshold or if the maximum generation number is satisfied.

An evolved edition of the RCGA algorithm was created by the author himself, after his finding that the maps generated by the proposed automated learning models have higher density than the ones developed by human experts (Stach, Pedrycz, & Kurgan, 2012). This is mainly due to the fact that the weight matrices built by human experts involve more zero values (equals to fewer interrelations) than the corresponding maps created by learning and optimization processes. To address this issue, Stach et al. proposed sparse real-coded genetic algorithm (SRCGA) which is a variation of the original RCGA algorithm. Essentially, SRCGA introduces a new parameter to the model named density estimate which is responsible for the guidance of the whole optimization process. The target is to get a weight matrix with a pre-defined density estimate which will enable the system to give the desired results as defined by the available historical data.

Besides evolutionary algorithms, Particle Swarm Optimization (PSO) was also proposed for optimizing FCMs (Parsopoulos, Papageorgiou, Groumpos, & Vrahatis, 2003). PSO is a stochastic heuristic algorithm as well, and it uses a swarm (population) of particles which also represent a potential solution to the problem being optimized (in this case, the weight matrix of an FCM model). The particles move in the problem space with a certain velocity trying to find the optimum position. The position of each particle suggests a solution to the modeled problem. The idea is that the particle with the best position tends to attract other particles close to it, and therefore forming a bigger neighborhood of particles around the best position (best solution). The velocity of each particle depends on various parameters (e.g. the best position which was ever visited by any particle until a specific time point and the best position that the particle itself visited). Therefore each particle must "remember" its best position and each neighborhood must keep track of the best position among the particles comprising the neighborhood. The writers suggest that the weight should be bounded in intervals defined by experts. Therefore for each weight between two concepts, the experts define a minimum and maximum limit. The particles are then let to search within these concept values' domains. Once more, the experts must also define the output concepts which are more significant than others. In every iteration of the algorithm, the velocity of each particle is updated based on its present position, its own optimum scored position and the best particle's position from its neighborhood. Having calculated the velocity, the new position of the particle can be found (and therefore the particle moves to a new solution to the problem). The position of each particle is evaluated by a fitness function which essentially examines whether the final activation levels of the candidate FCM (suggested by the particle) fall into the bounding regions of each concept which were predefined by the experts. The termination criterion is the minimization of the fitness function after a certain number of iterations.

By this point all the population-based algorithms used to train FCMs share a very similar representation scheme for the participating individuals (either chromosomes or particles). However, in order to apply Ant Colony Optimization on FCMs (Chen, Mazlack, & Lu, 2012), a different way of encoding the weight matrix was adopted. Each interrelation of a FCM is modeled as a node of an ant's path. The nodes are sequentially connected in a way that their position in this sequence is an indication of the index of the corresponding weight degree in the weight matrix. During the simulation of the algorithm, each ant has to build a path by visiting all the nodes. Yet, each node is connected with the next node through multiple links. Each link represents a different arithmetic degree. These degrees are scaled and bounded in a pre-defined interval. The ants choose the link to proceed to the next node based on the "pheromone" amount assigned to each link and some probabilistic factors. Each ant's path is converted to a weight matrix which is used to simulate different system cases taken from historical data. The success of an ant is to provide a weight matrix (through its selected path) which gives FCM results close to the historical data. The pheromone of each link is calculated based on how successful the ants which used the particular link for their paths. The algorithm again, terminates under specific criterions.

Only a small subset of all the learning and optimization schemes that were proposed for FCMs were presented in this section. Although all the aforementioned algorithms comprise the core set of the automated construction of FCM systems, many other learning and optimization processes have been proposed. Such works involve the use of simulated annealing (Ghazanfari, Alizadeh, Fathian, & Koulouriotis, 2007) and chaotic simulated annealing (Alizadeh & Ghazanfari, 2009), tabu search (Alizadeh , Ghazanfari , Jafari , & Hooshmand , 2007), Artificial Bee Colony Optimization (Yesil, Ozturk, Dodurka, & Sakalli, 2013) , multi-step gradient methods (Yastrebov & Piotrowska, 2014), etc. Furthermore, in some other cases, a hybrid combination of evolutionary and hebbian learning approach is utilized to retrieve better results (Papageorgiou & Groumpos, 2005; Zhu & Zhang, 2008).

Concluding, the structure of a FCM system is a key factor for obtaining reliable results. To build successfully the structure of a FCM, one can consult experts who are active in the problem's domain, exploit available historic data or do a combination of these two. There are some literature references about how a FCM handler can combine knowledge extracted from different experts during FCM building phase and a much more extensive literature about constructing a FCM based on automated intelligent methods (mainly based on Hebbian and population-based methods). Despite the fact that learning and optimization methods might be considered more suitable in terms of subjectivity for the schematization of the FCM weight matrix, they have one very basic pre-requisite. They demand the existence of historic datasets to work with. Still, there are many other systems for which it is impossible to have related datasets due to the complexity and the subjective character of the parameters. Such systems can be found in the social/political/economical fields. Besides, FCM model is the descendant of Cognitive Maps which were designed to represent the causal behaviour of social systems. The ability to simulate such a system by using social / political or economic factors described in linguistic terms is one of the most attractive characteristics of FCMs. However, in order to remove, as much as possible, the mantle of subjectivity, the experts must have a clear picture of how FCMs work and then they must be directed in such a way that they will give targeted information about the modeled system. Hence, a methodology which will be able to guide the experts to give well-representative descriptions of a modeled system is needed to fill this research gap.

2.5 Medical Decision Making using FCMs

In 2004, Khan et al. makes a characteristic statement about the limited application of FCMs in the decision support arena (Khan & Quaddus, 2004). A decade later, the FCM model finds a position in this arena and more specifically in the area of medical decision support problems. One can effortlessly reach to this conclusion by just considering the domain character of the FCM application studies during the last few years. As seen in Figure 2.17, the medical/diagnostic applications dominate over the rest categories of FCM applications. The fact that many researchers who are active in the FCM research area seem to be oriented in the development of medical FCM systems can be partly explained by the wider research trend in modeling medical decision support systems (Iakovidis & Papageorgiou, 2011).

Besides, Diagnostic Decision Support Systems (DDSS) already count approximately 50 years of presence in academic research (Miller, 1994) and they have gradually raised high interest upon them during the last two decades. Their main advantage is that they can provide doctors with person specific information regarding a medical diagnosis. The patient-centered and time saving character of a DDSS can turn out to be very beneficial for all the participants in a healthcare system enhancing the quality of people's life and doctors' working conditions.

Medical Systems have been always characterized by complexity, yet nowadays this issue has been increased because of the aggregated large amount of data related to different healthcare problems. Not only that, but also, medical data is drawn from interdisciplinary sources (e.g. physical examinations, blood-tests, genetic issues, behavioural aspects, etc.) complicating even more the already rough multi-dimensional surfaces of medical problems. At the same time, such systems are meant to be used by doctors, in their everyday clinical life, on humans. Hence, clinicians must be able to comprehend with the medical DSS in order to trust them and incorporate them into their everyday medical diagnosing routine. By considering all above diverse requirements, medical DSS must be designed to present intelligent, flexible and reliable behaviour by exhibiting user-friendly characteristics (Groumpos, 2012). To integrate these features into a DDSS system, researchers resort to methods which adopt learning capabilities by exploiting either historical datasets, human knowledge or a hybrid combination of them. These methods must also allow DDSS to handle adequately imprecision and uncertainty of information which is a common characteristic of medical data.

Computational intelligence is a field from where one can derive such intelligent methods to be used as the main engine of a DDSS. Artificial Neural Networks, Support Vector Machines, Evolutionary Computing techniques and Intelligent Agents, constitute only a small sample of such intelligent systems. Yet, the fact that medical diagnosis problems strongly depend on practitioners' knowledge and experience introduce some kind of uncertainty and vagueness into the formulation of the diagnosis information (Sikchi, Sikchi, & Ali, 2013).

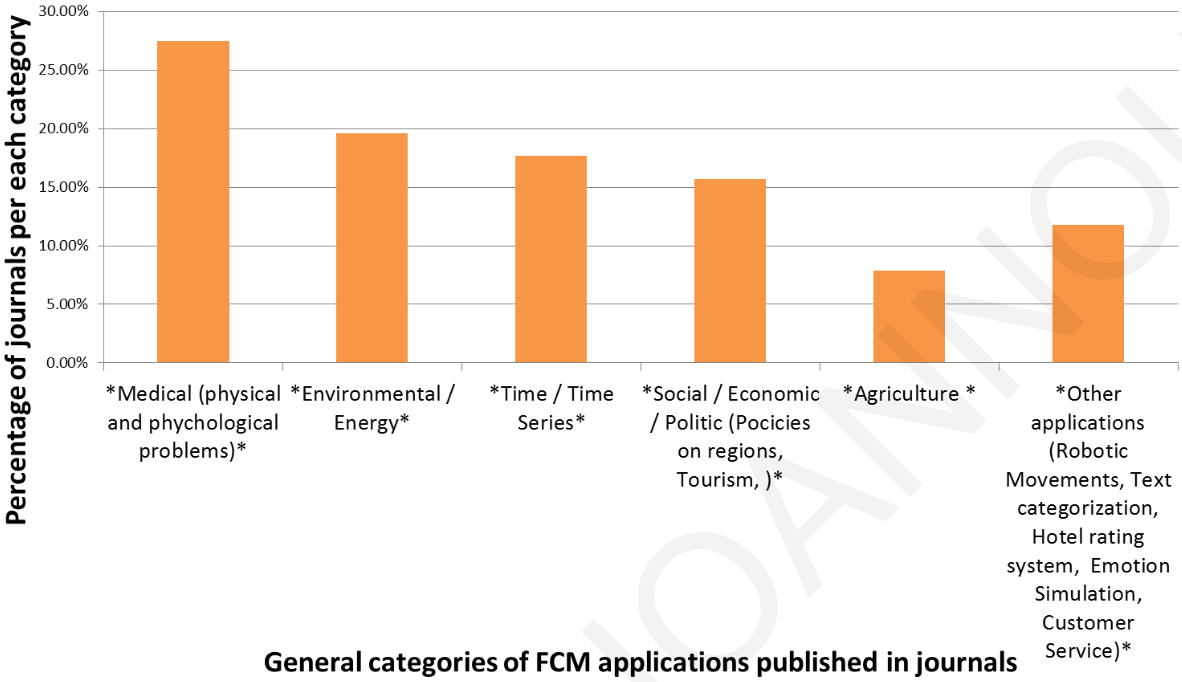

Figure 2. 17: Percentage of FCM applications per different domains from 2010 - 2016

Fuzzy Logic (FL) offers an alternative and powerful in many cases, solution in capturing and modeling the uncertainties in the world of medicine. Physicians think like humans think; that is, approximate rather than exact. Expressions like "the fetus is small" or "the pain is bearable" comprise only a small sample of what a doctor might say or hear through a conversation with a patient. Such linguistic descriptions for several medical parameters don't give information with actual precision, yet the doctor can evaluate them and use them to solve a specific diagnosing puzzle. Hence, it is very challenging to impart this human medical reasoning process to the medical diagnostic systems which can be actually achieved by utilizing FL. Although, the inspiration of FL by Zadeh (Zadeh, 1965) counts approximately equal number of years with the emergence of medical diagnostic systems, bridging them together has met an exponential research growth only the last fifteen years (Sikchi et al., 2013).

FCMs comprise a paradigm of medical decision support systems which utilize fuzzy set theory. Their simplicity in use along with their ability to process vague and not exact medical information makes FCM a tempting model to use for diagnostics. Apart from that, FCMs' transparency and interpretability allow the physicians to comprehend better with the modeled system (Papageorgiou, 2011b). Indeed, medical decision-making is a complex procedure which regularly requires from the medical experts to consider various different parameters which are interrelated through different paths. The graphical visualization of these causal paths along with the fuzzy knowledge representation enhances doctors' ability to understand the DDSS and use it more effectively in their daily clinical routine (Dhar & Stein, 1997).

The use of FCM DDSS is not limited into a specific category of diagnostic applications but rather it is spread over a big spectrum of medical problems. This is important, since problems taken from distinct medical areas are described by different type of data, may be more or less demanding in terms of knowledge representation and they are characterized by multi-level complexity degrees. Hence, the requirements of modeling such problems are diverse and thus it is difficult to propose a uniform way of addressing them. Still, as one can infer from relative literature, FCMs are flexible enough to model different kind of problems and response to all the above requirements. More specifically, medical FCMs are active for mental disorders (Papageorgiou & Kannappan, 2012; Georgopoulos & Stylios, 2009), psychological problems (Billis et al., 2015; Giabbanelli, Torsney-Weir, & Mago, 2012), cancer (Büyükavcu, Albayrak, & Göker, 2016; Froelich, Papageorgiou, Samarinas, & Skriapas, 2012; Papageorgiou, Subramanian, Karmegam, & Papandrianos, 2015; Subramanian, Karmegam, Papageorgiou, Papandrianos, & Vasukie, 2015), infections (Lopes et al., 2013; Papageorgiou & Froelich, 2012), therapy and drug administration (Nápoles, Grau, Bello, & Grau, 2014; Papageorgiou, 2012; Papageorgiou et al., 2013; Salmeron & Papageorgiou, 2012) and many other problems coming from other subfields of Medicine (Anninou & Groumpos, 2014c; Stylios & Georgopoulos, 2010; Georgopoulos & Stylios, 2013; Salmeron, Rahimi, Navali, & Sadeghpour, 2017; Shan Mei et al., 2014).

The target of a FCM DDSS is not always the same. There are diagnostic FCMs which, essentially, apply classification amongst some known classes of diseases or disorders. Some others try to categorize the severity of a reported problem. Finally, there is another set of FCM DDSS which examine the trend of a diagnosed disease by answering the question whether the problem will be improved or not. Each one of the aforementioned categories demands different design of the network.

If the diagnostic goal is to classify the problem through a number of specific diseases / disorders then the "maximum wins" FCM is proposed. This FCM scheme involves the categorization of the participating concepts into *factor* and *decision concepts* (Papageorgiou, 2012). The factor concepts may represent any medical information about the patient where the decision concepts resemble different diagnosis / therapies / decisions for the patient's problem. Accordingly, the factor concepts are allowed to causally interact with each other and with the decision concepts. The patient's data is input to the network which is simulated until it converges to a steady state. The *decision* concept with the maximum value is crowned as the winner and the answer of the network for the modeled problem. Competitive FCMs comprise a sub-category of this scheme (Stylios & Georgopoulos, 2008) which extends the causal interactions of the network by forcing the decision concepts to influence each other in a mutual exclusive way. In that way, if the factor concept states favor through causal paths one decision, the rest decision concepts back down.

To examine the severity of a medical problem, FCMs consist, once more, by factor concepts which have the same interpretation as explained above. However, there is only one output/decision concept. The output concept resembles one specific disease / disorder / therapy. As mentioned in previous sections of this work, a FCM concept state can take values in the interval [0, 1] or [-1, 1]. Thus, different regions of these intervals are assigned to different levels of severity for the modeled problem. The medical experts and the FCM handler must define the decision lines which best divide the output interval into the desired subclasses. To achieve that, the medical experts pre-define *k-1* thresholds where k is the number of the output categories. To proceed to a diagnosis about a specific patient case, the factor concepts are triggered by the patient's information leading the system to run until its convergence. Finally, the case is categorized according to the results of the comparison between the converged output state value and the thresholds (Billis et al., 2015; Papageorgiou & Kannappan, 2012).

The systems which investigate how a disease will respond to certain actions share a similar structure with the previous FCM DDSS paradigm. In this case though, the output state interval is not divided into specific regions assigned to pre-defined labels. Rather, the change on the converged output state value is interpreted as the trend of the disease resulting from the initial actions taken on the factor concepts. Hence, an increase to the output/decision concept might be interpreted as the disease's worsening and vice versa (Papageorgiou & Froelich, 2012).

As shown in Figure 2.18, classifying the levels of a disease / disorder / therapy is by far ahead of the rest FCM DDSS types, gathering approximately the 70% of the proposed medical diagnostic systems using FCM in the last few years. The "maximum wins" class of FCM DDSS follows, holding a score of almost 30% when aggregated with the competitive systems leaving last in preference the use of FCM DDSS systems for examining the trends of a disease under some specific circumstances.

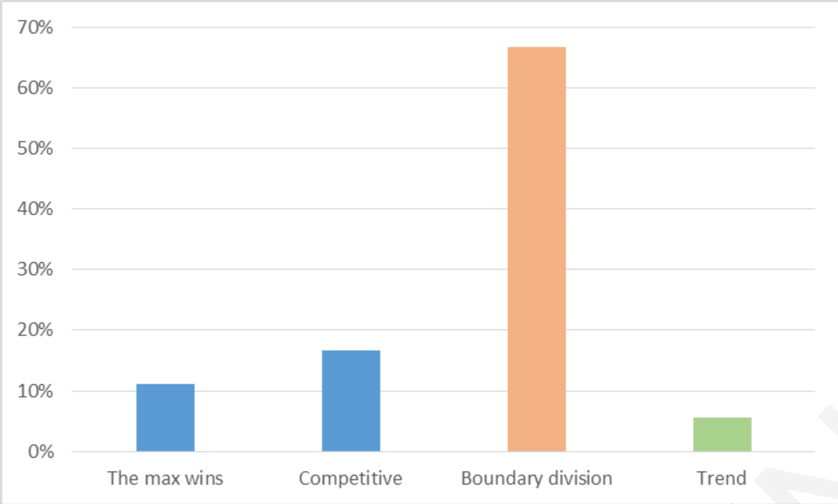

Figure 2. 18: How the diagnosis is made by FCMs as reported by journal papers from 2010-2016

Undoubtedly, researchers who are active in the area of developing medical applications with the help of FCMs, choose to work with diagnostic systems which aim at deciding whether a medical problem is present or absent and, in many cases, also specify the level of disease occurrence. This particular authors' preference could be explained by analyzing the diagnostic results of the FCM applications. Where the disease's severity classification FCM applications present varying diagnostic yields from 79% to 95%, the second in preference FCM DDSS category, named "the maximum wins" has almost none diagnostic yield. The applications drawn from this category cannot support their functionality through validation tests since there are not available datasets to be used towards this direction. As a result, the authors are bounded in simulating a very small number of patient cases given by a group of physicians and asking the physicians to validate the model (Georgopoulos & Stylios, 2009). Of course, there are some exceptions (Papageorgiou, 2012; Papageorgiou et al., 2013) where there exists a dataset describing the problem and hence the functionality of the system is validated using a number of the dataset cases as the testing set. Still though, the dataset size is small and not adequate to make generalized conclusions.

Actually, the lack of available datasets is a considerable problem for all the types of FCM DDSS. This can be clearly seen in Figure 2.19. The fact that the biggest part of these applications uses a dataset with size smaller than 10 cases to discuss the validity of their results is remarkable. As a matter of fact, the medical applications of FCM which test their functionality and efficiency with testing datasets with less than 50 cases hold together the 75% from which only a few use the cross validation methodology (Froelich, Papageorgiou, Samarinas, & Skriapas, 2012; Papageorgiou & Froelich, 2012).

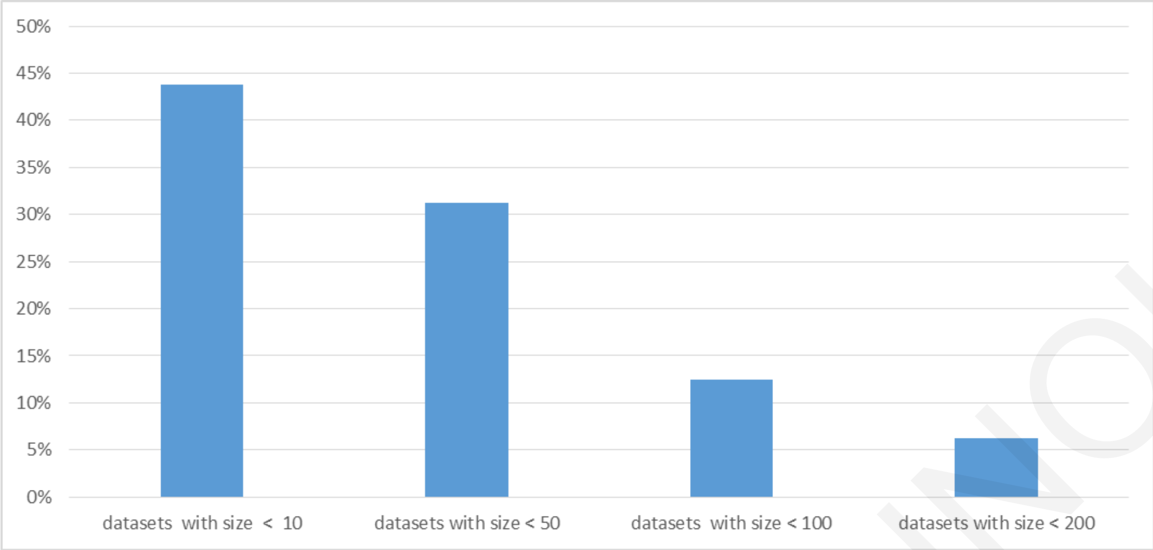

Figure 2. 19: The figure presents the percentage of FCM DDSS applications using different dataset sizes to validate their results (taken from FCM DDSS proposed from 2010-2016

It seems though, that the cause of this problem is not the unwillingness of the authors to use bigger datasets, but rather it is the difficulty they face to find datasets which adequately describe the problem. This can be justified by studying the type of the data which is input to the concepts they use for the proposed applications. The input data for all the FCM DDSS can be examination tests, measurements, observations, behaviors, demographic information, familial information, etc. Where many times the patient's information is given in arithmetic form (e.g. heart rate pressure, temperature, etc.), there are other cases where the patient's information is descriptive and hence is linguistically given (e.g. how well a patient socializes, how healthy his nutrition is, etc.).

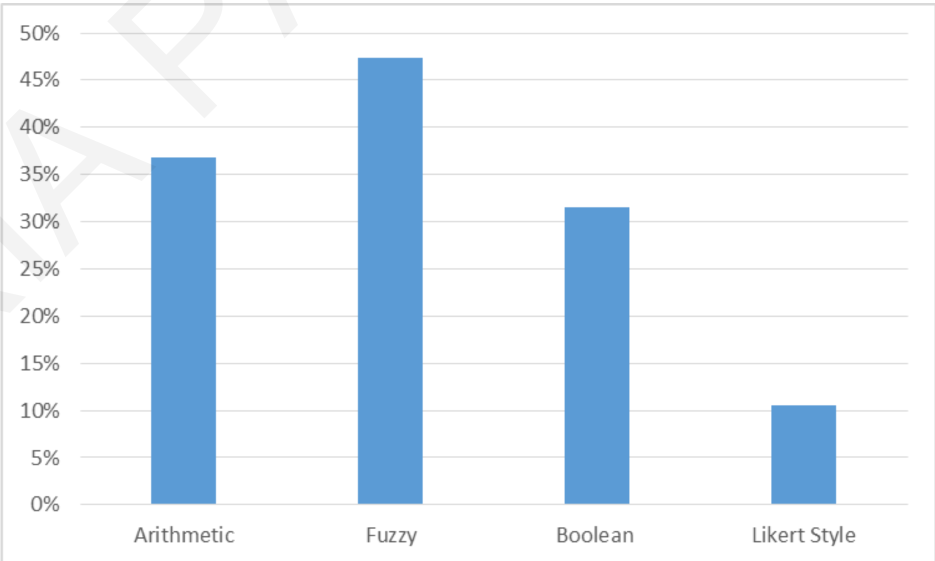

Figure 2. 20: Percentage of use for different types of input data for FCM DDSS (taken from FCM DDSS proposed from 2010 - 2016

The fact that FCMs utilize fuzzy logic in knowledge representation enables the DDSS designers to incorporate to the diagnostic systems, concepts which accept fuzzy input. This addition not only enriches the actual diagnostic system with important information about the patient but also enhances the interaction of the clinicians with the diagnostic systems since they can “talk” the same language. That is why the majority of FCM DDSS (almost 50%) use concepts in a fuzzy manner (Figure 2.20). The concepts which are defined using arithmetic and Boolean numbers hold the second and the third place correspondingly. The concepts which are defined under a Likert scale scheme come last in preference. The states of these concepts are graded into different levels which are assigned to different values taken in the interval of [0, 1] (or [-1, 1]). Therefore, if a concept can be linguistically described by the terms {low, moderate, high} the corresponding values can be {0, 0.5, 1} (Anninou & Groumpos, 2014c).

Although introducing fuzziness to a DDSS is advantageous for the doctors and the patients in many ways as explained above, there is one big limitation. There are not enough datasets describing medical parameters in a fuzzy form. Although the medical fuzzy systems can be built based on experts' extracted experience and knowledge, their diagnostic power cannot be tested only by experts but rather real patient cases are needed to be used to perform validation tests. Hence, although FCM medical applications incorporate fuzzy concepts to their systems, the lack of fuzzy datasets makes it difficult for the authors to test the diagnostic abilities of their systems with real data. This limitation might stand as an obstacle in the introduction of the FCM DDSS applications to the real life routine of doctors or patients.

Therefore, the lack of fuzzy datasets along with the use of a FCM technology to model a medical problem given in thousands of patient cases comprise a hypothesis of this thesis and will be further explained in the next chapter.

2.6 Time in FCMs

FCM comprises a dynamic modeling tool which can capture future states of a system under certain circumstances. Therefore FCMs exhibit a temporal aspect due to feedback presence in their dynamic operation. However FCM model “runs” as a discrete simulation. After presenting an initial set of activation levels, the model is free to iterate through several concept states until converge to the final steady states which represent the behavioral response of the system to the initial conditions. The set of the activation levels at each iteration represents a snapshot of an intermediate system's state between the initial conditions and the final converged state.

Unfortunately, FCM model is unable to define the time period in which all these changes will occur. As a result, the model does not give any information about how long it will take to the system to present the final steady state behavior given that the specific initial conditions apply. The model is only in position to answer "WHAT-IF" questions while it would be of greatest importance if it could also answer "WHATandWHEN-IF" for scenario building and decision making in several domains (e.g. political/economic sciences).

Although introducing time dependencies into FCM model is a very challenging extension to classic FCM, there is no equivalent interest in research area. Only few researchers have been involved in this field. The first approaches to this subject proposed modeling time for FCM should be done in discrete space, stating that introducing time in continuous space is a very difficult task (Hagiwara, 1992; Park & Kim, 1995). The proposed models require from experts to define a discrete time unit (e.g. one month, year so on) with which they must afterwards describe every causal relationship for every pair of concepts. If a relationship is assigned to more than one time units (e.g. 6 months) then dummy nodes are added in between the corresponding pair of concepts and the weight of each new added edge is $\sqrt[m]{W_{ij}}$ where m is the number of the causal links between the two original concepts and W_{ij} is their former weight (before adding dummy nodes in between). They assume that initially a concept C_i is stimulated. At the next iteration, the indirect and total effects on its neighbors (effect concepts) C_j are calculated and they become stimulated. Therefore, at each iteration n the indirect and total effects are calculated for the concepts which are distanced by n edges from the very first stimulated concept (following causality paths). Finally the total effects are given for each concept and therefore one can infer the type of causality on a certain concept. The process is quite complicated and they do not clarify how the final states of the concepts could be given using this kind of dynamic analysis.

The next attempt of representing time relations in FCMs was the Rule Based FCM (Carvalho & Tomé, 2001). According to the writers, RBFCM is more flexible to encode time relations between the concepts than classic FCMs by using fuzzy rules describing each causal relationship. Once more, the experts must define the time unit which will be represented by an iteration (e.g. one iteration could be one month, ten days etc.) which means that time dimension lies in discrete space for the RBFCM models as well. Then the experts use fuzzy rules to describe the causal relationships amongst the concepts. A fuzzy rule should define the type of the effect on a concept (positive or negative) and its strength which will appear in the time period defined by the predefined time unit. During FCM inference process, an iteration represents one time unit. Therefore, during FCM inference partial effects (as defined in the fuzzy rules) will be applied on concepts which will be aggregated to the total effect as soon as the model converges. Experts should keep in mind the time unit, represented by an iteration, when defining the strength of the effect in a causal relation. For example, consider two concepts, C1 and C2, describing the concepts of greenhouse effect and ice melting percentage respectively. If the defined time unit is one day then the strength of the effect on C2 (caused by C1) should be much smaller than when the time unit is 10 years! The writer refers to the time period represented by an iteration as Based-Time. All the causal relations of the model are defined based on the B-Time. The B-Time variable is decided by the designer and the experts of the system depending on the type of the system being modeled and the potential scenarios they would like to examine on the modeled system. If the designer wishes to examine the system's behavior in long term period then a big B-Time (e.g. 1 year) should be defined while if they would like a short-term system's reaction to a change then a small B-Time (e.g. 1 day) is suggested. Additionally, the writers state that if the system exhibits a chaotic behavior then the B-Time should be decreased, the experts should reconsider the fuzzy rules and allow the model to "rerun".

The proposed model also tries to deal with the time delay often observed in cause-effect systems. Many times, the effect concept reacts after a certain time period (not immediately) to the change of the causal concept. This phenomenon is called dead-time which begins from the exact moment a change happens to a cause concept and ends at the same time that the state of the corresponding effect concept changes (from its previous state value). A very well-known real life example describing this phenomenon is the time delay observed in changing the oil price in gas stations after the price per barrel changes. To encode this phenomenon, the writer suggests that a number of iterations should pass until the effect concept changes for the first time its state value. The number of the "delay" iterations are equal to the time delay (given as a natural number) divided by the B-Time (time delay / B-Time). The experts are also responsible to define the time delay (if any) for every causal relationship.

Indeed, RBFCM overcome some of the limitations of classical FCMs since they incorporate fuzzy calculations during the simulation of the network and it is easier to introduce some time features in the relations' structure. However, as stated by the author himself, their construction is more complex which makes it more difficult to be used. That is why there exist hundreds of applications using classical FCMs where there are only few using RBFCM. More precisely, recently only two applications of RBFCM have been proposed, one for examining how different policies affect the routine life of fishermen from a specific region of Portugal and the populations of specific fish swarms (Wise, Murta, Carvalho, & Mesquita, 2012) where another application is used to apply decision making related to student-centered education systems (Peña-Ayala & Sossa-Azuela, 2014). It is important to note that only the first one also uses the time RBFCM as described above.

Temporal FCMs (tFCM) also discuss time dependencies in FCMs (Zhong, Miao, Shen, & Feng, 2008). Following to this model, each causal relationship is described by two different linguistic variables. The first one is the time phases characterizing the particular relationship and the other one is the type of the effect. The time phases of a causal relationship, *S*, essentially describe the time length of an effect's duration (time length) and they are given by linguistic values. For example a set of linguistic values could be $S_n \in$ {short term, medium term, long term}. Each one of them comprises a fuzzy set and therefore its membership function must be defined $\mu_{ij}^{n}(t)$ (Figure 2.21). The type of the effect is defined as a number in the interval $\gamma_{ij} \in [-1, 1]$ which in turn comprise a singleton membership function with membership degree one. Then fuzzy rules are defined by the experts for every causal relation between two concepts C_i and C_j as:

$$\{R^n | R^n: S^n \rightarrow \gamma_{ij}^{n}\} \qquad \text{Equation 2. 25}$$

where S^n denotes the n^{th} time set (defined for this relation) and γ_{ij}^{n} is a singleton number defining the strength of the effect and it is assigned to the n^{th} time phase.

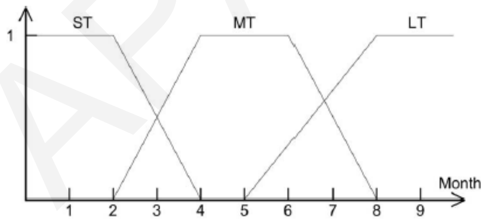

Figure 2. 21: Three membership functions describing three time phases of a causal relationship. The time unit is one month.

Each iteration is considered to count as one time unit (in Figure 2.21 is one month). Therefore at each iteration *t*, the causal relation belongs to a degree to one or more time phases (given by $\mu_{ij}^{n}(t)$) and so modus ponens is applied to move from the firing premises (of the fuzzy rules) to the effect degree (conclusions of the rules). Then, since a concept might accept effects from many other concepts, fuzzy logical operators are used to aggregate the partial effects (AND or OR). Finally, the Center of Gravity defuzzification method is used to calculate the total effect $h_{ij}(t)$ which is the effect the concept C_j accepts from the cause concept C_i at that certain iteration *t*:

$$h_{ij}(\text{t}) = \frac{\sum \gamma_{ij}^{n} \mu_{ij}^{n}(t)}{\gamma_{ij}^{n}} \qquad \text{Equation 2. 26}$$

The last model, presented by C. Neocleous, defines that the weight degree of each FCM relation will be given by a function dependent on the iteration number (Neocleous & Schizas, 2012). Thus, each relation must be described by a function giving the value of the weight per each iteration. This function is constructed by a quad for each associationship between concept *i* and concept *j*. This quad is stated to be time-dependent and it involves the minimum values of the sensitivities (weights) between concept *i* and concept *j*, $s_{ij,min}(t)$, the corresponding maximum values $s_{ij,max}(t)$, the time delays $D_{ij}(t)$ and the time constants $T_{ij}(t)$. The user can add more time delays and time constants in order to give the relation between the iterations and the weight the form he wishes. An example of a relationship described by two time delays and two time constants is shown in Figure 2.22. The equation giving the curve presented in Figure 2.22 is presented in Equation 2.27.

$$s = \min(\min(S_{max}, \max(S_{min}, f_2)), \max(S_o, f_1)) \qquad \text{Equation 2. 27}$$

The proposed approach has been implemented to investigate the effects of oil exploration on the peaceful coexistence of the two main communities in Cyprus. The model presented some interest results as discussed in the corresponding work. Nevertheless, an open issue regarding this work is that the definition of the time constants and delays must be provided by experts.

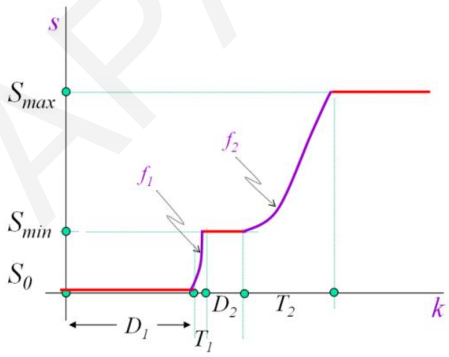

Figure 2. 22: How a potential weight degree can vary through iterations. Axis Y is for the weight degree where axis X is for the iteration counter

Another research trend in this field is the use of FCMs for modeling time-series problems. This trend emerges from a plethora of relative FCM applications proposed during the very last few years (Billis et al., 2015; Bourgani, Stylios, Manis, & Georgopoulos, 2015; Buruzs, Hatwágner, & Kóczy, 2015; Froelich & Papageorgiou, 2014; Froelich & Salmeron, 2014; Homenda, Jastrzebska, & Pedrycz, 2015; Lu, Yang, & Liu, 2014; Papageorgiou & Froelich, 2012; Poczęta & Yastrebov, 2015; Lu, Yang, & Liu, 2014; Coban, Cevik Onar, & Soyer, 2015).

FCM time-series modeling can be divided into two main categories. The first category concerns the cases where the weight matrix is learnt based on a customized learning procedure. The second category allows the experts to determine the weights' matrix (Homenda, Jastrzebska, & Pedrycz, 2014).

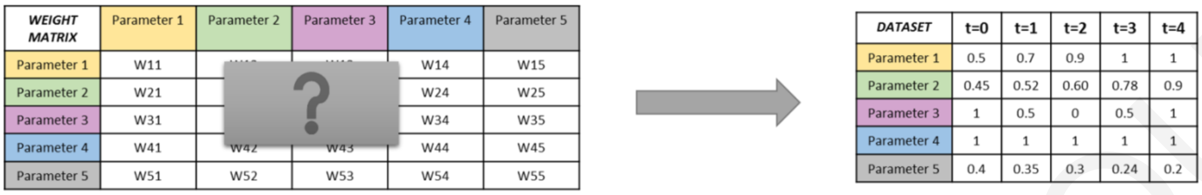

Figure 2. 23: - Time series problems solved by FCMs: Find a proper weight matrix to forecast successfully the values written to a dataset

Clearly, to implement a time-series FCM model drawn from the first category, there must exist datasets related to the modeled problem. These datasets should describe the behavior of the modeled system for a number of time units (e.g. for some months, some year etc.). During the simulations of these models, each iteration is assigned to a time unit. For example, if the time unit is one month, then after the running of one update cycle, the concept states are thought to exhibit the state of the modeled system after the pass of one month. Thus, the main goal of this procedure is to train the FCM model to forecast the state of a concept after the pass of k time units (hence after the pass of k iterations / update cycles). The training algorithm which will be used is called to find a weight matrix that will minimize the error between the concept states per each iteration and the corresponding written states in the available dataset (Figure 2.25).

The evolutionary and swarm based algorithms are the most popular family of algorithms which are used to find a proper weight matrix for different time-series problems using FCMs. The structural steps followed for each application of this kind are very similar and they are schematically described in Figures 2.24 and 2.25. Initially, the causal relations of the system as retrieved from experts or relative literature are input to the selected optimization algorithm without defining the character or the degree of intense of the relations. This initial step might be skipped and proceed to the second step directly for which the optimization algorithms randomly proposes a number N of solutions for the weight matrix of the specific time-series problem (Figure 2.24). Then, each one of the weight matrices proposed by the algorithm is input to the modeled FCM which is initialized with the parameter values as recorded in the dataset for the very first time point ($t=0$). Then, the system is let to run but for each iteration, the error/distance between the FCM model's concept state values and the corresponding recorded dataset values is calculated. When reaching to the last iteration of the network (defined by the total number of time points written in the dataset) the total error of the particular weight matrix is aggregated based on the error per each iteration and the fitness of this solution is calculated accordingly. Based on the calculated fitness and some other stochastic parameters, some of the solutions pass to the next generation (round) mutated or not while some others are rejected by the algorithm. This procedure is repeated for a number of rounds depended on the termination criteria. The fittest solution from the last round is kept as the weight matrix for modeling the particular time-series problem. FCM time-series systems model problems taken mainly from the Medical area (Billis et al., 2015; Froelich, Papageorgiou, Samarinas, & Skriapas, 2012; Froelich & Papageorgiou, 2014; Papageorgiou & Froelich, 2012) and the environmental area (Buruzs et al., 2015; Froelich & Salmeron, 2014; Poczęta & Yastrebov, 2015).

One reason justifying the selection of problems drawn from these two areas for implementing time-series modeling could be the availability of datasets describing the variation of the system’s parameters for different time points. Medical datasets describe the evolution of the patients’ health state through time while environmental datasets usually describe how some weather features (e.g. temperature) change over certain time points. The access to such datasets is easier and hence the development of FCM time-series models in these areas is more feasible.

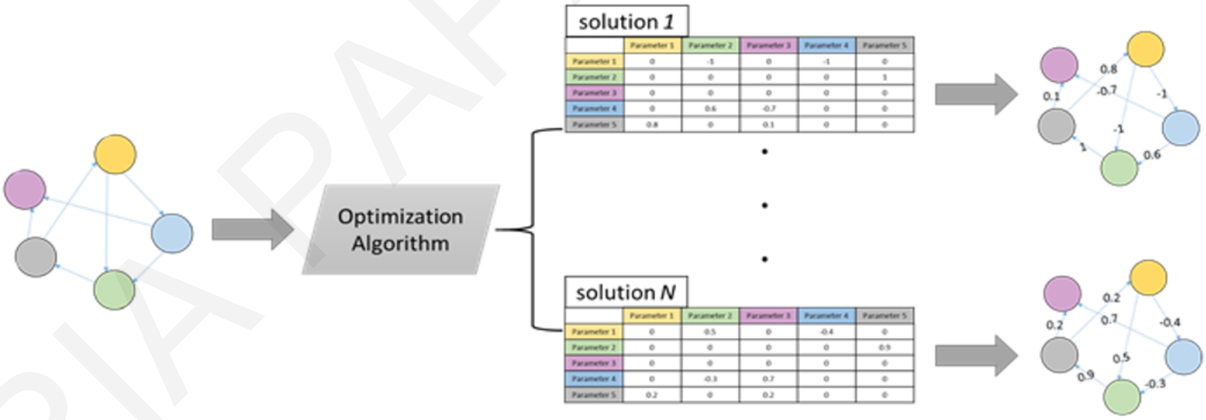

Figure 2. 24: Use an optimization algorithm to propose a number of solutions for weight matrices for a time-series problem

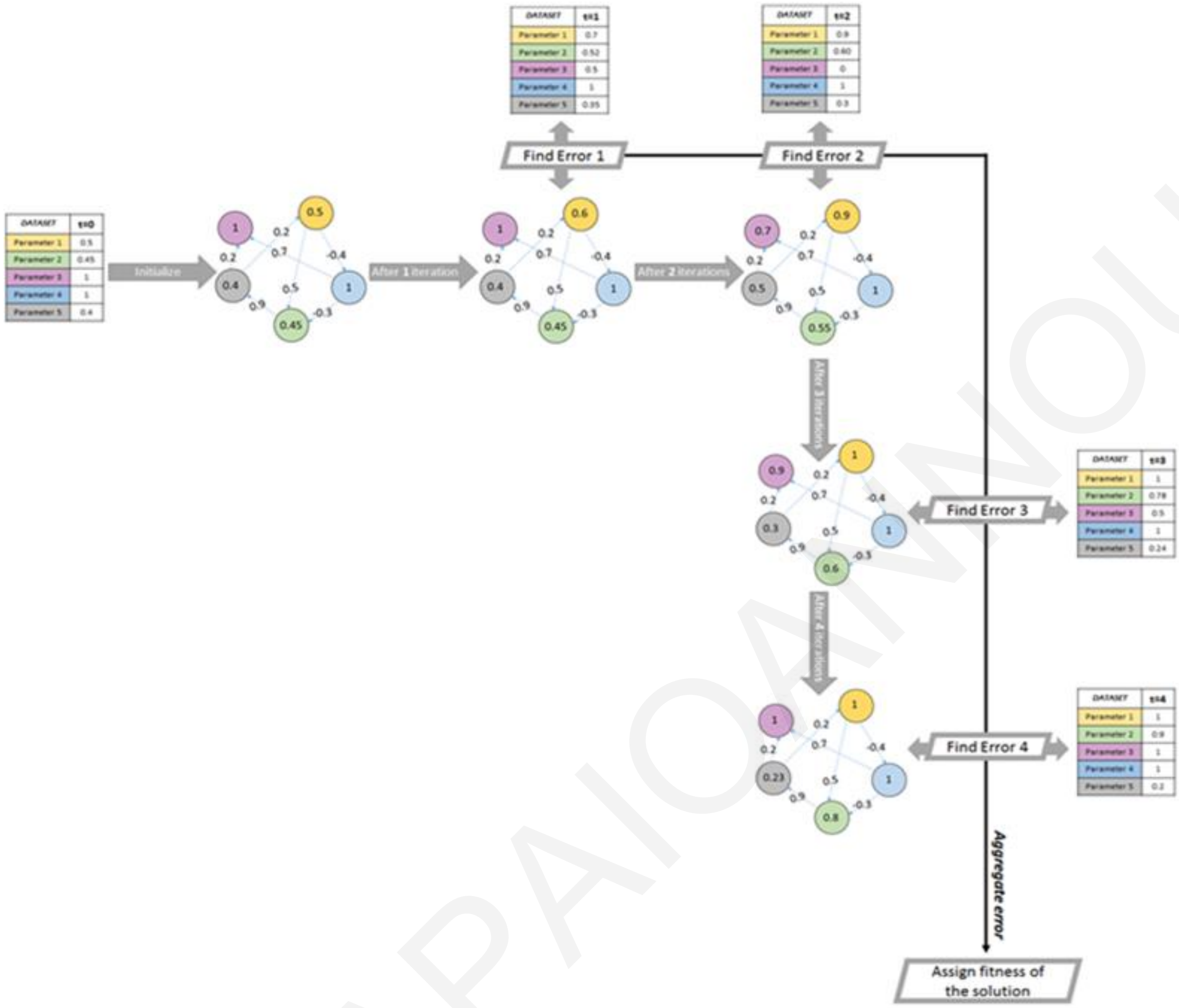

Figure 2. 25: How to evaluate the fitness of a weight matrix proposed by an optimization algorithm

However it would be equally, if not more, interesting if there was a FCM paradigm for modeling time or time-series problems where no dataset is available. Actually, Bourgani et al. proposed a methodology for capturing time dynamics in FCMs using the knowledge and experience taken from experts to apply classification between two decisions (Bourgani et al., 2015). The two decisions are represented by two different concepts in the system. The rest concepts are factor concepts which somehow influence each other and the two decision concepts. Following to this work, the experts are called to design a different FCM weight matrix per each time unit. Furthermore, the experts draw different weight matrices for the same time point to model possible synergies that might happen to the system. The system is then allowed to run, with different weight matrices at every iteration as pre-defined by the experts. The system is thought to converge when the distance between the state values of the two decision concepts is adequately big (case depended). Similarly to time RBFCM, this model is promising but rather complex and demanding in terms of experts' involvement. Experts must make a great effort to orient their thought on what alternations happen to the system's dynamics and the potential synergies per each time unit and built proper weight matrices per each case. Although the authors state that this methodology has been applied on a real medical problem of distinguishing between two pulmonary diseases for a patient, no results were presented in the paper and thus the validity of this methodology cannot be examined.

Concluding, introducing time dimension if FCMs has always been spotted as a very important contribution to FCM research area (Papageorgiou & Salmeron, 2013). Despite the fact that some variations of the classical FCMs try to handle time through causal relations in different ways, their application to real life problems is limited due to complexity factor. The subject is still open and challenging.

3. Expert-based FCMs (a construction methodology)

The proposed FCM construction methodology was inspired by the need of building valid communication channels with experts for modeling systems for which datasets are absent. Thus, experts are regarded as the only pool of information which the FCM handler can extract information about the elements comprising the FCM model. Problems drawn from political, social and economic arenas are very common to belong to this category. On the other hand, experts of these fields are not familiar to intelligent systems representations. Hence, a methodology which will act as a cross-road directing the communication between the FCM handlers and the experts in a problem's domain is proposed in this chapter.

In the context of this work, a new way of applying activation on FCM concept states is also proposed. The need to introduce a different activation method from what is already used emerges from the nature of the socio-economico-political problems. More particularly, by the fact that in order to initiate a causal effect on such a system, a *change* must precede to one or more factors of the system. Additionally the proposed activation method avoids the use of transformation functions along with all their adverse effects on the actual system's output.

3.1 Proposed Activation Function

The importance of the activation function has been underlined in Chapter 2. Essentially, an activation function in FCMs defines the way the system will process causality for simulation purposes. An activation function calculates the updated state values for each concept after interacting with its influencing neighbors.

The activation function used by conventional FCMs requires the additional use of a transformation function to bound the concept states into the desirable interval of [0, 1] or [-1, 1]. The structure and the functionality of the FCM model lies in the causal systems' theoretical field. The structural and functional elements of the system can be explained and interpreted by the theoretical background of causal systems. However, the use of the squashing functions during the update of the concept states through the inference phase cannot be justified in this framework. The squashing (or transformation) functions are used only for normalization reasons. Although some support their use in the context of FCMs by bringing up the argument that squashing functions are also used in ANNs, the truth is that the mathematical and theoretical background of these two models along with the type of use of these models has some severe differences and hence they cannot be compared. The activation function should be reflecting how the concepts of a system causally interact with each other under a given scenario.

Consequently, a slightly different approach from the established FCM activation functions formalism is adopted in this thesis. FCMs comprise a computational intelligent paradigm of modeling systems whose parameters are linked together through causal relations. Besides from achieving a visualized form of knowledge representation (something that could be also achieved by the use of simple Cognitive Maps), FCMs can be used to run specific scenarios on a modeled system towards decision making. It might be that this is the strongest attribute of this technology. However, the interpretation of the converged concept states of different FCM models is not done in a systematic way. This can be explained by the fact that the meaning of the concept states and the concepts' interrelations is not clearly and uniformly understood in the same manner by all researchers who are active in FCM modeling area. As indicated by Carvalho, the usual approach when interpreting the relations and the concepts of a FCM system is to define the concepts to express their states into absolute values during simulation phase (e.g. "Theft is presently *low*") (Carvalho, 2013). Therefore, the interrelations of these concepts are expressing causality between constant states (e.g. "If theft is presently low, police is presently low"). The interpretation of this relation though is not clear since a constant state cannot cause a change to any other parameter, especially when all the parameters are defined in constant states and, hence the system is regarded to be in equilibrium. Therefore, following to this philosophy, there is nothing to trigger the interaction amongst the parameters. How to break equilibrium to reach a new equilibrium when the parameters have constant character? That is why, Carvalho suggests that the semantics of the causality definition is supposed to represent how a change on a concept causes in the consequent (Carvalho, 2013). That way, a change happening to a concept triggers the breaking of the current equilibrium. That way it initiates the causal interaction of the concepts allowing them to integrate the effects of causal changes happening to the system during each simulation cycle. This should be the interpretation of the relations in the context of FCMs which essentially answers the question "If parameter A changes its state, what change will happen to parameter B?".

Consequently, the central idea of the proposed activation function is that an impact is created onto the FCM system when and only when a parameter changes its equilibrium state value. Therefore it is the change itself that causes the system perturbation and forces it to reach a new equilibrium state. Accordingly, the concept state should be updated by taking into account, the changes that happened during each iteration to its influencing neighbors. Additionally, the interrelations should be also interpreted in this manner, by essentially expressing the extend of the change that will happen to a concept as a response to a change happening in an antecedent concept.

All above characteristics of causal systems' behavior regarding the way of initiating a causal effect are specifically reported for social systems (including political and economic) (Carvalho, 2010). At this point, it should be noted that the proposed activation function in this section was designed to reflect the way social systems behave and express their causal dynamics.

Nevertheless, since a change is required to escape from a system's equilibrium state, the activation function should use the change illustrated in the influencing concept' states during the last two successive iterations to calculate the total impact in each concept during the specific iteration. In this framework, Equation 1 shows how the impact of the neighboring concepts can be calculated.

$$impact(A_j^t) = \sum_{i=1}^{n} w_{ij}(A_i^t - A_i^{t-1}) = \sum_{i=1}^{n} w_{ij} dA_i^{t,t-1} \quad \text{Equation 3. 1}$$

where A_i^t is the concept state of the influencing concept in iteration *t*, w_{ij} is the weight value of the interrelation between concepts C_i and C_j, A_j^t is the influenced concept state given in iteration *t* and $impact(A_j^t)$ is the total impact that the specific concept will accept during iteration *t*.

However, it is reported in FCM literature, that the objective is not studying the absolute concept values but the trends which appear by the stabilization of the system (Pelaez & Bowles, 1995; Carvalho, 2010; Gray, Zanre, & Gray, 2014; Soler, Kok, Camara, & Veldkamp, 2012). This is especially crucial for socio-politcal-economic systems which are very hard to define in absolute values due to their complexity especially for long term effects.

In statistics, trend analysis evaluates a system's behavior over a period of time. In our case, since FCMs run over discrete iterations, the system's behavior over successive iterations should be considered. One way to apply trend analysis is to calculate and analyze the percent change from one period to the next. The trend percentage is calculated as the change (increase or decrease) illustrated in a parameter value between two time points divided by the earlier parameter's state. By using trend percentage to apply trend analysis we can take into consideration the importance of the change expressed in a parameter. For example, consider two parameters *p1* and *p2* which take values in the interval of [0, 1]. The two parameters appear to increase their values in the same period by 0.1. However, if we know that the earlier state of *p1* was *p1 = 0.1* and the earlier state of *p2* was *p2 = 0.9*, we can infer that the first parameter presents a more powerful increasing trend since it exhibits a 100% increase where the second parameter presents only a 11% increase. Hence, one can conclude that the trend presented in the first parameter is more powerful than for the second one. In this manner, the trend percentage can be also used to calculate the impact each concept accepts from its neighbors during two successive iterations as in Equation 3.2.

$$impact(A_j^t) = \sum_{i=1}^{n} w_{ij} \frac{(A_i^t - A_i^{t-1})}{A_i^{t-1}} = \sum_{i=1}^{n} w_{ij} \frac{dA_i^{t,t-1}}{A_i^{t-1}} \qquad \text{Equation 3. 2}$$

In that way, trends are incorporated in the way causal effects are calculated in a causal system and results can be interpreted in this context. The last step is to apply the calculated impact on the influenced concept. Using Equation 3.2 the impact is calculated as a weighted percentage (impact percentage). Thus, the influencing concept Aj must change its current state by the specific impact percentage. To do so, we multiply the current state of the influencing concept with the impact percentage to get the change that has to be applied on the specific concept.

$$change\left(A_j^t\right) = A_j^t * impact(A_j^t) \qquad \text{Equation 3. 3}$$

In Equation 3.3, $change\left(A_j^t\right)$ represents the change that must be applied on the concept C_j in iteration *t*. Consequently, the updated state of the influencing concept (A_j^{t+1}) is given as its earlier state (A_j^t) aggregated with the calculated change for the iteration *t* (Equation 3.4).

$$A_j^{t+1} = A_j^t + change\left(A_j^t\right) = A_j^t + A_j^t \sum_{i=1}^{n} w_{ij} \frac{dA_i^{t,t-1}}{A_i^{t-1}} \qquad \text{Equation 3. 4}$$

Although the update function reflects how the concepts process the impact they accept from their neighbours to change their state, it is obvious that their new states might exceed the desirable interval of [0, 1]. The key factor in addressing this issue is the weight degrees (w_{ij}). The weight degrees are critical factors of regulating how drastically a concept will change its concept state value per simulation cycle. Their definition should be done in a very thoughtful manner, ensuring that the intense of each degree truly resembles the causality expressed through the particular relation. Having these in mind, a way of defining the weight degrees in such a way that the concepts are not allowed to exceed the proper limits is proposed and described in the following section.

3.2 FCM Experts' Based Building Methodology

Essentially, a FCM is developed by integrating the existing experience and knowledge regarding a cause – effect system in a dynamic manner. This can be achieved by applying either of two general construction methodologies. The first methodology involves some kind of automated machine learning (e.g. Hebbian, evolutionary, etc.) that is used to identify the influencing parameters and the intensities of their interactions. This approach has limitations for socio-politico-economic modeling, as the historic data are abundantly available. For these systems, the second FCM building methodology is more appropriate and more often used. In this approach, a group of human experts is called to describe the system's structure and behaviour in different conditions (Glykas, 2010; Stach, Kurgan, & Pedrycz, 2010; Stylios & Groumpos, 1998). This approach in FCMs has been criticized for the fact that its construction relies predominantly on humans, thus increasing the possibility that the model does not adequately represent the system. Nevertheless there are systems, that human experience and knowledge is valuable and most of the times it is the only available source of information describing the inner characteristics of it. Therefore, it is substantially crucial to establish a certain methodology for developing FCM models within desirable levels of quality. However, the success of the FCMs' developmental phase is based on an accurate extraction of expert knowledge or experience. A framework of such a methodology is proposed in this work specifying certain steps for building FCMs. The framework was actually implemented for a real system. A small introduction to the subject of the modeled system follows.

As stated in the beginning of this report, there is a strong will in contributing at the most in addressing issues concerning Cypriot reality. Having this in our mind, an intricate system describing concepts of the Cyprus banking system and economy back in 2012 was used to implement the steps of the proposed methodology. It is well known that Cyprus and Greece have strong bonds in historical, cultural, political and economic levels. At the time of implementing the proposed methodology, Greece was already counting sequential downgrades by the International Credit Rating Agencies, one bailout package and a series of strong austerity measures under the threat of a national bankruptcy. In 2012, Greece was given a second bailout package which was accompanied with a restructuring agreement with the participation of Greece's private lenders through a private sector involvement (PSI) scheme. The debt restructuring deal involved private holders of Greek government bonds suffering a 53.5% so-called “haircut” to the nominal value of Greek debt. Eventually, in March 2012, the bond swap was implemented with an approximately 75% effective write-off.

Since the Greek and the Cypriot economies are strongly related and connected, this led to serious repercussions to the Cyprus economy. More specifically, the Cypriot banking system was heavily exposed to Greek sovereign debt. The three major Cypriot banks were holding bonds with a nominal value of around 5.3 billion euros in 2011 at a time when their deposits and also the loan portfolio both stood at approximately 62 billion euros. Effectively they lost more than 3 billion euros through a write down that they suffered by participating in the PSI. The Cyprus economy already in a state of stagnation suffered a major shock. The Government of Cyprus and the Cypriot bankers had to deal with an unprecedented situation which was extremely difficult to handle since they could not estimate the overall impact of the Greek PSI on Cyprus economy and the Cyprus banking system. Using the proposed FCM construction methodology, a FCM was built to model the dynamics of the above problem.

In that way, we could build a FCM using experts’ knowledge to study its dynamics and the interrelations among some important aspects of the Cyprus financial system and the economy at large. The main target of this application, as set by the experts, was to study the banking system as a result of the Greek PSI, the Cyprus economy downgrading by the credit rating agencies and the Cypriot banks recapitalization by private equity.

Two basic scenarios were implemented and tested for the purposes of this work. The first scenario aims to examine the implementation of the Greek PSI when accompanied with a sharp downgrading of the Cyprus economy by Rating Agencies. The second scenario involves the implementation of the Greek PSI followed by successful recapitalization of Cypriot banks by private equity.

It is worth noting that the first scenario depicts what actually happened to the banks and the Cyprus economy at large after the implementation of PSI. The alternative scenario examined here represents a brighter turn of events, something that did not materialized in the end.

The methodology proposed for construction of FCM expert-based systems follows divided in four basic steps. Examples using the modeled Cypriot banking system are used per each part in order to enhance the reader’s understanding.

3.2.1 Steps of the Proposed Methodology for FCM construction

3.2.1.1 Step 1: Specification of the time period

The very first step of the proposed FCM construction methodology is to specify the time period in which one wishes to study the system. This will greatly help the experts to specify appropriate concepts and meaningful influencing factors. FCMs offer the availability of simulating highly complicated systems which often contain parameters whose states are characterized by high fluidity with regards to time. Specifying the time horizons in which the experts are asked to describe the system helps to limit the amount of information that is needed to properly define the system.

The position of the time window depends highly on the system´s behaviour and its rhythm of change. It also depends on what the experts expect to examine by using the FCM modeling on their system; in other words, the testing scenario the experts choose to apply on the FCM model.

Hence, in order to define the initial values of a system, the experts should define a specific time point. For example, in this work, the experts were asked to study the economic consequences of Greek PSI in combination with two other possible events. The down-grade of Cyprus economy by the credit rating agencies and the recapitalization of Cypriot banks by private equity. Therefore the experts stated that the initial values of the system should reflect the situation of the parameters just after the implementation of the Greek PSI, so they chose the time point to be the April of 2012.

After this step, the experts should specify, based on their experience about the system, a time period, around the specified time point, in which the system presents a constant behaviour (e.g. constant deterioration, constant improvement, constant rotation between deterioration and improvement, etc.). By doing that, the experts will be able to gather a satisfactory quantity of information and data regarding the system in the specified period which will eventually help them to do a sampling of the data they will use to define the initial values of the system until they have a view of the general picture about the system at the defined time point. During this process, the experts should keep in mind the general momentum of change which characterizes the specific system. One system might need a number of years to change where another system might need some hours.

In this case the experts defined the time window at +/- 3 months from the April of 2012 and the valuation of the parameters' states were done based on material, statistics or any other information describing them in the specified time window.

3.2.1.2 Step 2: Identification of the FCM concepts and their special features

Keeping in mind the time period, the experts must identify and define the principal parameters that they consider as the most important in the dynamics of the modeled system. FCMs are mainly used to model complex systems that are not easily modeled by analytical paradigms. Such models comprise a large number of parameters. Many times, the conceptual distinction of two parameters is not easy. On the other hand, introducing an unnecessary or even an irrelevant parameter to the system may affect the quality and the accuracy of the FCM simulation (Pang, 2013; Santhi, 2012). Thus, it is important that the experts identify and describe the truly important parameters that affect the system being modeled. This is central to the proper simulation of the system.

Even though the experts have good knowledge, experience or even skills in a particular field, they may need to enhance their knowledge on the specialized system. To help them towards that direction, in our case study, the experts were asked to fill a table of different fields describing the system's parameters. In the first column the experts had to write a formal definition for each one of the parameters derived from their specific knowledge or taken from relevant bibliography. This enhances their perception about the actual and up-to-date interpretation of each concept, without semantic confusion. Furthermore, they were asked to define each concept's measurement units where possible, since not all types of parameters could be numerically appraised. For example the parameter *Confidence of people and companies in the banking system* cannot be numerically measured whereas the parameter *Level of deposits of Cypriot citizens in Cyprus banks* can be easily measured in monetary terms.

The next step involved the finding of the minimum and the maximum value recorded for each numerically measured concept in the predetermined time window. Added to this, the actual value describing the concepts' state at the exact time of study had to be decided. It was noted that the experts may had to justify their findings, by proper reference to reliable relevant sources (newspaper articles, bibliography, etc.). Finally, the experts were asked to define the expected degree of variation of a parameter given a certain scenario for every parameter. They had to establish whether a change in a particular concept could result in a positive or a negative change in the other connected concepts. Then, the experts had to select a linguistic term to describe the intensity of the variation. In the presented case study, they specified the changes as *low*, *medium* or *high*. Table 3.1 presents the aforementioned characteristics for a sample of concepts of the developed FCM system as described previously.

Table 3. 1: An example of the definitions and characteristics of some of the concepts of an FCM. Case of Cyprus economy in April 2012

Parameter Name	Parameter Description	Measurement	Max	Min	Actual Value in April 2012	Initial Value	Degree of Variation
Degree of Deposits of Greek citizens and companies into Cyprus Banks	How much money is being transferred and deposited in Cyprus banks, by Greek citizens and/or companies.	In euros	8 billion euros	1 billion euros	4 billion euros	0.4	Low (-)
Degree of Deposits of Cypriot citizens and companies into Cyprus Banks	How much money is being deposited in Cyprus banks, by Cypriot citizens and/or companies?	In euros	35 billion euros	44 billion euros	42 billion euros	0.78	High (-)
Confidence of People and companies in Cyprus Banking system	The degree by which the people are willing to deposit money, to make loans, to buy bank shares, etc.	High / Medium /No confidence	100% = Very confident	0% = No confidence at all	80%	0.8	Medium (-)

3.2.1.3 Step 3: Definition of the Initial States of the Concepts

The initial activation value of each concept has been normalized to a scale of 0 to 100% (or 0 to 1). This was done as follows. For each concept *i*, the experts had given its definition, its expected minimum (Min_i) within the time span being observed, the expected maximum

(Max_i) and the estimated actual initial activation of the concept (V_i) at the time when the system was studied. The normalized initial value of the activation of a concept was implemented through the following equation:

$$A_i = \frac{V_i - Min_i}{Max_i - Min_i} \qquad \text{Equation 3. 5}$$

For example, to calculate the initial value of the parameter *Stock market value of banks* (denoted as C7 in Table 3.2) the stock market values of the three largest Cypriot banks, for the specified period of the system's study, were obtained through press articles. The minimum average stock market value of that period was close to 10 cents whereas the corresponding maximum value was approximately 60 cents. The average stock market value of the three banks was almost 30 cents in April of 2012. Therefore, the initial value of the parameter *Stock market value of banks* was calculated as:

$$A_7 = \frac{30 - 10}{60 - 10} = 0.4 = 40\%$$

The above formulation is also used in the case of linguistic descriptions of the range of changes of a concept. Some parameters such as the *Level of Greek crisis* are fuzzy and hence cannot be measured or easily specified in raw numbers. For that parameter (and for other similar ones), the experts had to define the limits of its value based on their accumulated knowledge and lengthy experience. The maximum possible value was defined as 100% which meant that Greece is under a state bankruptcy and the minimum value as 0% meaning that the country has a healthy economy and thus no PSI is needed, or any form of other outside help. Based on their personal estimations the level of the Greek crisis in April of 2012 (just after the illustration of Greek PSI) was 0.8.

3.2.1.4 Step 4: Definition of the Interconnection Sensitivities (Weights)

A cause-effect system is mainly characterized by the effects that a change on a concept causes to its neighbours. The dynamics of the impact of this change are given through the weights/sensitivities connecting the changed concept to all others. The sensitivities of the weights between the concepts should be defined keeping in mind that they are responsible for manipulating the momentum of the impact a concept can cause to another.

Nevertheless, according to the FCM applications paradigms, the weights are positioned by the experts in a scale between minus one and one in a rather abstracted way. What would be essentially useful during the FCM construction phase is to ensure that experts fully understand what the sensitivity value means in FCM modeling and how it is used during the simulation of the system. To deal with this, the role of the sensitivities in FCM modeling was examined. So, the proposed FCM update function (Equation 3.4) was analysed towards the sensitivity factor. The overall target was to examine how a sensitivity value between two specific concepts is mathematically defined in FCM technology.

Based on Equation 3.4, the new state value of a concept C_j having only one influencing neighbour C_i is:

$$A_j^{t+1} = A_j^t + A_j^t w_{ij} \frac{dA_i^{t,t-1}}{A_i^{t-1}} \qquad \text{Equation 3. 6}$$

By analysing Equation 3.6 towards the weight degree w_{ij}, we can derive the equation giving the weights given in Equation 3.9:

$$\frac{A_j^{t+1} - A_j^t}{A_j^t} = w_{ij} \ \frac{A_i^t - A_i^{t-1}}{A_i^{t-1}} \qquad \text{Equation 3. 7}$$

$$\frac{dA_j^{t+1,t}}{A_j^t} = w_{ij} \ \frac{dA_i^{t,t-1}}{A_i^{t-1}} \qquad \text{Equation 3. 8}$$

$$w_{ij} = \frac{\frac{dA_j^{t+1,t}}{A_j^t}}{\frac{dA_i^{t,t-1}}{A_i^{t-1}}} \qquad \text{Equation 3. 9}$$

Where $dA_j^{t+1,t}$ describes the difference of the value of the j^{th} system parameter between the two successive discrete iterations *t+1* and *t*. Equation 3.9 clearly shows that a sensitivity value between two concepts is actually the percentage of the change happening to the influenced concept during this simulation cycle to the percentage of change that happened to the influencing concept in the preceding iteration.

By examining the Equation 3.7 one can reach to the conclusion that a sensitivity can be calculated by answering the question “How much will parameter A change as a response to a specific change happened to parameter B”. When discussing this perspective with the experts, they stated that this would be much easier for them than specifying an absolute value in the range [-1, 1] to characterize the type and the degree of the causal relationship. According to the experts this approach is much closer to their mentality and way of thinking about the parameters of the system.

The suggested procedure of calculating the sensitivities of an FCM model is different from the traditional way of defining it and using it in the FCM bibliography. The reasoning behind this deviation from the conventional FCM, is because we have a different apprehension of what substantially a sensitivity value means in the context of FCM as described above. Thereafter it is important to clarify the definition of the sensitivity. A sensitivity value indicates the degree of the influenced concept’s change in respect to the change of the influencing concept's state. The sensitivity of the relation describes the impact of changing the state of C_i on the concept C_j.

Hence, in order to define the sensitivity of every relation, the experts had to make the following assumption: "The states A_i^{t-1} and A_j^t are equal to the initial values of the corresponding concepts as defined in the previous stage of development" and then answer the following question: "If the state of the concept A_i becomes x (in Equation 3.9 this is denoted by A_i^t) what will be the new state of concept A_j (denoted byA_j^{t+1})?".

Accordingly, for each parameter, a simple scenario of changing its initial state was developed. The degree of that change was based on the corresponding degree of variation as the experts had already defined in the previous FCM developmental stage.

For example, consider the relation between the *Stock market value* (C7) and the *Recapitalization by private equity* (C6). The experts defined the initial states of C7 and C6 as 40% and 20% respectively. Furthermore, they expected a negative relationship of high intensity of the degree of variation for the *Stock market value* as a result of the implementation of the Greek governmental bonds "haircut". Therefore the question for this sensitivity was finally formed as:

"If the level of the parameter *Stock market value* gets reduced from 40% to 0%, what will be the new state of the concept *Recapitalization by private equity* if now is 20%?". For this example the experts answered 0%. However, measuring the change of the two consequent states of a concept, as a percentage of its initial value gives a better feeling about the strength of the variation. Therefore by applying the Equation 3.9 the resulting sensitivity between the concepts C7 and C6 is:

$$S_{7,6} = \frac{\frac{0-0.2}{0.2}}{\frac{0-0.4}{0.4}} = 1$$

In that way, each expert forms his own sensitivity matrix reflecting his own beliefs about the system's structure and behavior. These sensitivities resemble the total impact a concept accepts by its influencing neighbor. However, the total impact appears only at the end of the system´s simulation where these values are used to weight the change of a concept neighbors at each iteration. Thus, if we want to calculate the impact a concept accepts by its neighbor concepts at each iteration the above sensitivities should be divided by the number of iterations the system needs to converge. So, towards calculating the final sensitivities values, the FCM system is let to "run" until it reaches equilibrium by using this sensitivity matrix along with the already set initial values. At this point, the number of iterations the system needs to converge is regarded as the duration period the system needs to reveal the total impact on each concept. Hence, in order to calculate the effect that each concept receipts per iteration, the sensitivities are divided by that number of iterations (needed by the system to settle to stable values the very first time).

In that way, the weights are set to equally divide the total influential power of a relation into the total number of iterations needed to be expressed leading the concepts to keep their states from exceeding the interval of [0, 1] without the use of any squashing function. Essentially, the containment of the activation values within realistic values is effected from the proper and realistic modeling, and not from any artificially imposed squashing function.

For the Cypriot banking system application, the network needed 10 iterations to converge and thus the values of the sensitivities were divided by 10 (e.g. $S_{7,6}$ = 0.1). These were called “absolute sensitivities”.

3.2.2 – Implementation of the methodology for a real system – The effect of Greek PSI onto the Cyprus Banking System

To implement the proposed methodology in building a real system, the Cypriot banking system and economy system was chosen to investigate the impact sourced from the implementation of the Greek PSI.

Two experts and knowledgeable persons in political and economic fields were pooled to contribute in building an FCM model for investigating the repercussions of two scenarios involving the Greek PSI, on the Cypriot economy and the banking system. The experts complied with the FCM developmental steps as previously described in this work.

In the very first place, the experts had to clearly define the time window of the system they were about to construct. The Greek PSI was completely implemented by March of 2012. The experts decided that it would be interesting to investigate different scenarios for the Cypriot banking system and economy reactions to the Greek PSI immediately after its implementation. Therefore they set the time window for the modeled system to April of 2012.

Table 3. 2: The various influencing parameters that have been studied and their initial values as set by the experts

	CONCEPT NAME	INITIAL VALUE
C1	Cost of Money	50%
C2	Liquidity of Cyprus Banks	60%
C3	Degree of PSI of Greek Government Bonds	0%
C4	Degree of Deposits of Greek citizens and companies in Cyprus Banks	40%
C5	Degree of Deposits of Cypriot citizens and companies in Cyprus Banks	78%
C6	Degree of Success of Bank Recapitalization by Private Equity	20%
C7	Stock Market Value of Banks	40%
C8	Evaluation of the Cyprus Economy by Authoritative Rating Agencies	27%
C9	Confidence of People and companies in Cyprus Banking system	80%
C10	Level of Greek Economic Crisis	80%
C11	Level of Greek workforce that comes to Cyprus for work	60%
C12	Degree of Bank Recapitalization done by the Republic of Cyprus	50%
C13	Level of Cyprus Economy	50%
C14	Probability of the Republic of Cyprus entering EU Support Mechanism	30%
C15	Probability of Cutoff of the Cypriot Bank branches that operate in Greece	20%

According to the proposed FCM building methodology, the next step involves locating the parameters that represent adequately the system to be modeled. After a series of discussions, the experts concluded that they had to use 15 influencing parameters. These are: Cost of Money, Liquidity of Cyprus Banks, Degree of PSI of Greek Government Bonds, Level of Deposits of Greek citizens and companies in Cyprus Banks, Level of Deposits of Cypriot citizens and companies in Cyprus Banks, Degree of Success of Bank Recapitalization by Private Equity, Stock Market Value of Banks, Evaluation of the Cyprus Economy by Authoritative Rating Agencies, Confidence of People and companies in Cyprus Banking system, Level of Greek Economic Crisis, Level of Greek workforce that comes to Cyprus for work, Degree of Bank Recapitalization done by the Republic of

Cyprus, State of the Cyprus Economy, Probability of the Republic of Cyprus entering EU Support Mechanism and Probability of Cut-off of the Cypriot Bank branches that operate in Greece. These are the most significant concepts of the system for testing the repercussions of the Greek PSI when implemented accompanied by sharp downgrading of the Cyprus economy by rating agencies and alternatively with a 100% recapitalization success of Cyprus banks, on the Cypriot banking system in April of 2012 (Table 3.2).

Subsequently, the experts were given a certain amount of time to gather relevant material regarding the system's set parameters. The majority of the collected material was based on various scientific articles, press articles, statistical analysis results and other sources. Afterwards, they spent adequate time to carefully study the collected data and crystallize their apprehension about each parameter's role and meaning. The experts were involved in this procedure of refreshing their knowledge about the specific parameters of the system in order to be updated about the parameters' details and precision in setting their initial values and their interconnection sensitivities. As a result by the end of the FCM building phase, a table with fifteen parameter definitions, measure units, minimum, maximum values and the actual values for the time period defined as well as the estimated degree of variation was created. The aforementioned characteristics are presented for a sample of parameters in Table 3.1.

Using this table as a reference and having in mind the specific time period that the modeled system is positioned, which was April 2012, the experts decided on the initial value of each concept. The calculation of the initial state values of the concepts was illustrated as reported in preceding sections of this study.

Along with the table describing a general outline of each parameter, the experts also provided the corresponding references to the press articles and other relevant information for documenting and supporting their initial state estimations. The initial values describing the states of the concepts as they were in April of 2012 are also given in Table 3.2. Nevertheless, it is important to note that there are some parameters which are too complex to be objectively quantified, analysed and described based on raw numbers. An example of such a parameter is the concept *Confidence of people and companies in the Cyprus banking system*. This parameter cannot be actually measured using a known metric system but rather an expert with socio-economic knowledge and experience can estimate by instinct the trends for this parameter. A different example of these concepts is the *State of Cyprus Economy* which encompasses characteristics like GDP, unemployment rate, housing, Consumer Price Index, stock market prices, industrial production, etc. In such cases the experts had to define the state of the concept based only on their “feeling” and their understanding of the dynamics of the system.

Table 3. 3: FCM adjacency matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1	0	0.04	0	0.13	0.01	0	0	0	0	0	0	0	-0.10	0	0
C2	-0.06	0	0	0	0	0	0.08	0.10	0.08	-0.01	0.03	0	0.12	-0.13	-0.40
C3	0	-0.10	0	0.04	0	0	-0.15	-0.11	-0.08	-0.08	0	0	-0.12	0.10	0.45
C4	0	0.13	0	0	0	0	0	-0.40	0.10	0.05	0	0	0.08	0	0
C5	0	0.09	0	0.05	0	0.10	0.03	0	0.03	0	0	0	0.02	0	-0.21
C6	0	0	0	0	0	0	0.05	0.03	0.03	0	0	0	0.01	0	-0.05
C7	0	0	0	0.01	0.01	0.13	0	0	0.03	0	0	0	0	0	-0.03
C8	0	0	0	0.07	0.02	0.07	0.13	0	0.05	0	0.08	0.08	0.03	-0.09	-0.07
C9	0	0.09	0	0.13	0.03	0.07	0	0	0	0	0.07	0	0.05	0	0
C10	0.24	-0.07	0	0.15	-0.04	-0.40	-0.30	-0.20	-0.20	0	0.13	-0.16	-0.24	0.53	0
C11	0	0	0	0.08	0	0	0	0	0	0.04	0	0	0.06	0	0
C12	0.04	0.03	0	0	0	0	0.05	0.04	0.01	0	0	0	-0.02	0	0
C13	-0.07	0	0	0.11	0.05	0.08	0.04	0.13	0.04	-0.02	0.11	0.10	0	-0.28	0
C14	0	0.01	0	-0.01	-0.01	-0.02	-0.02	-0.01	-0.01	0	-0.01	0.02	0.01	0	0
C15	0	0.01	0	0.04	0.00	0.05	0.05	0.03	-0.01	0	0	0	0.01	-0.02	0

The final stage of the proposed FCM construction methodology was about setting the sensitivities of links between the concepts. Therefore, each expert had to go through the process of calculating the sensitivities amongst the causal relationships of the systems. The whole process was implemented through expert-computer interaction. The expert was set in front of a computer screen. For each possible interrelation of the system the computer screen presented to the expert the initial value of the potential affecting concept and how this is altered after applying the corresponding degree of variation (a factor of the table the experts created during prior construction phase). The computer also presented the initial value of the potential affected concept and right after the expert was asked to give the resulting new activation value of the potential affected concept. For each interrelation, the experts inserted their own estimations and the computer automatically calculated their sensitivities using the formula given by Equation 3.9.

As a result each expert created his own sensitivity matrix. Inevitably, there were some discrepancies between the values given by each expert. Eventually, the average of the sensitivities was used to form the final sensitivity matrix which is presented in Table 3.3.

3.2.3 – Results – Scenario Analysis

Two different scenario cases were characterized by the experts as interesting and hence they were implemented and tested using FCM technology as described in previous sections. The first scenario involved observing how a 75% loss of value due to the Greek PSI (concept C3) and a step decrease into the parameter describing the evaluation of the Cyprus economy by credit rating agencies (concept C8) affects the remaining parameters of the system. In this case, the concepts annotated by C3 and C8 comprise the concepts of interest of the first scenario. The second scenario aimed at investigating the effects of a

75% Greek PSI (C3) along with a 100% Cypriot bank recapitalization by private equity (C6) done in parallel. Accordingly, the concepts of interest are the C3 and C6 for the second scenario.

For the FCM simulation purposes, the average sensitivity values of the concepts' interrelations given by the experts were used as shown in Table 3.3. For each scenario the initial values of the system's parameters were set as defined by the experts as shown in Table 3.2. Thereafter, the new altered initial values of the concepts of interest were introduced to the system. For example the initial value of the concept *Degree of success of bank recapitalization by private equity* (C6) given by the experts was 20%. In order to implement the second scenario, the corresponding concept of interest initial value was altered to 100%.

Additionally, the values of the concepts of interest were "locked" in such a way that they would not being further changed during simulation period as a result of interference with their causality neighbors but rather remain constant. Hence, in the context of the second aforementioned scenario, the state value of the concept C6 would remain 100% through the whole process of simulation.

The rest of the parameters were let free to interact through causality paths using the update rule presented in Equation 3.4, leading the system to an iterative behaviour until it converged to steady state value. That means until the concept state vector was the same between two consecutive iterations. The values of the steady state concept vector were taken as the future response of the modeled system to the actions implemented in the concepts of interests.

However, when working with an FCM model the actual final values of the concepts are not the objective but rather the trends. This is what a decision maker usually wants in order to make substantial conclusions and take decisions over them. That is why the main purpose of using FCM technology is the qualitative analysis and modeling of the dynamics of the system which includes tendencies and the directions of changes of the concepts' values under the study of specified scenarios. Hence, the absolute values are rather meaningful for the system's analysis whereas the relative changes are the ones which can shed some light on the decisions needed to be made. That is why in the figures of this work, the percentage change between the final state value of the concepts and their corresponding initial values, which happened in response to a certain scenario implementation, are presented. The various changes and associated trends that have been investigated in the context of this study are shown in Figures 3.1 – 3.5 so that they will be more readable and clear to the reader. The results regard the simulations of the two scenarios, as described above. In all of the figures, the horizontal axis exposes the parameter names. The vertical axis is showing the resulting percentage changes in the system's parameters lying in the horizontal axis, which are due to the implementation of the two aforementioned scenarios.

Finally, the effects of the Greek PSI in combination with an abrupt downgrade of Cyprus economy by credit rating agencies are compared to the effects of the Greek PSI when followed by a 100% Cypriot bank recapitalization by private equity. The first scenario actually happened, since in reality the three rating agencies proceeded to successive downgrades of Cyprus economy right after the implementation of the Greek PSI. As the experts expected, the impact of this scenario on Cypriot economy and banking system was negative. The second scenario did not happen in reality. However the experts expressed their confidence that such a scenario would have overall a positive impact on the Cypriot banking system. That is why the experts expressed the desire of a comparison between the two scenarios, a scenario that was actually implemented with negative character and another that they thought it would be beneficial for Cyprus banking sector but didn't happen.

Therefore, to implement the first scenario which was a real scenario, the desired value of Greek PSI (C3) and the value of the *Evaluation of the Cyprus Economy by Authoritative Rating Agencies* (C8) parameter were "locked" to 75% and 27% respectively. The position of the initial value of C8 was not arbitrary. On the contrary, the experts collected information from the official sites on Cyprus sovereign ratings a short period before Greek PSI and a short period after. By examining the gathered data, it seems that Cyprus economy was downgraded by approximately 66% by the authoritative rating agencies in a short time distance. Therefore, the same scale of downgrading was applied into C8 parameter of this system.

To implement the second scenario, which was hypothetical, the desired values for the concepts of interest were locked to 75% for the Greek PSI concept and 100% for the *Degree of Bank Recapitalization by private equity.*

At first glance, it is clearly obvious that the factors of the system become more unfavourable for Cyprus economy and banking sector when the Greek PSI is illustrated followed by a sharp downgrading.

The Greek government, which seems to benefit from PSI since the level of the Greek crisis decreases to a small degree, remains unaffected by a strong downgrading as well as by a successful banking recapitalization since the difference between the two results is close to zero. However things are different when comes to the Greek workforce coming to Cyprus for work factor, which gets a further decrease when the downgrading of Cyprus economy accompanies the implementation of the Greek PSI.

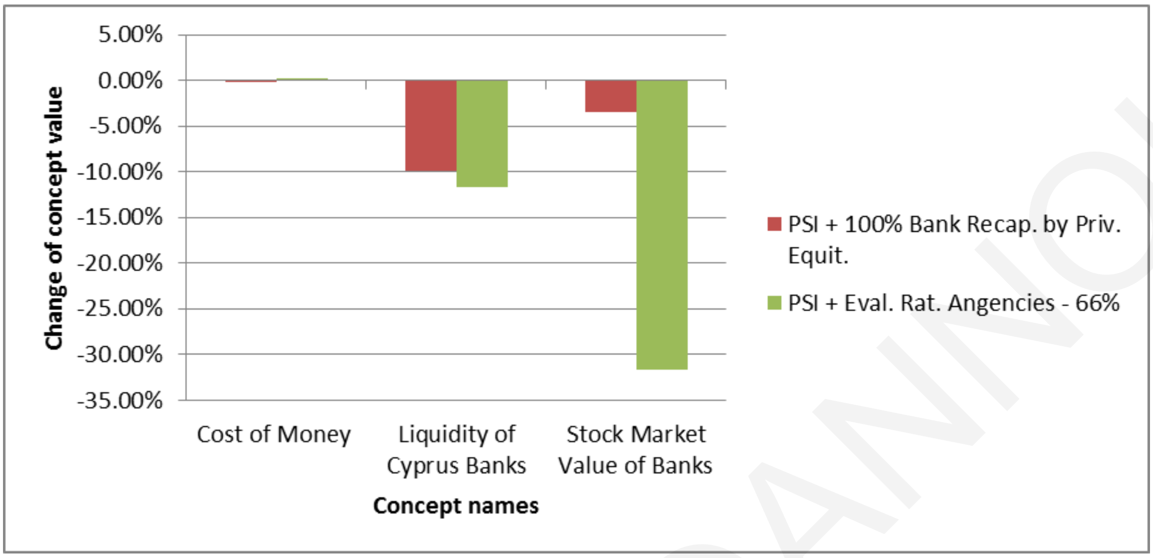

Figure 3. 1: The impact of the two implemented scenarios on various parameters

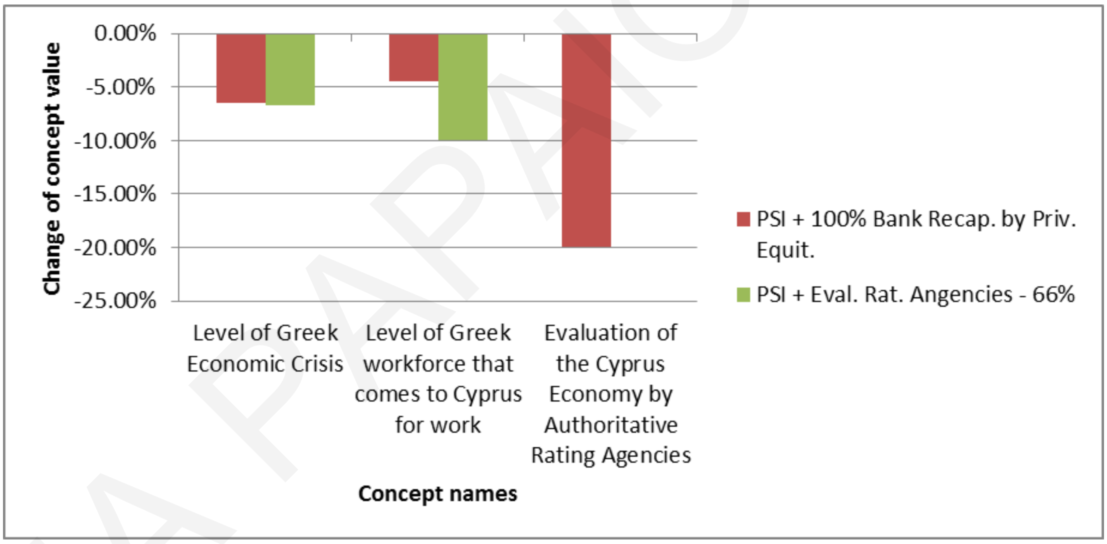

Figure 3. 2: The impact of the two implemented scenarios on various parameters

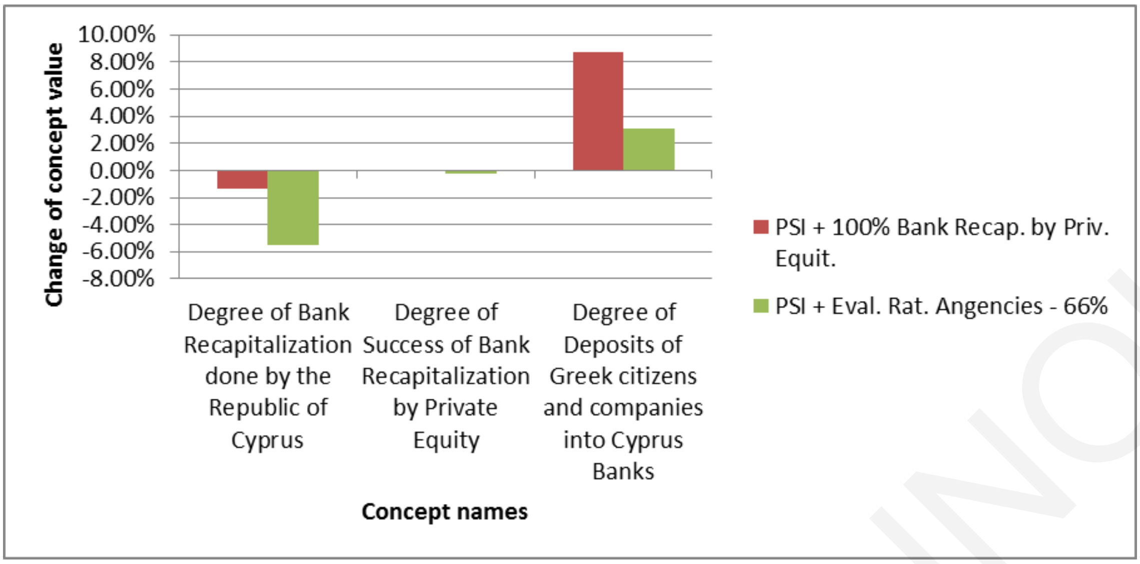

Figure 3. 3: The impact of the two implemented scenarios on various parameters

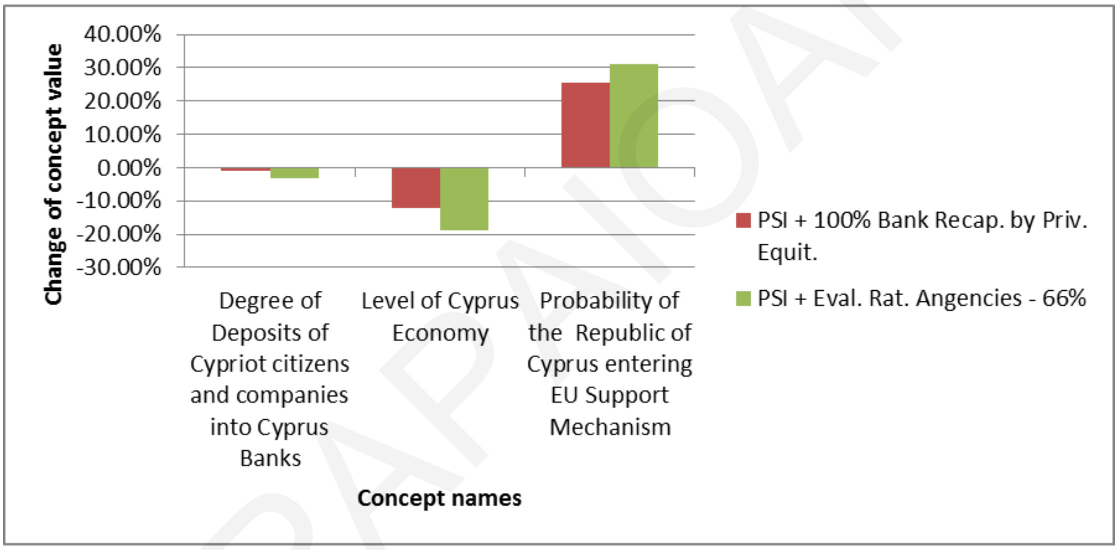

Figure 3. 4: The impact of the two implemented scenarios on various parameters

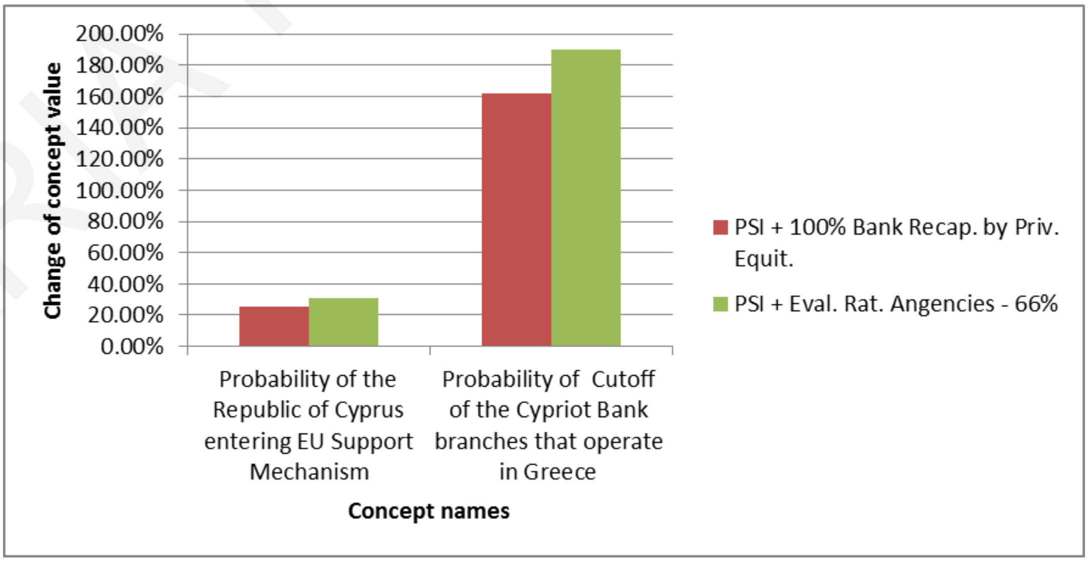

Figure 3. 5: The impact of the two implemented scenarios on various parameters

Furthermore, the State of the Cyprus economy is negatively affected as a response to both scenarios, though less severely when the capitalization scenario is tested. This result can be justified since during the period that this system was modeled, the Cyprus economy was facing other internal fiscal and economic problems. Thus, a steep downgrading could only create even more problems whereas the Cypriot bank recapitalization could not by itself solve all these problems.

In addition, since the rating agencies aim at informing certain people about the business and investors community on the financial health of a country, the downgrading of the Cyprus economy strongly decreases the confidence of the people and companies to the Cypriot banking system. On the contrary, when the Greek PSI is accompanied by the Cypriot banks recapitalization the parameter *Confidence of People and Companies in Cyprus Banking System* is slightly increased.

However, the liquidity of the Cypriot banks does not seem to be substantially affected by any of the two scenarios even though banks are supposed to attract extra capital in the recapitalization scenario.

Furthermore, the flow of Cypriot deposits abroad is slightly increased in both cases although in the case where a successful bank recapitalization happens, the flow is more limited. Similarly, Greek deposits in Cyprus exhibit a higher increase in the case of the combination of Greek PSI and private bank recapitalization. The change in the cost of money remained to the same levels for both scenarios.

Along with that, the stock market value of banks exhibits a much higher decrease for the first scenario when compared to the second. Since the Cypriot economy is weakened by the losses caused by the Greek PSI (losses that were equivalent of 20% of Cyprus annual GDP) the probability of the Republic of Cyprus applying for EU Support is elevated in both scenarios. Also, the Probability of a cut-off of the Cypriot bank branches in Greece shows an increase by more than 150% in both scenarios.

3.2.4 – Sensitivity analysis of the results

In order to analyse the sensitivity of the final results for the inaccuracies of the weight values given by the experts, some extra simulations of our system were ran. To do so, we chose to alter by [-20%, -15%, -10%, -5%, +5%, +10%, +15%, +20%] the weights of the interconnections related to the concept of interest "C9: People's confidence towards the Cyprus banking system". It is important to note that the altered weights constitute the 28% of the whole set of interconnections. Then, we ran the same scenarios, as presented above, with the new adjacency matrices.

The results, which are presented in Figure 3.6 and Figure 3.7, are encouraging since for the maximum change on the weights (~20%) the values of the stable states of the most of the concepts were changed by less than 10%. Hence, the trends presented in the final states of the concepts are approximately still the same.

The concepts that presented a higher than 10% change into their final converged states are: Cost of Money, Degree of Deposits of Greek Citizens and Companies in Cyprus Banks, Degree of Deposits of Cypriot Citizens and Companies in Cyprus Banks, Degree of Success of Bank Recapitalization by Private Equity, Level of Greek Workforce that Comes to Cyprus for Work.

However, the experts noted that these parameters are strongly and directly dependant by the people's confidence towards the Cyprus banking system and therefore it was expected that these parameters to be more sensitive to changes regarding the concept of interest C9. Concluding, possible small inaccuracies that might happen during the weights estimation would not alter greatly the results.

3.3 Discussion of the results with the experts

Several interesting conclusions were drawn from the outcomes of the two tested scenarios when discussed with the participating experts. The results on the Confidence of People and Companies in the Cyprus Banking System are noteworthy since the parameter displays different behavior as a response to the two scenarios. More analytically, when the Cyprus economy is downgraded after the Greek PSI implementation, the confidence of the people and companies in the Cyprus banking system is significantly decreased. Reversely, when the Cypriot banks are 100% recapitalized by private equity along with the implementation of a 75% Greek PSI, not only the confidence of people and companies in Cyprus banking system does not decrease but appears slightly increased. Based on this observation, the experts noted that a Cypriot banks recapitalization by private equity would have had a strong impact on the recovery of people´s trust towards the banking system. The Stock Market Value of Banks is another parameter with interesting behavior triggered by the two implemented scenarios. Although in both cases, the parameter activation value is decreased, the change happens to a different extent. Particularly, in the case when the Greek PSI is happening in parallel with a decrease in the ratings of the Cyprus economy, the stock market value of the banks appears to fall by 30% whereas when the Greek PSI is followed by a successful recapitalization of the Cypriot banks the fall is limited to less than 5%.

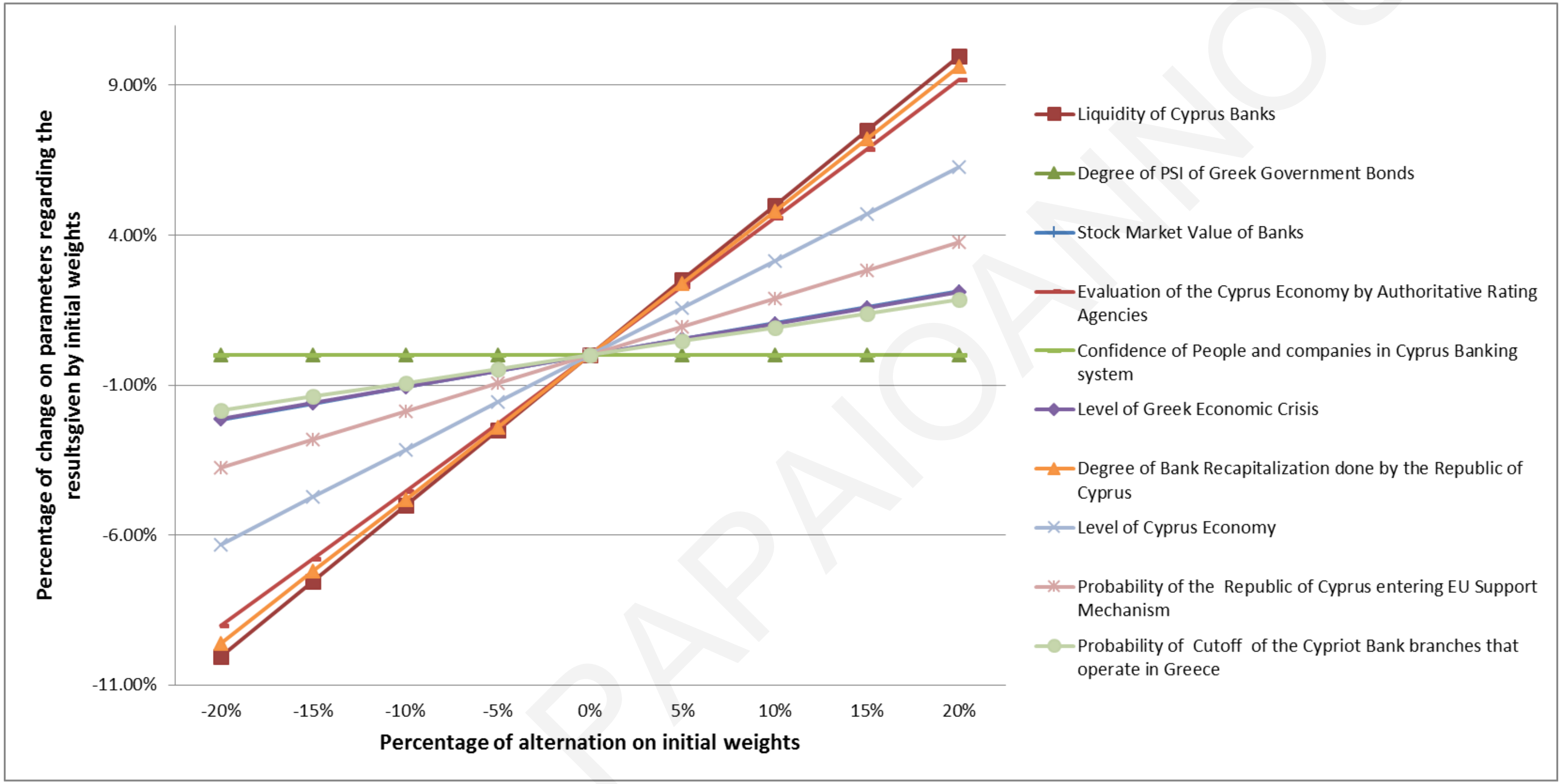

Figure 3. 6: The percentage of the change on the system´s parameters final states when the weights are changed by [-20%, -15%, -10%, -5%, +5%, +10%, +15%, +20%] regarding the final concept states given by the same scenario with the initial weights.

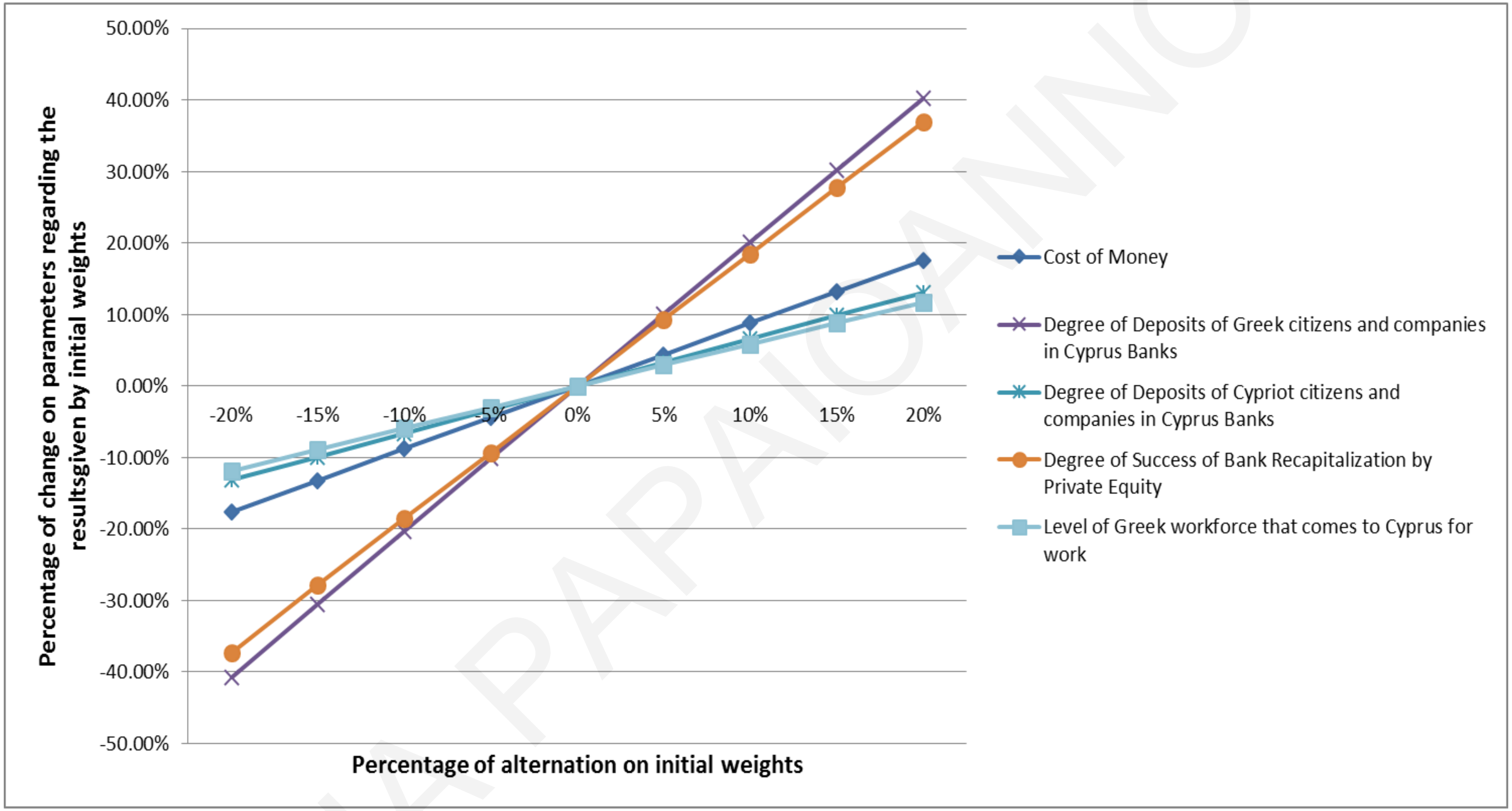

Figure 3. 7: The percentage of the change on the system´s parameters final states when the weights are changed by [-20%, -15%, -10%, -5%, +5%, +10%, +15%, +20%] regarding the final concept states given by the same scenario with the initial weights.

These two parameters, the Confidence of People and Companies to the Banking system and the Stock Market Value of Banks, strongly indicate that banks would have been in much better position, had they managed to achieve recapitalization through private funds. This is confirmed by the results of the system regarding the level of deposits coming from Greek and Cypriot citizens and companies in Cypriot banks and also level of Greek workforce coming to Cyprus for work. The system predicts a 50% smaller decrease in Greek workers seeking work in Cyprus when the banks succeed in recapitalizing compared to the scenario in which the Cyprus economy is severely downgraded. At the same time, the reduction in the flow of deposits of Cypriot citizens and companies into Cyprus banks when the bank recapitalization happens is the one third of the corresponding reduction in the case of the intense downgrading of Cyprus economy, though it has to be said that absolute values of the changes to these parameters are small.

Additionally, the parameter Evaluation of Cyprus Economy by Credit Rating Agencies is of particular interest. In the context of the scenario where the Greek PSI is done and at the same time the banks achieve their recapitalization by private equity, Cyprus rating is cut by 20%. In reality though, based on the mapping of the agencies´ metric system in the range of [0, 100] the decrease of the ratings of Cyprus was 66%. Thus, the successful recapitalization of banks by private equity would have acted as an ameliorating factor in terms of Cyprus ratings cuts.

Overall though, the parameter which exhibited the largest scale impact was the Probability of cut-off of the Cypriot bank branches that operate in Greece. A higher than 150% increase of this parameter was observed in both scenarios. Evidently, the probability avoiding the cutting off of the Cypriot branches in Greece would have remained low regardless of the scenario. Such probability is significantly increased in either the case the Greek PSI is implemented along with a successful bank recapitalization or with a strong downgrading of the Cyprus economy. In other words, the results of the modeled system state that the probability of cutting off the Cypriot bank branches that operate in Greece is mostly unaffected by the intense downgrading of Cyprus economy as well as by a successful bank recapitalization by private equity. This observations lead to the remark the Cypriot banking system could not escape from the decision of selling the Cypriot bank branches in Greece. In fact, in March of 2013 the Marfin Popular Bank and the Bank of Cyprus, the two largest banks in Cyprus, were forced to sell their branches in Greece. Thus, the system revealed the existence of strong causal paths connecting the concept of the Greek PSI and the Probability of cut-off of the Cypriot bank branches that operate in Greece.

Analogous conclusions can be drawn about the parameters, State of the Cyprus Economy and Probability of the Republic of Cyprus entering the EU Support Mechanism. Specifically, these parameters presented adverse responses to both scenarios. The state of the Cyprus economy deteriorates by 12% in the PSI plus successful recapitalization scenario and 18% in the PSI plus 66% downgrading scenario. Similarly, the probability for Cyprus entering the EU Support Mechanism appears to increase by 22% and 30% respectively in these scenarios. Hence, it can be argued in conformity with the modeled system, that the Greek PSI implementation was a significant factor in Cyprus having to ask for EU mechanism support. On the other hand, the results indicate that recession in Cyprus would have been milder, had the banks manage to replenish their lost capital through private sources.

3.4 Experimentation with other activation functions

As stated in a previous section of this chapter, the activation function presented in Equation 3.4 has been proposed as a more appropriate method of modeling causal integrations in social, political and economic systems. For this category of systems, FCMs are often used to analyze expressed trends in the concepts. Thus, the proposed activation function allows the effects to be calculated as trends to create the impact percentage which is finally aggregated with the earlier state of each concept.

It is interesting though to test how a different choice of activation functions may affect the results of a modeled system. For that reason, two of the most popular activation functions which also use self-causation were used to model four scenarios which were also simulated by the proposed activation function in Equation 3.4. It is true that one cannot reach to general conclusions about the usefulness and the efficiency based on the results given for a limited number of scenarios about the same system. However, it is difficult to design and implement a big number of such systems since the experts and the FCM handler must spend lot of amount of time to provide qualitative modeling for each system. Hence, this comparison is only done to show that the selection of an activation function might comprise the key of a good modeling schema based on what the FCM handler and the experts are asking for. For the modeled system, the objective was to model a social system in order to study the trends expressed in its concepts under different scenarios.

The three activation functions used for this purpose are Equation 2.12, Equation 2.13 and Equation 3.4. The modeled system is the same described in previous sections of this chapter (The Cypriot banking sector and economy). Then, four scenarios were implemented including the parameters of *Greek PSI* (C3) and *People's Confidence to the Cypriot banking system* (C9). According to the scenarios, a 75% Greek PSI was introduced to the system along with a gradual decrease in the level of confidence of people to the Cypriot banking system by 0%, 25%, 50% and 75%. During simulations, the changed values of the concepts of interest were "locked" in such a way that they would not be further changed during the simulation period as a result of interference with their causality neighbors, but rather remain constant. Hence, in the context of the first aforementioned scenario, the state value of the concept of Greek PSI would remain 75% through the whole process of simulation.

In the beginning, the Equation 2.12 and Equation 2.13 were used without the use of any transformation function. However, by using these two activation functions, the system exhibited chaotic behavior in all scenarios since it could never converge to a stable state. The Figures 3.8 and 3.9 depict this behavior of the system for the first scenario (only Greek PSI implemented and no decrease in people's confidence) for the Equations 2.12 and 2.13 respectively. Similar figures were produced by the network for the other three scenarios. The simulations were repeated allowing the network to reach 1000 iterations but still the concept states just kept increasing or decreasing, showing no stabilization to a steady state.

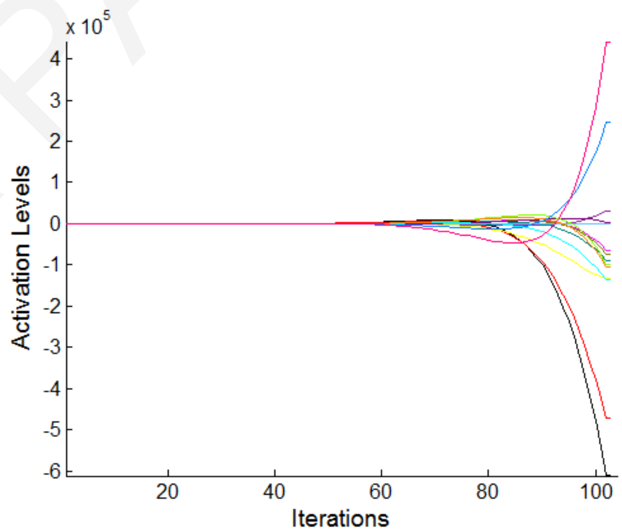

Figure 3. 8: Concept States per iteration using Equation 2.12 with no transformation function

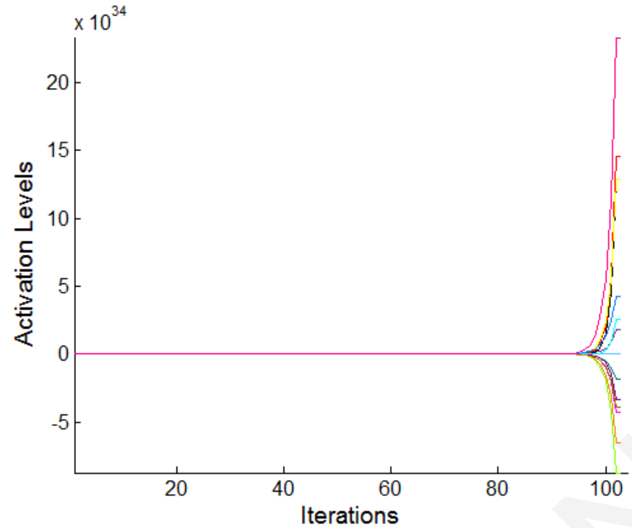

Figure 3. 9: Concept States per iteration using Equation 2.13 with no transformation function

The scenarios were simulated again using the same activation functions with the use of the sigmoidal transformation function as suggested by the authors who proposed these two activation functions. The scenarios were also implemented on a system using the Equation 3.4 as an activation function. The results of the three different systems under the four scenarios are presented in Figures 3.10-3.21. For the convenience of the reader the parameters of the system were divided into four groups. In that way, the results are more clearly presented and the reader can compare the results per parameter and make his/her own conclusions.

The first group (*Group 1*) includes the parameters *Cost of Money*, *Liquidity of Cyprus Banks*, *Stock Market Value of Banks* and *Level of Greek Economic Crisis*. The Figures 3.10 – 3.12 are related to the parameters of *Group 1*. The two most important results are given by the parameters *Liquidity of Cyprus Banks* and *Stock Market Value of Banks*. For these specific parameters, the activation function proposed in this work provides an obvious scaled decreasing trend for the four scenarios. For the same parameters, Equation 2.12 presents equally increasing trend. Equation 2.13 agrees with Equation 3.4 about the decreasing trend in *Liquidity of Cyprus Banks* but then again it presents a highly increasing trend in *Stock Market Value of Banks.* However, not only it is logical that the implementation of the Greek PSI and a decrease in people’s confidence to the banking sector will cause a negative effect on the stock market value of Cypriot banks but later history verified the results given by Equation 3.4. Thus, although Equation 2.13 seems to give more consistent results regarding the parameters of this group compared to Equation 2.12, it seems to lack the power to capture the negative effect presented in the parameter *Stock Market Value of Banks.*

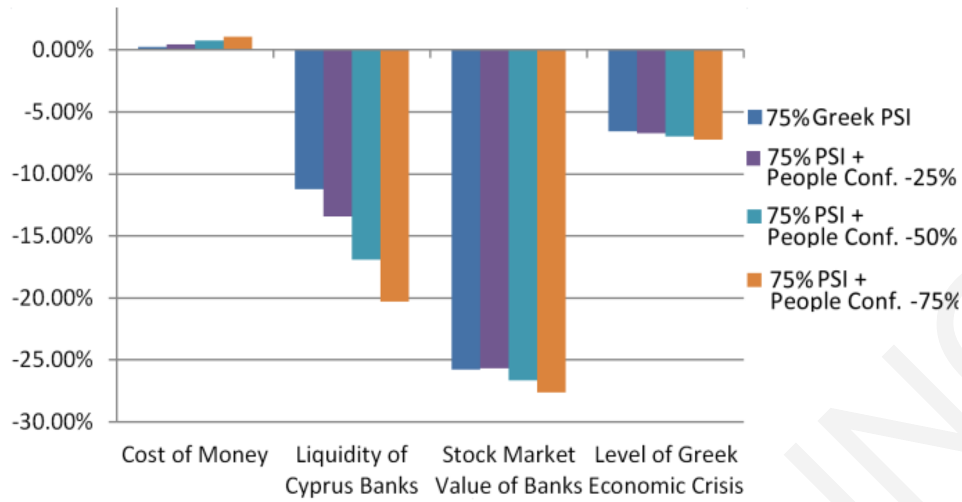

Figure 3. 10: Results for the 4 scenarios for *Group 1* parameters using Equation 3.4

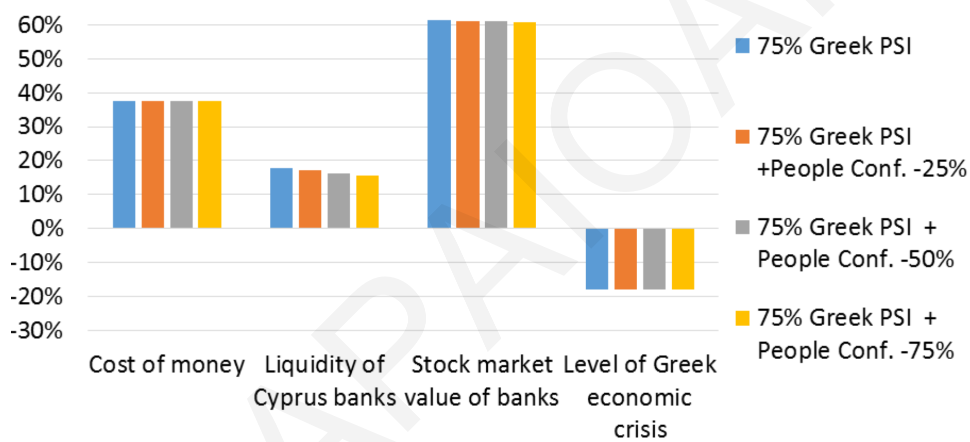

Figure 3. 11: Results for the 4 scenarios for *Group 1* parameters using Equation 2.12

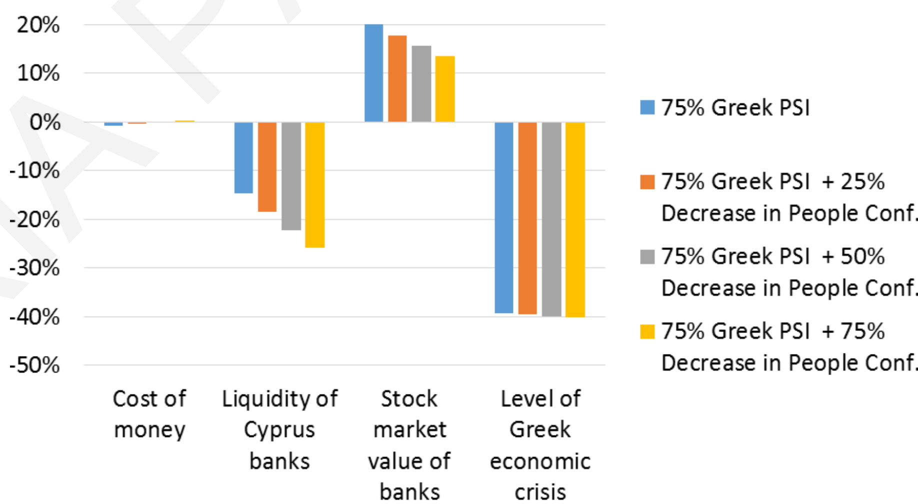

Figure 3. 12: Results for the 4 scenarios for *Group 1* parameters using Equation 2.13

The second group (Group 2) involves the parameters *Evaluation of the Cyprus Economy by Authoritative Rating Agencies, Degree of Bank Recapitalization by the Republic of Cyprus* and

Degree of Bank Recapitalization by Private Equity. The relevant results to this group are presented in Figures 3.13-3.15. The result which gains the most interest for this group regards the parameter *Evaluation of the Cyprus Economy by Authoritative Rating Agencies*. The system using Equation 3.4 presents a highly decreasing trend for this parameter where the systems using the other two activation functions exhibit extremely high increase! The results are very contradictive. But again, the reality verifies the system using the Equation 3.4 since a series of downgrades of the Cyprus economy followed after the implementation of Greek PSI.

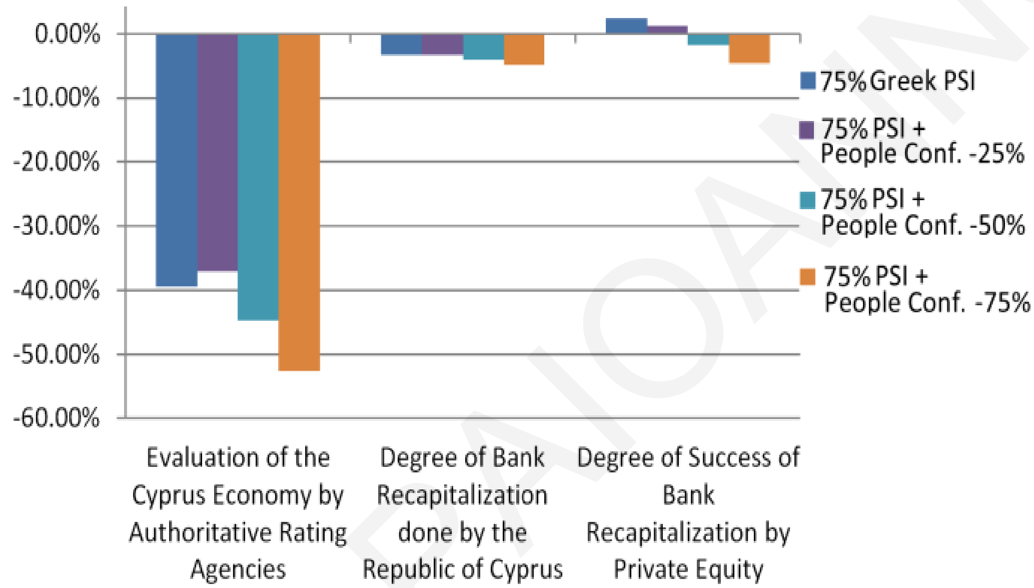

Figure 3. 13: Results for the 4 scenarios for *Group 2* using Equation 3.4

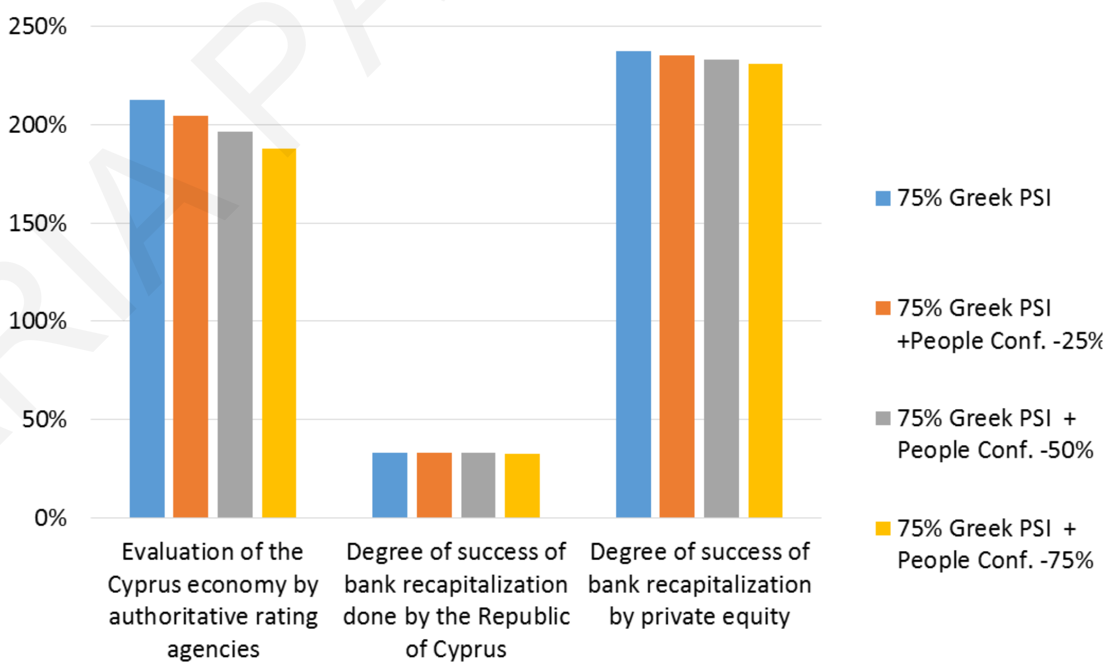

Figure 3. 14: Results for the 4 scenarios for *Group 2* using Equation 2.12

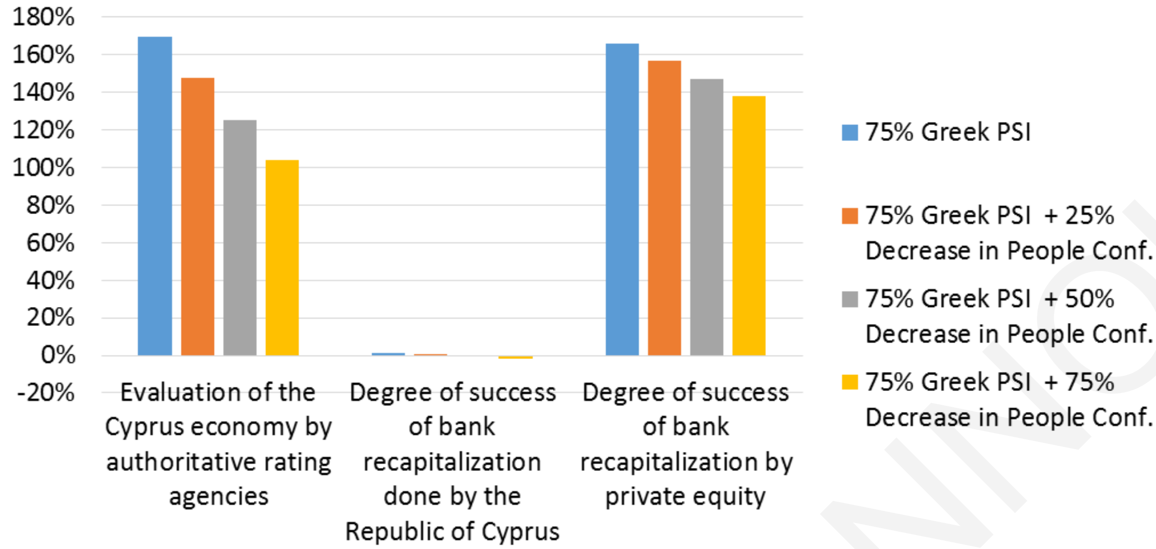

Figure 3. 15: Results for the 4 scenarios for *Group 2* using Equation 2.13

The parameters *Level of Greek Workforce that Comes to Cyprus for Work*, *Degree of Deposits of Greek Citizens and Companies into Cyprus Banks*, *Degree of Deposits of Cypriot citizens and Companies into Cyprus Banks* and *Level of Cyprus Economy* belong to the third group (*Group 3)*. Their trends presented for each scenario are shown in Figures 3.16-3.18. As in previous groups, the system using Equation 212 exhibits a totally opposite behavior from both of the other systems for the most of the parameters. Nevertheless, the other two systems have a strong disagreement regarding the parameter *Degree of Deposits of Greek Citizens and Companies into Cyprus Banks*. The system using Equation 3.4 exhibits a small increasing trend for the two first scenarios (no decrease in people's confidence and a 25% decrease) but as the people's confidence gets further reduced, a decreasing trend is expressed in the particular parameter. The particular phenomenon is not depicted in system 2 which presents a high increase for all of the scenarios. However, again, in reality only a small increase was observed in this parameter after the implementation of Greek PSI, according to the experts.

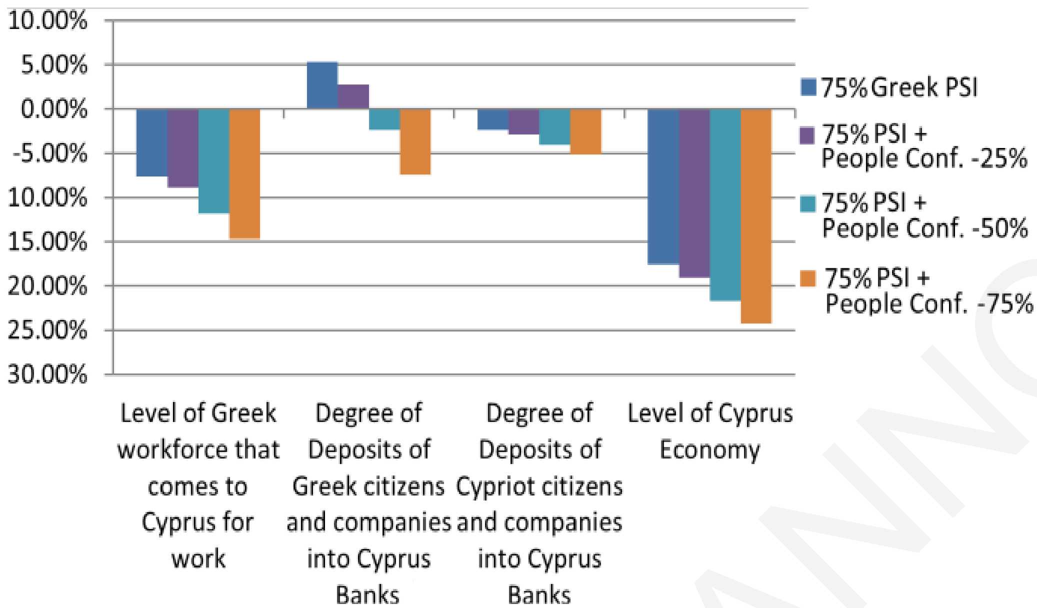

Figure 3. 16: Results for the 4 scenarios for *Group 3* using Equation 3.4

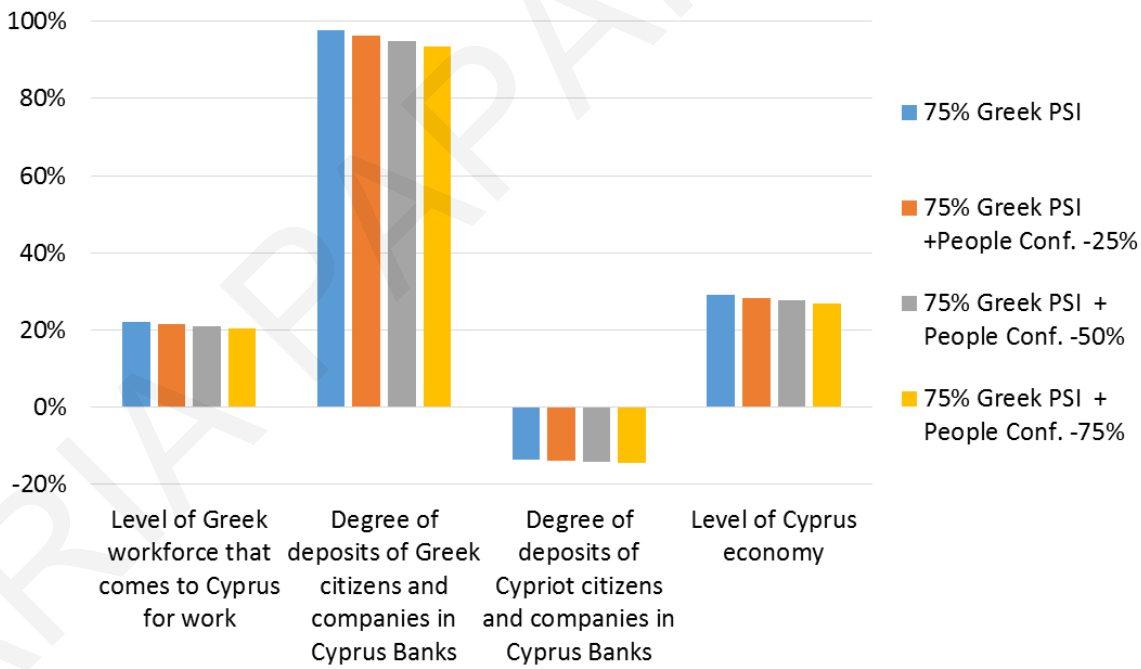

Figure 3. 17: Results for the 4 scenarios for *Group 3* using Equation 2.12

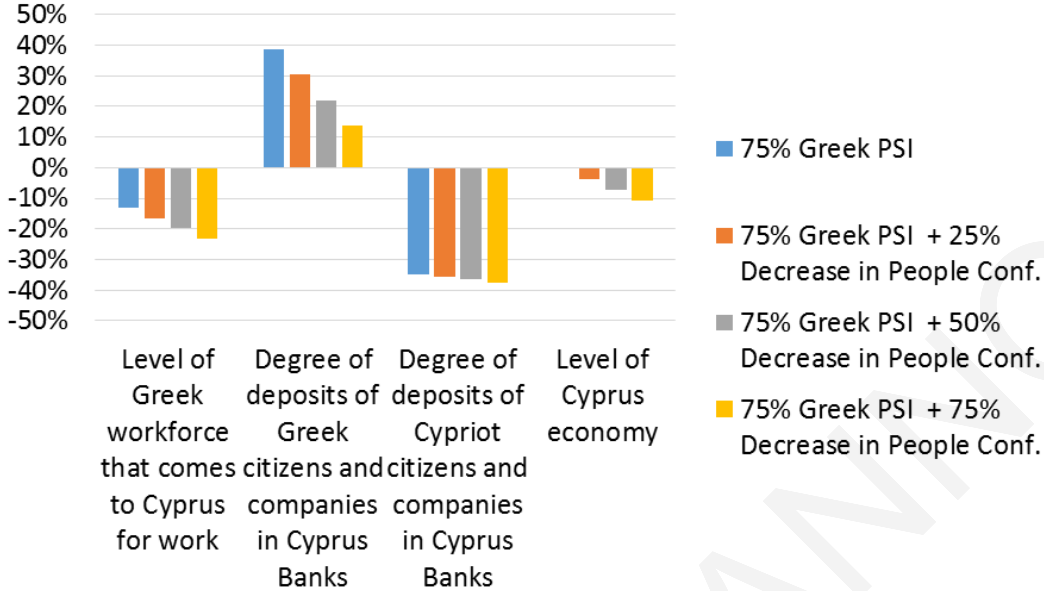

Figure 3. 18: Results for the 4 scenarios for *Group 3* using Equation 2.13

Finally, the last group (*Group 4)* concerns only two parameters, the *Probability of the Republic of Cyprus entering EU Support* and the *Probability of Cutoff of the Cypriot Bank Branches that Operate in Greece.* The results regarding these two parameters are presented in Figures 3.19-3.21. The only thing which is notable for the results provided by this group of parameters is that all the three systems agree on the direction of their trends. Thus, no further comment can be made.

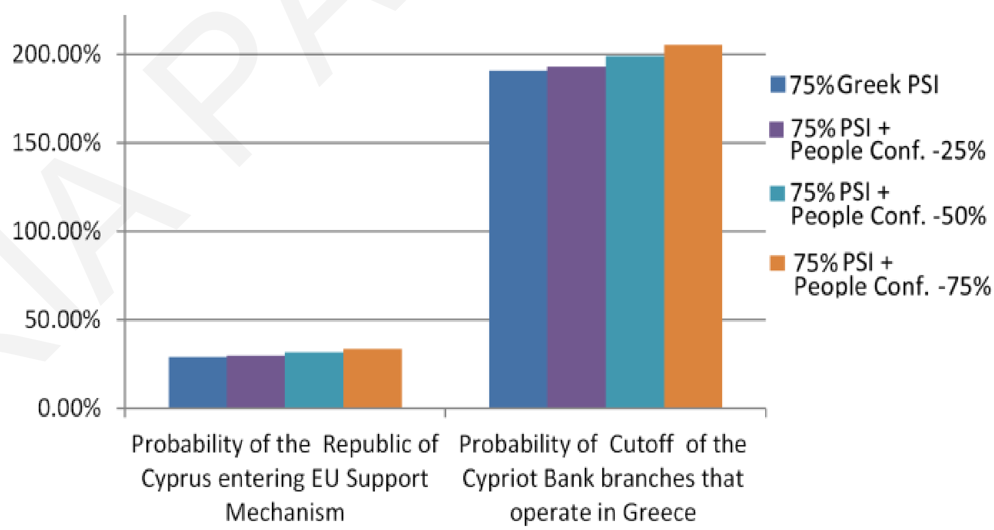

Figure 3. 19: Results for the 4 scenarios for *Group 4* using Equation 3.4

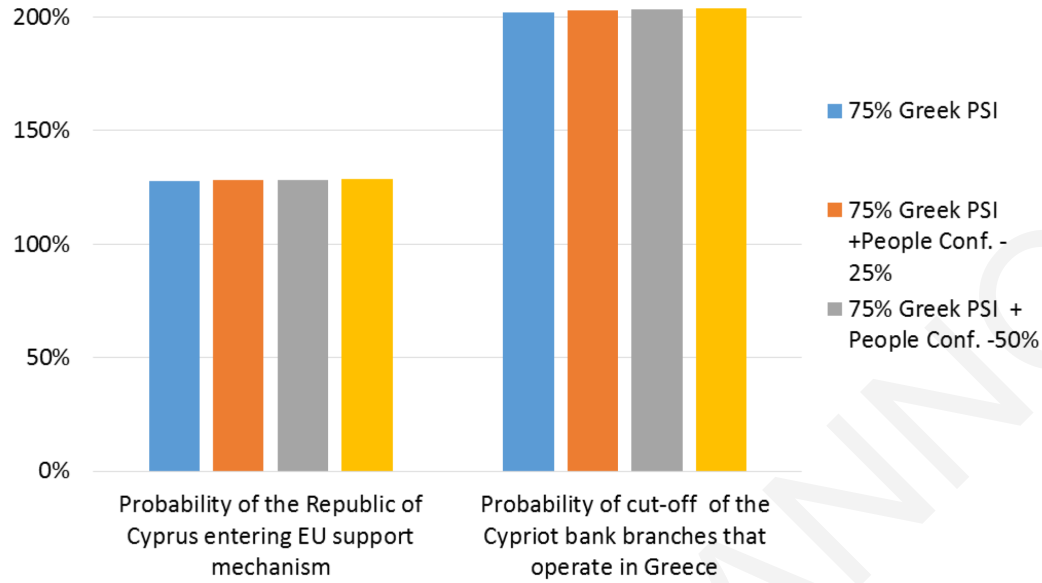

Figure 3. 20: Results for the 4 scenarios for Group 4 using Equation 2.12

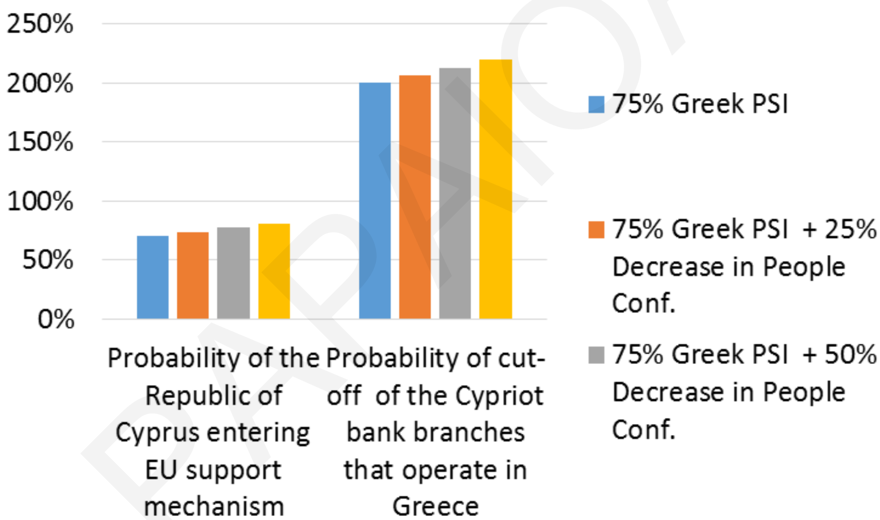

Figure 3. 21: Results for the 4 scenarios for Group 4 using Equation 2.13

In general Equation 2.12 failed to capture the obvious trends under the implementation of the four scenarios presenting equal trends for all of the scenarios almost for every parameter of the system. Not only that, but for the most of the parameters the particular system provided increasing trends something which was in contradiction with what actually happen to the system in reality. Equation 2.13 presents much more sensible results related to the modeled system. However, for some parameters the results were strongly contradictive with the results provided by the system using Equation 3.4 and with what actually was implemented in reality after the implementation of the Greek PSI. Namely, these parameters are the *Liquidity of Cyprus Banks (Group 1)*, the *Stock Market Value of Banks (Group 1)*, the *Evaluation of the Cyprus Economy by Authoritative Rating Agencies (Group 2)*, the *Degree of Success of Bank*

Recapitalization by Private Equity (Group 2) and the *Degree of Deposits of Greek Citizens and Companies into Cyprus Banks (Group 3).*

As stated in the beginning of this sub-section, no general conclusion can be drawn based on the comparison given above between the three activation functions. The only safe conclusion to be made is that for the specific modeling social, political and economic problem the proposed activation function given in Equation 3.4 seems to give more consistent results with what actually happened in reality. This fact is encouraging about the usefulness of the proposed activation function especially for the modeled system since we could not have these results by using the other two activation functions.

3.5 Comment on this work

FCM models can act like decision-making indicators helping the handlers of the modeled system to consider all relevant impacts when taking a certain action on their system. In this framework, a novel FCM methodology has been proposed as regards to the proper identification, definition and initialization of the concepts and sensitivities, as well as on the updating rule. The proposed methods have been applied on a real system taken from Cypriot reality modeling a complicated, up-to-date with high interest problem of that period regarding the states of Cypriot economy and Cypriot banking sector.

The conclusions by experts presented in Section 3.3 verify the interpretability of the model. The experts admittedly stated that they could easily understand the results of the network and express their opinion on them. The experts could easily draw the trends of the system under the implementation of each scenario.

However, it is important to mention that the target of FCM modeling is not to reproduce the predictions or the beliefs of the experts regarding the final outcome of the simulation of a modeled system. The target of using FCM technology, especially in the social and political domain, is to exploit the experts' knowledge about how the causal interrelations work locally, to give the aggregated, gross and dynamic causal behavior of the system under the implementation of a specific scenario. Thus, there might be cases for which the experts will have disagreement with the results presented by the network. Actually, the experts who participated in constructing the proposed Greek PSI system expressed their disagreement with the result presented in parameter *Probability of Cutoff of Cypriot Bank Branches that Operate in Greece.* The particular parameter was an initiator of a discussion with the experts since, back in that time they insisted that the high increasing trend presented to that parameter was excessive. As they stated, although it was a potential scenario (cutting of Cypriot bank branches in Greece), the probabilities of reaching to that point were very limited. Few months later though, the system was fully confirmed in reality since in March of 2013, the Marfin Popular Bank and the Bank of Cyprus, two of the largest banks in Cyprus, sold their branches to Piraeus Bank of Greece. So, it is quite impressive that the same people, who gave their knowledge to build the system, disagreed with its outcome, just to be verified almost a year later. The above example signifies the fact that humans can learn and understand the causal relations between the concepts but may lack the ability of simulating how causality flows and aggregates through causal paths created in the system's network. This is the contribution of using FCMs in such cases to approach such complex problems.

When a real system is modeled under the guidance of human experts only, allowing time verifying the "prognostic" results is probably the only way for the modeled system to gain some kind of credibility. Thus, it is important to highlight that most of the trends presented by the modeled system as a response to the aforementioned scenario, were also implemented in real life with the parameter "Probability of cut-off of the Cypriot bank branches that operate in Greece" being the leading actor of this scenario.

Conclusively, this work comprises another positive sign that FCMs can be used as a tool for helping humans to make wiser and more pragmatic decisions. The verification of the results of the pre-described FCM system by later history enhances the belief in the constructive role that the FCM model approach can play in decision making for socio-political-economic systems. Such domain areas often include weakly-formalized and ill-structured problems. Thus, they can be proved to be very important tools for helping humans to make decisions in short time distance where no other analytical method can help. The FCM users can directly see the effects of their possible choices on the system of their interest. They are given the opportunity of testing scenarios on their FCM system for free and with no adverse consequences whereas in real life such decisions may be risky. That is why it is worthwhile devoting effort and time in methods to increase FCM credibility and fine-tuned operation. For example, it would be interesting to expand the functional capabilities of the network in order to have more quantitative results since there is not, to my knowledge, any other method of providing such dynamic analysis of such complex systems. Thus, to introduce to the network the capability of providing more quantitative results the aspect of time must be addressed. Time is ill-defined in FCMs and thus the actual effects per time unit cannot be calculated. The constant weights of the FCMs imply a linear causal relation between any two factors of the system which is not true for most of the social systems. Maybe that is exactly the reason we prefer to study the trends of the parameters and not their absolute values. Thus, if the interrelations between the concepts can be described by non-linear functions which will give the impact sourced from each relation per iteration where each iteration will have a specific meaning in time terms, we will be more able to apply a more quantitative analysis of the results.

However, the particular work presented in this chapter is characterized by specific limitations. First of all, the fact of that Fuzzy Cognitive Maps are used as models of representation of expert knowledge reflecting a subjective vision of a situation means there might be a divergence in the way that one expert thinks about the important parameters and their interconnection sensitivities from another. An FCM system which is thought as sufficiently modeled by an expert may be criticized as incomplete by another. The system could certainly benefit in reliability and objectivity by the involvement of more expert opinions and the incorporation of the public opinion through a wide range questionnaire. Additionally it could become more realistic by incorporating fuzzy integration methods for the parameters that cannot be defined numerically but they are rather fuzzy. Finally, it is important to note that the proposed FCM expert-based construction methodology and the proposed activation function have been designed especially for systems taken from social, political and economic fields where we are more interested in studying the trends expressed in the system's concepts rather than studying the absolute values. Systems lying out of these areas could benefit more from other building approaches and different activation function selection depending on the nature and the type of the problem. However, although the proposed activation function and construction methodology can be easily used to build any system characterized by causality for which we are interested in studying the trends under the implementation of a specific scenario, it cannot guarantee the high quality of the results. Thus, if one wishes to adopt the proposed methods to build and use a FCM it is more appropriate to apply many contradictive or extreme scenarios to the modeled system to examine the quality of the system's responses. Additionally, one could experiment with different activation functions to explore which one fits the modeled system better. This was implemented for this work as well and the results were presented in section 3.4.

4. Implementation of a fuzzy medical FCM using a crisp dataset

Diagnostic Decision Support Systems (DDSS) already count approximately 50 years of presence in academic research (Miller, 1994) and they have gradually raised high interest upon them during the last two decades. Their main advantage is that they can provide doctors with person specific information regarding a medical diagnosis. The patient-centered and time saving character of a DDS system can turn out to be very beneficial for all the participants in a healthcare system enhancing the quality of people’s life and doctors’ working conditions. The fact that medical diagnosis problems strongly depend on practitioners’ knowledge and experience introduce some kind of uncertainty and vagueness into the formulation of the diagnosis information (Sikchi et al., 2013).

Computational intelligent systems provide, in many cases, the main engine of a DDSS. Artificial Neural Networks, Support Vector Machines, Evolutionary Computing techniques and Intelligent Agents, constitute only a small sample of such intelligent systems.

Fuzzy Logic (FL) comprises another field of Computational Intelligence which has been extensively used in medical DDSS. FL offers an alternative and powerful in many cases, solution in capturing and modeling the uncertainties in the world of medicine. Medical uncertainties can be attributed to the limitations of medical doctors or any other health care practitioner. Physicians think like humans think; that is, approximate rather than exact. Humans tend to be imprecise in their communication and in their way of thinking, using linguistic phrases and expressions to express a situation or a problem. Expressions like “the fetus is small” or “the pain is bearable” comprise only a small sample of what a doctor might say or hear through a conversation with a patient. Such linguistic descriptions for several medical parameters don’t give information with actual precision, yet the doctor can evaluate them and use them to solve a specific diagnosing puzzle through structured reasoning. Essentially, FL allows the mathematical representation of linguistic knowledge. That is one major reason why fuzzy DDSS have had exponential growth during the last fifteen years

(Sikchi et al., 2013). They manage to handle reasonably well the existing uncertainties of medical data and knowledge.

However, building a fuzzy DDSS, most of the times, requires a satisfactory collection of data describing the individual parameters affecting the diagnosis system. Experienced clinicians have been collecting anonymously, for many years, medical information about their patients forming several datasets, mostly in crisp form (El Gayar, Schwenker, & Palm, 2006) and thus limiting the range of medical problems which can be solved by the development and application of a fuzzy DDSS. To address this issue, we present an idea of transforming crisp medical concepts to fuzzy ones, reflecting the way relevant medical specialists think and reason for a specific diagnosis problem.

The proposed methodology is applied on a real medical dataset describing several features of the Trisomy 21 (T21) diagnostic problem. The features recorded in the used dataset essentially comprise measurements and examinations done in the context of a non-invasive diagnostic prenatal test for T21. T21 is a chromosomal abnormality, widely known as Down Syndrome, which can be diagnosed in foetuses during pregnancy either using invasive or non-invasive methods. Invasive procedures such as amniocentesis can diagnose T21 with high accuracy. Amniocentesis, though, is an expensive procedure which bears a risk of miscarriage. To deal with this, alternative non-invasive statistical and computational intelligent methods have been developed and are currently used for diagnosing T21 during pregnancies (Neocleous et al., 2016). However, all the proposed non-invasive methods have a basic pre-requisite. This is to accept exact measures of the various markers, with high precision taken during prenatal tests by trained and appropriately equipped sonographers (Dragusin et al., 2012).

The objective of this work is to investigate whether a sonographer or even a common gynaecologist can express the states of these specific markers in a more fuzzy way, using linguistic terms, and still utilize computational techniques to get an acceptable diagnosis of T21 early enough in pregnancy. In that way the examiner will not be bound on being strictly precise when measuring certain T21 markers or having specialized systems to implement the prenatal tests. The transformed "fuzzified" dataset was then used to build a medical FCM.

There are many types of medical FCMs. More specifically, the applications of FCMs in the medical field could be divided into 4 general tasks: diagnosis, classification, prediction and decision-making (Amirkhani, Papageorgiou, Mohseni, & Mosavi, 2017). The diagnostic FCMs essentially apply categorization amongst some known classes of diseases or disorders.

Some others try to classify the severity of a reported problem forming the classification FCMs. There is another set of FCM DDSS which examine the trend of a diagnosed disease by predicting whether the problem will be improved or not. Finally, medical FCMs have been used to apply decision-making by modeling treatment decisions on certain diseases and examining which one fits the best per for the cure of the disease. Each one of the aforementioned categories demands different design of the network.

In the framework of this work, a diagnostic FCM has been implemented which aims in diagnosing whether a fetus has T21 or not based only on non-invasive examinations which are partly given in vague, fuzzy form.

4.1 - Dataset Fuzzification

4.1.1 – Methodology Description

Essentially, the proposed methodology transforms a crisp dataset into fuzzy, using insight knowledge from relevant medical specialists. The motivation of transforming a crisp dataset to fuzzy is driven by the desire to capture the way clinicians think when they describe a specific medical problem.

Hence, the first step is the selection of a group of medical experts with experience and expertise in a medical domain which is relevant to the dataset. The experts must be familiar with the parameters included in the dataset in theoretical and practical manner. They must have adequate experience with patients related to the dataset's problem domain. This will ensure that the participating experts have interacted with enough patients and hence they can comfortably analyze in linguistic terms the parameters in terms of how different levels of states can affect the diagnosis. Besides, the underlying motivation of transforming the dataset is the construction of a model which will process information the way doctors do. Quality time must be spent with the group of the doctors to present them what they have been called for by giving them real life examples and allowing them to participate in the process of analyzing the diagnostic procedure they follow to address different issues.

For the second step, the selected experts are called together in order to write down the different expressions they use to describe different states of each dataset's parameter. To do so, each concept of the dataset is presented to them and the experts agree on the linguistic values (labels) they routinely use to describe the particular concept.

Having the set of linguistic values each parameter can take as given by the experts, a sample of the raw dataset is created satisfying one condition: each concept of the sampled data must be evenly distributed; that is, covering approximately all possible unique values of the concept in the raw dataset. The linguistic values and the sample of the dataset are pre-requisites for the implementation of the third step which is the creation of a questionnaire.

The questionnaire will be given to the experts, asking them to assign each recorded crisp value of the sample dataset with one of the pre-defined labels based on their "feeling/assessment". More specifically, the unique crisp values of each parameter of the sampled dataset will be presented to the doctors. The doctors will have to select one of the expressions/labels they defined in previous step, to describe the particular value.

Each label (linguistic value) will be basically modeled as a fuzzy set. The answers of this questionnaire will be used to extract the features defining each fuzzy set. A fuzzy set is mathematically defined by a membership function. Therefore, the target is to form the membership functions describing each dataset's parameter. Consider a parameter *p1* and the doctor *d1* who assigned the label *A* for the crisp value x_i^{p1}. Since, this particular value is at least once assigned to the particular label, we say that the value x_i^{p1} participates to the fuzzy set *A* (of the parameter *p1*) with a certain membership degree, μ_{labelA} (x_i^{p1}) in the interval (0, 1]. Accordingly, the same parameter's value might be categorized to the same label by other participating doctors as well. Therefore, all the values of the parameter *p1* which were assigned to the same fuzzy set, labelled *A*, will belong to the fuzzy set A with μ_{labelA} $(x_i^{p1}) > 0$ and will comprise its support set.

Two scenarios might stand for each unique value x_i^{p1} of a parameter *p1*. The first scenario is that all participating medical experts assigned this value to the same exact label (let it be the label *A*). The values of the parameter *p1* for which the above scenario is true, comprise the **core set** of the corresponding fuzzy set, with μ_{labelA} $(x_i^{p1}) = 1$. The diagram in Figure 4.1 presents the algorithm of assigning a parameter's value into the core and support sets of three different fuzzy sets. More specifically, the parameter presented is the *maternal weight* which was linguistically divided into three sets named *Low, Normal* and *Increased.*

Still, there will be some other values x_j^{p1} which the experts described selecting different labels (e.g. label *A* and label *B*). These values belong to both sets with $0 < \mu_{labelA}\ (x_j^{p1}) < 1$ and $0 < \mu_{labelB}\ (x_j^{p1}) < 1$. The exact membership degrees can be calculated after the derivation of the membership function per each label. For the purpose of this study, the designs of three types of membership functions are described. Particularly, the trapezoidal (Equation 4.1), triangular (Equation 4.2) and Gaussian (Equation 4.3) membership function were incorporated to design the membership function of the fuzzy sets.

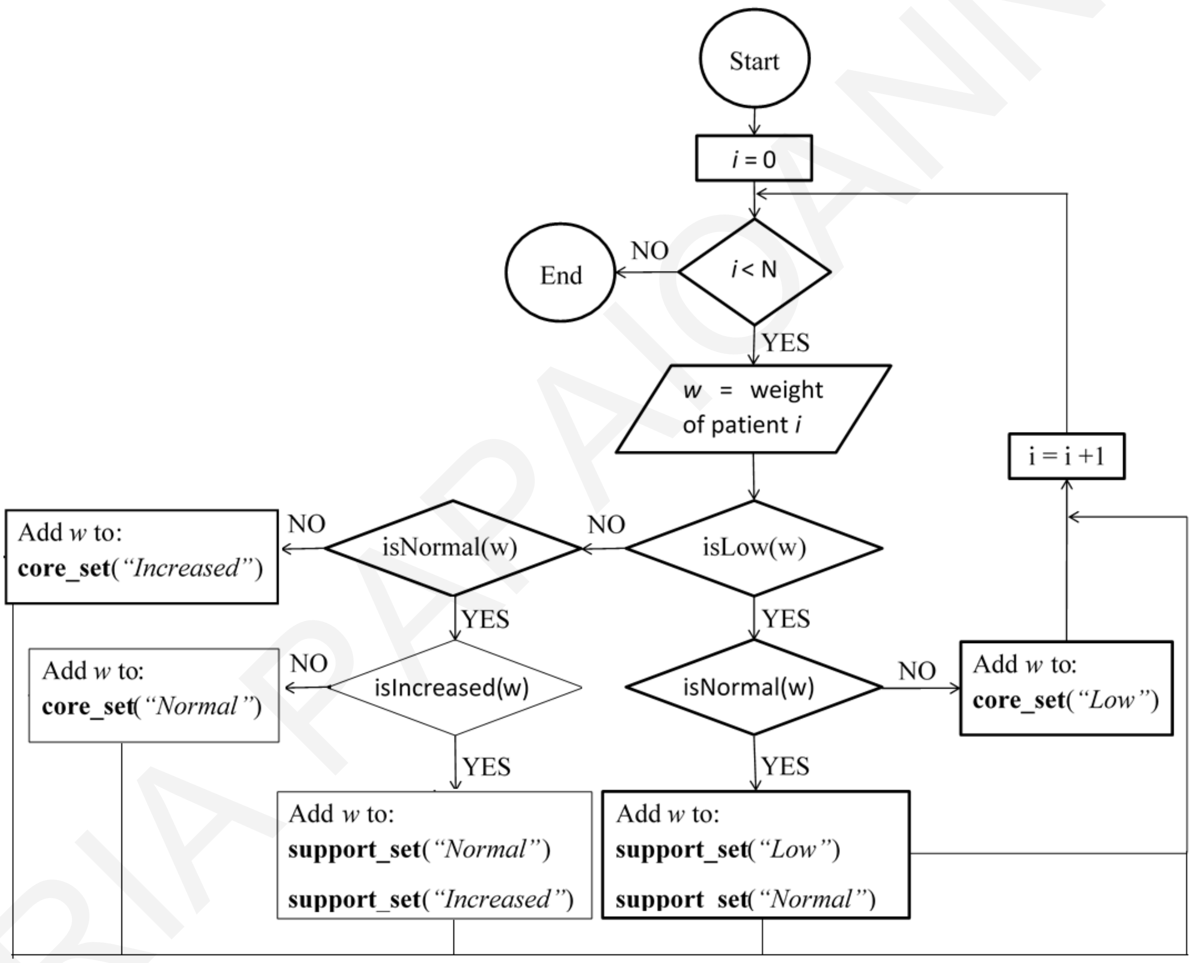

Figure 4. 1: The logic diagram of how a parameter's value is assigned to core and support sets of three fuzzy sets named Low, Normal and Increased

To design the membership function of a fuzzy set, the corresponding core set and support set must be formed. Then, to derive the trapezoidal function describing a specific fuzzy set, the set of four points *{a,b,c,d}*, as presented in Equation 4.1, must be defined. The position of these points on a trapezoidal function are graphically presented in Figure 2.3. The point *a* is the minimum value of the support set, *b* is the minimum value of the core set, *c* is the maximum value of the core set and finally, *d* is the maximum value of the support cell.

$$f(x; a, b, c, d) = \max(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0) \qquad \text{Equation 4. 1}$$

A similar process is adopted to find the form of a triangular membership function. The point *a* is the minimum value of the corresponding support set, the point *c* is the maximum value of the support set and the point *c* is the mean of the values comprising the core set.

$$f(x; a, b, c) = \max(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0) \qquad \text{Equation 4. 2}$$

To find the structure of a Gaussian membership function (Equation 4.3), the expected value *μ* is equal to the mean value of the core set where the variance *σ* can be calculated following Equation 4.4 where *w* can be adjusted by the user to set the desirable width of the function. For the purposes of this work, this parameter was set equal to 3 in order to allow the boundary values of the support set to participate to the membership function with the smallest possible degree but still larger than 0.

$$f(x; \sigma, \mu) = e^{-(x-\mu)^2 / 2\sigma^2} \qquad \text{Equation 4. 3}$$

$$\sigma = \frac{\mu - \min(\text{support}_{\text{set}})}{w} \qquad \text{Equation 4. 4}$$

At the final step of the proposed methodology, the fuzzy sets and their corresponding membership functions are known for each parameter of the dataset. The only thing left is to create a new dataset with the fuzzified version of the parameters. To do so, the crisp concept values (contained in the raw crisp dataset) must be replaced by the fuzzy values. To carry out this task, three cases must be considered:

1. The case where a parameter's crisp value participates to a specific fuzzy set with a 100% membership degree. In that case, the label assigned to the specific fuzzy set will replace the particular parameter's crisp value.
2. A different approach is adopted for the cases where a parameter's crisp value belongs partially to two fuzzy sets (e.g. with labels *A* and *B*). In that case, the fuzzy set with the highest membership degree (suppose this is fuzzy set *B)* is modified using the *dilatation fuzzy modifier* (Kerre & De Cock, 1999) to give a new fuzzy set under the label of "almost B". Thus, the membership function of this new fuzzy set will be given by Equation 4.5.

$$\mu_{label\_almostB} = \mu_{label\_B}(x)^{0.5} \qquad \text{Equation 4. 5}$$

Consequently, the corresponding fuzzy value to be written down in the new dataset will be the label "almost B".

3. There is another case, where a parameter's crisp value gets exactly equal membership degrees for two different fuzzy sets. In this case, a new fuzzy set will be created by the conjunction of the two fuzzy sets under the label "between A and B". Accordingly, the fuzzy value "between A and B" will be entered in the corresponding index of the new dataset.

All the steps of transforming the crisp values of a parameter into fuzzy should be repeated for every parameter of the dataset wished to be fuzzified. The outcome fuzzified dataset can be then used to train a fuzzy intelligent system in decision making for a medical problem.

4.1.2 – Methodology Implementation

In order to investigate if the proposed methodology is applicable to a real medical problem, a real dataset of pregnancy cases that included both Trisomy 21 (T21) genetic disorder as well as normal cases was used. More detailed information about the T21 disorder and the prenatal tests used for its diagnosis are given in the Chapter 5.

The dataset provided in an anonymized form by the Fetal Medicine Foundation (FMF) of London. FMF is a UK registered charity under Professor Kypros H. Nicolaides. The main target of the foundation is to improve the health of pregnant women and their babies. To do so, they invest on research regarding non-invasive statistical and intelligent models which can help in early diagnosis of different fetal abnormalities. They have been also building for many years databases with data related to different pregnancy cases.

The dataset included 50900 cases of pregnant women (from the greater London area and South-East England) attending routine clinical ultrasound assessment for the risk of chromosomal abnormalities. The maternal age with another 13 pregnancy examination measurements were recorded. Two gynecologists were chosen to be the medical experts in this study. Four parameters of the dataset were chosen by the experts to be fuzzified: Mother's Age, Mother's Weight, Heart Pressure, and Delta Nuchal Translucency, being the difference in fetal Nuchal Translucency measurement from the normal median for fetus with the same crown-rump length (Nicolaides, 2011). The gynecologists defined the linguistic expressions they routinely use to describe each parameter. These expressions are presented in Table 4.1.

The next step involves developing a questionnaire which will facilitate the medical experts in assigning each unique crisp value of each selected parameter to a fuzzy expression. The set of the fuzzy expressions per each parameter is ready. The only thing left was the creation of a dataset sample with all the unique crisp values of each parameter. This sampled dataset was created with 241 cases. An interacting computer-based questionnaire was then developed and given to the experts to respond (Figure 4.2).

Table 4. 1: The labels/fuzzy sets describing each parameter

Parameter name	Fuzzy Set 1	Fuzzy Set 2	Fuzzy Set 3
Mother's Age	Teenage	Young	Old
Mother's Weight	Low	Normal	Increased
Heart Pressure	Normal	Increased	-
Delta Nuchal Translucency	Normal	Increased	-

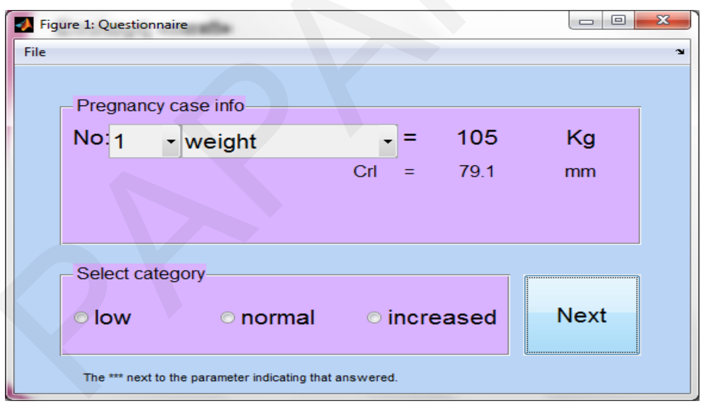

Figure 4. 2: A screen shot of the questionnaire given to the gynaecologists

The gynecologists could answer the questionnaire on their computers from wherever they wished under the restriction of doing it individually and having no communication with each other regarding this.

The answers given by the two medical experts were processed as described previously in order to identify the core set and the support set of each fuzzy set defined for a parameter. Then the membership function describing each fuzzy set were built according to the methodology proposed. In figures (A-D) presented in Figure 4.3, the answers for each parameter given by the two doctors (doctor *A* and doctor *B*) are presented in blue and red star points respectively.

The points are positioned in different Y-axis levels only to be clearly distinguishable. The approximated membership functions derived by the doctors' answers following the proposed methodology are also presented on the same figures. In Figure 4.4 a part of the fuzzified Mother Age data is presented.

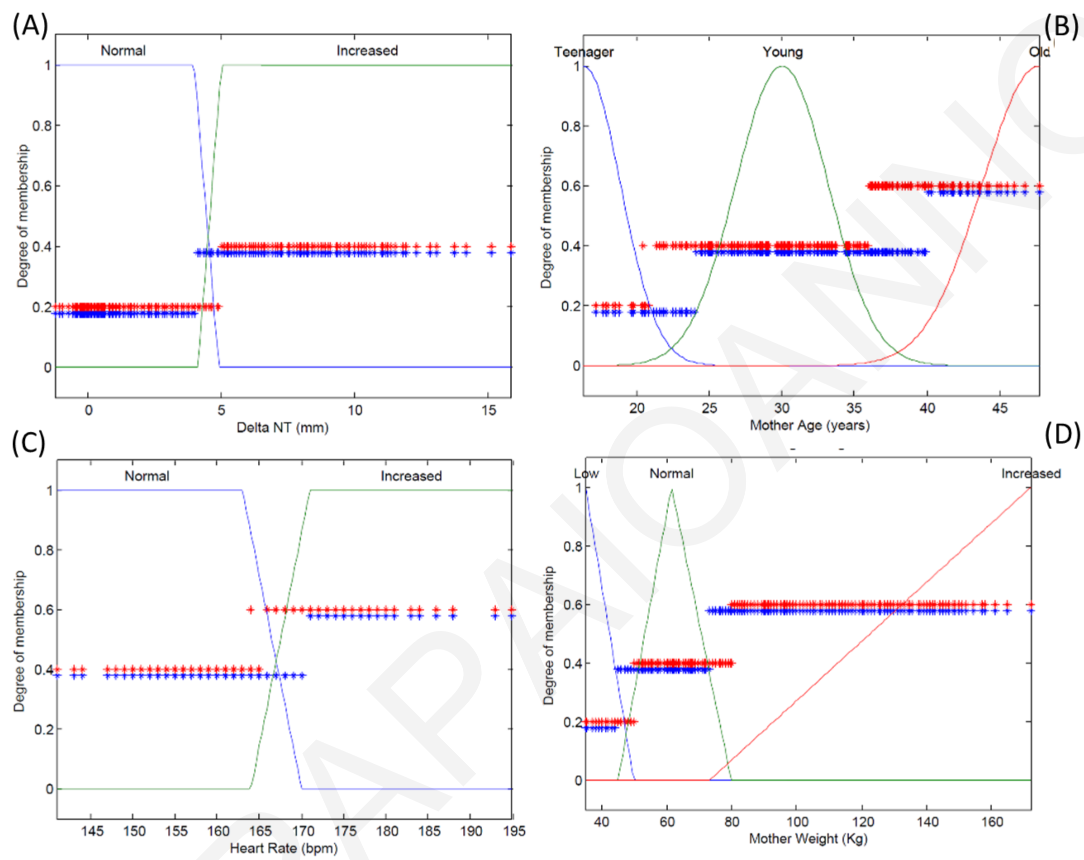

Figure 4. 3: Doctors' answers and corresponding approximated member functions (from left to right): (A) Mother's Age, (B) Fetus Heart Rate, (C) Delta NT, (D) Mother's Weight

Age	37,53	34,58	20,61	31,45	22,06	20,46	19,73	45
Label Age	Almost Young	Young	Almost Teenager	Young	Between Teenager and Young	Teenager	Teenager	Old

Figure 4. 4: Sample of the transformed dataset into fuzzy for the parameter "Mother's Age"

4.2 FCM DDSS based on a "fuzzyfied" dataset

The new fuzzy dataset on T21 was used to build a fuzzy DDSS. The motivation behind this was to examine whether the information given by the transformed dataset can actually give enough information about the modeled problem so that the intelligent system can achieve sufficient diagnostic results.

FCMs model has been selected to comprise the inference engine of this fuzzy DDSS for three main reasons:

1. FCMs can accept as input information in a fuzzy form.
2. FCMs have gained a big popularity as an approach of modeling fuzzy DDSS.
3. FCMs comprise the core element of interest of this thesis.

Essentially, the concepts of the modeled FCM represent the states of the T21 markers for each pregnancy case. Extensive literature exists describing the relation of several pregnancy markers with the T21 disorder for different gestation ages (a more analytical analysis on the parameters is given in the following chapter). The selection of the markers that were used in building the FCM model where taken from the research work of Professor Kypros Nicolaides, who is a pioneer in fetus medicine (Nicolaides, 2011). Each marker is represented by a concept in the FCM model. Hence, the measure of a marker of a specific pregnancy case is reflected in the state of the FCM concept.

The FCM model was built to make a diagnosis between T21 aneuploidy and euploid cases. Thirteen different markers for 50900 pregnancy cases from which only 407 cases were proved to bear the T21 disorder were used. The measurement of the specific markers was done during routine clinical ultrasound assessment for the risk of chromosomal abnormalities. The concepts of the network are presented in the first column of Table 4.2. Besides the four concepts which were transformed to fuzzy using the proposed methodology in this Chapter, the rest of the concepts remained in crisp form.

Additionally, as reported in the literature, a subset of a pregnancy's parameters are so important in T21 diagnosis that they are used to calculate the a-priori risk of diagnosing T21 for each pregnancy case (Nicolaides, 2004). These parameters are: "*Mother's Age*", the previous pregnancies with trisomies, the "*b-HcG"* and the "*PAPP-A*". We shall refer to these parameters as the "*a-priori parameters*". For the statistical methods, which are currently used by the gynaecologists to calculate the likelihood for a fetus bearing T21, the a-priori risk is used to weight the likelihoods of other prenatal tests (e.g. the nasal bone). To capture this idea in the T21 FCM model, an extra node was inserted, named "*a-Priori Risk*", which accepts the effects of the "a-priori parameters". Then, on its turn, the "*a-priori Risk"* concept affects the rest of the parameters to a certain degree (Figure 4.5).

In summary, 13 prenatal test markers were available through a dataset of 50900 pregnancy cases. Four of them were used in FCM model in fuzzy form where the rest were used in crisp numerical or boolean form. Another extra concept was introduced to the model, to represent the a-priori risk. Finally, the diagnosis of the system is represented by one output concept named “*Output*”. All the information about the concepts is presented in Table 4.2 and Figure 4.5.

Table 4. 2: The type of the input concepts of the T21 FCM DDSS

Concept Name	Fuzzy (F) Numerical (N) Boolean (B)	Initial State Value
Mother Age	F	0.4591
Previous Pregnancy with T21	B	0
Previous Pregnancy with T13	B	0
Previous Pregnancy with T18	B	0
Delta Nuchal Translucency	F	0.0012
b-HcG	N	0.0350
PAPP-A	N	0.1041
a-Priori Risk	N	0
Ductus Venosus	B	0
Tricuspid Valve Flow	B	0
Smoker	B	0
Heart Rate	F	0.5513
Nasal Bone	B	0
Weight	F	0.3640

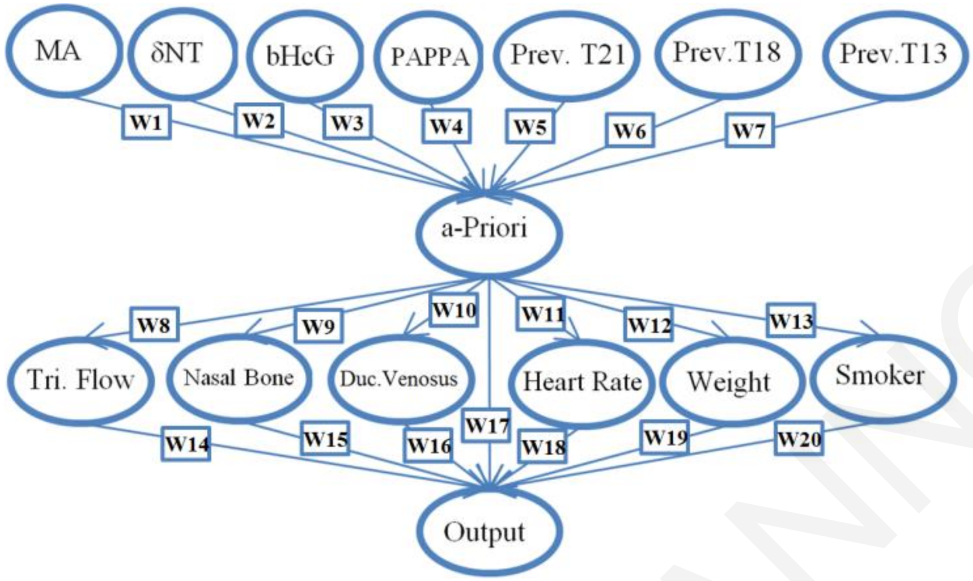

Figure 4. 5: The T21 FCM model

The concepts of a FCM represent the parameters of the modeled system. Usually, FCM concepts get values in the interval of [0, 1] where 0 stands for the full deactivation of the corresponding parameter in the system. On the contrary, a concept state of 1 means that the parameter is totally activated in the system. To normalize the T21 dataset into the desired interval of [0, 1] the four fuzzified parameters were firstly defuzzified using the center of gravity method (Equation 2.26). Then, all the parameter of the new dataset were normalized in the interval of [0, 1] using Equation 4.6.

$$parameter_i(j)' = \frac{parameter_i(j) - min(parameter_i)}{max(parameter_i) - \min(parameter_i)} \qquad \text{Equation 4. 6}$$

where $parameter_i$ is the i^{th} parameter of the dataset and j is the j^{th} pregnancy case of the dataset.

For the simulation of the T21 model, a slightly different approach is implemented than in other FCM DDSS. The reason of this alternation is the nature of the problem itself. As reported in literature of chromosomal abnormalities, and more specifically for T21, there is a deviation between the medians of normal pregnancy marker values and the T21 corresponding values (Nicolaides, 2004). Inspired by this finding, an *initial state vector (in)* was created, including the median values for each concept/marker taken only from the normal cases of the normalized dataset. The initial state values of all the parameters, resembling the medians of the normalized T21 dataset, are given in Table 4.2.

To run T21 FCM over the n^{th} pregnancy case and a get a diagnosis result, the vector with the corresponding normalized parameter values was introduced to the network. We shall refer to this vector as the *pregnancy state vector* (ps^n). Then, each concept state C_j was calculated as the differentiation between the corresponding parameter value (ps_j^n) and the normal median of the parameter (in_j) as shown in Equation 4.7.

$$C_j = ps_j^n - in_j \qquad \text{Equation 4. 7}$$

The function used to update the concept states during the simulation, is given in Equation 4.8. The new state of a concept C_j is calculated as a summation of its previous state with the aggregated weighted states of its influencing neighbours (as given from Equation 4.7).

$$C_j = C_j + \sum_i^C w_{ij} C_i \qquad \text{Equation 4. 8}$$

In the case of the concept "*a–Priori Risk"* the initial state value, as well the starting state value, were both set to zero. Therefore, the new state of the "*a-Priori Risk"* concept is just the weighted sum of the effects it accepts from the "a-priori parameters". The same applies for the "*Output",* concept whose state is the weighted sum of effects coming from the "*a-Priori Risk"* and the rest of the concepts as shown in Figure 4.5.

The identification of the existing causal relations amongst the T21 FCM model was made based on reported findings from literature, about the influence that each marker holds on other markers, and on the final diagnostic risk. So, the aforementioned "a-priori parameters" are connected with the *"a-Priori Risk"*. The "*a-Priori Risk"* is thought to influence the importance of the rest of the prenatal tests, so it is connected with all of them and with the output risk. The rest of the concept/markers are connected only with the output risk, since no causal relation between them was found to exist.

Evolutionary strategies were employed for the calculation of each interrelation's weight value. Each chromosome is represented by a vector with size equal to the number of the interconnections existing in the T21 FCM model. Each cell of the chromosome vector, called gene, corresponds to weight value of a specific interconnection of the system, as shown in Figures 4.5 and 4.6.

Gene1	W1
Gene2	W2
Gene3	W3
Gene4	W4
Gene5	W5
Gene6	W6
Gene7	W7
Gene8	W8
Gene9	W9
Gene10	W10
Gene11	W11
Gene12	W12
Gene13	W13
Gene14	W14
Gene15	W15
Gene16	W16
Gene17	W17
Gene18	W18
Gene19	W19
Gene20	W20

Figure 4. 6: The structure of the chromosomes used by evolutionary strategies for the T21 Fuzzy Cognitive Map. As seen in Figure 4.5, there are 20 interconnections. Their corresponding weight values are represented by the genes of the chromosome as presented in this figure

Since the weights of a FCM are bounded in the interval of [-1, 1], each gene (interconnection weight) was initialized by a random value in the same interval. The evolutionary strategies were free to explore different state values for each weight under some conditions extracted from T21 literature. For example, we know that, as the mother age increases the risk of the fetus bearing T21 increases. This means that, the interrelation between the "*Mother's Age"* and the "*a-Priori Risk"* is direct. Accordingly, the evolutionary strategies were bounded to explore only positive weights for the interrelation between the "*Mother's Age"* and the *"a-Priori Risk"* parameters. Similarly, the rest of the weights were bounded to desired intervals.

For each generation, the evolutionary strategies produced a population of chromosomes representing different weight vectors of the T21 FCM. By the end of each generation, the fitness of each chromosome had to be estimated. To do so, the T21 FCM was let to run for a number of pregnancy cases, using the weights proposed by each chromosome. For each pregnancy case, the *pregnancy state vector* (ps^n) was created and the T21 FCM was let to simulate. At the end of the simulation, the diagnosis of the T21 FCM was categorized as "normal" if the state of the "*Output"* concept was above 0.5 and abnormal for the rest of the cases.

Finally the total error, and correspondingly the fitness of each chromosome, was calculated. The number of T21 cases was particularly small, especially when compared to the large number of normal cases. That is why there was a high probability that the evolutionary strategies would, eventually, promote, through generations, chromosomes which achieve a high correct diagnosis score on the normal cases only. To avoid this, the error of each chromosome was calculated separately, as a percentage, for the two categories of normal and abnormal cases (Equations 4.9 – 4.10). The final error of each chromosome is the mean of the *normal* and the *abnormal* errors (Equation 4.11).

$$errorT21 = \frac{\sum_{i}^{N_{T21}} \left| Output_i^{real} - Output_i^{FCMpredicted} \right|}{N_{T21}} \quad \text{Equation 4. 9}$$

$$errorNormal = \frac{\sum_{i}^{N_{norm}} \left| Output_i^{real} - Output_i^{FCMpredicted} \right|}{N_{norm}} \quad \text{Equation 4. 10}$$

$$total_{error} = \frac{errorT21 + errorNormal}{2} \quad \text{Equation 4. 11}$$

In order to run evolutionary strategies to find the weights of the T21 FCM, a training set with several pregnancy cases was needed. Accordingly, to evaluate the winner chromosome by the end of the evolutionary strategies, a testing set was required. Therefore, the training and testing datasets were created out of the original dataset. The 67% of the pregnancy cases of the dataset were chosen to comprise the training set and the rest 33%, of the total cases, the testing set. Due to the high imbalance between the normal and the abnormal pregnancy cases, there was a high probability of having too few or even none abnormal case, especially, in the testing dataset. Only a 0.82% of the total pregnancy cases were proved to be abnormal. Hence the selection of the cases, for both training and testing datasets, was made under the restriction that the 0.82% of their pregnancy cases should be abnormal.

The fittest chromosome/weight vector was selected after running evolutionary strategies with a population of 20 parents, an equal population of offspring, using discrete recombination for chromosomes, intermediate recombination for the strategy parameters and mutation. The selection was applied using the $\mu+\lambda$ selection scheme where λ is the number of the offspring chromosomes resulted after applying recombination and mutation on the population of μ chromosomes (called parents). Using the particular selection scheme, the chromosomes that will pass to the next generation are selected from a pool containing both the parents and the offspring. The evolutionary strategies ran for 40 generations.

At the final stage, the testing dataset was used to assess the efficiency of the fittest chromosome over unknown pregnancy cases. The T21 FCM ran for every pregnancy case from the testing dataset using the weights proposed by the fittest chromosome. The results include the percentage of the normal cases and the abnormal cases that were correctly diagnosed by the model along with the sensitivity and specificity indicators of the model (Table 4.3) as given by Equations 4.12 & 4.13 respectively.

Table 4. 3: Results of T21 FCM on unknown pregnancy cases (testing dataset)

Total number of cases (in testing dataset)	16999
Number of cases that DID NOT HAVE chromosomal anomalies	16858
Number of cases that HAD chromosomal anomalies	141
Number of cases that DID NOT HAVE chromosomal anomalies and were correctly predicted (True Negative)	14498
Number of cases that DID NOT HAVE chromosomal anomalies and were NOT correctly predicted (False Positive)	2360
Number of cases that HAD chromosomal anomalies and were correctly predicted (True Positive)	109
Number of cases that HAD chromosomal anomalies and were NOT correctly predicted (False Negative)	32
Sensitivity (%)	77%
Specificity (%)	86%

$$sensitivity\ rate = \frac{TP}{TP+FN} \qquad \text{Equation 4. 12}$$

$$specificity\ rate = \frac{TN}{TN+FP} \qquad \text{Equation 4. 13}$$

As shown in Table 4.3, the results give an average to good screening/diagnostic yield for the totally unknown data set using fuzzy terms, especially for the specificity. It is the first time, to our knowledge, that someone approaches this complex and multivariate diagnostic problem, using fuzzy logic to describe some parameters. Other approaches, used to solve this problem, demand from the sonographers to take exact prenatal test values with high accuracy. To satisfy this demand, some of these prenatal tests need to be made on specialized equipment. Still, there are cases that a test must be done repeatedly to achieve a valid measure. Cases like these are time consuming for the sonographers and stressful for the pregnant woman.

Having a fuzzy DDSS which expects from the sonographers to approximate these values in a vague way, based on what they see during the screening test and on their knowledge and experience, would be a way of handling uncertainty and would allow to less specialized sonographers or even gynaecologists to complete such diagnostic tests in a shorter time.

When the results were discussed with the participating gynaecologists, they stated that it is more important to have a higher specificity than sensitivity. That is because, it is less psychological stressful for the parents to be warned that the fetus might be abnormal and eventually to find out through amniocentesis (which is the next step proposed by doctors) or through delivery of the baby (if amniocentesis is not desirable by the parents) that the baby is normal. Having that in mind, the T21 FCM, which was built based on a fuzzified dataset, exhibits some encouraging results achieving a good specificity.

4.3 Comment on this work

In this work a methodology of exploiting a crisp medical dataset to provide a fuzzy medical dataset has been presented. The methodology uses the experience and the knowledge of medical experts to:

1. Linguistically divide the selected dataset parameters
2. Identify the core and the support set of each fuzzy set
3. Define the features of the corresponding membership functions

Further analysis of the experts' answers is done to assign a linguistic value to each crisp value during the transformation of the dataset.

The methodology was applied to a real medical dataset concerning the T21 disorder. The resulting partly fuzzified dataset was used to guide the Evolutionary Strategies to optimize FCM in terms of the adjacency matrix.

A new approach was adopted in the initialization of the model's concept states regarding the medical diagnostic FCMs. Each concept's state is the difference of the parameter's value from the normal median value. This initialization scheme was chosen as to give a more informative description of the concept states based on the finding that T21 values have a big difference with the normal median values.

The diagnostic results are satisfying considering that two (out of four) of the most important and determinant diagnostic markers for this diagnostic problem (maternal age and nuchal translucency) have been given to the created DDSS in a fuzzy form. In current T21 diagnostic systems these parameters are handled with high accuracy in order to provide good diagnostic rates. Additionally, it is important to state that the medical experts who participated to this work were not certified well experienced sonographers (who are responsible to perform such examinations as the nuchal translucency measurement) but instead they were two young gynecologists who voluntarily gave their help where needed. The selection of common gynecologists instead of specialized sonographers was done intentionally, since we want to create a T21 diagnostic system which will be used during routine pregnancy examinations by gynecologists without specialized machinery and certificates.

So, the importance of incorporating fuzziness in this diagnostic model is still increased especially for the parameter of the nuchal translucency (NT). Measuring NT comprises a very difficult examination done only by well-experienced and certified sonographers. The process of measuring this parameter can be time consuming and painful for the pregnant woman. Even well-trained and experienced sonographers have to wait until the fetus to take a specific position to take valid and accurate measurements. The same applies for the paramters of *Nasal Bone*, *Tricuspid Flow* and *Ductus Venosus Flow*. That is why further work must be done to improve the behavior of the system. Thus, future work must overcome some limitations characterizing this work. Beginning with the small number of gynecologists who contributed during the dataset's fuzzification. A much larger number of participating medical experts might be considered including different levels of experience and expertise. Involving more gynecologists could give a better fuzzy approximation of the crisp dataset through the construction of the membership functions for each parameter. It is also true that factors as the low number of abnormal chromosomal cases of pregnant women in the data sets compared to the number of the normal cases can affect the success of the model. There are several ways of dealing with the phenomenon of imbalanced datasets (Japkowicz & Stephen, 2002; Menardi & Torelli, 2014) which in any case must be examined towards providing better optimization results on behalf of the Evolutionary Strategies. Additionally, more fuzzy modifiers must be explored during the fuzzification of the parameters and see how this affects the final output of the model. Furthermore, it is interesting to test how other fuzzy systems, rather than FCM, perform on a fuzzified dataset of T21 diagnostic problem.

Furthermore, Evolutionary Strategies were employed to find the adjacency matrix for the FCM presented in this work. One can observe that while the number of the normal cases is very big, the number of the T21 cases is rather highly limiter. Thus, ES ran over a dataset which was highly imbalanced. Although, the error provided by each chromosome was calculated by taking the average of the percentage of the misclassified normal cases and the percentage of the misclassified T21 cases calculated as separate percentages, other more advanced techniques could be used to deal with this problem. For example, SMOTE Bagging, comprises a recent proposal on how one can handle efficiently the use of an algorithm over a dataset including only a small number of cases of the minority class, especially when compared to the number of the majority class. Essentially the proposed method combines the advantages of the bagging algorithm along with the oversampling method known as SMOTE (Hanifah, 2015). This algorithm can be used in combination with the random subspace method (RSM) to deal with the class imbalanced problem (Huang, 2012). Thus, there is a space for experimentation with such advanced techniques as to facilitate the network to provide better diagnostic results for both the true negative rates and the true positive rates.

Finally, it would be very interesting to test how the proposed system in this chapter can be combined with a crisp classifier as to create an integrated two – level classification model for Trisomy 21 diagnosis. Neocleous et. al suggested ANN to solve this diagnostic problem providing very good diagnostic results (Neocleous et al., 2016). More particularly, the proposed ANN system provided a 100% specificity rate and 96% sensitivity rate. The diagnostic result of this model is undoubtedly very good and shows the significance of this model in approaching this hard problem through a non-invasive method. However, this model works on parameter values which must be measured with high accuracy and precision by specialized and certified sonographers as we stated in precious paragraphs. Until today, such examinations cannot be made by the gynecologist of a pregnant woman in a routine examination. All pregnant women are referred to a specialized medical pregnancy sonographic center to take the specific measurements. The cost of these examinations is rather increased since specialized machinery is also required to accomplish such precise measurements. Nevertheless, it would be interesting if a fuzzy system like the one presented in this work could be implemented in classifying pregnancies into high risk and low risk. The particular tool could be then used by a common gynecologist during routine examinations to assign each pregnancy case as high risk or low risk. The high risk pregnancy cases would then be referred to specialized pregnancy centers to make more precise measurements which will be input to the ANN system along with the estimation of the fuzzy system to provide a more accurate diagnostic result. As a result, a big percentage of women would escape the need of visiting such centers saving money, time and any psychological impact.

5. Data based-FCM Diagnostic Decision Support System using probabilistic models and dynamic weights

The writer of this thesis had the chance to become more familiar to the Trisomy 21 diagnostic problem in the context of the work presented in Chapter 4. The interaction of the writer with this area raised new questions on how the FCMs could be developed in such a way as to gain a better knowledge representation and still satisfy the main motivation behind the selection of FCMs for approaching this problem; that is to remove the need of accuracy and precision of specific examinations in order to make the process less costly and painful for the pregnant women.

Concerning the matter of improving the representation of this problem the causal dynamics of the system should be redesigned based on knowledge and experience related to this problem. FCMs provide the visualization of the medical problem's causal dynamics. Hence, if the doctors have already targeted causal relations amongst the medical problem factors, and if they already can give an indication about the structure of the diagnostic system, FCMs can be used to model exactly that, the doctors' mental conception of the problem. The general objective of the Trisomy 21 research area is to model a diagnostic system using information taken from non-invasive prenatal tests. Due to the increased research work implemented over the last years, clinicians have manage to target specific markers which somehow indicate the existence of the disorder and specify the causal relations between the problem markers' and the diagnostic risk of Trisomy 21 (T21) (Cicero, Rembouskos, Vandecruys, Hogg, & Nicolaides, 2004; Czuba et al., 2016; Faiola, Tsoi, Huggon, Allan, & Nicolaides, 2005; Maiz, Valencia, Kagan, Wright, & Nicolaides, 2009; Nicolaides, 2011; Scott et al., 2004). The obvious existence of causality amongst the markers and the diagnostic risk initiated the idea of using FCM technology to model this system.

Another characteristic of this diagnostic problem is that the magnitude of the impact a marker has on the diagnostic risk varies depending on the states of other markers (Nicolaides, 2004). This medical observation led to the design of a different FCM structure where the weight values between the markers and the diagnostic risk are not constant for all pregnancy cases, rather they are variable, changing during simulation depending on the states of the rest system's concepts. Hence, different combination of concept states give different network's weights.

Billis et al also proposed the use of variable weights per different combination of input states to model a depression severity classifier (Billis et al., 2015). In this work, the input concept states and the weight values are given in the form of fuzzy sets. Then they use modus ponens rules to connect different states of an influencing concept with different weight values of the relations initiating from the specific concept. The approach presented in this paper differs in two parts. Firstly, a mathematical curve is used to describe how a weight is related to the states of the concepts. Secondly, a weight value is not only affected by the concept state initiating the specific relation but rather it is affected by all the concepts which are regarded to be of higher diagnostic importance for the specific diagnostic problem.

Furthermore, the fact that the biggest part of the literature related to the current T21 diagnostic systems use statistical analysis based on historical data to calculate the diagnostic risk (Cicero, Rembouskos, Vandecruys, Hogg, & Nicolaides, 2004; Faiola, Tsoi, Huggon, Allan, & Nicolaides, 2005; Gasiorek-Wiens et al., 2010; Illa et al., 2013), generated the idea of using statistical analysis and probabilistic models to define the FCM concept states and weight values. Mixture of Gaussian model was selected to describe the parameter Nuchal Translucency which is one of the most decisive and important markers for diagnosing T21. Due to the difficulty of measuring this parameter, it is important to build models which require less accuracy and precision from what is currently used for T21 diagnosis. The use of Mixture of Gaussians to describe this parameter decreases the accuracy and the precision of this parameter and thus the motivation behind the implementation of such a system is partly satisfied. To be fully satisfied, the mixture of Gaussians can be transformed to fuzzy sets in the context of future work (Gan et al., 2005; Verma & Hanmandlu, 2007). A FCM system which will resemble medical knowledge representation and, at the same time, it will allow the input of the concept states in linguistic form will be beneficial for the clinicians since they will be able to pass "fuzzy" values not being bounded in making exact and accurate examinations.

Such examinations are costly since they require specific training and specific medical machinery. They are also time-consuming since the fetus has to be in a specific position to allow valid measurements (Illa et al., 2013; Ozkaya, Sezik, Ozbasar, & Kaya, 2010). On the other hand, such examinations are painful for pregnant women as well, not only for their financial cost, but because of the pressure they accept until the fetus to take the right position. Allowing the system to be less exact but still valid will make the examination a more pleasant process for both participants.

The existence of a big dataset facilitated the incorporation of probabilistic models for describing the concepts of the network. As a result, a construction methodology is proposed which essentially assigns each FCM concept with two specific distributions, the normal (euploid) and the abnormal (T21) distribution. The two distributions are used to derive the likelihood ratio per each case which indicates whether the state of the specific concept/marker favours euploid or T21 hypothesis case. The information of the likelihood ratio is used to define the states of all the components of the proposed FCM network. Only few previous works in FCM research area have attempted to connect somehow FCM technology and probabilistic models. Min et al. presented a theoretical framework of FCM technology which uses dependent probabilities to describe the relations between the concepts (Min, Hui, Lu, & Jiang, 2006). However, what they actually use is a relation-weight measurement matrix which essentially assigns a different weight value per each combination of input states. The background philosophy is very close to the one presented in (Billis et al., 2015) with the difference that in this case the potential weight values are derived by Descent Gradient Methods and Simulated Annealing. Hence, no actual probabilistic model is used to describe these values. Another attempt of incorporating probabilistic knowledge in FCM technology was implemented by (Sacchelli & Fabbrizzi, 2015). The proposed model is applied only on FCM application which are implemented to test different policies on the modeled system (to apply decision-making). Using the Dempster-Shafer Theory (DST) of Evidence (Shafer, 1976) to define the uncertainty characterizing the system under a specific policy and an optimization algorithm, the authors present a methodology to minimize the uncertainty of a FCM system under specific conditions. A different approach was adopted by Cheah et al, who suggested a methodology for translating a FCM map into Bayesian Belief Network (Cheah, Kim, Kim, & Yang, 2011). To implement this idea, a methodology which associates the FCM's direct links with dependent variables was presented. Additionally, in the context of the same methodology, and the links connecting variables in an indirect way are removed and thus, the specific variables are named as conditionally independent variables. The final outcome is a Bayesian Belief Network which is used for further analysis and FCM is used only as a middle step for their creation.

Conclusively, this is the first time that information coming from probabilistic models is exploited in defining explicitly the FCM's elements and retrieving the network's causal weights.

5.1 Existing Methodologies and Background

Trisomy 21 disorder is mostly known as Down Syndrome and comprises a member of a wider family of chromosomal abnormalities called aneuploidies. Methods of screening for aneuploidies have been proposed ever since the identification of the genetic cause of Down syndrome. These methods can be divided into invasive and non-invasive.

5.1.1 Invasive Methods

The very first test suggested for prenatal diagnosis for chromosomal abnormalities was the *amniocentesis test.* Later on, *chorionic villus sampling* was also proposed. Yet, both of them can be characterized as invasive processes since the doctors remove either a sample of amniotic fluid or placental tissue, to distinguish the fetal DNA and make the needed examinations for aneuploidies (Alfirevic, Mujezinovic, & Sundberg, 2003). Although these methods can give valid results whether the fetus is euploid or aneuploid, the procedures carry a risk of associated miscarriage up to 1% as well as a risk of limb problems in the offspring (Liu et al., 2015). These risks act as an obstacle in the spread of invasive methods as routine prenatal screening; rather they come out as an option when the pregnancy is characterized as high risk for chromosomal aneuploidies.

5.1.2 Non-Invasive Methods

The high risks carried by invasive methods led researchers in the domain to think about alternative non-invasive procedures in order to shrink the percentage of the pregnant women who proceed to amniocentesis. There exist three proposed approaches of addressing this important matter. The first one applies statistical analysis for appraising the probability of fetal aneuploidy, the second one is done by using maternal cell-free DNA screening and the last approach employs Artificial Neural Networks (ANN) to detect chromosomal abnormalities.

To begin with, the oldest non-invasive prenatal screening test for aneuploidies is the first-trimester combined screening by the maternal age and a set of epiphenomena associated with fetal aneuploidy taken from ultrasound and biochemical examinations (Gratacas & Nicolaides, 2014). The likelihood ratio per each factor is calculated and then multiplied with the likelihood ratios of the preceding screening and biochemical tests (Snijders, Johnson, Sebire, Noble, & Nicolaides, 1996). The likelihood ratio for a given sonographic or biochemical measurement is calculated by dividing the percentage of chromosomally abnormal fetuses by the percentage of normal fetuses with that measurement (Nicolaides, 2004).

The concept of maternal cell-free DNA (cfDNA) testing became possible after the discovery in 1997 that a high proportion of cfDNA fragments in maternal plasma are of fetal origin (Gratacas & Nicolaides, 2014). The main goal of the majority of clinically available methods for cfDNA is the isolation of the fetal DNA from maternal DNA. Then, the fetal DNA is used to compare a trisomic chromosome to disomic reference chromosomes (Nicolaides, Syngelaki, Gil, Quezada, & Zinevich, 2014). Then statistical analysis is applied to derive the final decision of trisomy diagnosis. Maternal cfDNA was initially proposed for Trisomy 21 identification while during the last years cfDNA have been proposed for other trisomies as well.

The last word in non-invasive diagnostic methods for trisomies in fetuses arised from the computational intelligence area by using ANN, SVM and k-NN models. This approach involves the development of a system predictor, which takes as input a number of parameter values sourcing from different origins, collected at certain prespecified times during pregnancy (Neocleous et al., 2016). ANN implementation outperforms the other two intelligent predictors (SVM and k-NN). The proposed ANN was built as a feed-forward neural network with one hidden layer. Selected factors of the medical problem were represented in input layer and the output was represented by one node. The output value was dichotomized by a threshold into normal and abnormal classes.

The first approach, first-trimester screening, constitutes the traditional "gold standard" for prenatal diagnosis of Trisomy 21 and it is currently applied worldwide in a big number of medical pregnancy health centers. These screening strategies have been shown to achieve detection rates for Down syndrome of 90% with false positive rates of 5% (Nicolaides et al., 2014). However, amongst the three proposed non-invasive screening tests, the cell-free DNA provides the most effective method for screening Trisomy 21 with a reported detection rate of

99% and a false positive rate of less than 0.1% (Gratacas & Nicolaides, 2014) followed by the ANN approach which gives a 100% detection rate for euploid cases and 3.9% false positive rate for Trisomy 21 cases. Apparently, the cfDNA methods gives slightly better results (in terms of the false positive rate) compared to ANN method. However, some arguments have been set against cfDNA method such as the relatively high cost of the test and the lack of consensus about the optimal way of its introduction in routine clinical practice (Gratacas & Nicolaides, 2014). Neocleous et al. also state that it is difficult to achieve DNA isolation, requiring high skilled operators (Neocleous et al., 2016). Yet, the need of high skilled operators also stands for the other two approaches (first trimester screening and ANN) since they use markers which must be measured by trained and experienced sonographers.

Concluding, regarding the ANN method, time must be given to receive relative medical responses since it was only published few months ago. Between the other two approaches, although cfDNA yields the lowest detection rates, the first-trimester combined screening is the one still used by clinicians for trisomy 21 diagnosis. It is interesting though to note that pioneers in this field suggest that the only way of its introduction as a routine test is to be used in combination with the first-trimester screening for fetal defects and not to substitute them (Gratacas & Nicolaides, 2014).

This last argument enhances the development of alternative diagnostic systems which will be based on the first-trimester screening markers and will provide additional benefits. Our proposal aims in the development of a model which will allow the visualization of the problem as stated by the health care providers in the area. This model will be interpretable by the clinicians and it will be also easily adaptable to any new knowledge provided in the relative medical field. Additionally, the proposed FCM model can be extended in the future to include fuzzy concepts by transforming Mixture of Gaussians to fuzzy sets. This perspective is very challenging since first-trimester screening and ANN approaches demand exact and highly accurate measurements to be successful (Neocleous et al., 2016; Hyett, Mogra, & Sonek, 2014). However, examinations like Nuchal Translucency, which comprises one of the many ultrasound markers, are characterized as very demanding examinations requiring from the fetus to be in a specific position and the sonographer to be highly experienced and well-trained having specific certifications. Having a FCM system which will resemble medical knowledge representation and at the same time it will allow the input of the concept states in linguistic form will be beneficial for the clinicians since they will be able to pass “fuzzy” values not being bounded in making exact examinations. Such examinations are costly since they require specific training and specific medical machinery. They are also time-consuming since the fetus has to be in a specific position to allow valid measurements (Illa et al., 2013; Ozkaya et al., 2010). On the other hand, such examinations are painful for pregnant women not only for their financial cost, but also because of the pressure they accept until the fetus to take the right position. Allowing the system to be less exact but still valid will make the examination a more pleasant process for both participants.

5.2 The T21 Diagnostic Problem

Screening for fetal aneuploidies has made considerable advances in the last 20 years. Prenatal screening for chromosomal abnormalities has become standard practice in many countries worldwide utilizing first-trimester ultrasound and biochemical screening increasingly (Geipel, Willruth, Vieten, Gembruch, & Berg, 2010). The most known chromosomal aneuploidies (also called trisomies) are the Trisomy 13, Trisomy 18 and the Trisomy 21 (T21) which is the most common aneuploidy also known as the Down syndrome.

Down syndrome is a genetic disorder caused by a structural chromosome defect, more specifically, the presence of all or part of third copy of chromosome 21. Furthermore, fetuses with T21 have higher probabilities of surviving and achieving a complete pregnancy cycle in contrast with the other cases of trisomies which have a much higher risk to die *in utero*. Hence, the diagnosis of T21 gains much more interest than the prognosis of the rest trisomies.

As already reported, the existence of influential relations between the markers and the final diagnosis of a trisomy inspired us to use FCM to model this medical system. The additional finding that the causal contribution of each marker dependently varies on the states of the other markers (Nicolaides, 2011) gave the working field to implement the idea of developing a FCM model with dynamic weights capturing synergies caused by different combinations of concept states.

5.2.1 Background study of the parameters

An extensive study of each marker separately preceded before the design and the implementation of the FCM model. The initial target of this study was the understanding of the causal relations between each marker and the final diagnosis. In other words, how different states of a marker strengthens or weakens the hypothesis that the fetal bears trisomy 21.

The oldest recorded factor which indicates whether the fetus has increased probability of T21 or not is the mother's age (Alldred et al., 2015). An older mother is under higher risk of T21 than a younger one. The curve describing the relation between the maternal age and the risk of bearing different aneuploidies is given in Figure 5.1.

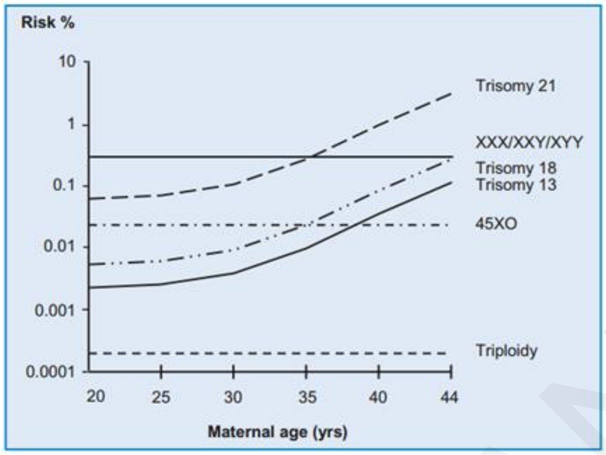

Figure 5. 1: The risk for Trisomy 21 and other trisomies based on maternal age (Nicolaides, 2004)

The factor of maternal age can be described as the most misconceived marker for Down syndrome. Many people believe that until the age of 35, women deal no problem of bearing a fetus with T21 but only after they pass their 35th birthday, the problem is visible and threating (Alldred et al., 2015). Unfortunately, this mistaken belief is still alive until nowadays. However, nothing special happens to the women by the age of 35. The true statement is that as the women grows older, the risk of aneuploidy increases as well (Abele, Luthgens, Hoopmann, & Kagan, 2011). It is important to understand that all women, regardless of age, address a higher or lower risk of presenting T21 and as time passes, the risk just gets bigger.

Another important marker is the nuchal translucency (NT) which is the collection of fluid under the skin at the back of the fetus' neck counted in millimeters. Similarly to maternal age, the higher the NT value, the higher the risk of T21 (Abele et al., 2015; Scott et al., 2004).

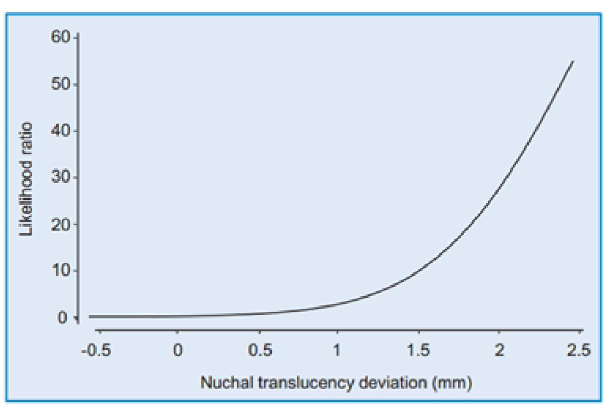

Figure 5. 2: The Likelihood ratios for T21 in relation to the delta NT from the normal median for CRL (Nicolaides, 2004)

Nevertheless, the interpretation of this marker strongly depends on the value of another marker, named, the crown rump length (CRL) which is the length of the fetus' starting from the top part of the head and ending to the bottom of the buttocks (Wright, Kagan, Molina, Gazzoni, & Nicolaides, 2008). This measurement is also done in millimeters. The curves showing the relations between the NT values and the risk differ per each CRL measurement. Thence, if two foetuses have the same NT value, the fetus with the smallest CRL value will have higher T21 diagnostic risk than the other one. Hence, fetal NT normally increases with gestation (crown–rump length) (Nicolaides, 2004). To incorporate this correlation between the two markers, researchers have proposed different methods. The first approach, is called the DELTA approach which includes the calculation of the normal median NT value per each CRL measurement (Spencer, Spencer, Power, Dawson, & Nicolaides, 2003). Then, per each pregnancy case, the deviation of the measured NT value from the normal median NT value for the corresponding CRL category is calculated and used to calculate the overall likelihood ratio for this marker.

An alternative method involves the conversion of the measured concentration into a multiple of the median (MoM) of unaffected pregnancies for the same CRL. Then, the derivation of the Gaussian distributions of log10 (NT MoM) for T21 and unaffected cases follows, and thus, the likelihood ratio for a particular MoM is considered to be the height of the distributions at the corresponding MoM.

So far we have examined one demographic and one sonographic marker. The next two markers are biochemical measurements from maternal blood. The maternal serum free ß-human chorionic gonadotropin (free b-hCG) and pregnancy-associated plasma protein-A (PAPP-A) which are type of hormone and protein respectively. As the fetus' gestation increases, the b-hCG levels decrease for the euploid cases while they increase for the T21 cases (Kagan, Wright, Spencer, Molina, & Nicolaides, 2008; Nyberg, Hyett, Johnson, & Souter, 2006).

On the contrary, the PAPP-A level in maternal blood normally increases with gestation and in trisomy 21 pregnancies the level is decreased (Kagan, Wright, Spencer et al., 2008; Nyberg et al., 2006). Consequently, the higher the level of b-hCG and the lower the level of PAPP-A the higher the risk for trisomy 21 (Alldred et al., 2015). To calculate the contribution of each one of the two biochemical markers to the final risk of T21, the gestational multiple of the medians (MoM) are calculated and used to find the likelihood ratio per each.

Another important finding regarding a second sonographic marker was linked to T21 chromosomal disorder. The absence of the fetus' nasal bone increases the T21 risk (Cicero, Rembouskos, Vandecruys, Hogg, & Nicolaides, 2004; Kagan, Cicero, Staboulidou, Wright, & Nicolaides, 2009). However, sonographers should also bear in mind that the incidence of absent nasal bone is also increased for smaller fetal CRL measurements and for increased NT thickness (Czuba et al., 2016). Therefore, all these confounding factors should be taken into consideration when calculating the likelihood ratios for the nasal bone marker.

Finally, T21 disorder has been found to be associated with two more ultrasonographic observations in the tricuspid and ductus venosus flow (Ekelund et al., 2012; Maiz, Valencia, Kagan, Wright, & Nicolaides, 2009; Ozkaya et al., 2010). These two along with the nasal bone marker are handled as binary parameters. They are set as abnormal in the case of tricuspid regurgitation, increased impedance to flow in the fetal ductus venosus and absent or hypoplastic nasal bone respectively. In any other case they are regarded to be normal.

The maternal age comprises the a-priori or background risk for every woman (Nicolaides, 2004). The calculation of the likelihood ratio of the rest markers can either increase or decrease the a-priori risk yielding the pregnancy specific T21 risk (Hyett et al., 2014; Nyberg et al., 2006). The degree to which the results of every diagnostic prenatal test (either sonographic or biochemical) should affect the final diagnostic risk must be weighted by the severity of the results obtained by previous prenatal diagnostic tests on the same pregnancy case. Hence, the finding that NT value is 3.5 mm for a 45 years old pregnant woman is much more suspicious than for a 20 years old pregnant woman. Certainly, the knowledge of the specific value for NT will increase the final risk but not at the same way. Accordingly, the biochemical results will be interpreted accordingly with the states of maternal age and the nuchal translucency regarding their causal contribution to the pregnancy specific diagnostic risk.

At this point, it is worth standing to note that later studies revealed the importance of these four factors towards the aneuploidy diagnosis: the maternal age, nuchal translucency and the two biochemistry markers (Nicolaides, 2011). The maternal age is already regarded as the a-priori risk, the measurement of nuchal translucency thickness has been characterized as the most important ultrasound marker for chromosomal abnormalities (Shiefa, Amargandhi, Bhupendra, Moulali, & Kristine, 2012) and the two maternal serum markers, b-hCG and PAPP-A, are so crucial for diagnosing T21 that different policies place the biochemical screening as a necessary first step in diagnosing T21 (Nicolaides, 2011). Concluding, the diagnostic risk resulting from the combination of these four factors has a great impact on the final diagnosis on whether a fetus has T21 (Kagan, Wright, Spencer et al., 2008; Shiefa et al., 2012). Hence, from this point forward we shall refer to this group of factors as the a-priori markers for simplicity reasons.

5.3. Methodology

5.3.1 Structure of the network

The aim behind the study of the importance and the role of each participating factor in T21 diagnosis was to find some medical guidelines for the design of the T21 FCM network. From the study it comes out that all the markers exhibit some specific behaviors concerning the aneuploid population compared to the euploid cases and therefore there is a causal link between different markers' states and the diagnostic risk.

Additionally, another conclusion, made after the review of T21 diagnostic markers, is that there is a specific subset of sonographic and biochemical factors which have a special importance in the context of T21 diagnosis. For example, as reported earlier in this work, the maternal age is the heading factor for establishing the a-priori risk per each pregnancy. Finally, the degree to which each marker influences the final diagnostic risk depends on the states of previously measured markers. All these findings gave us the opportunity to develop a FCM medical system which is characterized by causality and which could also incorporate the adaptability of the weight degrees based on how certain concepts behave.

To begin with, each of the reported markers given in Table 5.1 was used to form the set of the FCM network's concepts. More precisely, four concepts represented the Maternal Age, the Nuchal Translucency, the maternal serum markers (free b-hCG and PAPP-A together) and the triplet of Nasal Bone, Ductus Venosus and Tricuspid Flow. We shall refer to these concepts as the *marker concepts* (blue circles in Figure 5.3). Each *marker concept* somehow affects the risk of a fetus bearing T21 chromosomal disorder. To introduce this phenomenon to the system, the *risk concepts* were created (red circles in Figure 5.3). As shown in Figure 5.3, each *marker concept* is linked to a *risk concept*. The maternal age forms the initial/background risk which is represented by the concept "Risk Level 1". The information sourcing from "Risk Level 1" and the information coming from the concept "NT" (Nuchal Translucency) is aggregated to define the state of "Risk Level 2". The same procedure is repeated for the concept "a-priori Risk" which essentially represents the aggregated risk by all the *a-priori* *parameters.* The *a-priori risk* influences the final risk along with the rest three markers, the nasal bone, the tricuspid and the ductus venosus flow (secondary sonographic markers).

Table 5. 1: Demographic, biochemical and sonographic features of trisomy 21

Marker's Name	Type
Mother's Age	Demographic
Mother's Ethnicity	Demographic
Mother's Weight	Demographic
Nuchal Translucency	Sonographic
Crown rump length	Sonographic
β-human chorionic gonadotrophin	Biochemical
Pregnancy-associated plasma	Biochemical
Nasal Bone	Sonographic
Tricuspid regurgitation	Sonographic
Ductus venosus reversed a-wave	Sonographic

It is obvious that the proposed FCM structure (as shown in Figure 5.3) implies the existence of a specific hierarchy amongst the *marker concepts*. More specifically, this structure implementation prioritizes each *marker concept* based on its importance in T21 diagnosis problem. The *marker concept* "Maternal Age" was positioned to be the head of this schema since the health providers related to the Trisomy 21 diagnostic area regard this factor as the basis for calculating the diagnostic risk (Nicolaides, 2004). The maternal age related risk forms the background risk for the first trimester screening and for many years (long ago) it had been used as the one and only diagnostic factor.

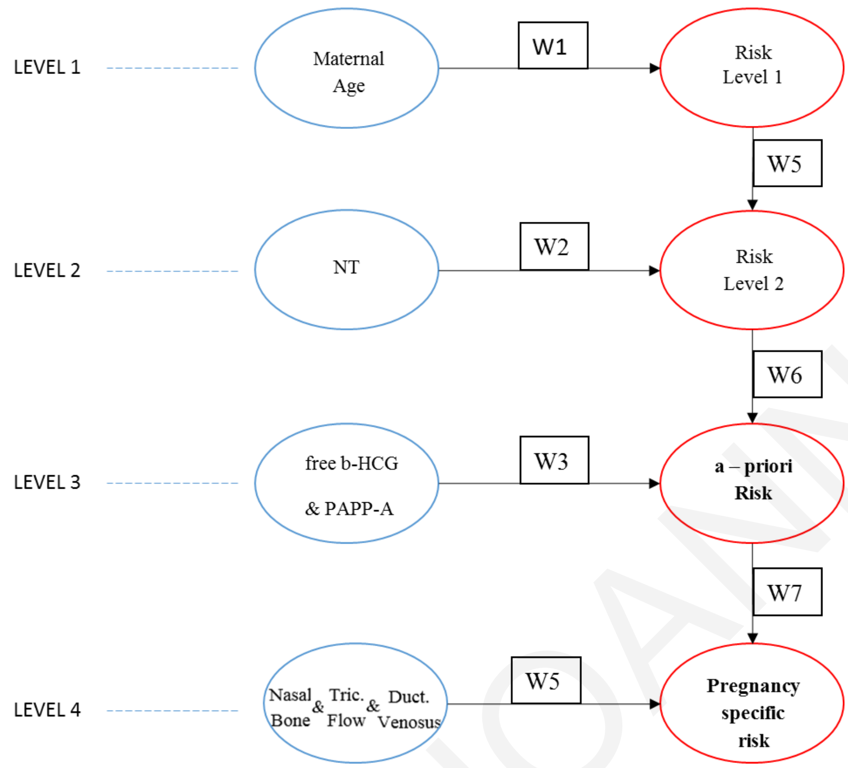

Figure 5. 3: FCM model for T21

Nuchal Translucency *marker concept* follows as second in order. The fact that NT is highlighted not only as the most important sonographic marker but also as a major factor which is highly predictive and presents big effectiveness in screening for fetal aneuploidy (Geipel et al., 2010; Hyett et al., 2014; Nyberg et al., 2006) led to its hierarchy position in the proposed FCM scheme for T21 diagnosis.

Biochemical screening is also described to have a very important role in prenatal screening for aneuploidies. Besides, it is the last piece of puzzle for calculating the T21 a-priori risk. The only reason for setting the order of the biochemical screening a level under the NT, is the higher contribution of the latter in T21 diagnostics (Salman Guraya, 2013; Spencer, Souter, Tul, Snijders, & Nicolaides, 1999).

Although, PAPP-A and free b-hCG comprise concentration measurements of different parameters of the maternal blood, they have been placed together under the same concept, that could be renamed *maternal serum screening*. The main reason behind their grouping, is that medical researchers for T21 diagnosis regard these examinations as equal in importance and point out that handling them in combination, rather than in individual, has a higher impact on T21 diagnostics (Alldred et al., 2015). Additionally, the two biochemical parameters take real values, they are of the same type in terms of describing different characteristics of the maternal blood and share the same dependencies on other pregnancy characteristics (Kagan, Wright, Spencer et al., 2008).

The last level (level 4) of the T21 FCM as shown in Figure 5.3 includes the ultrasound parameters of nasal bone (NB), tricuspid flow (TF) and ductus venosus flow (DV). In the context of this work, they were all categorized to be in the same hierarchy level, right after all the *a-priori parameters.* The fact that they are named as *secondary markers* in relative literature, especially when compared to NT which is also an ultrasound marker, justifies their level position in the FCM graph (Karadzov-Orlic et al., 2012). Similarly to the biochemistry variables, these sonographic markers are most often studied as a group of three, stating that best diagnostic results are gained by their study as a cluster than individually (Geipel et al., 2010; HYETT et al., 2014; Illa et al., 2013). Abele et al. also pointed out that these three markers are not entirely independent (Abele et al., 2015). Additionally, all of the three of them take binary values (normal/abnormal) and share similar dependencies on other pregnancy characteristics. Consequently, we decided to handle these variables as a group under the name of *secondary ultrasound markers.*

5.3.2 Statistical Analysis of each marker concept

In this section the methodology describing the way different pregnancy features were used to define the concepts of the T21 FCM is given in detail. More specifically, probabilistic models and statistical analysis were used to describe the concepts and their dependencies. Not all of the T21 markers were handled in the same manner. The type of each marker's measurements and their association with different other markers were taken into account to derive different probabilistic models. For that reason the pre-processing procedures will be explained separately per each category of the marker concepts.

Two main probabilistic models were chosen to represent the marker concepts of the FCM network; Mixture of Gaussians and Mixture of Bernoulli distributions. Mixture Models are probabilistic models which are mainly used for partitioning data points into a set of clusters. Different clusters (or components) are thought to model different sources of data points. Hence, data points lying in the same component are thought to share some similarities to a specific degree. One of the most appealing characteristics of mixture modeling is that they don't apply "hard labelling" but instead each data point is given the availability to belong to different components, up to a specific probability. Thus, Mixture Models have been chosen for modeling the distributions for a subset of the T21 FCM marker concepts since they were proven to provide a flexible, parametric framework for statistical modeling and analysis for a big spectrum of multi-disciplinary problems (Marin, Mengersen, & Robert,). Additionally, the selection of Mixture Models serves well the idea of transforming some of the marker concepts of the proposed FCM to fuzzy in future work, as stated in previous section.

Table 5. 2: Dataset Parameters

Parameter	Type
Pregnancy Unique Numer	Numerical
Maternal Age	Numerical
Maternal Weight	Numerical
Maternal Ethnicity	Categorical
Nuchal Translucency (NT)	Numerical
Crown Rump Length (CRL)	Numerical
Delta-NT	Numerical
Nasal Bone	Boolean
Tricuspid Flow	Boolean
Ductus Venosus Flow	Boolean
PAPP-A	Numerical
Free b-hCG	Numerical
T21 Karyotype	Boolean

A dataset describing the parameters of several T21 and normal pregnancy cases was provided by the Fetal Medicine Foundation (FMF) of London. More specifically, the dataset contained the values of 13 different parameters for 50900 pregnancy cases (from the greater London area and South-East England). In this data set only 407 cases proved to bear the T21 disorder. The measurement of the specific markers was done during routine clinical ultrasound assessment for the risk of chromosomal abnormalities. The dataset included measurements for different pregnancy parameters which are presented in Table 5.2.

All the required calculations and analysis that was implemented in the context of this work was made on the same dataset. In total, the dataset included 50900 pregnancies cases from which there existed 407 T21 cases and 50493 euploid cases.

From Table 5.2, one can easily spot that there are more parameters included in the dataset than the ones represented in T21 FCM model (Figure 5.3). The *marker concepts* which were described in Section 5.3.1 consist the basis of prenatal diagnosis for aneuploidies. The rest parameters might not have a direct association with the T21 aneuploidy but they exhibit specific dependencies with the basic *marker concepts*.

Based on the dataset different probabilistic models were designed and created for the *marker concepts* except from *Nuchal Translucency (NT)*. For the latter, the model of Mixture of Gaussians inspired by Wright et al (Wright et al., 2008) was adopted. Wright's work rejects delta and MoM approaches (referred earlier in this work) as inappropriate to fulfill specific assumptions underlying their use in calculating the normal and T21 likelihood (Gasiorek-Wiens et al., 2010; Wright et al., 2008). Instead, the authors propose the use of a mixture of Gaussians to describe the distribution of of normal and abnormal nuchal translucency. More particularly, they found that the normal and the abnormal NT values are best described by a 2 component Gaussian Mixture model. Both sets of NT values, normal and abnormal, follow one Gaussian distribution which is dependent on the fetal crown rump length (CRL) and another Gaussian distribution which is CRL independent. The CRL dependent distribution is common for the both models. Therefore, given a pregnancy case, the NT normal and abnormal likelihoods are calculated as the probability density of the normal mixture of Gaussians and the abnormal mixture of Gaussians at the specific CRL and NT value, correspondingly. The likelihood ratio is then derived by dividing the division of the probability density of T21 pregnancies by the probability density for normal pregnancies (abnormal likelihood / normal likelihood).

Mixture of Gaussians (MoG) was also selected to model the distribution of maternal serum marker concept (free b-hCG & PAPP-A) since they are continuous variables. Since these two parameters are grouped together, they were handled as a two dimensional variable. A parameter which was found to be associated with both of these markers is the maternal weight (Spencer, Bindra, & Nicolaides, 2003). As the maternal weight increases the PAPP-A and the b-hCG normally decrease. Additionally, the ethnicity of the pregnant woman is another parameter which is associated with these two markers. More precisely, Afro-Caribbean pregnant women present increased values for b-hCG and PAPP-A compared to other ethnicities (Krantz, Hallahan, Macri, & Macri, 2005). Hence, the abnormality of the biochemical factors should be filtered through the maternal weight and the ethnicity of the mother. To deal with this fact, the dataset values of the maternal serum markers were categorized firstly per ethnicity and secondly per weight category. The weight data points were right-censored and left-censored so that if $w < 45 \rightarrow w = 45$ *and if* $w^n > 135 \rightarrow w = 135$. As a next step, Equal-Width Binning was applied to *Weight* parameter in order to apply discretization. As a result, there were 11 different weight groups for each ethnicity category

(Afro-Caribbean Vs Non-Afro-Caribbean) which yields 2 x 11 = 22 categories of pregnancy cases.

For each one of the categories a mixture of Gaussians (MoG) distribution representing the biochemical values should be built. To derive the parameters of each MoG, the Expectation-Maximization (EM) algorithm (Dempster, Laird, & Rubin, 1977) was employed. Particularly, the EM algorithm ran over the data points of each combination of ethnicity and weight category separately for normal and T21. Figure 5.4 exhibits how the normal Afro-Caribbean cases were fed into EM algorithm to produce a 2-component MoG. In the same figure, $\boldsymbol{x}^{\boldsymbol{n}}_{\boldsymbol{b-hCG}}$ and $\boldsymbol{y}^{\boldsymbol{n}}_{\boldsymbol{PAPP-A}}$ stand for the free b-hCG value and PAPP-A value of the n^{th} pregnancy case, respectively. Prior to applying EM algorithm, the *K*-means algorithm was run in order to find a suitable initialization for the MoGs. The covariance matrices were initialized to the sample covariances of the clusters found by the *K*-means algorithm and the mixing coefficients were set to the fractions of data points assigned to the respective clusters (Bishop, 2006).

Another problem was the unknown number of the components of each mixture of Gaussians (MoG). To address this issue, EM algorithm ran for every ethnicity-weight category for different numbers of components. For each number of components the Bayesian Information Criterion (BIC) was calculated. Essentially, BIC is a way to assess the fit of a model proposed by Schwarz (Schwarz, 1978). BIC is a measurement of the trade-off between the quality of the model fitness and its complexity in terms of the number of parameters. Introducing more parameters to a model might indeed increase the likelihood of the model. However increased complexity might lead to overfitting which is an undesirable situation. Thus, BIC criterion penalizes the complexity of a model (Bishop, 2006). Hence, the model with the lowest BIC implies to have a better balance between model's complexity and model's fitness. A two component MoG gave the lowest BIC value for all of the ethnicity-weight categories.

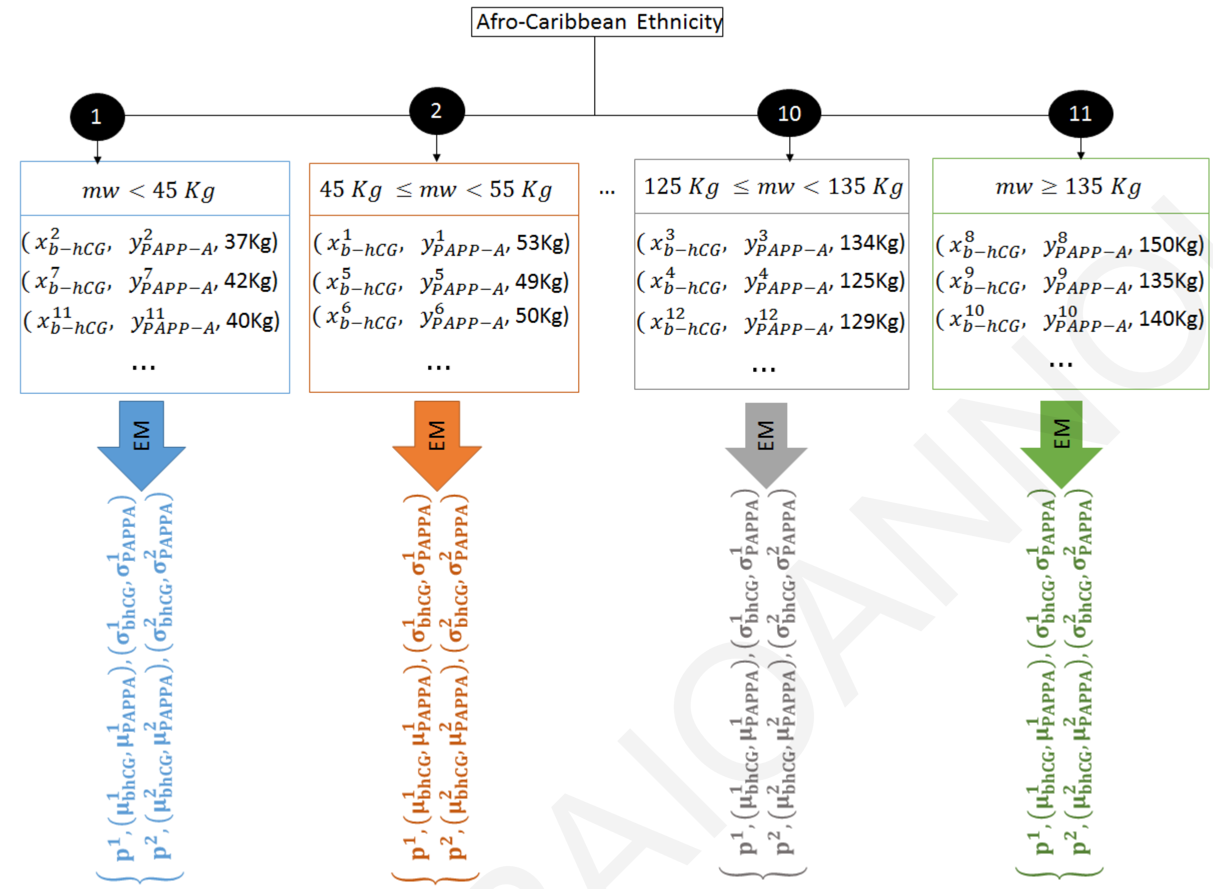

Figure 5. 4: How different Mixture of Gaussians are derived for different weight category for the ethnicity Afro-Caribbean. The same process is followed for the MoG in the case that the ethnicity is not Afro-Caribbean

Figures 5.5-5.6 present the mean values of the MoGs, for b-hCG dimension, per each weight category for all the normal Afro-Caribbean and non-Afro-Caribbean pregnancy cases. By observing these figures, the association of the maternal weight with the biochemical marker can be extracted. As the weight increases the means of the MoG decrease for both ethnicities. Furthermore, it is notable that the means of the normal MoGs of the Afro-Caribbean cases are increased compared to the ones of the other category for the same weight categories. Consequently, it seems that the MoGs produced by the EM algorithm captured the associations between the maternal weight and ethnicity with the factors under study.

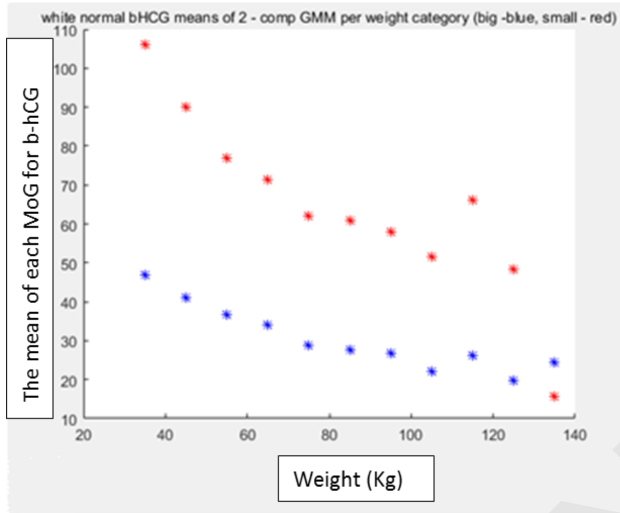

Figure 5. 5: The means of the two components (red and blue colour) of each normal MoG for the b-hCG feature per each weight category (non-Afro-Caribbeans)

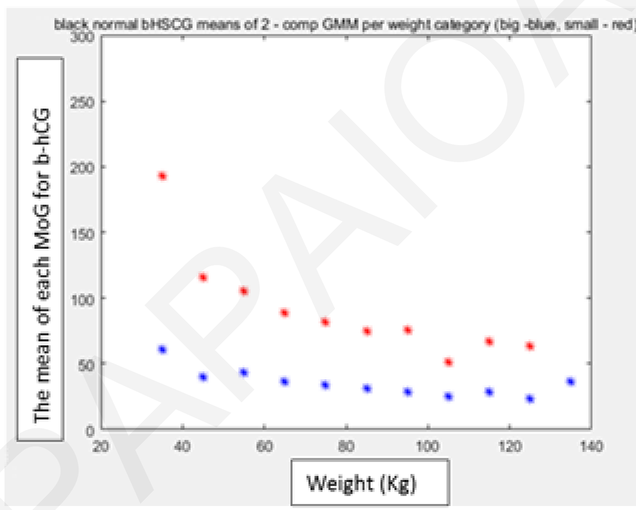

Figure 5. 6: The means of the two components (red and blue colour) of each normal MoG for the b-hCG feature per each weight category (Afro-Caribbeans)

Given the parameters of the MoGs describing the distribution of PAPP-A and b-hCG for normal and T21 (abnormal) cases, the likelihood ratio of a pregnancy case regarding the maternity serum marker could be calculated. Firstly, the maternal ethnicity and weight is input into the system and the appropriate MoG can be retrieved from normal and abnormal distributions. Then, the maternal serum values are entered into the selected MoGs resulting a *normal likelihood* and an *abnormal likelihood* by the use of the corresponding probability density functions. Similarly with the NT concept, the likelihood ratio is derived by dividing the abnormal likelihood by the normal likelihood.

The last marker concept of the T21 FCM is the *secondary ultrasound markers* which include a triplet of ultrasound pregnancy features namely, the Nasal Bone, the Tricuspid Flow and the

Ductus Venosus Flow. The sonographer is responsible to assess the values of these parameters. Nasal Bone is set as *Abnormal* if the sonographer spots an absence or a hypoplasia of the fetus' nasal bone.

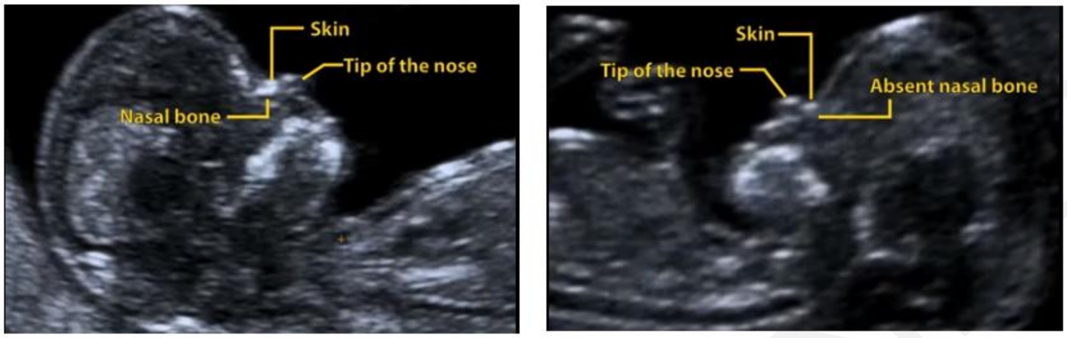

Figure 5. 7: (Left) Normal Nasal Bone (Right) Abnormal Nasal Bone (source: https://fetalmedicine.org/)

Accordingly, when the phenomenon of tricuspid regurgitation (Figure 5.7) is recognized, the tricuspid flow is marked as *Abnormal.* The same applies, in the case of an absent or reversed a-wave in ductus venosus flow. In any other case, the three parameters are defined as *Normal.*

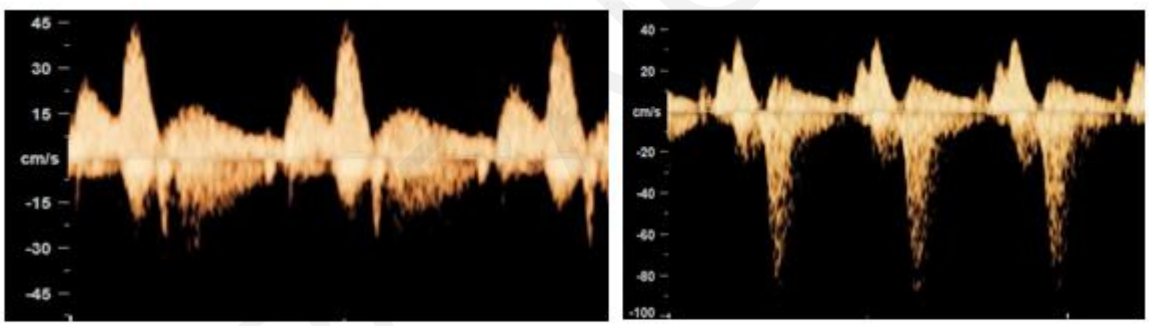

Figure 5. 8: (Left) Normal Tricuspid Flow (Right) Abnormal Tricuspid Flow or Tricuspid Regurgitation (source: https://fetalmedicine.org/)

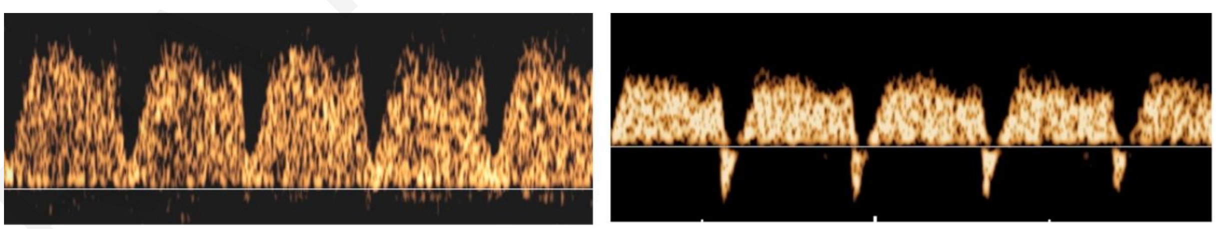

Figure 5. 9: (Left) Normal Ductus Venosus Flow (Right) Abnormal Ductus Venosus Flow or Reversed A-Wave (source: https://fetalmedicine.org/)

Since their states vary between *normal* and *abnormal*, *secondary markers* concept can be handled as a multivariate binary variable. Initially, the Mixture of Bernoulli model was selected to represent this marker. The three secondary sonographic markers share a common dependency on NT and CRL values (Cicero, Rembouskos, Vandecruys, Hogg, & Nicolaides, 2004; Czuba et al., 2016; Illa et al., 2013; Kagan et al., 2009; Stressig et al., 2011). To introduce this phenomenon into our model, the *delta NT* feature was selected. As mentioned in previous section of this work, *Delta NT* measures the distance a specific *NT* value from the normal median NT value of the specific *CRL* category. Thus, *delta NT* combines both NT and CRL information. To find the association of the mixture components and the *delta NT*, the interval of the delta NT (*δNT)* was discretized into equal-width bins and right-censored at value 5 mm. Once more, the EM algorithm was used to derive the parameters of each mixture component. For model selection (in terms of the components number) the BIC criterion was anew used. However, BIC values were extremely close for different number of clusters except from the case where number of components was equal to 1 yielding a much lower BIC degree.

To verify the results, a second model selection methodology was employed using maximum likelihood estimator in combination with *10-fold cross validation.* In this case, the dataset was partitioned into 10 random equal size samples. Then, per each *δNT* category the EM was allowed to run over the 9 sample datasets (training sample). The resulted components were then used to estimate the log likelihood of the model over the excluded sample dataset (testing sample). The procedure was repeated until all the data samples were used for testing. By the end of this procedure the resulting average log likelihood was calculated. If the average log likelihood is increased compared to the one gained by the previous number of components mixture model, then the number of clusters is increased by one. The process terminates when the yielded log likelihood is smaller than the preceding model's log likelihood. The results verified that the model is best described by one cluster of Bernoulli mixture which is essentially a multivariate Bernoulli distribution. The procedure was repeated for normal and abnormal cases separately. Hence, per each *δNT* category a different multivariate Bernoulli distribution was formed for normal and abnormal cases to give the corresponding normal and abnormal likelihoods through the probability density function. The likelihood ratio was calculated in the same manner as for NT and Maternal serum marker.

The only marker concept which was not described by a probabilistic model was the *maternal age*. Rather, the actual maternal age value was used to initialize the concept. Maternal age is the only marker which is actually used by prenatal screening based diagnostic systems in its raw form since it's already very informative about the related diagnostic risk (Snijders, Sundberg, Holzgreve, Henry, & Nicolaides, 1999). Thus, the first *a-priori* risk is basically given by a curve relating maternal ages with the diagnostic risk (Kagan, Wright, Baker, Sahota, & Nicolaides, 2008). Each point of the curve indicates the prevalence of trisomy 21 per age (Nicolaides, 2004). Since maternal age is not associated with other markers recorded in the dataset and current diagnostic systems already use it in its raw form with no further information in bibliography about the distribution describing this parameter, we intentionally adopt its raw form to describe the corresponding marker concept.

5.3.3 Initialization of the System

Each pregnancy case results a likelihood ratio per each *marker concept* besides maternal age. The mother's actual age along with the three likelihood ratios are used to initialize the T21 FCM. Concepts and weights are initialized in different ways presented in the upcoming sections.

5.3.3.1 Concept States

Likelihood Ratio intervals range over a big spectrum of values for euploid (normal) and for aneuploidy (abnormal) cases. Although normal and abnormal likelihood ratio intervals are similarly wide, it was noticeable that a percentage of approximately 95%-97% of the normal cases lied in a much shorter interval. In this shorter interval, only an approximate percentage of 30%-40% of the abnormal cases were included. This was true for all of the three *marker concepts* described by likelihood ratios. Based on this observation, the shorter interval is kept for applying normalization and the cases ranging beside the specific interval are considered to exhibit a totally abnormal behavior.

Thus, the algorithm used to calculate the initial values of each *marker concept* is described by the following steps:

1. Per each *marker concept* category (e.g. per CRL category for *NT marker*, per Weight category for *Maternal Serum marker*, per Delta-NT category for *Secondary Marker*):
    a. Find the median value of the likelihood ratios given only by the euploid cases included in the specific category. We shall refer to this value as the *normal median.*
    b. Given a pregnancy case (euploid or aneuploid) of this category, calculate the likelihood ratio and find its distance from the corresponding *normal median*.
2. By the end of the first step, the distance between the likelihood ratio of each pregnancy case and the corresponding normal median is calculated. For simplicity reason we name this value as δLR. Normal δLR refer to the values given by euploid pregnancy cases and abnormal δLR refer to the values given by Trisomy 21 cases.
3. Find a threshold value U for which 95% of the normal δLR satisfies the condition:

$$\delta LR < U \qquad \text{Equation 5. 1}$$

4. Set the value *T21underU* to be the percentage of the *abnormal δLR* which falls under the threshold *U*.
5. Set the value *T21under0* to be the percentage of the *abnormal δLR* which falls under the threshold *0* (zero distance from normal median).
6. Given the δLR of the *i*th pregnancy case for a specific *marker concept* (δLR^{i}_{marker}) calculate the corresponding initial value C^{i}_{marker} following the equations 5.2 & 5.3, where $\delta LR_{T21}$is the number of the *δLR* values sourcing from abnormal cases from the training dataset. In other words, $T21under\delta LR$ is the percentage of the aneuploidy cases (taken from training dataset) which fall under the δLR^{i}_{marker}.

$$T21under\delta LR = \ countif(\delta LR_{T21} < \delta LR^{i}_{marker})/number(\delta LR_{T21}) \qquad \text{Equation 5. 2}$$

$$C^{i}_{marker} = \frac{T21under\delta LR - \mathrm{T21under0}}{T21underU - \mathrm{T21under0}} \qquad \text{Equation 5. 3}$$

For the maternal age marker, the same steps were repeated and instead of the likelihood ratio, the actual maternal age value was used.

So far, a description has been given about the way that *marker concept* states are initialized to model a pregnancy case. Of course, the network comprises another 4 concepts, the *risk concepts*. Since the philosophy of this network is to calculate the distance between each pregnancy case from the expected normal case, the risk concepts are initialized with 0, implying that the expected risk for a normal case should have no risk.

5.3.3.2 Weight Values

According to FCM theory, a relation between two concepts can be direct or indirect. In the case of a direct relation the weight values can be larger than 0 up to 1. On the other hand, the indirect weights take values in the interval [-1, 0). A direct relation implies that a potential increase in the influencing concept state will cause an increase to the affected concept of the relation. Nonetheless, a potential decrease will certainly cause a decrease in the affected concept's state as well. All the relations in the T21 FCM are direct which means that as the states of the influencing *marker concepts* increase, the states of the *risk concepts* also increase.

As stated in previous sections, an attempt of introducing dynamic weights was implemented in the context of this work. To do so, the weight values are initialized to a specific value and then they are altered during simulation depending on other *marker concept* states.

Due to the lack of communication with experts in the domain, the initial weight value used for the T21 FCM has been decided through experimentation to be 0.8. The details of the experimentation will be given in Section 5.5 of this paper. The weight values of the relations connecting the *risk concepts* have been set to 1 implying that all the *risk concepts* contribute to the formulation of the final risk to the highest degree.

5.4 Dynamic FCM

This work contributes to the FCM research area in two ways. Firstly, by the proposal of the concepts' initialization using probabilistic models and secondly by introducing the use of dynamic weights to the system.

In particular, the weight degrees are allowed to change during simulation by different levels of the *marker concepts*. The idea behind this alternation from conventional FCMs is that, when the states of the "higher in hierarchy" markers already imply that the risk of T21 is increased, the system must become stricter with the rest markers. In such a case, the weights between the rest *marker concepts* and the diagnostic risk are increased indicating that even a small increase from what is supposed to be normal can be very suspicious in a diagnostic manner.

On the opposite site, when the "higher in hierarchy" marker concepts exhibit a normal behavior, a small divergence in the "lower in hierarchy" *marker concepts* from what is considered to be normal will have a smaller effect on the risk concept. Not only that, but if the system exhibits a very normal behavior in previous hierarchy levels and the remaining *marker concepts* also lie in what is expected to be normal (e.g. initial values close to 0) then the corresponding *marker-risk* weights should decrease in order to reduce the diagnostic risk.

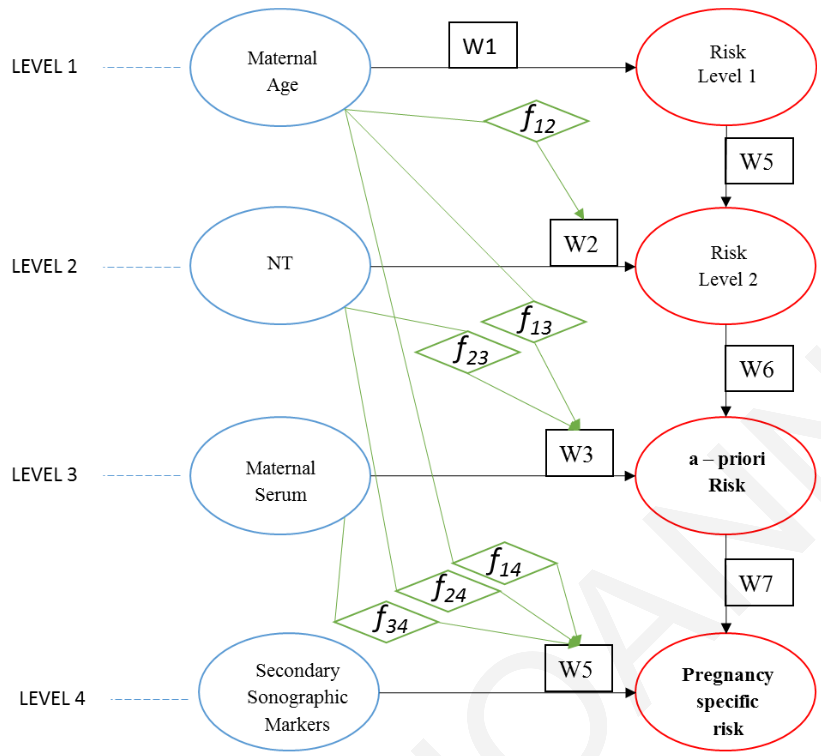

Figure 5. 10: The proposed FCM structure for the T21 diagnostic problem. The network is built divided in hierarchy levels. The marker concepts appear in blue circles where the risk concepts in red. The weights of the relations between the concepts appear in rectangles. The functions regulating the weights during simulation based on the states of other concepts appear in green rhombus.

The process is schematized in Figure 5.10. Substantially, the proposed weight degrees will be given by functions of the marker concepts lying in the previous levels. Consequently, the weights of the proposed FCM model can be characterized as pregnancy specific weights, since their values depend on the marker values which differ pear each pregnancy case. For example, if the maternal age is increased (compared to what is expected to be normal maternal age) then the concept "Risk Level 2" will be more sensitive to the "NT" concept. This effect is implemented by increasing the weight "W2". Essentially, for this example, the state of the marker concept "Maternal Age" regulates the state of the weight "W2".

Table 5. 3: Combinations between Higher Level Concepts and Lower Level Concepts

Combination Number	Higher Level Concept Marker	Lower Level Concept Marker
1	Maternal Age	NT
2	Maternal Age	Maternal Serum
3	Maternal Age	Secondary Markers (NB+TF+DV)
4	NT	Maternal Serum
5	NT	Secondary Markers (NB+TF+DV)
6	Maternal Serum	Secondary Markers (NB+TF+DV)

The rest of the weights are also affected by the preceding levels' marker concepts, accordingly. To implement this, the same procedure was repeated for every combination of the *marker concepts* presented in Table 5.3.

The procedure can be analyzed in the following steps:

1. Given the training dataset, calculate the initial values of each pregnancy case as described in Section 5.3.3.1. The initial values of each concept range in the interval [0, 1].
2. Divide the intervals of the initial values into equal width bins of length 0.2 (we shall call them initial value bins).
3. Per each combination of the *marker concepts* of Table 5.3:
    a. For every combination of the initial value bins between the higher level concept and the lower level concept do:
        i. Calculate the percentage of the abnormal cases which lie in both the initial value bins (abn_perc).
        ii. Calculate the percentage of the normal cases which lie in both the initial value bins (norm_perc).
        iii. Find the difference between abn_perc and norm_perc.
    b. By this point a matrix (Table 5.4) is formed where the rows represent the initial value bins of the higher level *marker concept* and the columns the initial value bins of the lower level *marker concept.* Each cell of this matrix indicates whether the most of the pregnancy cases existing in the two sub-intervals of initial values are normal (negative number) or abnormal (positive number).
    c. The target is to see how each bin of initial values of the higher level concept affects the behavior of the lower level concept. Thus, each row of the matrix is averaged along columns (lower level concept bins) yielding a 5x1 vector with the mean values. A positive mean value shows a prevalence of the abnormal cases when the higher level concept lies in the specific sub-interval where a negative mean value indicates the opposite.
    d. Interpolate a curve relating the higher level concept initial values with the average difference between abnormal and normal percentage as calculated above. The resulted function is used to regulate the weights between the *marker*

concepts and the risk concept of the same level (e.g. $f_{12}, f_{13}, f_{23}, f_{14}, f_{24}, f_{34}$ of Figure 5.10).

4. Consequently, during the simulation, the weight of the relation connecting a *marker concept* of level N (as shown in Figure 5.10) with the *risk concept* of the same level is calculated by Equation 5.4 where W_N is the weight of level N, $f_{iN}(\cdot)$ is the function relating the state of the *marker concept* of level *i* (C_i) with the change that must be applied to the weight of the N^{th} level. A maximum and a minimum value are applied on weights in order to retain the weights in the interval of [-1, 1].

$$W_N = W_N + \sum_{i=1}^{N-1} f_{iN}(C_i) \qquad \text{Equation 5. 4}$$

Table 5. 4: Matrix indicating the prevalence of normal or abnormal cases per each combination of initial value bins

			Lower Level Marker Concept				
			C1	C2	C3	C4	C5
Higher Level Marker Concept		Initial Value Bins	0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	0.8-1
	R1	0-0.2	abn_perc^{11}- norm_perc^{11}	abn_perc^{12}- norm_perc^{12}	abn_perc^{13}- norm_perc^{13}	abn_perc^{14}- norm_perc^{14}	abn_perc^{15}- norm_perc^{15}
	R2	0.2-0.4	abn_perc^{21}- norm_perc^{21}	abn_perc^{22}- norm_perc^{22}	abn_perc^{23}- norm_perc^{23}	abn_perc^{24}- norm_perc^{24}	abn_perc^{25}- norm_perc^{25}
	R3	0.4-0.6	abn_perc31- norm_perc^{31}	abn_perc^{32}- norm_perc^{32}	abn_perc^{33}- norm_perc^{33}	abn_perc^{34}- norm_perc^{34}	abn_perc^{35}- norm_perc^{35}
	R4	0.6-0.8	abn_perc^{41}- norm_perc^{41}	abn_perc^{42}- norm_perc^{42}	abn_perc^{43}- norm_perc^{43}	abn_perc^{44}- norm_perc^{44}	abn_perc^{45}- norm_perc^{45}
	R5	0.8-1	abn_perc^{51}- norm_perc^{51}	abn_perc^{52}- norm_perc^{52}	abn_perc^{53}- norm_perc^{53}	abn_perc^{54}- norm_perc^{54}	abn_perc^{55}- norm_perc^{55}

5.5 Results

Having the concept states and the weights initialized according to the process described earlier, the FCM can run using an activation function and a transformation function. The first one is used to update the concept states through simulation and the latter is used to map the output of each concept in the desired interval of values in order to make the results interpretable. The activation function used for this work is presented in Equation 5.5 (Stylios & Groumpos, 1999) where C_i^t is the state of the i^{th} concept during simulation time *t* and w_{ji} is the weight value between the j^{th} and i^{th} concept.

$$C_i^t = C_i^{t-1} + \sum_{j \neq i}^{N} C_j^{t-1} * w_{ji} \qquad \text{Equation 5. 5}$$

The transformation function used for this work is the logistic, since the desired interval of output is [0, 1].

Whether a pregnancy case was categorized as abnormal or normal was decided based on the risk concept *Pregnancy Specific Risk* shown in Figure 5.10. If the state value of this concept was less than the threshold, the pregnancy case was labelled as normal (euploid) otherwise the pregnancy was regarded as abnormal (bearing T21). Experimentation with the threshold value had be done to find the one that gives the most valid results in the context of achieving the best combination of specificity (true negative) and sensitivity (true positive) rates. True Negative (TN) number refers to the euploid pregnancies which have been categorized correctly. True Positive (TP) value describes the number of T21 pregnancies which have been also categorized correctly. False Negative (FN) and False Positive (FP) give the number of pregnancies that have been classified inaccurately for euploid and T21 cases respectively.

When looking for the final threshold to be used, two conditions were set:

1. Satisfy a false positive rate of 5% (in order to compare the results with the *first-trimester combined screening results.)*
2. Calculate the accuracy and the Matthews correlation coefficient (MCC) to compare the results with the work done in (Neocleous et al., 2016). According to this work, the accuracy is defined as the sum of true positives and true negatives divided by the total length of population where the MCC is a metric of how well models achieve binary classifications, especially in the case where the dataset is highly imbalanced. MCC takes values in the interval of [-1, 1] where -1 indicates a total disagreement between the classification and the desirable output, 0 indicates that the classifier has done nothing more than random prediction and 1 stands for the perfect classification.

$$MCC = \frac{TP*TN-FP*FN}{\sqrt{(TP+FP)*(TP+FN)*(TN+FP)*(TN+FN)}} \qquad \text{Equation 5. 6}$$

Two systems were tested, one with constant weights (system 1) and one with dynamic weights (system 2). The first step was to decide the initial weight value. Since the relations are direct, the system was simulated for different weight values in the interval [0, 1]. The ROC curves were then calculated and the weight with the highest area under the curve (AUC) value was selected. As seen in Figure 5.11 the system with constant weights gave equal AUC values for all weights which were not helpful in deciding the initial weight for this system. On the other hand, the system with dynamic weights gave the highest AUC value when its weights were initialized with the value of 0.8 (Figure 5.12). Consequently, the weights were initialized in both systems to 0.8. The threshold satisfying the aforementioned conditions was 0.7 for System 1 and 0.68 for System 2.

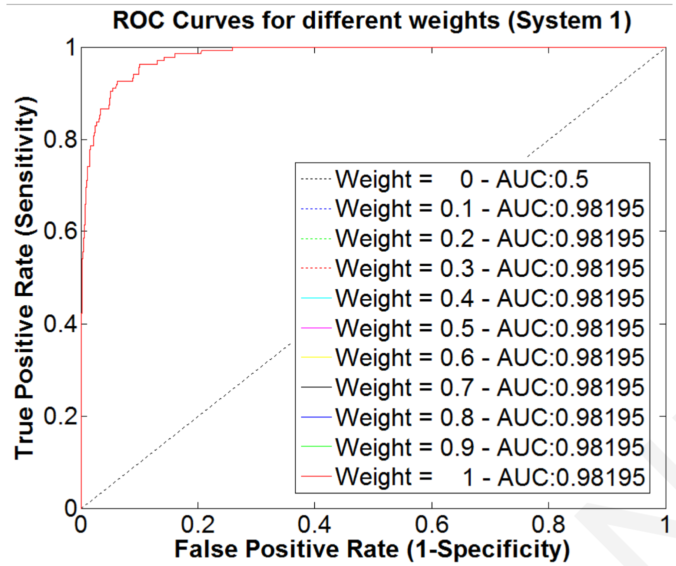

Figure 5. 11: ROC curves for different constant weights (System 1). All the weights produce equal Area Under the Curve values (except zero weights)

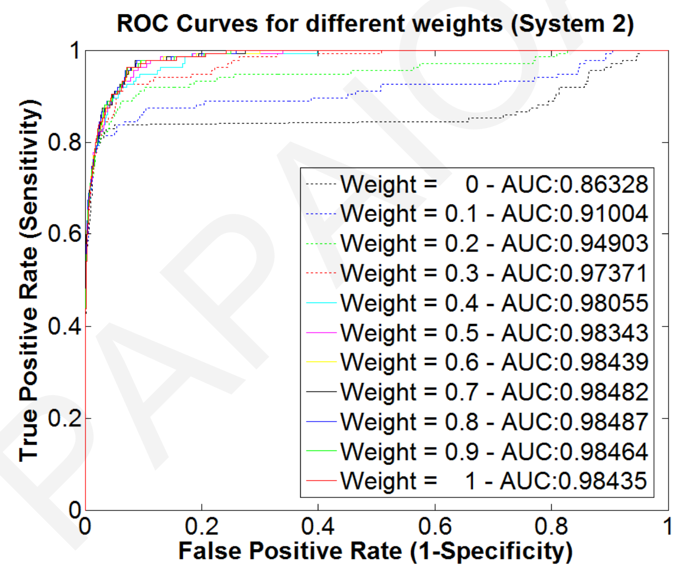

Figure 5. 12: ROC curves for different initial weights (System 2). The weight 0.8 gives the highest Area Under the Curve value

Table 5. 5: Accuracy and MCC value on the two implemented systems

	True Negative Rate	True Positive Rate	Accuracy	MCC
System 1 (Constant Weights)	95%	87%	0.95	0.31
System 2 (Dynamic Weights)	95%	91%	0.95	0.32

The two systems were then let to run over the testing dataset which was kept unknown during the FCM building process. The results are presented in Table 5.5. It shows that when both systems achieve a 5% false positive rate, System 1 with constant weights scores an 87% true positive rate whereas System 2 increases this rate by 4% yielding a 91% TPR using dynamic weights.

In the first place, it is important to mention that a FCM system (system 1) which was built entirely on information taken from the problem's relative literature, without the contribution of any medical or any other kind of experts neither the use of an optimization algorithm, achieved a detection rate of 87% with accuracy 0.95. This can be classified as good diagnostic yield based on related literature. What is more significant though, is that system 2 has managed to raise the detection rate to 91% by the use of dynamic weights. It seems that when we enabled the network to adapt the weights of the system for each pregnancy case provided better classification of the aneuploid cases. Thus, the knowledge of how "normal" were the states of the other concepts leading to the decrease or increase of a specific relation's weight enhanced the system to spot more T21 cases correctly.

First-trimester combined screening provided a 95% specificity rate and 90% sensitivity rate where the ANN approach gave a 100% detection rate for a 4% false positive rate. Alternatively, cfDNA outperforms any other non-invasive screenings with a 99% detection rate and a false positive rate being less than 0.1%. Due to many matters related to the implementation and the cost of cfDNA, medical practitioners in this area suggest its use to be done in combination with other screenings, and we suggest that the proposed FCM-DDSS can be used in combination for minimizing the total cost of screening.

The diagnostic yield of this study can be judged as successful. Firstly, it provides similar results with first trimester screening with slightly increased sensitivity rate. It might not outperform ANN approach, but it provides to clinicians and medical related personnel a classifier which resembles medical knowledge modeling, rendering it fully interpretable by them. Additionally, the T21 FCM is transparent, interpretable and strongly adaptive to new medical knowledge (in terms of introducing new concepts or change weights and relations). This is something which can be hardly done with an ANN machine which is basically a black box. Furthermore the proposed model defeats SVM and k-NN models in terms of accuracy rate and MCC values (Neocleous et al., 2016). More specifically, SVM scores a 0.93 accuracy and 0.31 MCC where k-NN holds a lower accuracy of 0.92 and 0.28 for MCC.

Not only that, but this is actually the second time FCM is tested on this problem. The first application of FCMs on this medical problem was presented in Chapter 4 and provided a 86%

specificity rate for a 77% sensitivity rate. On the contrary, first-trimester combined screening has been developing for more than 15 years and Artificial Neural Networks have also been developing on this problem for almost 7 years (Neocleous, Nicolaides, Neokleous, & Schizas, 2010; Neocleous, Nicolaides, Neokleous, Schizas, & Neocleous, 2011; Neocleous et al., 2012; Neocleous, Neocleous, Petkov, Nicolaides, & Schizas, 2016).

So, by applying improvements and by enhancing the proper knowledge representation by at least one medical expert, the proposed FCM schema can be improved to provide even better results. For example, the inclusion of more pregnancy features which participate as markers in the first-trimester combined screening and the ANN approach. History of previous trisomies is an example of such markers. Whether a pregnant woman had previous pregnancies with trisomy 21, trisomy 18 or trisomy 13 proved to be associated with aneuploidy diagnostic risk. Another marker that could participate to our network is the ductus venosus pulsatility index for which already a mixture of Gaussians model has been proposed (Maiz, Wright, Ferreira, Syngelaki, & Nicolaides, 2012). The reasons for not including them in this work, is the lack of information related to the history of trisomies and their associations with diagnostic risk and other markers in bibliography. Concerning the ductus venosus pulsatility index, it was not used as it was not included in the dataset we had to work with.

5.6 Comment on this work

In this work, we have presented a FCM schema which is novel in three main aspects:

1. Its construction is entirely based on information extracted from the modeled problem's research area.
2. The collected information is used to develop and use probabilistic models to describe the concepts of the FCM.
3. Functions are derived to regulate the weights of the network during simulation depending on different concept initial states.

To sum up, the proposed methodology can be applied in cases where experts are not available (due to distance or communication problems) but at the same time the problem is extensively described through published work by pioneers in the problem's domain.

The positive effect of using dynamic case-specific weights has been demonstrated with the results, since system 2 provided better AUC values in the ROC curves and a better true positive rate. The use of dynamic weights can be used to introduce to the network some kind of flexibility when handling cases for which the aggregated state of the system favors a specific class. Hence, the system is allowed to be stricter when the majority of the concepts tend to be abnormal and less strict in the opposite case.

The proposed FCM schema is characterized by some limitations. Firstly, the existence of a dataset including a satisfying number of cases per class is a pre-requisite. The proposed FCM paradigm cannot be used in cases with lack of dataset. Not only that, but since the construction of the network's structure is strongly dependent on information taken from the problem's research domain, the FCM handler must have a good understanding of the problem's elements and features being able to comprehend with the language and terminology used in relative published work. Additionally, the proposed methodology uses in many cases discretization to divide continuous intervals into bins. The equal-width binning is collected amongst the unsupervised discretization techniques. However, many problems were reported related to using equal-width or equal-frequency discretization methods highlighting their vulnerability to outliers (Liu, Hussain, Tan, & Dash, 2002).Thus, more sophisticated discretization algorithms can be explored and compared in order to conclude to the one which adapts the interval cuts to the context of the modeled problem in a more efficient way (Ramírez-Gallego et al., 2016; García, Luengo, Sáez, López, & Herrera, 2013).

Furthermore, another potential limitation of this study might be the use of Expectation-Maximization algorithm. The EM algorithm has been proven to be an elegant and powerful method for finding maximum likelihood solutions for models with broad applicability (Bishop, 2006). Although, EM achieves large jumps in parameter space, particularly in the initial iterations, there is no guarantee that EM will not get trapped into a local maxima (Barber, 2012). Hence, alternative mixture model formulation techniques might be considered and compared to see if they manage a better description of the concepts and thus if they provide better diagnostic results.

Finally, another limitation of the system is the use of equal weight values for all the relations between *marker concepts* and *risk concepts.* Unfortunately, such information was not easy to be extracted from bibliography. Hence, an expert could crystalize the power of each relation indicating the importance of each *marker concept* in the context of the modeled problem. Contacting such an expert is in our future plans and thus we can overcome this limitation in future work.

6. Conclusions and Future Work

The core subject of this research work is the model of Fuzzy Cognitive Maps (FCMs) which belongs to the field of Computational Intelligence. This model was proposed as an extension of Cognitive Maps (CM) which was mainly used to represent social scientific knowledge. Kosko introduced the idea of using fuzzy sets to define the participatory elements of the network and thus, FCMs were born. Although the use of the ancestor of this model was oriented in problems from political sciences, FCMs have managed to spread their selection on multi-domain problems.

The ability of FCMs to express complex systems by avoiding difficult reasoning processes and precise mathematical models initiated my motivation for selecting this model as my thesis' subject. The interconnections of the system resemble cause-effect relations which can be emulated to imitate the way humans think and understand the dynamics of a system. Additionally, FCMs present attributes like time lag, abstraction, flexibility and adaptability allowing researchers to experiment with systems in any desired set-up. Any system which is characterized by causality can be designed by FCMs either by using expert knowledge, datasets or both.

In order to use FCM, a problem must be characterized by causal interrelations between its parameters. Thus, someone could prefer using FCM technology amongst other more classical computational intelligence models (e.g. ANNs) only for problems for which representing their causal dynamics can be beneficial in terms of approaching their solution. Additionally, FCMs can also be used whenever the involvement of human medical experts is important for solving the specific problem as they can understand and comprehend better with the system. Consequently, if the causal representation of a system is either not possible (due to the total absence of knowledge regarding the causal relations of the system or due to the fact that such relations are not existent in reality) or useless (due to the fact that there is no benefit by allowing the interaction between the system modeling and the human experts), other methods taken from Computational Intelligence field can be adopted instead (e.g. like ANNs).

In this work, three different ways of building FCMs have been proposed. The first way, concerns the cases for which dataset is not available and thus, the whole building process must be mainly supported by human experts in the problem's domain. Areas which are characterized by dataset absence are the political, social and the economical. Such areas face problems with a big number of multi-disciplinary parameters which are hard to quantify and thus record them in a dataset.

The other two FCM building methods, proposed in this thesis, process a dataset to extract information about the FCM network initialization and representation in a very different way. The first approach utilizes experts help in combination with the dataset. As mentioned in previous sections of this study, the concepts and the weights of a FCM system can be defined using fuzzy sets. Along these lines, a methodology of transforming crisp dataset parameters into fuzzy has been proposed and used to build a real FCM system. Experts participate in the process by giving some insight into the way they interpret different parameters of the dataset. The third building methodology requires only the existence of a dataset and can be used in the absence of experts. Instead, relative literature is thoroughly studied and important information about the factors/concepts of the system and their interdependencies are extracted and used to define the network's structure. Based on the guidelines extracted from the bibliography a methodology of using the dataset to derive probabilistic models and their use for FCM initialization was presented.

In the context of the latter work, a hierarchical structure FCM was also proposed. The specific structure allows the representation of the *importance* of each system's concept. Therefore, the most important concepts lie in the first level and the lower in importance concepts follow in the rest layers of levels accordingly. Finally the notion of dynamic weights was also presented. Thus, the weights of the FCM do not remain constant for all the cases but they are allowed to change depending on the states of the "higher in hierarchy" concepts.

The three proposed FCM construction methodologies do not refer to all kind of causal problems. On the contrary, different causal problems might be addressed better by one or another methodology. A general framework on how one can select which approach might be better to be adopted for a specific problem is described below. Three questions mainly guide the proper selection of the approach. The first question is whether experts related to the problem are available in participating in the process of developing a potential FCM system. The second question concerns the existence of a dataset describing different parameters of the problem. The last questions is about the purpose of using FCM for that specific problem. For example are the FCM modelers interested in studying the trends or the absolute values of the system? The different answers given to these questions, define a different proper selection on the approach which is presented in Table 6.1. The suggestions of the approaches (as presented in this thesis) that can be used per each combination of answers are described further down.

Suggestion 1: All three approaches can be used. The user can experiment with all and see what suits the modeled system better. The only thing that should be mentioned, is that for the cases the user selects the approach given by Chapter 4 or Chapter 5, the activation function used should be changed to Equation 3.4.

Suggestion 2: The second and the third approaches (presented in Chapters 4 and 5) are more suitable for this case.

Suggestion 3: The first approach presented in Chapter 3 should be adopted in this case.

Suggestion 4: In this case, none of the presented approaches is suitable and thus the user should explore other FCM methodologies proposed in relative literature.

Suggestion 5: The last approach, presented in Chapter 5 should be considered using the activation function given by Equation 3.4 to simulate the network.

Suggestion 6: The last approach presented in Chapter 5 should be adopted.

Suggestion 7: None of these approaches could work without the existence of available data or experts related to the system.

Table 6. 1: Framework defining how to select a FCM approach presented in this thesis

Question 1 (experts available)	Yes	Yes	Yes	Yes	No	No	No	No
Question 2 (data available)	Yes	Yes	No	No	Yes	Yes	No	No
Question 3 (study trends?)	Yes	No	Yes	No	Yes	No	Yes	No
Suggestion	1	2	3	4	5	6	7	7

As one might observe, in many cases the experts are needed to construct a FCM system. Thus, a question about the number of the involved experts participating in a FCM building process might be raised. There is not any reported work on how one should choose either the involved experts or their number in order to provide a good FCM modeling result. However, when selecting the involved experts one should consider one important question: *"What is the target* *of this modeling? What is the hypothesis behind the design of the system?"*. Thus, if the target is to approach the model using the most experienced and valid way, the selection of one and only one expert can be enough as long as this expert has been specialized on the specific problem, proven by his interaction with this problem to have a high degree of understanding the causal dynamics of the problem and the structure of the problem itself. However, if the hypothesis behind the modeling of a causal system is to "measure" the public opinion about a system of a general interest (e.g. a social system) then the involvement of more experts should be certainly considered as to have a more global picture of the system as possible. In the cases though, for which different experts' opinions are highly contradictive, then the FCM handler should certainly not aggregate their opinions and average them as this will remove any important information about the causal dynamics of the system. In such cases, the FCM modeler can either choose the group of experts expressing more convincing arguments on their ideas or consider providing different FCM systems resembling separately the contradictive ideas of the different groups of experts. So, for example if one wishes to design a FCM system representing the public opinion and the experts are divided in two main groups supporting different ideas about the causal dynamics of the system, the FCM modeler can provide two different systems and use the FCM models to compare different scenarios and allow the experts to make their own conclusions about where they can be right or wrong.

6.1 Contributions of the research work

The important contributions of the research work implemented under this thesis are listed below.

- Expert-based FCMs have many times been criticized for their subjectivity (Papageorgiou & Stylios, 2008; Salmeron, 2010; Stach, Kurgan, & Pedrycz, 2010b). Since, such FCMs are built to resemble humans' state of mind about the modeled problem and since humans tend to be subjective in their nature, such an argument seems to be justified. However, what is considered to be FCM's weakness can be proven to be its strength. Although the importance of building intelligent systems based on real data exploring different patterns and extracting information from proper data analysis is not debatable, it is also true that there are cases for which human expertise and experience comprise key elements for solving problems in various areas. There are three main categories of problems for which humans' knowledge can be exploited to build intelligent systems:

1. The cases for which a human or a group of humans has been proven to have comprehensive and rational understanding of the problem and its dynamics through time. In these cases their perception of the system is valuable and thus, having a model which represents their knowledge can be used repeatedly for answering different questions concerning the modeled system without the need of the specific humans' presence.
2. The cases for which we intentionally want to explore the system's behaviour using the dynamics as understood by a group of people who share a common way of thinking (e.g. members of political parties). In such cases, we can explore the behaviours of a specific system under different comprehensions of its causal dynamics. In that way, further analysis of the results of such experiments can be done by the participants themselves and by the experts in the problem's domain regarding the validity of their perceptions. Not only that, but the participants will have the opportunity to understand the importance of specific concepts through experimentation with the modeled system.
3. In the cases where modeling and simulating scenarios on specific system is very useful, yet no dataset is available as an alternative solution.

A FCM construction methodology has been proposed for the three aforementioned categories of problems. The methodology is divided into specific steps of specifying system's modeling time period, collection of information about the modeled system in that period from many sources, identification of the principle parameters and some relative information about them, initialization of the concept states based on the collected information and definition of the weight values through an interactive procedure with the experts. The whole procedure aims at helping the experts who might be irrelevant in using FCMs to clarify what kind of information the system needs to be modeled and simulated. This is the first time to my knowledge that a FCM building methodology's main objective is the guidance of the experts to give the exact information needed in the context of FCMs. Other proposed expert-based building methodologies aim at penalizing the experts whose opinion diverge from the average. These methodologies can be used in combination with the one proposed in this thesis to form a two-level FCM building methodology where each expert will build its own FCM map according to the methodology proposed in this work and then the FCM handler will apply a penaltybuilding methodology considering that averaged opinions are more powerful than a specific individual's one.

- A new activation function during FCM simulations has been proposed. The proposed activation function can be used for simulating scenarios on a modeled system towards answering specific "What-If" questions. In such cases, the modeled system is initially regarded to be in an equilibrium state. Then, by applying some changes on the parameters' states, the system initiates a loop of propagating influences through causal paths until reaching another equilibrium state. Finally, the system's response can be interpreted considering the applied scenario. Thus, the impact on the system's parameters is expressed when and only when at least one parameter changes its initial equilibrium state value (according to the simulated scenario). The use of the proposed activation function implies, that a concept exhibiting stable behaviour can not cause change to the system's gross behavior but it is the change of a parameter's state which causes the system perturbation and forces it to reach a new equilibrium state. So far, the activation functions used allow the absolute value of the concept states to create effects and impacts in the system. However, for some type of systems (especially taken from social, political and economic sectors) the magnitude and the direction of the change illustrated in the concepts, as part of a scenario testing, is very important into representing how the causal dynamics process in the network. The use of the proposed activation function on a complex problem taken from Cypriot social and economic reality provided sensible results which were verified later by history. On the same problem, the use of other activation functions failed to capture part of the verified results. Additionally, on the same problem, the other tested activation functions failed to provide any results without the use of a squashing function. On the contrary, the proposed activation function in this work avoids using transformation function and so its use overcomes the limitation presented of sigmoid function as described in Chapter 2.
- Introducing some kind of vagueness into knowledge-based decision support medical systems is of immense significance. Besides, health practitioners often handle medical information in an abstract way. Abstraction may be defined as the ability of human beings to recognize and select the relevant properties of real-world phenomena and objects to make specific decisions (Adlassnig, 1986). Thus, humans think, reason and decide in an imprecise, abstract way. In this framework, fuzzy sets can be used to incorporate

abstraction and vagueness into data-driven knowledge-based decision support models. Fuzzy set theory has been proven, through its use in medical systems, to provide tools of handling imprecise information characterized by incompleteness, inaccuracy and inconsistency. One of the most appealing, though, characteristics of fuzzy sets is that they provide a linguistic approach in defining problems which enables the direct and easy communication of fuzzy systems with human users. Hence, by the use of fuzzy set theory, conceptual models can be constructed to represent certain medical problems. A construction methodology like that includes two steps. The first step is about the medical data-to-concept conversion where the second step concerns the identification of the medical relationships driving from medical concepts to decisions. For the first step, clinicians or other medical healthcare staff must record examination descriptions and parameters in linguistic form. After the collection of a decent number of patient descriptions, the resulted dataset can be used to guide the building of a fuzzy system. However, it is generally known that most of the doctors do keep records of their patient information in crisp form, following the Galileo Galilei suggestion "measure what is measurable, and make measurable what is not so" (Seising, 2009). There exist very large volume datasets for different medical problems but most of them in crisp form which are available to be used to derive a medical or diagnostic decision support system but not a fuzzy one. It might take years or decades to recreate corresponding datasets of the same volume in fuzzy form and it could be the case that clinicians may be reluctant to such a process since they have already spent an important amount of time in providing crisp patient datasets. Recognizing this need, a methodology of exploiting a crisp dataset to create a fuzzy one was proposed. By applying the methodology, a new dataset is resulted which can be totally or partly in fuzzy form dependent on the clinicians' wish. That means that certain parameters which were described in crisp form are now expressed using linguistic terms that clinicians use to describe different states of the specific problem's aspect. The proposed methodology is a novel approach since it offers the opportunity to contribute to the design and implementation of new fuzzy diagnostic decision support systems combining the clinicians' way of thinking and existing medical datasets.

- The methodology was applied on a real medical problem using FCMs to represent the medical relationships which lead to a decision. The selected problem is about the diagnosis of Trisomy 21. Current diagnostic systems used for this problem require extremely high accuracy and precision in the different pregnancy measurements to provide valid diagnostic results. At the same time, performing such measurements demands highly experienced, specialized and certified sonographers. Hence, the diagnosis cannot be done by common gynecologists during a routine visit and so pregnant women are referred to specialized medical centers. Using the proposed methodology, a FCM DDSS was created under the assumption that a common, uncertified gynecologist will be using it by reporting specific measurements in words. This is the very first time the specific problem is approached in this perspective.

- There are cases for which contacting a medical expert or a group of medical experts is not possible due to time and distance limitations and communication problems. On the other hand, providing a medical dataset is feasible and extensive bibliography is available describing different aspects of the problem. Taken that the concepts of the problem are characterized by causality into the way they interfere, FCMs can be used to represent and simulate this system. Thus, a new methodology was proposed which takes an advantage of existing published work around a specific problem's research area to extract information about the participating concepts and the structure of the network. Probabilistic models are then derived using a dataset, to describe the distributions of the network's concepts. Probabilistic modeling has emerged as one of the principle and practical approaches for designing machines that learn from data providing plausible models which explain observed data (Ghahramani, 2015). Computational and Artificial intelligence areas have only recently allowed to probabilistic approaches to become main-stream (Murphy, 2012). Similarly, FCMs present limited work in incorporating probabilistic models in their structure, function or both. Thus, no previous recorded FCM approach has employed probabilistic models to describe the concepts nor the likelihood ratio has ever been used to extract information about the FCMs' concepts initialization. In this study, the FCM concepts are described by probabilistic models which achieve to represent the associations between the network's concepts and other pregnancy factors. Then, the information of the likelihood ratio which is the fraction of the abnormal likelihood divided by the normal likelihood, is used in a proposed way to initialize the FCM network. This is a novel approach for initializing a medical diagnostic FCM which uses a synthesized and denser form of information to describe the states of the concepts rather than the raw actual value of the medical factor.

- Imbalanced datasets have been reported to hinder the performance of many standard classifiers since the model tends to focus on the prevalent class and to ignore the rare events (Japkowicz & Stephen, 2002; Menardi & Torelli, 2014). Imbalanced datasets comprise a common phenomenon for binary medical/diagnostic problems for which mostly the *normal class* dominates the *abnormal class (infected class)*. However, by deriving probabilistic models separately for normal class and abnormal class limits the dominating effect of the majority class. The fact that the main information used to define the FCM concepts of the proposed methodology was the likelihood ratio combining *normal* and *abnormal* likelihoods sourcing from different distributions allowed the FCM classifier to escape from problems related to imbalanced class datasets.
- A new dynamic FCM model was proposed and developed. The main purpose of this dynamic model was to appraise the dynamic nature of different combinations of concept states their impact on the weight strength of specific interrelations. Thus, the proposed system implies that the strength of impact which one concept exerts upon another is not independent from the behaviour of the rest network's concepts. On the contrary, the degree to which a concept influences another concept depends on the states of other concepts. This scheme was proposed as a way of handling potential *synergies*. Hence, a parallel existence of a specific combination of concept states might lead to a positive synergy (increasing the weight of a specific relation) or to a negative synergy (decreasing the same weight). The proposed method can be used to systems whose relations are not constant under all conditions but their interpretation can vary depending on the behaviour of other factors which also participate in the same network. The change illustrated to each weight is given by a function which accepts as an input the state of another concept of the system. Concluding, this is the first time the weights of a FCM are regulated by a function during simulation and that the specific function is derived from the analysis of a dataset.

6.2 Future Work

The primary objective of this thesis was to propose ways and methods for representing knowledge about systems characterized by causality in their interrelations, using FCMs. The proposed methods in this work involve expert-based and data-based construction methodologies, data fuzzification, dynamic weights scheme and system's initialization based on probabilistic information. The resulting methodologies and models presented in the context of this thesis can be extended and exploited in certain ways as to improve the quality of the results and at the same time make the model more user-friendly in terms of human-model interaction.

6.2.1 Introducing fuzziness in expert-based FCM building methodology

The methodology presented in Chapter 3 was proposed to ensure, to a degree, that the experts follow the logic and the philosophy behind the FCM model and hence they give the information needed to satisfy the requirements of the model. Besides from being beneficial for the right building of a FCM system, this process also facilitates the experts in understanding more quickly what we need from them.

However, the fourth step of this methodology requires from experts to define each interconnection's weight by setting a question on the interrelated concepts. Consider, concept A and B to be the preceding and the ascending concepts of the relation respectively. The question then is: "If concept A changes its state from $State1_A$ to $State2_A$what will be the new state of concept B if its current state is $State1_B$?". The experts answer this question by defining the new state of concept B ($State2_A$). All the concept states in the question formulation are given in a crisp form. Similarly, the expert answers back using a crisp value for the expected changed state of the concept B. Then, the weight degree is calculated based on their answer. Essentially, the distance between the two crisp states of the influenced concept is divided by the distance between the crisp states of the influencing concept.

Nevertheless, this methodology is proposed especially for building systems with social, economic and politic character. The concepts of this kind of systems are many times very hard to be quantified and thus, people, who have expertise in these areas, may prefer expressing their ideas and thoughts in a more qualified way. Since our target is to widen the channel of communication between the experts and the FCM designer, there should be a way of describing some concepts and their interconnections in a fuzzy way.

Hence, future work will be considered in extending the methodology by using fuzzy concepts whose states will be divided into a number of linguistic values. Still, the interrelations' weights will be defined by the experts in a similar manner but this time, experts will have the potentiality to express their thoughts in words rather than crisp numbers.

A study amongst the methods calculating the distance between fuzzy sets must be implemented. The selected distance metric must resemble not only the value of distance but also the direction of the measured change. In that way, the experts will have the choice of describing in total the modeled FCM system using their natural language.

6.2.2 Using Structural Equation Modeling for verifying FCM structures

Since FCMs comprise a valuable tool for modeling systems taken from Social sciences, the perspective of combining the Structural Equation Modeling (SEM) approach with the FCM technology might be considered. More specifically, as we have already mentioned, human experts comprise the basic source of information when building a social FCM. Experts are called to identify the set of concepts which comprise the FCM network along with their interconnections. However, there is another option where we can extract information about a system's concepts. That is to give questionnaires to a big number of people asking questions about the participating concepts of the system. For example, this approach would fit better in defining the states and the relations of the parameter "People's Confidence in Cypriot Banking Sector" of the system presented in the second section of Chapter 3. Asking a big number of people whether they feel confident or not and how their feeling influence their actions regarding the other parameters of the system could certainly give a more objective picture of what is actually going on. SEM can be actually used to analyze such data (sourced from questionnaires) and use them to test the theoretical FCM model as defined by the experts! If the SEM results do not support the mental model defined by the experts, the experts will have to reconsider whether changes must happen to the structure of the network or not and then apply SEM again to test their hypothesis model.

6.2.3 Building FCM negotiation model

The methodology presented in Chapter 3 can be used to model the systems of two parts going under negotiations. The two systems will be interconnected allowing interference between them. Specific goals and standards can be set on the desired concepts on behalf of each system. Then, different scenario cases of negotiation schemes can be simulated and tested by evaluating the satisfaction degree on the goals set to each concept. The distance between the converged states of the goal concepts and the desired intervals will be calculated. The negotiation scheme model will be able to be used for testing different scenarios depending on different negotiation strategies. Such a tool can be very useful for social-political negotiation systems but also for other type of negotiations like the need of an agreement for a potential merging between two companies.

6.2.4 Extensions on Trisomy 21 FCM DDSS

The following suggestions for future work concern the T21 FCM which was described in Chapter 5.

6.2.4.1 Cooperation with experts in Trisomy 21

As mentioned in Chapter 5, the structure of the T21 FCM was mainly based in relative bibliography regarding T21 diagnostic problem. There was no direct communication with any expert on this problem and thus, all the findings sourced from literature.

Although a successful model has been implemented even without the contribution of medical experts, it is very interesting to examine whether a collaboration with experts in the specific domain can bear fruit in terms of increasing the quality of the diagnostic results. The experts can shed some light whether the selected knowledge representation truly reflects the causal dynamics of the system as they understand it. Furthermore, they can help towards the initial assignment of the weights between the *concept markers* and the *risk markers.*

Finally, another challenging part would be to build a separate T21 FCM DDSS explicitly based on experts' point of view and compare the results to the one implemented explicitly based on relative bibliography and data.

6.2.4.2 Extend mixture of Gaussians to fuzzy

The use of mixture of Gaussians to describe specific concepts of the network can be extended in future work to transform these concepts to fuzzy (Gan et al., 2005; Verma & Hanmandlu, 2007). This perspective strongly applies for the marker nuchal translucency. This is one of the most difficult examinations to perform since the fetus has to be in a very precise position in order to take valid measurements. It is a difficult examination that only trained, certified and experienced sonographers can make it and it requires specific pregnancy medical centers (Hyett et al., 2014; Illa et al., 2013; Nyberg et al., 2006). First trimester screening and ANN approaches depend on the validity and accuracy of such measurements for providing accurate diagnostic results. However, allowing to a diagnostic system to use fuzzy values for these factors will have adverse benefits for both clinicians (gynecologists) and pregnant women. The gynecologists will be able to perform such examinations in their office instead of referring to specialist medical centers and pregnant women will be able to have a less painful and stressful examination not to mention less costly. As a first step, the differentiation between low and medium-high risk groups can be done by the proposed system and thus becoming unnecessary for many pregnant women to have to visit expertise pregnancy medical centers.

6.2.4.3 Elaboration of learning and optimization algorithms to optimize T21 FCM

Additionally, learning and optimization algorithms can be used to optimize the initial adjacency matrix (weights) and/or the functions and coefficients used to regulate the weight change during simulations. Relative literature shows that there is a big interest in employing such methods for building FCM weight matrix and thus this perspective must be examined if needed (Papageorgiou, 2011a). Taken from the survey implemented for the purposes of this work, the algorithms *Non-Linear Hebbian Learning* (Papageorgiou et al., 2003) , its extension *Data-Driven Non-Linear Hebbian Learning* (Stach et al., 2008) and the RCGA algorithm (Stach et al., 2005) are the most frequently adopted approaches to optimize medical FCMs weight matrices. Therefore, the incorporation of them to achieve better results might be considered.

6.3 Concluding Remarks

As humans grow and mature, they learn how to think creatively and critically, to reason, and to ask questions. Asking questions comprises a way of learning since intelligent questions stimulate, provoke, inform and inspire (Sloane, 2010). That is the reason large scale companies support the questions' formulation as part of their strategy process with Eric Schmidt, former CEO of Google, stating that "We run this company on questions, not answers" (Caplan, 2006).

FCM technology gives the opportunity to formulate questions regarding a causal system taken from any domain. The questions are expressed by designing specific scenarios, involving different set-ups of the participating parameters. The answers are taken by simulating the modeled system using the states defined by the testing scenario. Consequently, FCM offers a modeling tool of human-friendly knowledge representation in graphical form which can be used to answer "What-If" questions about a system and gain a clearer insight on how the causal dynamics of a system drive its behaviour to certain paths.

The intuitive nature of FCMs is their most appealing characteristic which in turn led me to define specific questions about how we can extend this model in different aspects:

- How can we build a FCM without data?
- How can we build a FCM with data?
- How can we use crisp data to train fuzzy set systems?
- How can we incorporate synergies into FCM model?
- How can we utilize the power of probabilistic models to build FCMs?

This thesis gave me the opportunity to approach the answers to these questions. The journey leading to the answers has been adventurous and beautiful at the same time. The answers were presented in this work and comprise the main body of this thesis. It is true, that the given answers might be characterized by specific limitations. However, the limitations do not act as barriers but rather, as challenges and opportunities for formulating new questions and setting up the environment of a new journey, in the context of future work. Still, the results are encouraging enough to continue and extend the work presented in this thesis towards overcoming these limitations.

REFERENCES

Abele, H., Lüthgens, K., Hoopmann, M., & Kagan, K. O. (2011). Impact of the maternal age-related risk in first-trimester combined screening for trisomy 21. *Fetal Diagnosis and Therapy, 30*(2), 135-140.

Abele, H., Wagner, P., Sonek, J., Hoopmann, M., Brucker, S., Artunc-Ulkumen, B., et al. (2015). First trimester ultrasound screening for down syndrome based on maternal age, fetal nuchal translucency and different combinations of the additional markers nasal bone, tricuspid and ductus venosus flow. *Prenatal Diagnosis, 35*(12), 1182-1186. doi:10.1002/pd.4664

Adlassnig, K. P. (1986). Fuzzy set theory in medical diagnosis. *IEEE Transactions on Systems, Man, and Cybernetics, 16*(2), 260-265. doi:10.1109/TSMC.1986.4308946

Aguilar, J. (2002). Adaptive random fuzzy cognitive maps. Paper presented at the *Proceedings of the 8th Ibero-American Conference on AI: Advances in Artificial Intelligence,* pp. 402-410.

Alfirevic, Z., Mujezinovic, F., & Sundberg, K. (2003). Amniocentesis and chorionic villus sampling for prenatal diagnosis. *Cochrane Database of Systematic Reviews,* (3) doi:10.1002/14651858.CD003252

Alizadeh , S., Ghazanfari , M., Jafari , M., & Hooshmand , S. (2007). Learning FCM by tabu search. *International Journal Computer Science*, 2, 142-149.

Alizadeh, S., & Ghazanfari, M. (2009). Learning FCM by chaotic simulated annealing. *Chaos, Solitons & Fractals, 41*(3), 1182-1190. doi:http://dx.doi.org/10.1016/j.chaos.2008.04.058

Alldred, S. K., Takwoingi, Y., Guo, B., Pennant, M., Deeks, J. J., Neilson, J. P., et al. (2015). First trimester serum tests for down's syndrome screening. *Cochrane Database of Systematic Reviews,* (11) doi:10.1002/14651858.CD011975

Amirkhani, A., Mosavi, M. R., Shokouhi, S. B., & Mohammadizadeh, F. (2012). A novel fuzzy cognitive map based method for the differentiation of intraductal breast lesions. Paper presented at the *2012 5th International Conference on Biomedical Engineering and Informatics (BMEI),* pp. 6-11. doi:10.1109/BMEI.2012.6513204

Amirkhani, A., Papageorgiou, E. I., Mohseni, A., & Mosavi, M. R. (2017). A review of fuzzy cognitive maps in medicine: Taxonomy, methods, and applications. *Computer Methods* *and Programs in Biomedicine, 14*2, 129-145. doi:http://dx.doi.org/10.1016/j.cmpb.2017.02.021

Anninou, A. P., & Groumpos, P. P. (2014). Modeling of parkinson's disease using fuzzy cognitive maps and non-linear hebbian learning. *International Journal on Artificial Intelligence Tools, 2*3(05), 1450010. doi:10.1142/S0218213014500109

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems, 2*0(1), 87-96. doi:http://dx.doi.org/10.1016/S0165-0114(86)80034-3

Axelrod, R. M. (1976). *Structure of decision: The cognitive maps of political elite*s Princeton University Press.

Barber, D. (2012). *Bayesian reasoning and machine learnin*g, Cambridge University Press.

Billis, A. S., Papageorgiou, E. I., Frantzidis, C. A., Tsatali, M. S., Tsolaki, A. C., & Bamidis, P. D. (2015). A decision-support framework for promoting independent living and ageing well. *Biomedical and Health Informatics, IEEE Journal of, 1*9(1), 199-209. doi:10.1109/JBHI.2014.2336757

Bishop, C. M. (2006). *Pattern recognition and machine learning (information science and statistics*). Secaucus, NJ, USA: Springer-Verlag New York, Inc.

Bourgani, E., Stylios, C. D., Manis, G., & Georgopoulos, V. C. (2015). Integrated approach for developing timed fuzzy cognitive maps. In P. Angelov, et al. (Eds.), *Intelligent systems'2014: Proceedings of the 7th IEEE international conference intelligent systems IS'2014, 2014, warsaw, poland, volume 1: Mathematical foundations, theory, analyse*s (pp. 193-204). Cham: Springer International Publishing. doi:10.1007/978-3-319-11313-5_19"

Bourgani, E., Stylios, C., Manis, G., & Georgopoulos, V. (2014). Time dependent fuzzy cognitive maps for medical diagnosis. In A. Likas, K. Blekas & D. Kalles (Eds.), (pp. 544-554) Springer International Publishing. doi:10.1007/978-3-319-07064-3_47

Bueno, S., & Salmeron, J. L. (2009). Benchmarking main activation functions in fuzzy cognitive maps. *Expert Systems with Applications, 3*6(3, Part 1), 5221-5229. doi:DOI: 10.1016/j.eswa.2008.06.072

Buruzs, A., Hatwágner, M. F., & Kóczy, L. T. (2015). Expert-based method of integrated waste management systems for developing fuzzy cognitive map. In Q. Zhu, & A. T. Azar (Eds.), *Complex system modeling and control through intelligent soft computation*s (pp. 111-137). Cham: Springer International Publishing. doi:10.1007/978-3-319-12883-2_4"

Büyükavcu, A., Albayrak, Y. E., & Göker, N. (2016). A fuzzy information-based approach for breast cancer risk factors assessment. *Applied Soft Computing, 3*8, 437-452. doi:http://dx.doi.org/10.1016/j.asoc.2015.09.026

Caplan, J. (2006). *Google's chief looks ahead. http://content.time.com/time/business/article/0,8599,1541446,00.html*

Carvalho, J. P. (2010). On the semantics and the use of fuzzy cognitive maps in social sciences. Paper presented at the *2010 IEEE International Conference on Fuzzy Systems (FUZZ),* pp. 1-6.

Carvalho, J. P., & Tomé, J. A. B. (2001). Rule based fuzzy cognitive maps - expressing time in qualitative system dynamics. Paper presented at the *10th IEEE International Conference on Fuzzy Systems.* pp. 280-283.

Carvalho, J. P. (2013). On the semantics and the use of fuzzy cognitive maps and dynamic cognitive maps in social sciences. *Fuzzy Sets and Systems, 21*4, 6-19. doi:http://dx.doi.org/10.1016/j.fss.2011.12.009

Cheah, W. P., Kim, Y. S., Kim, K., & Yang, H. (2011). Systematic causal knowledge acquisition using FCM constructor for product design decision support. *Expert Systems with Applications, 3*8(12), 15316-15331. doi:http://dx.doi.org/10.1016/j.eswa.2011.06.032

Chen, Y., Mazlack, L., & Lu, L. (2012). Learning fuzzy cognitive maps from data by ant colony optimization. Paper presented at the *Proceedings of the 14th Annual Conference on Genetic and Evolutionary Computation,* Philadelphia, Pennsylvania, USA. pp. 9-16. doi:10.1145/2330163.2330166

Cicero, S., Rembouskos, G., Vandecruys, H., Hogg, M., & Nicolaides, K. H. (2004). Likelihood ratio for trisomy 21 in fetuses with absent nasal bone at the 11–14-week scan. *Ultrasound in Obstetrics and Gynecology, 2*3(3), 218-223. doi:10.1002/uog.992

Coban, V., Cevik Onar, S., & Soyer, A. (2015). Analyzing dynamic capabilities via fuzzy cognitive maps. In C. Kahraman, et. al (Eds.), *Intelligent techniques in engineering management: Theory and application*s (pp. 173-201). Cham: Springer International Publishing. doi:10.1007/978-3-319-17906-3_8"

Czuba, B., Serafin, D., Węgrzyn, P., Cnota, W., Dubiel, M., Mączka, M., et al. (2016). Nasal bone in screening for T21 at 11–13 + 6 weeks of gestation — a multicenter study. *Ginekologia Polska, 8*7(11), 751-754. doi:10.5603/GP.2016.0082"

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society, Series b, 3*9(1), 1-38.

Despi, I., Song, G., & Chakrabarty, K. (2011). A new intuitionitic fuzzy cognitive maps building method. Paper presented at the *Fuzzy Systems and Knowledge Discovery (FSKD), 2011 Eighth International Conference on, , 1.* pp. 574-578. doi:10.1109/FSKD.2011.6019596

Dhar, V., & Stein, R. (1997). *Intelligent decision support methods: The science of knowledge wor*k. Upper Saddle River, NJ, USA: Prentice-Hall, Inc.

Dickerson, J. A., & Kosko, B. (1994). Virtual worlds as fuzzy cognitive maps. *Presence,* 3(2), 73-89.

Dragusin, R., Florea, M., Iliescu, D., Cotarcea, S., Tudorache, S., Novac, L., et al. (2012). The contribution and the importance of modern ultrasound techniques in the diagnosis of major structural abnormalities in the first trimester – case reports. *Current Health Sciences Journal*, *3*8(1), 20-24.

Ducheyne, S. (2006). Galileo's interventionist notion of "cause". *Journal of the History of Ideas, 6*7(3), 443-464.

Ekelund, C. K., Petersen, O. B., Sundberg, K., Pedersen, F. H., Vogel, I., & Tabor, A. (2012). Screening performance for trisomy 21 comparing first trimester combined screening and a first trimester contingent screening protocol including ductus venosus and tricuspid flow. *Prenatal Diagnosis, 3*2(8), 783-788. doi:10.1002/pd.3902

El Gayar, N., Schwenker, F., & Palm, G. (2006). A study of the robustness of KNN classifiers trained using soft labels. In F. Schwenker, & S. Marinai (Eds.), (pp. 67-80) Springer Berlin Heidelberg. doi:10.1007/11829898_7

Faiola, S., Tsoi, E., Huggon, I. C., Allan, L. D., & Nicolaides, K. H. (2005). Likelihood ratio for trisomy 21 in fetuses with tricuspid regurgitation at the 11 to 13 + 6-week scan. *Ultrasound in Obstetrics and Gynecology, 2*6(1), 22-27. doi:10.1002/uog.1922

Frede, M. (1980). The original notion of cause. In J. Barnes, M. F. Burnyeat & M. Schofield (Eds.), *Doubt and dogmatism: Studies in hellenistic epistemolog*y (pp. 217-249) Oxford: Oxford University Press.

Froelich, W., & Papageorgiou, E. I. (2014). Fuzzy cognitive maps for applied sciences and engineering: From fundamentals to extensions and learning algorithms.(Extended Evolutionary Learning of Fuzzy Cognitive Maps for the Prediction of Multivariate Time-Series), 121-131. doi:10.1007/978-3-642-39739-4_7"

Froelich, W., Papageorgiou, E. I., Samarinas, M., & Skriapas, K. (2012). Application of evolutionary fuzzy cognitive maps to the long-term prediction of prostate cancer. *Applied Soft Computing, 1*2(12), 3810-3817. doi:http://dx.doi.org/10.1016/j.asoc.2012.02.005

Froelich, W., & Salmeron, J. L. (2014). Evolutionary learning of fuzzy grey cognitive maps for the forecasting of multivariate, interval-valued time series. *International Journal of Approximate Reasoning*, *55*(6), 1319-1335. doi:http://dx.doi.org/10.1016/j.ijar.2014.02.006

García, S., Luengo, J., Sáez, J. A., López, V., & Herrera, F. (2013). A survey of discretization techniques: Taxonomy and empirical analysis in supervised learning. *IEEE Transactions on Knowledge and Data Engineering, 25*(4), 734-750. doi:10.1109/TKDE.2012.35

Gasiorek-Wiens, A., Kotsis, S., Staboulidou, I., Stumm, M., Wegner, R. D., Soergel, P., et al. (2010). A mixture model of nuchal translucency thickness in screening for chromosomal defects: Validation of a single operator dataset. *Prenatal Diagnosis, 30*(11), 1100-1106. doi:10.1002/pd.2625

Geipel, A., Willruth, A., Vieten, J., Gembruch, U., & Berg, C. (2010). Nuchal fold thickness, nasal bone absence or hypoplasia, ductus venosus reversed flow and tricuspid valve regurgitation in screening for trisomies 21, 18 and 13 in the early second trimester. *Ultrasound in Obstetrics and Gynecology, 35*(5), 535-539. doi:10.1002/uog.7597

Gelenbe, E. (1989). Random neural networks with negative and positive signals and product form solution. *Neural Computation*, *1*(4), 502-510. doi:10.1162/neco.1989.1.4.502

Georgopoulos, V. C., & Stylios, C. D. (2009). Diagnosis support using fuzzy cognitive maps combined with genetic algorithms. Paper presented at the *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 6226-6229. doi:10.1109/IEMBS.2009.5334647

Georgopoulos, V. C., Malandraki, G. A., & Stylios, C. D. (2003). A fuzzy cognitive map approach to differential diagnosis of specific language impairment. *Artificial Intelligence in Medicine, 29*(3), 261-278. doi:http://dx.doi.org/10.1016/S0933-3657(02)00076-3

Georgopoulos, V. C., & Stylios, C. D. (2013). Fuzziness and medicine: Philosophical reflections and application systems in health care: A companion volume to sadegh-zadeh's handbook of analytical philosophy of medicine.(Fuzzy Cognitive Map Decision Support System for Successful Triage to Reduce Unnecessary Emergency Room Admissions for the Elderly), 415-436. doi:10.1007/978-3-642-36527-0_27"

Georgopoulos, V., & Stylios, C. (2015). Supervisory fuzzy cognitive map structure for triage assessment and decision support in the emergency department. In M. S. Obaidat et. al (Eds.), (pp. 255-269) Springer International Publishing. doi:10.1007/978-3-319-11457-6_18

Ghahramani, Z. (2015). Probabilistic machine learning and artificial intelligence. *Nature*, *521*(7553), 452-459.

Ghazanfari, M., Alizadeh, S., Fathian, M., & Koulouriotis, D. E. (2007). Comparing simulated annealing and genetic algorithm in learning FCM. *Applied Mathematics and Computation, 19*2(1), 56-68. doi: http://dx.doi.org/10.1016/j.amc.2007.02.144

Giabbanelli, P. J., Torsney-Weir, T., & Mago, V. K. (2012). A fuzzy cognitive map of the psychosocial determinants of obesity. *Applied Soft Computing, 1*2(12), 3711-3724. doi: http://dx.doi.org/10.1016/j.asoc.2012.02.006

Glykas, M. (2013). Fuzzy cognitive strategic maps in business process performance measurement. *Expert Systems with Applications, 4*0(1), 1-14. doi: http://dx.doi.org/10.1016/j.eswa.2012.01.078

Glykas, M. (2010). *Fuzzy cognitive maps: Advances in theory, methodologies, tools and application*s (1st ed.) Springer Publishing Company, Incorporated.

Gratacós, E., & Nicolaides, K. (2014). Clinical perspective of cell-free DNA testing for fetal aneuploidies. *Fetal Diagnosis and Therapy, 3*5(3), 151-155.

Gray, S. A., Zanre, E., & Gray, S. R. J. (2014). Fuzzy cognitive maps as representations of mental models and group beliefs. In E. I. Papageorgiou (Ed.), *Fuzzy cognitive maps for applied sciences and engineering: From fundamentals to extensions and learning algorithm*s (pp. 29-48). Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-642-39739-4_2"

Groumpos, P. P. (2012). The challenge of modeling decision support systems for medical problems using fuzzy cognitive maps: An overview. Paper presented at the *IEEE 12th International Conference on Bioinformatics & Bioengineering (BIBE), 2012,* pp. 132-138. doi:10.1109/BIBE.2012.6399662

Hagiwara, M. (1992). Extended fuzzy cognitive maps. Paper presented at the *IEEE International Conference on Fuzzy Systems*, *1992*, pp. 795-801.

Hanifah, F. S., Wijayanto, H., Kurnia, A. (2015). SMOTE Bagging algorithm for imbalanced dataset in logistic regression analysis (Case: Credit of Bank X). *Applied Mathematical Sciences*, 9(138), 6857-6865.

Haoming Zhong, Chunyan Miao, Zhiqi Shen, & Yuhong Feng. (2008). Temporal fuzzy cognitive maps. Paper presented at the *IEEE International Conference on Fuzzy Systems, 2008. FUZZ-IEEE 2008. (IEEE World Congress on Computational Intelligence),* pp. 1831-1840.

Hengjie, S., Chunyan, M., & Zhiqi, S. (2007). Fuzzy cognitive map learning based on multi-objectiveparticle swarm optimization. Paper presented at the *Proceedings of the 9th Annual Conference on Genetic and Evolutionary Computation*, London, England. pp. 339-339. doi:http://doi.acm.org/10.1145/1276958.1277027

Homenda, W., Jastrzebska, A., & Pedrycz, W. (2014). Time series modeling with fuzzy cognitive maps: Simplification strategies. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8838*, 409-420. doi:10.1007/978-3-662-45237-0_38"

Homenda, W., Jastrzebska, A., & Pedrycz, W. (2015). Nodes selection criteria for fuzzy cognitive maps designed to model time series. *Advances in Intelligent Systems and Computing, 323*, 859-870. doi:10.1007/978-3-319-11310-4_75"

Huang, H. Y., Lin, Y. J., Chen, Y. S. & Lu H. Y. (2012). Imbalanced data classification using random subspace method and SMOTE. Paper presented at the *In: Proceedings of the 6th International Conference of Soft Computing and Intelligent Systems*, 817-820

Huerga, A. V. (2002). A balanced differential learning algorithm in fuzzy cognitive maps. Paper presented at the *In: Proceedings of the 16th International Workshop on Qualitative Reasoning 2002*

Hyett, J., Mogra, R., & Sonek, J. (2014). First trimester ultrasound assessment for fetal aneuploidy. *Clinical Obstetrics and Gynecology, 5*7(1)

Iakovidis, D. K., & Papageorgiou, E. (2011). Intuitionistic fuzzy cognitive maps for medical decision making. *IEEE Transactions on Information Technology in Biomedicine, 1*5(1), 100-107. doi:10.1109/TITB.2010.2093603

Illa, M., Mula, R., Arigita, M., Grande, M., Gonce, A., Borobio, V., et al. (2013). Likelihood ratios to apply for nasal bone, ductus venosus and tricuspid flow at the 11-13 weeks' scan in down syndrome screening. *Fetal Diagnosis and Therapy, 3*4(2), 116-120

Japkowicz, N., & Stephen, S. (2002). The class imbalance problem: A systematic study. *Intelligent Data Analysis,* 6(5), 429-449

Kagan, K. O., Cicero, S., Staboulidou, I., Wright, D., & Nicolaides, K. H. (2009). Fetal nasal bone in screening for trisomies 21, 18 and 13 and turner syndrome at 11–13 weeks of gestation. *Ultrasound in Obstetrics and Gynecology, 3*3(3), 259-264. doi:10.1002/uog.6318

Kagan, K. O., Wright, D., Baker, A., Sahota, D., & Nicolaides, K. H. (2008). Screening for trisomy 21 by maternal age, fetal nuchal translucency thickness, free beta-human chorionic gonadotropin and pregnancy-associated plasma protein-A. *Ultrasound in Obstetrics and Gynecology, 3*1(6), 618-624. doi:10.1002/uog.5331

Kagan, K. O., Wright, D., Spencer, K., Molina, F. S., & Nicolaides, K. H. (2008). First-trimester screening for trisomy 21 by free beta-human chorionic gonadotropin and pregnancy-associated plasma protein-A: Impact of maternal and pregnancy characteristics. *Ultrasound in Obstetrics and Gynecology, 3*1(5), 493-502. doi:10.1002/uog.5332

Kannappan, A., Tamilarasi, A., & Papageorgiou, E. I. (2011). Analyzing the performance of fuzzy cognitive maps with non-linear hebbian learning algorithm in predicting autistic disorder. *Expert Systems with Applications, 3*8(3), 1282-1292. doi:http://dx.doi.org/10.1016/j.eswa.2010.06.069

Karadzov-Orlic, N., Egic, A., Milovanovic, Z., Marinkovic, M., Damnjanovic-Pazin, B., Lukic, R., et al. (2012). Improved diagnostic accuracy by using secondary ultrasound markers in the first-trimester screening for trisomies 21, 18 and 13 and turner syndrome. *Prenatal Diagnosis, 3*2(7), 638-643. doi:10.1002/pd.3873

Kecman, V. (2001). *Learning and soft computing: Support vector machines, neural networks, and fuzzy logic model*s MIT Press.

Kerre, E. E., & De Cock, M. (1999). Linguistic modifiers: An overview. In G. Chen, M. Ying & K. Cai (Eds.), *Fuzzy logic and soft computin*g (pp. 69-85). Boston, MA: Springer US. doi:10.1007/978-1-4615-5261-1_5"

Khan, M. S., & Quaddus, M. (2004). Group decision support using fuzzy cognitive maps for causal reasoning. *Group Decision and Negotiation, 1*3(5), 463-480.

Khan, M. S., & Chong, A. (2003). Fuzzy cognitive map analysis with genetic algorithm. Paper presented at the *Iicai*, pp. 1196-1205.

Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machine Studies, 2*4(1), 65-75.

Kosko, B. (1988). Hidden patterns in combined and adaptive knowledge networks. *International Journal of Approximate Reasoning*, 2(4), 377-393. doi:10.1016/0888-613X(88)90111-9

Kosko, B. (1992). *Neural networks and fuzzy systems: A dynamical systems approach to machine intelligenc*e. Upper Saddle River, NJ, USA: Prentice-Hall, Inc.

Koulouriotis, D. E., Diakoulakis, I. E., Emris, D. M., Antonidakins, E. N., & Kaliakatsos, I. A. (2003). Efficiently modeling and controlling complex dynamic systems using evolutionary fuzzy cognitive maps (invited paper). *International Journal of Computational Cognition*, 1(2), 41-65.

Koulouriotis, D. E., Diakoulakis, I. E., & Emiris, D. M. (2001). Learning fuzzy cognitive maps using evolution strategies: A novel schema for modeling and simulating high-level behavior. Paper presented at the *Proceedings of the 2001 Congress on Evolutionary Computation* , pp. 364-371

Krantz, D. A., Hallahan, T. W., Macri, V. J., & Macri, J. N. (2005). Maternal weight and ethnic adjustment within a first-trimester down syndrome and trisomy 18 screening program. *Prenatal Diagnosis, 2*5(8), 635-640. doi:10.1002/pd.1188

Kreinovich, V., & Stylios, C. (2015). Why fuzzy cognitive maps are efficient. *International Journal of Computers Communications & Control, 1*0(6)

Lee, I. K., Kim, H. S., & Cho, H. (2012). Design of activation functions for inference of fuzzy cognitive maps: Application to clinical decision making in diagnosis of pulmonary infection. *Healthc Inform Res, 1*8(2), 105-114

Lee, I. K., & Kwon, S. H. (2010). Design of sigmoid activation functions for fuzzy cognitive maps via lyapunov stability analysis. *IEICE Transactions on Information and Systems, E93.D*(10), 2883-2886. doi:10.1587/transinf.E93.D.2883

Liu, H., Hussain, F., Tan, C. L., & Dash, M. (2002). Discretization: An enabling technique. *Data Mining and Knowledge Discovery, 6*(4), 393-423. doi:10.1023/A:1016304305535"

Liu, Y., Ye, X., Zhang, N., Zhang, B., Guo, C., Huang, W., et al. (2015). Diagnostic value of ultrasonographic combining biochemical markers for down syndrome screening in first trimester: A meta-analysis. *Prenatal Diagnosis, 35*(9), 879-887. doi:10.1002/pd.4626

Lopes,Maria Helena Baena de Moraes, Ortega, N. R. S., Silveira, P. S. P., Massad, E., Higa, R., & Marin, H. d. F. (2013). Fuzzy cognitive map in differential diagnosis of alterations in urinary elimination: A nursing approach. *International Journal of Medical Informatics, 82*(3), 201-208. doi:http://dx.doi.org/10.1016/j.ijmedinf.2012.05.012

Lu, W., Yang, J., & Liu, X. (2014). Numerical prediction of time series based on FCMs with information granules. *International Journal of Computers Communications & Control*, 9(3)

Maiz, N., Valencia, C., Kagan, K. O., Wright, D., & Nicolaides, K. H. (2009). Ductus venosus doppler in screening for trisomies 21, 18 and 13 and turner syndrome at 11–13 weeks of gestation. *Ultrasound in Obstetrics and Gynecology, 3*3(5), 512-517. doi:10.1002/uog.6330

Maiz, N., Wright, D., Ferreira, A. F. A., Syngelaki, A., & Nicolaides, K. H. (2012). A mixture model of ductus venosus pulsatility index in screening for aneuploidies at 11-13 weeks' gestation. *Fetal Diagnosis and Therapy, 3*1(4), 221-229

Marin, J., Mengersen, K., & Robert, C. P. Bayesian modeling and inference on mixtures of distributions. *Handbook of statistic*s (pp. 459-507) Elsevier. doi:http://dx.doi.org/10.1016/S0169-7161(05)25016-2

Mateou, N. H., & Andreou, A. S. (2008). A framework for developing intelligent decision support systems using evolutionary fuzzy cognitive maps. *Journal of Intelligent and Fuzzy Systems, 1*9(2), 151-170

Menardi, G., & Torelli, N. (2014). Training and assessing classification rules with imbalanced data. *Data Mining and Knowledge Discovery, 2*8(1), 92-122. doi:10.1007/s10618-012-0295-5"

Miller, R. A. (1994). Medical diagnostic decision support systems--past, present, and future: A threaded bibliography and brief commentary. *Journal of the American Medical Informatics Association,* 1(1), 8-27

Min, H. q., Hui, J. x., Lu, Y. s., & Jiang, J. z. (2006). Probability fuzzy cognitive map for decision-making in soccer robotics. Paper presented at the *2006 IEEE/WIC/ACM International Conference on Intelligent Agent Technology,* pp. 321-325. doi:10.1109/IAT.2006.102

Ming-Tao Gan, M. Hanmandlu, & Ai Hui Tan. (2005). From a gaussian mixture model to additive fuzzy systems. *IEEE Transactions on Fuzzy Systems, 1*3(3), 303-316. doi:10.1109/TFUZZ.2004.841728

Murphy, K. P. (2012). *Machine learning: A probabilistic perspectiv*e The MIT Press.

Nápoles, G., Bello, R., & Vanhoof, K. (2013). Learning stability features on sigmoid fuzzy cognitive maps through a swarm intelligence approach. In J. Ruiz-Shulcloper, & G. Sanniti di Baja (Eds.), (pp. 270-277) Springer Berlin Heidelberg. doi:10.1007/978-3-642-41822-8_34

Nápoles, G., Grau, I., Bello, R., & Grau, R. (2014). Two-steps learning of fuzzy cognitive maps for prediction and knowledge discovery on the HIV-1 drug resistance. *Expert Systems with Applications, 4*1(3), 821-830. doi:http://dx.doi.org/10.1016/j.eswa.2013.08.012

Neocleous, A. C., Nicolaides, K. H., & Schizas, C. N. (2016). First trimester noninvasive prenatal diagnosis: A computational intelligence approach. *IEEE Journal of Biomedical and Health Informatics, 2*0(5), 1427-1438. doi:10.1109/JBHI.2015.2462744

Neocleous, C. K., Nicolaides, K. H., Neokleous, K. C., & Schizas, C. N. (2010). Artificial neural networks for non-invasive chromosomal abnormality screening of fetuses. Paper presented at the *The 2010 International Joint Conference on Neural Networks (IJCNN),* pp. 1-4. doi:10.1109/IJCNN.2010.5596357

Neocleous, A. C., Neocleous, C. K., Petkov, N., Nicolaides, K. H., & Schizas, C. N. (2016). Prenatal diagnosis of aneuploidy using artificial neural networks in relation to health economics. In E. Kyriacou, S. Christofides & C. S. Pattichis (Eds.), *XIV mediterranean* *conference on medical and biological engineering and computing 2016: MEDICON 2016, march 31st-april 2nd 2016, paphos, cypru*s (pp. 936-940). Cham: Springer International Publishing. doi:10.1007/978-3-319-32703-7_182"

Neocleous, A. C., Nicolaides, K. H., Syngelaki, A., Neokleous, K. C., Loizou, G., Neocleous, C. K., et al. (2012). Artificial neural networks to investigate the importance and the sensitivity to various parameters used for the prediction of chromosomal abnormalities. In L. Iliadis, I. Maglogiannis, H. Papadopoulos, K. Karatzas & S. Sioutas (Eds.), *Artificial intelligence applications and innovations: AIAI 2012 international workshops: AIAB, AIeIA, CISE, COPA, IIVC, ISQL, MHDW, and WADTMB, halkidiki, greece, september 27-30, 2012, proceedings, part I*I (pp. 46-55). Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-642-33412-2_5"

Neocleous, C. K., Nicolaides, K. H., Neokleous, K. C., Schizas, C. N., & Neocleous, A. C. (2011). Artificial neural networks to investigate the significance of PAPPA and b-hCG for the prediction of chromosomal abnormalities. Paper presented at the *The 2011 International Joint Conference on Neural Networks,* pp. 1955-1958. doi:10.1109/IJCNN.2011.6033464

Neocleous, C., & Schizas, C. N. (2012). Modeling socio-politico-economic systems with time-dependent fuzzy cognitive maps. Paper presented at the *IEEE International Conference on Fuzzy Systems*

Nicolaides, K. H. (2011). Screening for fetal aneuploidies at 11 to 13 weeks. *Prenatal Diagnosis, 3*1(1), 7-15. doi:10.1002/pd.2637 [doi]

Nicolaides, K. H., Syngelaki, A., Gil, M. M., Quezada, M. S., & Zinevich, Y. (2014). Prenatal detection of fetal triploidy from cell-free DNA testing in maternal blood. *Fetal Diagnosis and Therapy, 3*5(3), 212-217

Nicolaides, K. H. (2004). *The 11–13+6 weeks sca*n. London: Fetal Medicine Foundation.

Nicolaides, K. H. (2011). Screening for fetal aneuploidies at 11 to 13 weeks. *Prenatal Diagnosis, 3*1(1), 7-15. doi:10.1002/pd.2637

Nyberg, D. A., Hyett, J., Johnson, J., & Souter, V. (2006). First-trimester screening. *Radiologic Clinics of North America, 4*4(6), 837-861. doi:http://dx.doi.org/10.1016/j.rcl.2006.10.017

Ozkaya, O., Sezik, M., Ozbasar, D., & Kaya, H. (2010). *Abnormal ductus venosus flow and tricuspid regurgitation at 11–14 weeks' gestation have high positive predictive values for increased risk in first-trimester combined screening test: Results of a pilot stud*y doi:http://dx.doi.org/10.1016/S1028-4559(10)60031-9

Pang, J. (2013). Intelligent modeling and decision making for product quality of manufacturing system based on fuzzy cognitive map . *IJCSI International Journal of Computer Science Issues, 1*0(1, No 2), 501-506.

Papageorgiou, E. I., & Froelich, W. (2010). Forecasting the state of pulmonary infection by the application of fuzzy cognitive maps. Paper presented at the *Proceedings of the 10th IEEE International Conference on Information Technology and Applications in Biomedicine,* pp. 1-4. doi:10.1109/ITAB.2010.5687739

Papageorgiou, E. I., & Iakovidis, D. K. (2013). Intuitionistic fuzzy cognitive maps. *IEEE Transactions on Fuzzy Systems, 2*1(2), 342-354. doi:10.1109/TFUZZ.2012.2214224

Papageorgiou, E., Stylios, C., & Groumpos, P. (2003). Fuzzy cognitive map learning based on nonlinear hebbian rule. *Lecture Notes in Computer Science,* (2903), 256-268

Papageorgiou, E. I. (2011a). Learning algorithms for fuzzy cognitive maps---A review study. *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews*

Papageorgiou, E. I. (2011b). A new methodology for decisions in medical informatics using fuzzy cognitive maps based on fuzzy rule-extraction techniques. *Applied Soft Computing Journal*, *1*1(1), 500-513.

Papageorgiou, E. I., & Groumpos, P. P. (2004). Two-stage learning algorithm for fuzzy cognitive maps. Paper presented at the *Intelligent Systems, 2004. Proceedings. 2004 2nd International IEEE Conference,* pp. 82-87.

Papageorgiou, E. I., & Groumpos, P. P. (2005). A new hybrid method using evolutionary algorithms to train fuzzy cognitive maps. *Applied Soft Computing Journal,* 5(4), 409-431

Papageorgiou, E. I., & Salmeron, J. L. (2013). A review of fuzzy cognitive maps research during the last decade. *IEEE Transactions on Fuzzy Systems, 2*1(1), 66-79

Papageorgiou, E. I., & Stylios, C. D. (2008). Fuzzy cognitive maps. *Handbook of granular computin*g (pp. 755-774) John Wiley & Sons, Ltd. doi:10.1002/9780470724163.ch34

Papageorgiou, E. I., Stylios, C. D., & Groumpos, P. P. (2004). Active hebbian learning algorithm to train fuzzy cognitive maps. *International Journal of Approximate Reasoning*, *3*7(3), 219-249

Papageorgiou, E. I. (2011). A new methodology for decisions in medical informatics using fuzzy cognitive maps based on fuzzy rule-extraction techniques. *Applied Soft Computing, 1*1(1), 500-513. doi:http://dx.doi.org/10.1016/j.asoc.2009.12.010

Papageorgiou, E. I. (2012). Fuzzy cognitive map software tool for treatment management of uncomplicated urinary tract infection. *Computer Methods and Programs in Biomedicine, 10*5(3), 233-245. doi:http://dx.doi.org/10.1016/j.cmpb.2011.09.006

Papageorgiou, E. I. (2013). Fuzzy cognitive maps for applied scien*ces and engineering: From fundamentals to extensions and learning algorithms* Springer Publishing Company, Incorporated.

Papageorgiou, E. I., & Froelich, W. (2012). Multi-step prediction of pulmonary infection with the use of evolutionary fuzzy cognitive maps. *Neurocomputing, 92*, 28-35. doi:http://dx.doi.org/10.1016/j.neucom.2011.08.034

Papageorgiou, E. I., Huszka, C., De Roo, J., Douali, N., Jaulent, M., & Colaert, D. (2013). Application of probabilistic and fuzzy cognitive approaches in semantic web framework for medical decision support. *Computer Methods and Programs in Biomedicine, 11*2(3), 580-598. doi:http://dx.doi.org/10.1016/j.cmpb.2013.07.008

Papageorgiou, E. I., Jayashree Subramanian, Karmegam, A., & Papandrianos, N. (2015). A risk management model for familial breast cancer: A new application using fuzzy cognitive map method. *Computer Methods and Programs in Biomedicine, 12*2(2), 123-135. doi:http://dx.doi.org/10.1016/j.cmpb.2015.07.003

Papageorgiou, E. I., & Kannappan, A. (2012). Fuzzy cognitive map ensemble learning paradigm to solve classification problems: Application to autism identification. *Applied Soft Computing, 1*2(12), 3798-3809. doi:http://dx.doi.org/10.1016/j.asoc.2012.03.064

Park, K. S., & Kim, S. H. (1995). Fuzzy cognitive maps considering time relationships. *International Journal of Human-Computer Studies, 4*2(2), 157-168. doi:10.1006/ijhc.1995.1007

Parsopoulos, K. E., Papageorgiou, E. I., Groumpos, P. P., & Vrahatis, M. N. (2003). A first study of fuzzy cognitive maps learning using particle swarm optimization. Paper presented at the *2003 Congress on Evolutionary Computation, 2003. CEC '03.* pp. 1440-1447 Vol.2. doi:10.1109/CEC.2003.1299840

Paz-Ortiz, I., & Gay-Garcia, C. (2014). Using fuzzy cognitive mapping and nonlinear hebbian learning for modeling, simulation and assessment of the climate system, based on a planetary boundaries framework. Paper presented at the *Proceedings of the 4th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2014),* pp. 852-862. doi:10.5220/0005140608520862

Pelaez, C. E., & Bowles, J. B. (1995). Applying fuzzy cognitive-maps knowledge-representation to failure modes effects analysis. Paper presented at the *Annual Reliability and Maintainability Symposium 1995 Proceedings,* pp. 450-456. doi:10.1109/RAMS.1995.513283

Peña-Ayala, A., & Sossa-Azuela, J. H. (2014). Decision making by rule-based fuzzy cognitive maps: An approach to implement student-centered education. In E. I. Papageorgiou (Ed.), *Fuzzy cognitive maps for applied sciences and engineering: From fundamentals to extensions and learning algorithms* (pp. 107-120). Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-642-39739-4_6"

Poczęta , K., & Yastrebov, A. (2015). Monitoring and prediction of time series based on fuzzy cognitive maps with multi-step gradient methods. In R. Szewczyk et. al (Eds.), *Progress in automation, robotics and measuring techniques: Control and automation* (pp. 197-206). Cham: Springer International Publishing. doi:10.1007/978-3-319-15796-2_20"

Ramírez-Gallego, S., García, S., Mouriño-Talín, H., Martínez-Rego, D., Bolón-Canedo, V., Alonso-Betanzos, A., et al. (2016). Data discretization: Taxonomy and big data challenge. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery,* 6(1), 5-21. doi:10.1002/widm.1173

Sacchelli, S., & Fabbrizzi, S. (2015). Minimisation of uncertainty in decision-making processes using optimised probabilistic fuzzy cognitive maps: A case study for a rural sector. *Socio-Economic Planning Sciences, 5*2, 31-40. doi:http://dx.doi.org/10.1016/j.seps.2015.10.002

Salman Guraya, S. (2013). The associations of nuchal translucency and fetal abnormalities; significance and implications. *Journal of Clinical and Diagnostic Research : JCDR,* 7(5), 936-941. doi:10.7860/JCDR/2013/5888.2989

Salmeron, J. L. (2009). Augmented fuzzy cognitive maps for modeling LMS critical success factors. *Knowledge-Based Systems, 2*2(4), 275-278. doi:10.1016/j.knosys.2009.01.002

Salmeron, J. L. (2010). Fuzzy cognitive maps-based IT projects risks scenarios. In M. Glykas (Ed.), *Fuzzy cognitive maps: Advances in theory, methodologies, tools and applications* (pp. 201-215). Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-642-03220-2_8"

Salmeron, J. L., & Papageorgiou, E. I. (2012). A fuzzy grey cognitive maps-based decision support system for radiotherapy treatment planning. *Knowledge-Based Systems, 3*0, 151-160. doi:http://dx.doi.org/10.1016/j.knosys.2012.01.008

Salmeron, J. L., Rahimi, S. A., Navali, A. M., & Sadeghpour, A. (2017). Medical diagnosis of rheumatoid arthritis using data driven PSO–FCM with scarce datasets. *Neurocomputing, 23*2, 104-112. doi:http://doi.org/10.1016/j.neucom.2016.09.113

Santhi.P, A. S. (2012). *Fuzzy cognitive map based prediction of pneumonia severity. International Journal of Engineering Research & Technology (IJERT),* 1(8)

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics,* 6(2), 461-464. doi:10.2307/2958889

Scott, F., Peters, H., Bonifacio, M., Mclennan, A., Boogert, A., Kesby, G., et al. (2004). Prospective evaluation of a first trimester screening program for down syndrome and other chromosomal abnormalities using maternal age, nuchal translucency and biochemistry in an australian population. *Australian and New Zealand Journal of Obstetrics and Gynaecology, 4*4(3), 205-209. doi:10.1111/j.1479-828X.2004.00205.x

Seising, R. (2009). Fuzzy sets and systems and philosophy of science. In R. Seising (Ed.), *Views on fuzzy sets and systems from different perspectives: Philosophy and logic, criticisms and application*s (pp. 1-35). Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-540-93802-6_1"

Shafer, G. (1976). *A mathematical theory of evidenc*e. Princeton, NJ: Princeton University Press.

Shan Mei, Yifan Zhu, Xiaogang Qiu, Xuan Zhou, Zhenghu Zu, A. V. Boukhanovsky, et al. (2014). Individual decision making can drive epidemics: A fuzzy cognitive map study. *IEEE Transactions on Fuzzy Systems, 2*2(2), 264-273. doi:10.1109/TFUZZ.2013.2251638

Sheng-Jun Li, & Rui-Min Shen. (2004). Fuzzy cognitive map learning based on improved nonlinear hebbian rule. Paper presented at the *Proceedings of 2004 International Conference on Machine Learning and Cybernetics, 2004.* pp. 2301-2306 vol.4.

Shiefa, S., Amargandhi, M., Bhupendra, J., Moulali, S., & Kristine, T. (2012). First trimester maternal serum screening using biochemical markers PAPP-A and free β-hCG for down syndrome, patau syndrome and edward syndrome. *Indian Journal of Clinical Biochemistry, 2*8(1), 3-12. doi:10.1007/s12291-012-0269-9

Sikchi, S. S., Sikchi, S., & Ali, M. S. (2013). Fuzzy expert systems (FES) for medical diagnosis. *International Journal of Computer Applications, 6*3(11), 7-16

Sloane, P. (2010). *How to be a brilliant thinker: Exercise your mind and find creative solution*s, Kogan Page

Snijders, R. J. M., Johnson, S., Sebire, N. J., Noble, P. L., & Nicolaides, K. H. (1996). First-trimester ultrasound screening for chromosomal defects. *Ultrasound in Obstetrics and Gynecology,* 7(3), 216-226. doi:10.1046/j.1469-0705.1996.07030216.x

Snijders, R. J. M., Sundberg, K., Holzgreve, W., Henry, G., & Nicolaides, K. H. (1999). Maternal age- and gestation-specific risk for trisomy 21. *Ultrasound in Obstetrics and Gynecology, 1*3(3), 167-170. doi:10.1046/j.1469-0705.1999.13030167.x

Soler, L. S., Kok, K., Camara, G., & Veldkamp, A. (2012). Using fuzzy cognitive maps to describe current system dynamics and develop land cover scenarios: A case study in the brazilian amazon. *Journal of Land use Science*, 7(2), 149-175. doi:10.1080/1747423X.2010.542495

Spencer, K., Souter, V., Tul, N., Snijders, R., & Nicolaides, K. H. (1999). A screening program for trisomy 21 at 10–14 weeks using fetal nuchal translucency, maternal serum free β-human chorionic gonadotropin and pregnancy-associated plasma protein-A. *Ultrasound in Obstetrics and Gynecology, 1*3(4), 231-237. doi:10.1046/j.1469-0705.1999.13040231.x

Spencer, K., Bindra, R., & Nicolaides, K. H. (2003). Maternal weight correction of maternal serum PAPP-A and free β-hCG MoM when screening for trisomy 21 in the first trimester of pregnancy. *Prenatal Diagnosis, 2*3(10), 851-855. doi:10.1002/pd.708

Spencer, K., Spencer, C. E., Power, M., Dawson, C., & Nicolaides, K. H. (2003). Screening for chromosomal abnormalities in the first trimester using ultrasound and maternal serum biochemistry in a one-stop clinic: A review of three years prospective experience. *BJOG: An International Journal of Obstetrics & Gynaecology, 11*0(3), 281-286. doi:10.1046/j.1471-0528.2003.02246.x

Stach, W., Pedrycz, W., & Kurgan, L. A. (2012). Learning of fuzzy cognitive maps using density estimate. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 4*2(3), 900-912. doi:10.1109/TSMCB.2011.2182646

Stach, W., Kurgan, L., & Pedrycz, W. (2008). Data-driven nonlinear hebbian learning method for fuzzy cognitive maps. Paper presented at the *IEEE International Conference on Fuzzy Systems, 2008. FUZZ-IEEE 2008. (IEEE World Congress on Computational Intelligence)*, pp. 1975-1981.

Stach, W., Kurgan, L., Pedrycz, W., & Reformat, M. (2005). Genetic learning of fuzzy cognitive maps. *Fuzzy Sets and Systems, 15*3(3), 371-401

Stach, W., Kurgan, L., & Pedrycz, W. (2010). Expert-based and computational methods for developing fuzzy cognitive maps. *Fuzzy Cognitive Maps Advances in Theory, Methodologies, Tools and Applications, 247*, 23-41. doi:10.1007/978-3-642-03220-2_2

Stach, W., Kurgan, L., Pedrycz, W., & Reformat, M. (2005). Genetic learning of fuzzy cognitive maps. *Fuzzy Sets and Systems, 15*3(3), 371-401.

Stressig, R., Kozlowski, P., Froehlich, S., Siegmann, H. J., Hammer, R., Blumenstock, G., et al. (2011). Assessment of the ductus venosus, tricuspid blood flow and the nasal bone in second-trimester screening for trisomy 21. *Ultrasound in Obstetrics & Gynecology, 37*(4), 444-449. doi:10.1002/uog.7749

Stylios, C. S., & Georgopoulos, V. C. (2010). Fuzzy cognitive maps for medical decision support — A paradigm from obstetrics. Paper presented at the *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology,* pp. 1174-1177. doi:10.1109/IEMBS.2010.5626239

Stylios, C. D., & Groumpos, P. P. (1999). Soft computing approach for modeling the supervisor of manufacturing systems. *Journal of Intelligent and Robotic Systems: Theory and Applications, 26*(3), 389-403

Stylios, C. D., & Groumpos, P. P. (2004). Modeling complex systems using fuzzy cognitive maps. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans, 34*(1), 155-162

Stylios, C. D., & Georgopoulos, V. C. (2008). Fuzzy cognitive maps structure for medical decision support systems. *Studies in Fuzziness and Soft Computing, 218*, 151-174. doi:10.1007/978-3-540-73185-6_7"

Stylios, C. D., & Groumpos, P. P. (1998). The challenge of modeling supervisory systems using fuzzy cognitive maps. *Journal of Intelligent Manufacturing, 9*, 339-345

Stylios, C. D., & Groumpos, P. P. (2000). Fuzzy cognitive maps in modeling supervisory control systems. *Journal of Intelligent and Fuzzy Systems, 8*(1), 83-98

Subramanian, J., Karmegam, A., Papageorgiou, E., Papandrianos, N., & Vasukie, A. (2015). An integrated breast cancer risk assessment and management model based on fuzzy cognitive maps. *Computer Methods and Programs in Biomedicine, 11*8(3), 280-297. doi:http://dx.doi.org/10.1016/j.cmpb.2015.01.001

Taber, R. (1991). Knowledge processing with fuzzy cognitive maps. *Expert Systems with Applications*, 2(1), 83-87. doi:http://dx.doi.org/10.1016/0957-4174(91)90136-3

Tsadiras, A. K. (2008). Comparing the inference capabilities of binary, trivalent and sigmoid fuzzy cognitive maps. *Information Sciences, 17*8(20), 3880-3894. doi: 10.1016/j.ins.2008.05.015

Verma, N. K., & Hanmandlu, M. (2007). From a gaussian mixture model to nonadditive fuzzy systems. *IEEE Transactions on Fuzzy Systems, 1*5(5), 809-827. doi:10.1109/TFUZZ.2006.889821

Wei Lu, Jianhua Yang, & Xiaodong Liu. (2014). The hybrids algorithm based on fuzzy cognitive map for fuzzy time series prediction. *Journal of Information &computational Science, 1*1(2), 357. doi:10.12733/jics20102682

Wise, L., Murta, A. G., Carvalho, J. P., & Mesquita, M. (2012). Qualitative modeling of fishermen's behaviour in a pelagic fishery. *Ecological Modeling, 22*8, 112-122. doi:http://dx.doi.org/10.1016/j.ecolmodel.2011.12.008

Wright, D., Kagan, K. O., Molina, F. S., Gazzoni, A., & Nicolaides, K. H. (2008). A mixture model of nuchal translucency thickness in screening for chromosomal defects. *Ultrasound in Obstetrics and Gynecology, 3*1(4), 376-383. doi:10.1002/uog.5299

Yastrebov, A., & Piotrowska, K. (2014). Synthesis and analysis of multi-step learning algorithms for fuzzy cognitive maps. *Intelligent Systems Reference Library, 54*, 133-144. doi:10.1007/978-3-642-39739-4_8"

Yesil, E., Ozturk, C., Dodurka, M. F., & Sakalli, A. (2013). Fuzzy cognitive maps learning using artificial bee colony optimization. Paper presented at the *2013 IEEE International Conference on Fuzzy Systems (FUZZ)*, pp. 1-8. doi:10.1109/FUZZ-IEEE.2013.6622524

Zadeh, L. A. (1965). Fuzzy sets. *Information and Computation/information and Control*, 8, 338-353. doi:10.1016/S0019-9958(65)90241-X

Zhu, Y., & Zhang, W. (2008). An integrated framework for learning fuzzy cognitive map using RCGA and NHL algorithm. Paper presented at the *2008 4th International Conference on Wireless Communications, Networking and Mobile Computing*, pp. 1-5. doi:10.1109/WiCom.2008.2527

APPENDIX

Publications during PhD work

Refereed archival journal papers

Papaioannou, M., Neocleous, K. C., Papageorgiou, C., & Schizas, C. N. (2014). A fuzzy cognitive map system to explore the repercussions of Greek PSI and bank recapitalization on the Cyprus economy. *International Journal of Engineering Intelligent Systems*, (3/4)

Papaioannou, M. & Schizas, C. N. (2017). Introducing Probabilistic Information in Diagnostic Dynamic Fuzzy Cognitive Maps. *IEEE Transactions on Fuzzy Systems*. Manuscript submitted for publication.

Refereed papers in full conference proceedings

Neocleous, C., Schizas, C., & Papaioannou, M. (2011). Fuzzy cognitive maps in estimating the repercussions of oil/gas exploration on politico-economic issues in cyprus. Paper presented at the *Fuzzy Systems (FUZZ), 2011 IEEE International Conference on*, pp. 1119-1126. doi:10.1109/FUZZY.2011.6007655

Neocleous, C., Schizas, C., & Papaioannou, M. (2011). Important issues to be considered in developing fuzzy cognitive maps. Paper presented at the *IEEE International Conference on Fuzzy Systems (FUZZ), 2011*, pp. 662-665. doi:10.1109/FUZZY.2011.6007694

Papaioannou, M., Neocleous, C., Papageorgiou, C., & Schizas, C. (2013). A fuzzy cognitive map model of the repercussions of greek PSI on cypriot economy. Paper presented at the *CINTI 2013 - 14th IEEE International Symposium on Computational Intelligence and Informatics, Proceedings*, pp. 255-260. doi:10.1109/CINTI.2013.6705202

Papaioannou, M., & Schizas, C. N. (2015). Exploitation of medical crisp database for fuzzy diagnostic decision support systems. *Studies in Health Technology and Informatics, 213*, 83-86.

Papaioannou, M., Neocleous, C., Papageorgiou, C., & Schizas, C. N. (2014). A fuzzy cognitive map system to explore certain scenarios on the cyprus banking system. Paper presented at the *Proceedings of the International Conference on Fuzzy Computation Theory and Applications (IJCCI 2014)*, pp. 103-110. doi:10.5220/0005039701030110

Papaioannou, M., Neocleous, C., & Schizas, C. N. (2013). A fuzzy cognitive map model for estimating the repercussions of greek PSI on cypriot bank branches in greece. In H. Papadopoulos, A. S. Andreou, L. Iliadis & I. Maglogiannis (Eds.), *Artificial intelligence*

applications and innovations: 9th IFIP WG 12.5 international conference, AIAI 2013, paphos, cyprus, september 30 -- october 2, 2013, proceedings (pp. 597-604). Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-642-41142-7_60"

Papaioannou, M., Neocleous, C., & Schizas, C. N. (2016). Non-invasive trisomy 21 diagnosis using fuzzy cognitive maps. In E. Kyriacou, S. Christofides & C. S. Pattichis (Eds.), *XIV mediterranean conference on medical and biological engineering and computing 2016: MEDICON 2016, march 31st-april 2nd 2016, paphos, cyprus* (pp. 731-736). Cham: Springer International Publishing. doi:10.1007/978-3-319-32703-7_140"

Papaioannou, M., Neocleous, C., Sofokleous, A., Mateou, N., Andreou, A., & Schizas, C. (2010). A generic tool for building fuzzy cognitive map systems. In H. Papadopoulos, A. Andreou & M. Bramer (Eds.), (pp. 45-52) Springer Berlin Heidelberg. doi:10.1007/978-3-642-16239-8_9