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EXPLORATION AND DEVELOPMENT OF METHODOLOGIES FOR COMPLEX SYSTEMS MODELLING AND DECISION-MAKING SUPPORT USING ADVANCED FUZZY LOGIC AND COGNITIVE MAPS TECHNIQUES

by

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ΤΜΗΜΑ ΠΛΗΡΟΦΟΡΙΚΗΣ ΚΑΙ ΤΗΛΕΠΙΚΟΙΝΩΝΙΩΝ

Διδακτορική Διατριβή

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ABSTRACT

Modelling and simulating complex dynamic systems have always been a demanding and challenging task especially when considering the formulation of strategies and the development of certain policies in the context of decision-making, with respect to sustainability planning. In this direction, Fuzzy Cognitive Maps (FCMs) which constitute a powerful Neuro-fuzzy quasi-quantitative modelling methodology, are the right candidate to address both complexity and non-linearity with respect to complex systems' behavior. Additionally, they can handle the lack of reliable quantitative data along with the presence of uncertain information, in terms of knowledge representation and reasoning during the simulation process. Moreover, they seem to be a promising tool to incorporate human experience and other existing knowledge as well as new aggregation participatory approaches for aggregating numerous individual models designed by experts or stakeholders, that will produce more reliable models for decision-making. Afterall, FCMs have found extreme and extensive applicability in multiple research domains which is proved by the enormous list of publications in the literature, over the last decade.

In the context of policy-making, energy demand forecasting is another significant and challenging task for tailoring efficient policies towards energy sustainability management and planning. Thus, the selection of accurate forecasting techniques is important for policy-makers to apply precise forecasts highly essential for supporting them in choosing the right strategies. Most of the forecasting methods until recently, are characterized by structure complexity, while they are slow and difficult to use by inexperienced Artificial Intelligence (AI) users. In this direction, FCMs, characterized by their learning capabilities, are emerged in the recent literature as simple, flexible and highly accurate soft computing methods, adequate to cope with relatively small datasets in data handling, and addressing fuzziness in a certain degree. Combining them with other efficient AI methods makes it a promising research direction in providing accurate predictions in the context of energy policy and demand forecasting.

This dissertation contributes to the subjects of FCM modeling, aggregation and scenario analysis of complex systems, through the introduction of a FCM development framework which can be used to perform an analysis of the systems' dynamics for efficient strategic social, economic and environmental sustainability planning. Two research directions are investigated within the framework of FCM development. They particularly concern the aggregation of FCMs proposed by multiple and numerous experts/stakeholders with a focus on scenario analysis, and a prediction algorithm deploying FCMs for demand forecasting purposes, with a focus on sustainable socio-economic and environmental planning.

The first direction focuses on a new aggregation method for FCM modeling based on learning Ordered Weighted Averaging (OWA) operators in the aggregation of weights. It aims at aggregating knowledge from multiple sources, thus improving the reliability of the examined model and eliminating possible erroneous beliefs provided by particular participants. This choice

of the OWA aggregation method was motivated by its efficiency to aggregate a sizeable amount of individual FCMs designed by experts and/or participants, considering their confidentiality. In this context, a new and easy to use java-based software tool is implemented for the automatic aggregation of individual FCMs based on the proposed OWA learning aggregation method. Additionally, a powerful and easy to use, web-based tool, namely FCMWizard, is incorporated to efficiently perform automatic FCM modeling and scenario analysis under different configurations in diverse domains. It is proved to have a supporting role for policy makers and governments in the analysis of complex real-life problems, predicting their behavior as well as eliciting accurate outcomes of proposed policies that deal with sustainable social-economic-environmental development strategies.

The second direction is oriented in a new and highly accurate demand forecasting method with generalization capabilities for time series prediction. It is comprised of an ensemble of AI-oriented models, based on evolutionary FCMs, artificial neural networks (ANNs), and their hybrid structure (FCM-ANN). Experimental evaluation based on a case study regarding natural gas load forecasting, reveals that the proposed architecture attains better accuracies and an improved overall performance against other individual AI and soft computing forecasting models, for the examined case study. At the same time, and for the same dataset, a promising Adaptive Neuro-Fuzzy Inference System (ANFIS) model architecture is investigated for consumption demand forecasting purposes. The proposed ANFIS approach reveals its remarkable prediction performance, in terms of its ability to tackle fuzziness in data handling, flexibility in large datasets, easiness of use and low execution time requirements.

On the whole, the innovations offered in this dissertation are devoted to the introduction of the aforementioned methodologies and newly developed FCM-based tools for modelling, aggregation and prediction tasks. Accordingly, they can help policy-makers and other regulatory authorities to identify suitable strategies towards efficient social, economic and environmental sustainability planning.

ΠΕΡΙΛΗΨΗ

Η μοντελοποίηση και προσομοίωση σύνθετων δυναμικών συστημάτων αποτελεί ένα δύσκολο και απαιτητικό πεδίο έρευνας ειδικότερα όταν αυτή εφαρμόζεται κατά τη διαδικασία διαμόρφωσης και σχεδιασμού στρατηγικών στο πλαίσιο της λήψης αποφάσεων. Όσον αφορά την περίπτωση του σχεδιασμού και της εφαρμογής κατάλληλων πολιτικών σε κοινωνικό, οικονομικό και περιβαλλοντικό επίπεδο, η διαδικασία μοντελοποίησης και προσομοίωσης θεωρείται κρίσιμη για τη βιώσιμη ανάπτυξη (sustainable development). Σε αυτή την κατεύθυνση, η συμβολή των Ασαφών Γνωστικών Δικτύων (ΑΓΔ) τα οποία κατέχουν αυξημένες δυνατότητες στη διαχείριση της πολυπλοκότητας, της μη γραμμικότητας και της έλλειψης αξιόπιστων ποσοτικά δεδομένων θεωρείται πολύτιμη. Τα ΑΓΔ αποτελούν μια μεθοδολογία που συνδυάζει τα βασικά χαρακτηριστικά της ασαφούς λογικής και των νευρωνικών δικτύων, ικανή να περιγράψει και να διαχειριστεί «ημι-ποσοτικά» δεδομένα, τα οποία χαρακτηρίζονται από αβεβαιότητα στην αναπαράσταση της γνώσης και της συλλογιστικής κατά τη διαδικασία της προσομοίωσης. Επιπλέον, φαίνεται να είναι ένα πολλά υποσχόμενο εργαλείο το οποίο ενσωματώνει την ανθρώπινη γνώση και πρότερη εμπειρία σε μορφή μοντέλων, που περιλαμβάνουν κόμβους (μεταβλητές) και αιτιατές συσχετίσεις μεταξύ των κόμβων, τα οποία μοντέλα σχεδιάζονται από ειδικούς ή άλλους εμπλεκόμενους φορείς στο εκάστοτε υπο-διερεύνηση αντικείμενο, για τη λήψη αποφάσεων μέσω της ανάλυσης δεδομένων και σεναρίων. Είναι άξιο αναφοράς ότι τα Ασαφή Γνωστικά Δίκτυα έχουν βρει εκτεταμένη εφαρμογή σε διάφορους ερευνητικούς τομείς, όπως αποδεικνύεται από τον τεράστιο αριθμό δημοσιευμένων εργασιών την τελευταία δεκαετία.

Η πρόβλεψη ζήτησης/κατανάλωσης είναι επίσης βασικό αντικείμενο της παρούσας διατριβής, καθώς αποτελεί αναγκαίο μέσο για τη χάραξη αποδοτικών πολιτικών αναφορικά με τη διαχείριση και τον σχεδιασμό της βιωσιμότητας της ενέργειας. Συνεπώς, η διερεύνηση κατάλληλων αποδοτικών εργαλείων πρόβλεψης όσον αφορά την ακρίβεια θεωρείται σημαντικό εφόδιο για τους φορείς διαμόρφωσης πολιτικής (policy-makers), στην προσπάθειά τους να επιλέξουν σωστές και αποδοτικές στρατηγικές. Τα Ασαφή Γνωστικά Δίκτυα αποτελούν επίσης αξιόπιστη λύση στο συγκεκριμένο αντικείμενο έρευνας καθώς είναι απλή, ευέλικτη και ιδιαίτερα αποδοτική τεχνική, όσον αφορά την ακρίβεια της πρόβλεψης, ενσωματώνοντας προηγμένες τεχνικές εκπαίδευσης που μπορούν να διαχειριστούν σχετικά μικρές ποσότητες δεδομένων και να εκπαιδεύσουν επαρκώς το μοντέλο, αντιμετωπίζοντας ως ένα βαθμό την ασάφεια.

Στόχος της παρούσας διδακτορικής διατριβής αποτελεί η ανάπτυξη προηγμένων μεθοδολογιών μοντελοποίησης και ανάλυσης πολύπλοκων μοντέλων και συστημάτων ως προς την κατεύθυνση της υποστήριξης και λήψης αποφάσεων, με έμφαση στους τομείς της κοινωνικο-οικονομικής συνοχής, της ενέργειας και του περιβάλλοντος. Πιο συγκεκριμένα, διαμορφώνονται δυο κύριες κατευθύνσεις στην διερεύνηση του προτεινόμενου πλαισίου αναφορικά με τη ανάπτυξη των ΑΓΔ για τη διαμόρφωση στρατηγικών και λήψη αποφάσεων.

Η πρώτη κατεύθυνση αφορά σε μια νέα τεχνική συνάθροισης (aggregation) πολλαπλών μοντέλων ΑΓΔ, η οποία βασίζεται στη χρήση των τελεστών OWA, τροποποιώντας κατάλληλα τις τιμές των βαρών των συσχετίσεων μεταξύ των κόμβων του ΑΓΔ. Το νέο συνολικό μοντέλο παρουσιάζει αυξημένη αξιοπιστία ενώ είναι απαλλαγμένο από πιθανές λανθασμένες αντιλήψεις των συμμετεχόντων. Το μοντέλο που προκύπτει συμβάλει στην βέλτιστη ανάλυση σεναρίων με σκοπό την εξαγωγή χρήσιμων συμπερασμάτων στο πλαίσιο χάραξης αποτελεσματικού στρατηγικού σχεδιασμού. Η προτεινόμενη μεθοδολογία συνάθροισης προέκυψε από την ανάγκη να συμπεριληφθούν και να συνδυαστούν οι γνώμες και αντιλήψεις ενός μεγάλου αριθμού εμπειρογνωμόνων ή/και συμμετεχόντων, συνυπολογίζοντας το βαθμό εμπιστευτικότητας (confidentiality) για τον καθορισμό του μοντέλου του υπό μελέτη συστήματος. Στην προσπάθεια αυτή συμβάλει η δημιουργία ενός νέου java-based υπολογιστικού εργαλείου το οποίο υλοποιεί αυτόματα τη διαδικασία της συνάθροισης πολλαπλών πηγών γνώσης, σύμφωνα με την προτεινόμενη μεθοδολογία. Επιπλέον, στο πλαίσιο της διατριβής, αναπτύχθηκε και εφαρμόστηκε ένα νέο, καινοτόμο και φιλικό προς τον χρήστη web-based εργαλείο, FCMWizard, το οποίο συμβάλει στην αυτόματη μοντελοποίηση Ασαφών Γνωστικών Δικτύων αλλά και την ανάλυση σεναρίων σε διάφορες συνθήκες και τομείς όπως αυτοί της ενέργειας, του περιβάλλοντος, της εκπαίδευσης και της κοινωνικο-οικονομικής βιωσιμότητας.

Η δεύτερη κατεύθυνση επικεντρώνεται στη διερεύνηση, το σχεδιασμό και την ανάπτυξη νέων καινοτόμων μοντέλων και προηγμένων μεθοδολογιών ασαφών γνωστικών δικτύων, ασαφούς λογικής, με δυναμικά χαρακτηριστικά μάθησης, καθώς και υβριδικών τεχνικών αυτών για τη διαχείριση της πολυπλοκότητας των συσχετίσεων μεταξύ των διαθέσιμων παραμέτρων που συντελούν στη λήψη αποφάσεων στον ενεργειακό τομέα. Πιο συγκεκριμένα, το προτεινόμενο μεθοδολογικό πλαίσιο έχει εφαρμοστεί σε δυο ξεχωριστά προβλήματα από το χώρο της ενέργειας. Το πρώτο αφορά στη μοντελοποίηση συστήματος και την πρόβλεψη αποδοτικών πολιτικών μέσα από την κατάλληλη εφαρμογή της ανάλυσης σεναρίου, έχοντας ως απώτερο στόχο τη βιώσιμη κοινωνική-οικονομική-περιβαλλοντική ανάπτυξη. Το δεύτερο πρόβλημα εστιάζει στην ανάπτυξη καινοτόμων μοντέλων πρόβλεψης βασισμένων στα ΑΓΔ και τους αλγορίθμους εκπαίδευσής τους, το οποίο μπορεί να εφαρμοστεί για την πρόβλεψη της ζήτησης με υψηλή ακρίβεια.

Για την επίλυση του πρώτου προβλήματος, το οποίο αναφέρεται σε ένα σύστημα βιώσιμης ενέργειας (φωτοβολταϊκή ηλιακή ενέργεια), αναπτύχθηκε αρχικά ένα μοντέλο ΑΓΔ με τη συνεισφορά των ειδικών από το συγκεκριμένο χώρο και στη συνέχεια ακολούθησε η εφαρμογή της προτεινόμενης μεθοδολογικής προσέγγισης που αφορά στην προσομοίωση του παραχθέντος μοντέλου σε διαφορετικές πιθανές καταστάσεις (σενάρια). Το προτεινόμενο μεθοδολογικό πλαίσιο το οποίο υλοποιήθηκε με τη συμβολή του προαναφερθέντος εργαλείου μοντελοποίησης και ανάλυσης σεναρίων, FCMWizard, συμβάλει στη διαδικασία λήψης αποδοτικών αποφάσεων αναφορικά με τον κατάλληλο σχεδιασμό και τη βέλτιστη ανάπτυξη του συστήματος ανανεώσιμων πηγών ενέργειας, καθώς και στην απόκτηση μιας εξαιρετικής κοινωνικο-οικονομικής δυναμικής της χώρας. Τα αποτελέσματα της ανάλυσης αποδεικνύουν την αποτελεσματικότητα και τη δυνατότητα γενίκευσης του εφαρμοζόμενου υπολογιστικού εργαλείου στη διαδικασία αυτόματης μοντελοποίησης μιας ευρείας περιοχής συστημάτων και τη διεξαγωγή ανάλυσης σεναρίου για τη διαμόρφωση κατάλληλων στρατηγικών αποφάσεων, μέσα από ένα απλό και εύχρηστο περιβάλλον χρήστη.

Το δεύτερο πρόβλημα επικεντρώνεται στην πρόβλεψη της ζήτησης της ενέργειας με εφαρμογή στην πρόβλεψη φυσικού αερίου, χρησιμοποιώντας μεθόδους ΑΓΔ, νευρωνικών δικτύων και νευρο-ασαφών μεθόδων (Neuro-fuzzy). Προτείνεται αρχικά η προσέγγιση ενός συνδυασμού αποδοτικών τεχνικών (ensemble method) βασισμένων σε εξελικτικά μοντέλα ΑΓΔ, Τεχνητά Νευρωνικά Δίκτυα και σε ένα υβριδικό συνδυασμό τους. Από τα παραγόμενα αποτελέσματα αποδεικνύεται ότι η προτεινόμενη αρχιτεκτονική επιδεικνύει μεγαλύτερη ακρίβεια και είναι περισσότερο αποδοτική συγκριτικά με άλλα αυτόνομα μοντέλα Τεχνητής Νοημοσύνης (ΤΝ). Εν συνεχεία, προτείνεται μια νέα, καινοτόμα προσέγγιση με την εφαρμογή της νευρο-ασαφούς μεθοδολογίας (ANFIS αρχιτεκτονική) για βραχυπρόθεσμη πρόβλεψη ζήτησης, η οποία εφαρμόστηκε ειδικότερα στο πρόβλημα πρόβλεψης της κατανάλωσης του φυσικού αερίου στην Ελλάδα. Τα ερευνητικά αποτελέσματα αποδεικνύουν την αξιοθαύμαστη απόδοση της μεθόδου αναφορικά με την ικανότητα πρόβλεψης, τη διαχείριση της ασάφειας, την ευελιξία σε μεγάλο όγκο δεδομένων, την ευκολία χρήσης και τον μικρό χρόνο εκτέλεσης. Συνολικά, τα μοντέλα που παράγονται μπορούν να ερμηνευθούν και να αξιοποιηθούν σε ανώτερο επίπεδο από εμπειρογνώμονες για την τελική λήψη αποφάσεων.

Συμπερασματικά, η ερευνητική καινοτομία της παρούσας διατριβής έγκειται στην προσπάθεια να εισαγάγει μια ολοκληρωμένη και στοχευμένη προσέγγιση η οποία περιλαμβάνει την εφαρμογή α) ασαφών, γνωστικών και ευφυών μεθοδολογιών και β) καινοτόμων υπολογιστικών εργαλείων βασισμένα σε ΑΓΔ για τη μοντελοποίηση και αποδοτική ανάλυση αλλά και την πρόβλεψη της δυναμικής σύνθετων συστημάτων που χαρακτηρίζονται από υψηλή πολυπλοκότητα. Η εφαρμογή της ερευνητικής προσέγγισης των ΑΓΔ κρίνεται ιδιαίτερα πολύτιμη στον καθορισμό αποτελεσματικών στρατηγικών για τη λήψη αποφάσεων όσον αφορά την προώθηση της κοινωνικής-οικονομικής-περιβαλλοντικής ανάπτυξης και βιωσιμότητας (socio-economic and environmental sustainability), καθώς και στην πρόβλεψη της ζήτησης στον ενεργειακό τομέα.

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Abbreviations

AHL – Active Hebbian Learning

ANFIS – Adaptive Neuro-Fuzzy Inference System

ANN – Artificial Neural Network

DD-NHL – Data-driven Nonlinear Hebbian Learning

DHL – Differential Hebbian Learning

FCM – Fuzzy Cognitive Map

GA – Genetic Algorithm

LSTM – Long Short-Term Memory

MAE – Mean Absolute Error

MAPE – Mean Absolute Percentage Error

MLP – Multi-Layer Perceptron

MSE – Mean Square Error

NHL – Nonlinear Hebbian Learning

OWA – Ordered Weighted Aggregation

PSO – Particle Swarm Optimization

RBF – Radial Basis Functions

RMSE – Root Mean Square Error

RCGA – Real-Coded Genetic Algorithm

SOGA – Structure Optimization Genetic Algorithm

SARIMAX – Seasonal Autoregressive Integrated Moving Average Model with eXogenous Inputs

Chapter 1

Introduction

1.1 Modeling Complex Systems under the perspective of Fuzzy Cognitive Maps

In their effort to describe and study modern technological systems in various domains, researchers need to deal with the modelling of such systems characterized by high complexity. Complex systems consist of numerous interacting components that make their understanding considerably difficult [1], while they feature distinct properties that emerge from their components' relationships, such as nonlinearity, emergence, spontaneous order, adaptation and feedback loops, among others. The complexity that these systems exhibit, stems from their behavior that cannot be easily inferred from their properties. Since these systems have non-linear behavior, conventional modelling has a limited contribution [2], therefore, modeling of complex systems requires new methods that can utilize the existing knowledge and human experience [3].

At present, a large variety of tools and methods such as artificial neural networks, genetic algorithms, nonlinear equation systems and agent-based modeling are available to tackle the complexity in such systems. Among these methods, Fuzzy Cognitive Maps (FCMs) have become a suitable knowledge-based methodology for modeling and simulating complex systems [4], providing a more flexible and natural ability for knowledge representation and reasoning, which are essential to intelligent systems [5, 6]. FCM is an interactive structure of concepts, each of which interacts with the rest showing the dynamics and different aspects of the behavior of the system [4].

When deciding a method for modelling complex systems, researchers must consider a rather serious concern like the nature of the data exploited. Quantitative data are important for successfully simulating a system's behavior, since they can offer a feasible dynamical analysis of the system through time, making the formulation of mathematical models easy [3, 7–9]. On the other hand, except from being slow, quantitative models can grow in size when the complexity of the system gets higher too. Low data availability and presence of uncertain information that need to be easily excluded from the model are considered significant barriers for the task of developing a system's quantitative model. These problems could be overcome by the use of qualitative data, which can offer low computational requirements for simulations [9] and model simplifications for isolating particular behavioral patterns. However, their weakness to construct a mathematical model described by formulas which involve uncertain numerical data, limits qualitative models' performance. Thus, there is a need for quasi-quantitative complex systems' modelling methods which could address the weak spots of both aforementioned methods.

In this context, based on the relevant literature, several semi-quantitative/mixed modelling methods have been investigated to tackle models' complexity [8]. Such methods can offer better, more context specific instruments, a more complete understanding of the research problem and a better explanation of the results in causal models [10]. Among them, FCMs emerge as the most promising quasi-quantitative method for modelling complex systems in various disciplines [9]. More specifically, Fuzzy Cognitive Mapping (FCM) as a graph-based modelling method, is able to represent the assumptions concerning a particular issue in diagrammatic format, thus allowing for ad-hoc structure [11]. The FCM approach deals with qualitative information based on the perception of expert knowledge [12], allowing researchers to overcome the lack of reliable quantitative data. In particular, the process of data capture in the FCM methodology is considered semi-quantitative because the quantification of concepts and links can be interpreted in relative terms [13].

FCMs were first introduced by Kosko [4, 14] as fuzzy-graph structures to describe causal reasoning, and provide a more flexible way for knowledge representation, while they serve as a soft computing technique, which combines fuzzy logic and neural networks [15]. They are formed with a set of concepts representing the key-elements of a given system and directed arcs defining the causal relationships between the nodes [16]. Specifically, FCMs encapsulate the notion of causality in these graph-models by drawing directed fuzzy-signed relations between concepts, thus determining the extend of causal influence that concepts have on each other. Furthermore, they include learning capabilities and characteristics as they can learn from historical data and previous knowledge to overcome the subjectivity of experts' opinions [17]. In other words, it is a quasi-quantitative method that offers the ability to develop dynamic and robust quantitative models through integration of diverse information sources, including qualitative knowledge from experts and/or stakeholders and scientific knowledge, to further increase system understanding and reduce uncertainties [3].

Recently, FCMs have been widely applied in different domains, such as engineering, business, medical decision analysis, environmental strategic decisions, political decision-making, fault detection, and data mining [18–21]. Due to their simple graph-based model structure and the fact that their disciplines do not require a strong mathematical background, FCMs have been also applied to model decision-making problems encountered in a variety of fields such as medicine, politics, environmental science, etc. [9, 22]. On the whole, FCM is a powerful modeling methodology that incorporates the main advantages of participatory modeling towards a better understanding of the structure and dynamics of complex systems.

1.2 Participatory Modeling and Scenario Analysis

Participatory modelling refers to a practice that includes knowledge diversity, local context, and increased legitimacy into the research process [23]. This can be achieved through the inclusion and direct involvement of policy makers and other stakeholders who can particularly contribute valuable first-hand knowledge for supporting decision-making, policy formulation, regulation, and management purposes [23]. They can be involved in providing essential ideas in the process of a model construction, the development of relevant scenarios and the interpretation of the concluding results in the context of certain strategies assessment.

However, participatory approach faces a few noteworthy challenges such as slow engagement into the process of stakeholders as well perception mismatching among them, ambiguous data difficult to cope with and difficulty of institutionalizing and sustaining inclusive and adaptive approaches [24, 25]. Despite these drawbacks, FCM-based participatory modelling is a powerful tool that can reduce conflicts among stakeholders by capturing different inter-sectorial synergies and tradeoffs. Voinov and Bousquet outline two major objectives that drive participatory modeling: i) to increase and share knowledge and understanding of a system and its dynamics under various conditions and ii) to identify and clarify the impacts of solutions to a given problem [23].

The development of participatory scenarios is a challenging process and shows great potential to contribute to decision making and planning, helping stakeholders to reach consensus in complex policymaking environments. Using participatory methods, policy makers and stakeholders are engaged in evaluating future states of the examined environment and can decide about future policies or adapt to changing conditions [26]. Public participation can offer significant and sometimes unexpected insights of the real-world problem and can help in tailoring suitable policies for those involved. On this basis, scenario planning constitutes a necessary process for consensus building and problem solving [27].

Over the last years, FCMs have attained great attention and popularity since they are able to implement modelling, analysis and simulation tasks, as well as test the influence of parameters and predict the behavior of the examined system [3]. Jetter and Schweinfort [28] have introduced FCM-based what-if scenarios to improve the quality of scenarios and increase the robustness of the scenario development step. Scenario analysis is a process of analyzing and evaluating the values, behavior, and relations of all concepts (nodes) constituting the FCM model, which graphically represents the complex system under investigation. The FCM-based simulation process is conducted by first clamping/activating one or more nodes (concepts) with an initial non-zero value and then several iterations follow. In particular, it is implemented using all concepts or a subgroup of concepts which are activated depending on the problem and the decision-maker’s concerns. Therefore, several policy scenarios are tested to evaluate the inference of the system [29]. The simulation process entails the application of the appropriate inference process and a sigmoid function with the parameter lambda=1, as a threshold function on the adjacency matrix, after it is multiplied with the input vector. The process is being iterated until the system either converges in a steady-state, accomplishes a preset number of steps or unveils a chaotic behavior [3, 9, 29]. The values produced for all concepts can be used to interpret the outcomes of certain scenarios and assess the overall dynamics of the modeled system.

1.3 Sustainability Planning and Decision Making (social, economic, environmental)

During the last few decades, several attempts and approaches have been made to explore sustainable planning in the social, economic, and environmental context. Making decisions on sustainability is of direct and primary concern for governments and policymakers who struggle to tailor strategies when dealing with complex decision-making problems in various domains such as energy, healthcare, transportation and so on. In general, sustainability can be understood as the qualities of human well-being, social equity, and environmental integrity. Sustainability can be literary described as the capacity to maintain a process or state indefinitely. Though, the most widely used definition of sustainability has been given as "*meeting the needs of the present without compromising the ability of future generations to meet their own needs*" [30]. This generally refers to environmental, social and economic sustainability [31], which do not have any exact and clear relationship with each other. Health, living standards, equity, education, employment, empowerment, accessibility and institutional stability are among the notions of social sustainability [32]. Growth, development and productivity are involved in economic sustainability. Finally, environmental sustainability entails ecosystem integrity, carrying capacity and biodiversity [32]. These three conceptual pillars of sustainability need to be integrated and inter-linked. According to Van der Vorst, Grafe-Buckens & Sheate, economic sustainability depends on environmental and social sustainability whereas social sustainability is directly connected to environmental sustainability [33].

In terms of policy, sustainable development can be translated into strategies for socio-economic and environmental development, so that the quality of human life is guaranteed, avoiding overexploitation and exceeding of the regenerative capacity of the environment. The three main pillars of sustainability: economic growth, environmental protection and social equality must be properly combined for economically efficient, socially equitable and environmentally acceptable sustainable development decisions. Sustainable development must be considered as a decision-making strategy since a decision needs to be made for every action that needs to be taken in this direction. Being a cognitive process resulting in the selection of a preferred option or a course of action among several alternatives, decision-making involves the design of a strategy, the definition of policies, and the execution of actions. The decision-making process requires a series of commonly used data, statistics, and economic, social, and environmental indicators [34]. In the context of sustainable development, decisions require the active engagement of stakeholders, who decide upon the preferred options or course of action for the many sustainability challenges we face. As regards stakeholders, they develop new insights that help them frame the decision problem, identify alternative scenarios, and discuss their possible consequences on the whole system using a dynamic perspective in a participatory framework [35]. Sustainability and decision-making can be considered as interconnected concepts under the notion that sustainable development is a decision-making strategy when the following challenges are taken into account: i) interpretation in terms of considering sustainability's principles in a given socio-environmental context, ii) information-structuring, that is, to determine the complexity of sustainability using certain indicators, and iii) influence, where sustainability information will formulate decision-making implementing sustainable development [36].

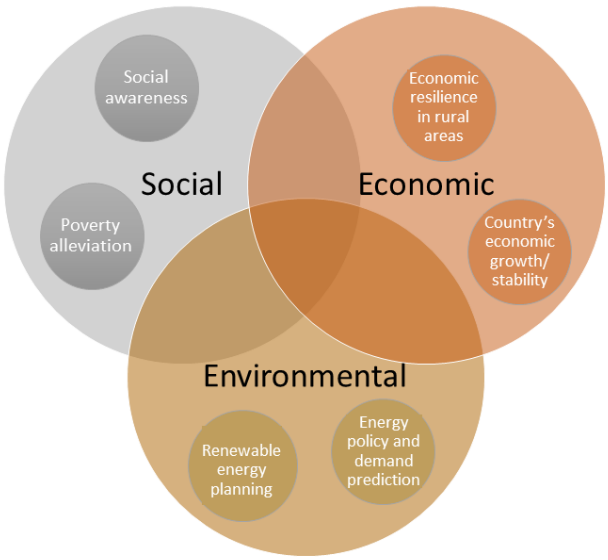


Figure 1.1: The pillars of sustainable development

Overall, decision-making on sustainability (social-economic-environmental) is considered a quite demanding and challenging task for policymakers since it has to deal with complex problems, conflicting decision-making criteria, diverse stakeholder opinions, ambiguous considerations of long-term assessment and imprecise data. Thus, new advanced modelling and analysis techniques are required as a means to integrate sustainability requirements in the decision-making process [37], allowing policy-makers to implement defined policies, strategies and actions. In this context, some preliminary works based on FCMs have tried to tackle the issue of decision making from the sustainability point of view [38]. However, the decision-making field needs to be further investigated from the FCMs perspective, exploiting their new and promising characteristics.

1.4 Energy Policy and Demand Forecasting

The increasing energy demand sparked from the recent technological revolution and the accelerating population growth, along with the environmental impact caused by certain forms of energy, constitute the two major interlinked energy issues that humanity faces in the 21st century. Therefore, global efforts towards energy sustainability management have been exerted to overcome world’s dependency to fossil fuels, reduce greenhouse gas emissions and mitigate global climate change [39, 40]. These challenges require certain policies and governance on energy resources in all policy levels, from local to global [41, 42]. At country level, governments and other regulatory authorities have already been engaged in formulating strategies and recommending energy policies for energy planning. More specifically, they have been trying to promote sustainable energy systems and effective policies over renewable energy generation along with conservation strategies [42]. With regard to conservation strategies, these are oriented to energy demand management which is essential for a country’s self-sufficiency and economic development and relies on the efficient demand forecasting of the energy source.

Energy demand forecasting is an essential yet not an easy task for tailoring efficient policies and energy planning in terms of energy supplies optimum management, emission reduction, as well as sustainable energy resources identification and prioritization [43]. This process involves a list of components such as appropriate models, historical data and other exogenous factors, whereas various limitations can be present during the development of relevant scenarios in different contexts. On this basis, deviations between reported energy demands and actual demands are quite often mainly due to limitations in the model structure or inappropriate assumptions [44], thus leading to the development of strategies which are not in the right direction. Therefore, accurate load forecasting models need to be developed worldwide in order to incorporate the renewable and sustainable energy sources for supporting the existing power supplies to a maximum degree [45]. In this context, demand forecasting has a quite significant role on the effective implementations of energy policies which determine the availability and reliability of energy sources. Overall, self-sufficiency and cost effectiveness seem to be the most premier concerns for energy demand forecasting, leading to a country’s sustainable economic development.

Concerning energy policies, most of them are focusing on the development of renewable and sustainable energy law and strategies which mainly aim at improving the use of such energy sources, minimizing possible costs and keeping power quality satisfactory [45]. Concerning the renewable and sustainable energy sources, Natural Gas seems to have increased its popularity as a clean energy source, with respect to environmental concerns, whereas photovoltaic solar energy arises as one of the most promising renewable energy sources to replace fossil fuels [46]. The need for project planning, tariff design, optimal scheduling of the supply system [47], indigenous production, infrastructures planning and cost reduction at different levels [48], along with distribution planning, make load forecasting a challenging task. Accurate demand forecasting could help policymakers all over the world to make complex decisions and choose certain strategies that could further assist in good government policymaking, taking into account various uncertainties and risks, such as socio-political, environmental and technological.

1.5 Motivation and Challenges

The formulation of suitable strategies in a variety of domains is considered a crucial, and demanding job in the context of decision-making and prerequisites a careful and elaborate modelling and simulating process of the examined complex dynamic systems. To the best of our knowledge considering soft computing methods that support the decision-making process, researchers face a variety of challenges. These challenges focus on the management of uncertainty, the modeling of complex systems, the aggregation of multiple experts' knowledge into a single overall model, the complexity of the correlations between certain variables and the ability to interpret the models produced.

So far, a wide range of methods has been developed to address real-world problems in terms of analyzing and predicting their behavior under certain circumstances, with the best possible prediction accuracy. However, complex dynamical systems which are described by numerous decision variables causally interrelated, demand a deeper understanding of their behavior, making conventional techniques insufficient to model and analyze these systems. Moreover, to improve the reliability of a model that represents a given system, the aggregation of knowledge from multiple sources needs to be included in it. This way, the single collective model is enriched with both the knowledge and the degree of confidence provided by multiple experts and/or stakeholders, thus becoming less susceptible to erroneous beliefs of a particular expert. Consequently, modeling of complex systems requires new methods incorporating the human experience and other existing knowledge [3, 8, 9] as well as new aggregation participatory approaches for aggregating numerous individual models designed by experts or stakeholders, that will produce more reliable models for decision-making. Overall, serving as a soft computing technique that combines fuzzy logic and neural networks, FCMs have become a key technique to describe causal reasoning, and provide a more flexible way for knowledge representation [15]. Furthermore, through the investigation of "what-if" scenarios, FCMs can allow the prediction of complex systems' future state and behavior, implementing the decision-making process.

Little progress has also been noted lately on the development of methods regarding the identification of proper strategies for sustainable development planning in the social, economic, and environmental domains. In this context, the given dynamical systems are characterized with a large number of variables that interact through cause-effect relationships and thus a dynamic modelling of causality between decision variables is needed. Consequently, a new participatory modelling approach is required to fill this gap, which can properly support policymakers in providing suitable policies that deal with social resilience and sustainable socio-economic-environmental development strategies.

In the context of decision-making for demand forecasting, the selection of accurate forecasting techniques is considered another challenge for policy-makers who find precise forecasts highly essential for supporting them in choosing the right strategies on a variety of research fields, ranging from environment to energy [49], finance [50], tourism [51], and electricity load [52]. Especially in time series forecasting, early attempts showed that potency forecasting of a model in advance, is often a difficult task, whereas accuracy is improved when different models are combined. Thus, the combination of forecasts from different models is a challenge for the prediction of future data [53]. Most of the forecasting methods reported in the literature are characterized by structure complexity, while they are slow and difficult to use by inexperienced AI users. Aiming to overcome these limitations, this research effort is directed in the exploration of new, simple, flexible and highly accurate soft computing methods with generalization capabilities, adequate to cope with the inherent fuzziness in data handling. The combined AI methods which exploit the advantageous characteristics of FCMs, ANNs and other hybrid methods emerge as suitable soft computing methods, resulting in more powerful outcomes in the context of energy policy and demand forecasting [53]. The only concern is to avoid the risk of combining models with poor performance resulting in an overall model with deteriorated forecasting accuracy.

Hence, the motivation of this work comes from

1) The inadequate research previously conducted with real-world datasets in modelling and analyzing the behavior of complex socio-economic and environmental systems,
2) The insufficient methodology for FCM models aggregation when a significantly large group of experts and/or stakeholders, considering their degree of confidence, are involved in designing complex systems,
3) The absence of a suitable tool that can provide the research community with an automated method of aggregating individual FCMs,
4) The capability of FCMs to provide an advanced approach for modelling, simulating and forecasting the future state of complex systems,
5) The lack of free and open-source software tools that can efficiently perform simulations for various “what-if” scenarios,
6) The gap that is noticed in the decision-making process using efficient FCM-based frameworks, regarding the sustainable social, economic, and environmental planning.

1.6 Scope and Research Goals

The general scope of this dissertation is to provide a framework for developing an advanced FCM approach that is capable to address the problem of modelling and analyzing the behavior of complex systems. Under the socio-economic and environmental scope of sustainable planning, and where a plethora of experts and/or stakeholders are involved in the designing of individual FCM models, this effort focuses on the investigation of certain FCM-based modelling, aggregation and simulation techniques, as well as demand forecasting approaches. This attempt will lead to the establishment of optimal and highly accurate policies by policymakers and governments, in this direction.

The general objective of this dissertation can be decomposed into more discrete yet specific goals, each one trying to address the challenges observed in the related literature so far and as listed above. On the whole, these goals are devoted to socio-economic and environmental sustainability planning and decision making, as well as on energy policy and demand forecasting, and are recorded as follows:

- To propose a new aggregation method for FCM modeling based on learning OWA operators in aggregation of weights. That is, to address the problem of aggregating a sizeable amount of individual FCMs designed by an equal number of experts and/or participants, considering their confidentiality.
- To implement a new and easy to use java-based software tool for aggregating individual FCMs based on the proposed OWA learning aggregation method.
- To design a framework for strategic sustainability planning using the dynamic capabilities of FCMs, the proposed aggregation method and scenario analysis.
- To develop a new, powerful and easy to use web-based tool that can efficiently perform FCM modeling and scenario analysis in diverse domains.
- To propose a new and highly accurate demand forecasting method with generalization capabilities for time series prediction. This methodology uses an ensemble of AI-oriented models, based on evolutionary fuzzy cognitive maps (FCMs), artificial neural networks (ANNs), and their hybrid structure (FCM-ANN).

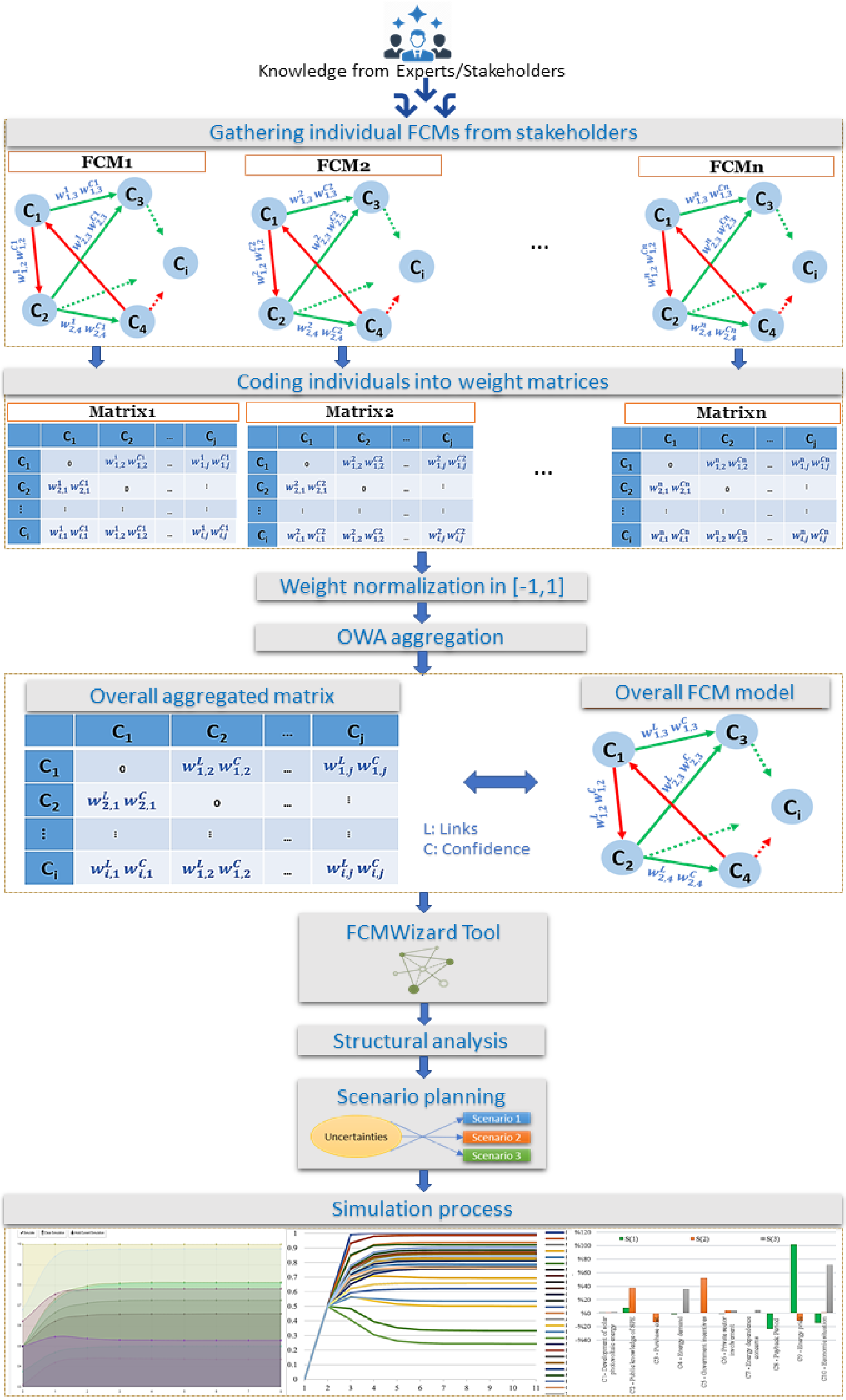


Figure 1.2: The general framework of the dissertation.

1.7 Research contribution

In this section, a set of theoretical contributions that this dissertation offers to a kind of limited field of FCM modelling and simulating research are provided. More specifically:

1. This thesis proposes a new framework in modelling and analyzing the behavior of complex systems under a socio-economic and environmental perspective through the development and investigation of various scenarios using an FCM-based simulation process (see Figure 1.2). The relevant literature lacks adequate research regarding the application of the FCM framework in policy-making, participatory modelling, scenario analysis and management in diverse domains, needed to tackle critical operational sustainability issues. In this work, the FCM technique is enhanced with a new aggregation method and a powerful easy-to-use tool to perform decision analysis for various case studies in the socio-economic and environmental field. The research conducted deals mostly with policy-making problems such as socio-economic sustainability in rural communities, climate change adaptations in the environmental domain as well as renewable energy planning.

2. The proposed new FCM aggregation method, based on the fact that FCMs have been proposed as a unique methodology able to aggregate diverse sources of knowledge, fills the absence of learning OWA operators in the aggregation of weights in FCMs. It is developed as an alternative to the common average method, revealing its high efficacy and applicability when a large group of participants/stakeholders is involved. This approach allows the automatic and fast aggregation of weights assigned by experts/stakeholders, also integrating the provided confidence level during FCMs construction. To accomplish this demanding task, a robust, user-friendly tool with advanced capabilities has been developed which can straightforwardly implement the tasks of aggregating FCM models and learning them using supervised and unsupervised algorithms.

3. Noticing the gap regarding the existence of a simple but powerful software to tackle the massive amount of data, as well as perform modelling, learning, and simulation tasks of complex systems, this dissertation introduces an innovative, efficient and easy to use modelling and simulation tool called FCMWizard. It was developed for the purposes of this thesis and can provide decision-making capabilities. More precisely, this web-based software offers simple designing and analyzing tasks or even more complex functions like learning and simulation tasks on FCM-based systems. Its fullest potential is revealed in this study through the exploration of various cases in diverse domains, including renewable energy development, energy consumption forecasting, social resilience and economic sustainability planning.

4. An ensemble-based forecast combination methodology is proposed in this thesis as an alternative to forecasting methods for time series prediction. This forecast combination approach that combines FCMs, ANNS, and hybrid FCM-ANN models, was specifically

selected due to the advanced features of each ensemble component and is applied in energy domain using a real-life historical dataset regarding natural gas consumption. This innovative non-linear time series model attains better accuracies when compared against other well-known, independent forecasting approaches, such as ANNs or FCMs, and LSTM, making it a useful tool for future works in this domain.

5. Unlike several ANN-based and hybrid forecasting methods reported in the relevant literature, lacking model simplicity and flexibility, while needing a large dataset to be trained and a relatively large number of features to make accurate predictions, this work develops a robust and flexible ANFIS model, which is at the same time fast, simple in structure and able to cope with fuzziness in data handling. It provides sufficient exploration of certain modelling aspects and can be easily used by inexperienced AI users.

1.8 Thesis outline

This thesis is about proposing novel and efficient methodologies for FCM modeling, aggregation and scenario analysis. It also introduces innovative and robust models for demand forecasting, implementing simulations on various FCM-based scenarios in the social, economic and environmental context, in terms of sustainable development. The outlook and context of this thesis were arranged in the following manner.

Chapter 2 describes in detail the Fuzzy Cognitive Mapping technique along with its mathematical foundations, whereas a new OWA-based FCM aggregation methodology is proposed incorporating a weight learning process using OWA operators. This chapter also introduces two robust and easy-to-use software tools that support FCM construction, analysis and aggregation process.

Chapter 3 provides the methodological framework with respect to FCM aggregation, modeling and simulation process. This framework incorporates a participatory modelling approach implemented by fuzzy cognitive maps, which is applied in two different approaches of the same case study, in the context of socio-economic sustainability. The performance of the proposed OWA-based FCM aggregation methodology is assessed conducting a straightforward comparison with the average method and the expert-based FCM model. In addition, this chapter investigates the impact that certain key concepts have on the examined system, helping the policy institutions develop and propose well-structured policies in this direction.

Chapter 4 is explicitly devoted to the investigation of certain factors and their influence on the development of the Brazilian Photovoltaic solar Energy with the help of FCMs. A semi-quantitative FCM-based model is designed to model the complex Renewable Energy system with the contribution of stakeholders from the specific energy domain. An FCM-based simulation process is conducted through the implementation of three plausible scenarios in order to support a decision-making process on PSE sector development and the country's economic potential.

Chapter 5 investigates two soft computing methodologies in order to produce accurate non-linear time series models for energy load forecasting. First, an easy to use, robust and flexible ANFIS model, which is simple in structure and able to cope with fuzziness, is explored and fine-tuned to determine its most appropriate architecture for an enhanced prediction performance. Next, an innovative ensemble approach is proposed which combines FCMs, ANNs, and hybrid FCM-ANN models, attaining better accuracies than other individual models. The same case study problem regarding natural gas consumption in Greece is used for both case studies to show the applicability of both the proposed architectures, whereas their performance is evaluated through a comparative analysis with other AI and soft computing models.

Chapter 6 reflects on the overall research reviewing the key points of this dissertation. More specifically, it includes the overall concluding remarks, the contribution to knowledge and future research directions.

Chapter 2

Fuzzy Cognitive Mapping framework and newly developed tools for modeling and scenario analysis

2.1 Introduction

Being a soft computing, powerful technique that combines the advantageous characteristics of both fuzzy logic and neural networks, FCM is particular useful and suitable for modeling and decision making for complex systems [14]. It is considered as an extension to Cognitive Maps (CM), introduced by Axelrod (1976) to graphically represent the cognitive state of a system in the decision-making process. Proposed by Kosko [4], FCMs indeed, introduced fuzziness to CMs applying fuzzy descriptions (fuzzy binaries) to the connections in order to demonstrate causal influences on the relations between concepts. From the structural point of view, FCM can be graphically represented as a fuzzy digraph, which has the ability to explain the behavior of complex systems by integrating causal reasoning that derives from the perception of expert knowledge. The system is defined as a collection of concepts, interconnected to each other with connections in the form of directed edges, reflecting the cause-effect relationships between the concepts [14].

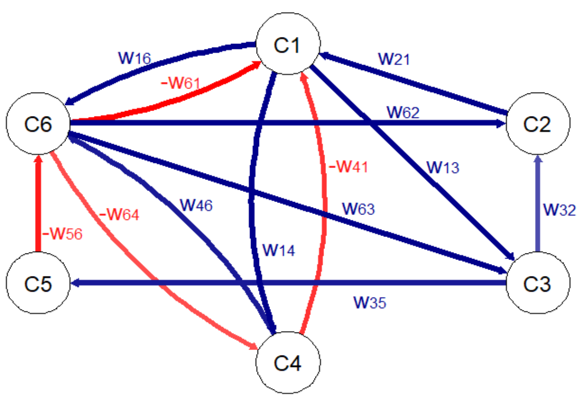
This chapter presents a detailed overview of the fundamental aspects of Fuzzy Cognitive Mapping technique which constitutes the basis of this study's proposed approach along with new user-friendly software tools developed for modeling and scenario analysis using FCMs. That is, to address the problem of modelling and analyzing real-world dynamic systems under the perspective of sustainable development.

2.2 Fuzzy Cognitive Mapping Background

Essentially, an FCM consists of two main components, the nodes and the edges. A node, which is commonly referred as concept, defines a variable, factor, state or an attribute of the examined system, whereas an edge reflects the causal relationship between two concepts. The FCM is comprised by a set of nodes $C = \{C_1, C_2,.., C_i\}$ where i denotes the number of variables of this network. The overall state of the FCM can be described by the state vector $A = \{A_1, A_2,..., A_i\}$, where the value A_i illustrates the degree of presence (activation level) of the concept C_i in the system at a particular time. Similarly, the degree of causal relationship (association) between two concepts C_i and C_j can be associated with a positive or negative sign and value usually expressed as weight $w_{ij} \in [-1,1]$. More specifically, a weighted edge between two concepts expresses the strength of influence that one concept has on the other. This degree of influence is initially provided by experts using linguistic values, since it is hard to express the strength of cause-effect relations with real numbers. The weights of the FCM that are associated with all the existent directed connections between all pairs of the concepts are stored in the weighted asymmetric adjacency matrix W. Concerning the causal relationships, there are three possible types of such interactions:

- $w_{ij} > 0$, indicating a positive causality between concepts C_i and C_j. That is, an increase (decrease) on the value of concept C_i produces an increase (decrease) on the value of concept C_j.
- $w_{ij} < 0$, indicating a negative causality between concepts C_i and C_j. That is, an increase (decrease) on the value of concept C_i produces a decrease (increase) on the value of concept C_j.
- $w_{ij} = 0$, indicating no causal relationship between concepts C_i and C_j.

Typically, a FCM of n concepts could be mathematically represented by a $n \times n$ weight matrix (W). Figure 2.1 shows an example of a FCM model with its corresponding adjacency weight matrix.



$$\Rightarrow \quad W = \begin{bmatrix} 0 & 0 & w_{13} & w_{14} & 0 & w_{16} \\ w_{21} & 0 & 0 & 0 & 0 & 0 \\ 0 & w_{32} & 0 & 0 & w_{35} & 0 \\ -w_{41} & 0 & 0 & 0 & 0 & w_{46} \\ 0 & 0 & 0 & 0 & 0 & -w_{56} \\ -w_{61} & w_{62} & w_{63} & -w_{64} & 0 & 0 \end{bmatrix}$$

Figure 2.1: Fuzzy cognitive map (left) and the corresponding weight adjacency matrix (right), showing the influence weights

2.3 Construction of Fuzzy Cognitive Map

When it comes to FCM model development, including the determination of system's concepts and the relationships between them, then two distinctive methods can be employed in this direction, based either on experts or data. The expert-based approach relies entirely on human expertise and domain knowledge about the system, whereas the computational-based method utilizes available historical data and a learning algorithm to substitute or help the expert and learn the model's structure [54, 55]. In both cases, the set of concepts is provided by a single or group of experts whereas the matrix W containing the causal links values is given either by the experts (following the expert-based method) or learned from raw data (in the data-driven method). Since the computational-based methods have been only introduced recently, the expert-based method was the only one used for the development of FCMs.

2.3.1 Expert-based method for FCM Construction

The expert-based process for developing an FCM is depending on a single or a group of experts who are only required to have a basic level of knowledge on FCMs and can contribute by providing their valuable experience on the system's model and behavior. This relatively simple method can be implemented through the simple process of drawing a graph to represent an FCM. More specifically, experts being highly knowledgeable about the factors of the examined system and the influences among them, can easily design individual maps that represent their own understanding of a system in their area of expertise.

The process of constructing an FCM requires certain steps that include:

(i) the determination of the number and kind of concepts,
(ii) the indication of interconnections between pairs of concepts and their signs, and
(iii) the assignment of the weights values (strengths) for each causal link [4].

Having conceived the examined system as a set of factors, the experts determine only the most important and relevant concepts, as a first step. Then, follows the identification of direct relationships between pairs of concepts along with their directions, revealing a preliminary graphical structure of the system under investigation. However, the main challenge that this methodology faces is to accurately estimate the strengths of the relationships. This can be achieved by describing each interconnection with an IF–THEN rule and then inferring a linguistic fuzzy term which will be later transformed into a numerical value.

The IF–THEN rules usually have the following form:

- **IF** a {no, small, medium, large, very large} change occurs in the value of concept C_i.
- **THEN** a {no, very small, small, medium, large, very large} change in value of concept C_j is caused.
- **THUS** the influence of concept C_i on concept C_j is *T{influence}*, means the linguistic weight w_{ij} is μ_B, where μ_B is a linguistic variable from the set *T*.

Influence is a linguistic variable that denotes the causal linkages among concepts taking values in the interval *U* = [−1, 1]. Its term set *T{influence}* is usually decided to comprise 12 different linguistic variables that describe the degree of influence of one concept on another in detail. For example, the twelve linguistic variables can be as: *T{influence}*={negatively very strong (nvs), negatively strong (ns), negatively medium (nm), negatively weak (nw), negatively very weak (nvw), zero (z), positively very weak (pvw), positively weak (pw), positively medium (pm), positively strong (ps), positively very strong (pvs), and positively very very strong (pvvs)}. Each variable is linked to a membership function in the range [-1,1], $\mu = \{\mu_{nvs}, \mu_{ns}, \mu_{nm}, \mu_{nw}, \mu_{nvw}, \mu_{z}, \mu_{pvw}, \mu_{pw}, \mu_{pm}, \mu_{ps}, \mu_{pvs}, \mu_{pvvs}\}$ as shown in Figure 2.2. In the last step, this linguistic weight is transformed into a crisp numerical value that belongs to the interval [−1, 1], using the defuzzification method of the Center of Gravity (CoG) [56].

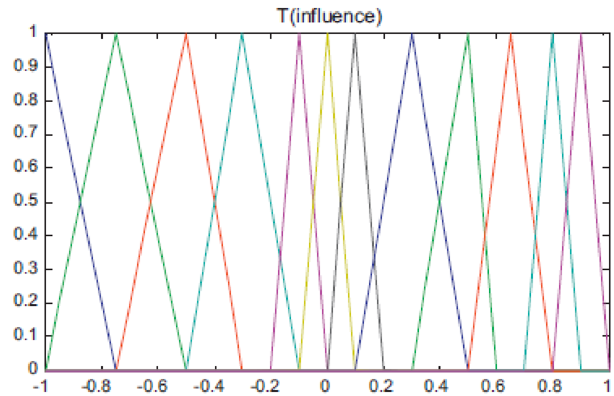


Figure 2.2: The twelve membership functions describing *T{influence}*

It is worth mentioning that the use of linguistic expressions to describe the degrees of causality in relationships allows experts to overcome the difficulty of specifying precise numerical values before draft model establishment.

2.3.2 Data-based method for FCM construction

In the case of the data-based approach, historical data are being used for the construction of the FCM model for a given system. In this direction, semi-automated or fully automated computational methods are employed to establish the FCM model using partial or no human intervention, respectively. In particular, after a set of concepts is provided a priori by the experts, the weighted matrix is learned from raw data [57]. The process for learning the model is implemented by utilizing various learning methods based on the notion of ANN training [54, 57]. More specifically, evolutionary algorithms can be applied to address the optimization problem of learning FCMs. Such problem can be tackled by minimizing the following objective function:

$$\arg\min_{w}: \mathrm{J} = \frac{1}{mnk}\sum_{s=1}^{m}\sum_{t=1}^{k}\sum_{i=1}^{n}\left(A_i^s(t) - \hat{A}_i^s(t)\right)^2 \qquad (2.1)$$

$$|w_{ji}| \leq 1, \qquad i,j = 1,2,\dots,n$$

where, m is the number of different initial state vectors, n represents the number of nodes in the FCM, and k is the length of the response sequences. $A_i^s(t)$ represents the target state value of the i_{th} node C_i at time t for the s_{th} initial state vector, and $\hat{A}_i^s(t)$ is the estimated value of the i_{th} node C_i produced by the FCM with the weight matrix W at time t for the s_{th} initial state vector, where $s = 1, 2, \dots, m$.

In this context, a variety of learning methods were developed to minimize the aforementioned function (Equation 2.1). In the case of population-based algorithms, experts are substituted by historical data and the corresponding learning or optimization algorithms are used to estimate the entries of the connection matrix W. Being usually oriented towards finding models that mimic the input data, the population-based learning algorithms serve as optimization techniques to minimize the error/cost or fitness function.

According to the relevant literature, there is a significant number of evolutionary methods (such as genetic algorithms, real coded genetic algorithms, particle swarm optimization, ant colony optimization, etc.) proposed within this research framework. In particular, evolutionary strategies [58], genetic algorithms [54, 58], real coded generic algorithm—RCGA [54, 55, 59], Swarm Intelligence [60], Chaotic Simulated Annealing [61], game-based learning [62], Ant Colony Optimization [63], extended Great Deluge algorithm [64] and Bing Bang-Big Crunch [65] have been proposed as population-based algorithms for training FCMs. A detailed description of these approaches can be found in [2, 57]. The learning capabilities of FCMs offer notable improvement to the modelling process regarding their structure, whereas FCMs' dynamic characteristics allow them to find great applicability in diverse research domains. Some of the main fields of FCM learning algorithms applications concern modeling/design, optimization, prediction and decision support.

2.4 Learning of Fuzzy Cognitive Map

The basic notion behind the learning process of an FCM is to learn the weights between the concepts of the examined FCM considering the available data given, thus reflecting the dynamic behavior of the FCM. The learning of FCMs constitutes a means to update the initial knowledge of human experts and include any knowledge from historical data in the development of an FCM. Given the weight matrix W of an FCM, a number of iterations is performed regarding the computation of weights values, starting from a prespecified initial state vector. The process finishes when a desired weight matrix is found, or the system converges to an equilibrium point.

Research community has come up with various approaches so far, to address this challenging task. In specific, the methods for learning FCMs can be classified into three generic groups depending on the learning paradigm used: Hebbian-based, evolutionary-type (population-based) learning algorithms and hybrid learning methods [66], which combine the methodological framework of the first two approaches. Among them, Hebbian-based learning methods are simple and fast, based on the given data and the Hebbian theory, that allows the iterative adjustment of FCMs weights.

Hebbian learning in FCMs constitutes the most efficient and well-known unsupervised method for learning FCMs [2]. The non-linear Hebbian learning emerges as one of the most used types of FCM learning for problems where experts' knowledge exists and no data are available for training the created models. The main aim of this algorithm is to find better interconnection weights than those provided by the experts. This algorithm is defined by Equation 2.2:

$$W_{ij}^{(k+1)} = \gamma W_{ij}^{(k)} + nA_j^{(k)}\left(A_i^{(k)} - sign(W_{ij}^{(k)})A_j^{(k)}W_{ij}^{(k)}\right) \tag{2.2}$$

where, n and γ are learning parameters. Moreover, the usage of two cost functions, working as termination criteria of the learning procedure was a significant novel feature. The two cost functions should be defined following the problem constraints, as defined in [2]. On the whole, the Hebbian rule for learning FCMs allows the automatic development of new knowledge from data and the correction of false prior knowledge, producing an improved FCM which encapsulates the ability of self-learning.

Hebbian-based learning has found great applicability in diverse domains with some promising ones like those of engineering and medicine, involving decision making and prediction tasks. On this basis, some preliminary efforts have been recently focused on the application of FCMs in designing innovative game-based learning models which provide students with a means of realizing a real situation and further support them in their learning process. In the following section, an example concerning an experiment conducted in digital game-based learning in education is presented to show the FCM modeling contribution in this domain.

2.4.1 Example of Digital game-based learning in education

It is common research ground that game-based learning processes can trigger students' interest as young students are extremely familiar with the form of gaming. Therefore, there is a growing trend in the use of games at the most diverse levels of education, taking into account essential characteristics of games, which are the playful aspects, the motivation and the involvement of students in learning [67]. Nowadays, digital games are being used to complement traditional teaching methods in order to grow students' interest, enable cognitive and social development, as well as stimulate behaviors such as problem solving, creativity, teamwork, following rules, and cooperation [68].

Based on FCMs which entail learning capabilities, an experiment regarding a digital game-based learning model developed in Scratch, during the course of robotics at the Universidade Tecnológica Federal do Paraná campus Cornélio Procópio (UTFPR-CP) is proposed [69]. The aim is to assist in the learning of an autonomous vehicle using a similar classic Atari 2600 game of war tanks. In this case study, applied to the class 2019/2, a student (player) controls a tank using the keyboard in a battle against another autonomous tank. In this game, certain fundamentals are presented, such as pose (position x, y and the angle formed in relation to the x axis), basic notions about controlled and autonomous robots, hierarchy of actions, modeling using finite state machine. These concepts were extracted through a questionnaire filled out by the students after the end of the games.

The development of the digital game was carried out on the Scratch platform, developed by researchers at the Massachusetts Institute of Technology (MIT) in 2007. The Scratch programming language is considered one of the most accessible, since the user does not need prior knowledge of any other programming language to use Scratch [70]. Its programming is carried out through a graphical interface. The desired actions are carried out by means of block insertion, which contains the functions to be performed. An example is shown in Figure 2.3.

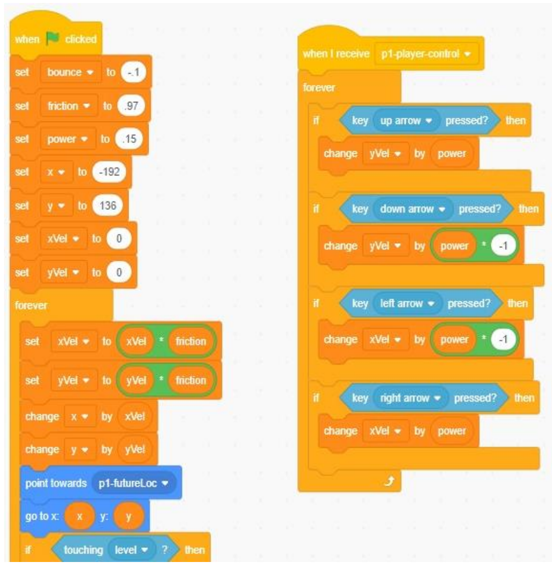


Figure 2.3: Example of a game screen using Scratch.

In this game (in initial phase shown in Figure 2.4), one tank is controlled by the player, and the other one is autonomous. The main objective of the controlled tank is the destruction of the other through shots, and the avoidance of fixed and mobile obstacles (opponent's shots). With the initial programming carried out, the next step focuses on the elaboration of the rules of the game and the consequent definition of the possible states of the tanks (players).

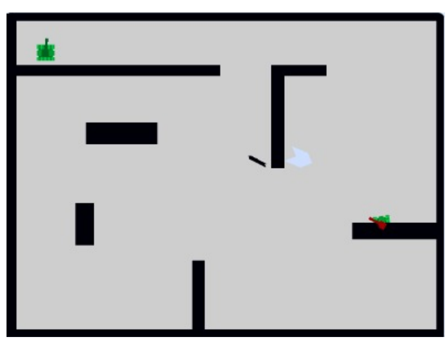


Figure 2.4: Representation of the first game.

The rules of the game were defined by the damage suffered and applied by the tanks. The game is won by whoever hits the opponent's tank three times first. Each shot equals one point of damage, and the impact on physical obstacles also equals one point of damage. The possible states for the tanks are the following:

a) Free movement.
b) Shooting.
c) Dodging static obstacle.
d) Dodging a moving obstacle (opponent's shot).

In a specific way, students should accomplish the following tasks:

- The finite-state machine of the tanks.
- Identify the position and pose of the tank, that is, the coordinates of the tank in the scenario and the angle formed with the x axis (robot pose).

The aim of the exercise was to help students understand the concepts of robotics that refer to autonomy, and the need for hierarchy. In the latter, there is the concept of priority in some control actions, such as the need to avoid obstacles in the scenario and only then aim at the targets (in this case, the opposing tank) [69].

Given the proposal, the task was to deliver a text file with the graphical representation of the finite-state machine with the description of the events, and a list of questions related to the topics of the activities. The questions are provided in Appendix A. In this experiment, there were approximately 27 students in the class. Due to the extended workspace, only a small sample of results and interpretations is presented as shown in Appendix A.

Considering the initially defined states, we proceed with the definition of concepts for FCM modeling, developing a preliminary model following the answers of the three students, with a focus on the concepts and interconnections designed by the participant students. The preliminary FCM is shown in Figure 2.5, in which the diamonds correspond to the decision-making process. In particular, if an obstacle is met, all the weights W_{ij} are modified in order to allow the robots to stop and make sharper turns. The authors tuned these causality levels empirically according to the event occurrence which defines each robot sub-behaviors'.

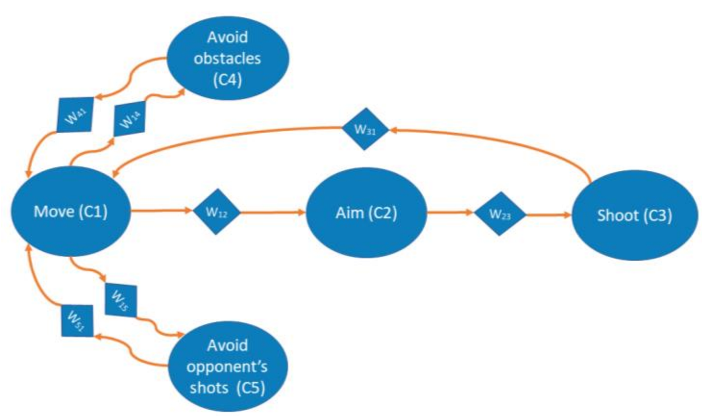


Figure 2.5: A preliminary FCM model for the game-based learning

The weights of the interconnections are updated/modified according to the rules of the game, the event occurrence and the autonomous tank sub-behavior. To properly modify the weights, Hebbian learning method is a suitable candidate for learning FCMs so as the produced game-based learning models acquire a dynamic behavior.

The results, although being preliminary, suggest the feasibility of the proposed gamification approach to create the tank war game and the 2DOF robotic manipulator using a graphic and object-oriented language such as Scratch. However, the main finding of the experiments was the fact that the students perceived important and relevant concepts of robotics through the game. It was observed that the students found the experiments as really intriguing. Despite the high level of students' engagement with the game, only few students answered the questions, portraying a difficulty in making the game a learning rather than an entertaining tool. Future work may focus on embedding the learned FCM on Arduino microcontrollers, due to its low computational cost and the possibility of transposing the game to real prototypes.

2.5 Aggregation methods for Fuzzy Cognitive Maps

Designing an FCM for modeling a given system often includes the aggregation of knowledge from a variety of sources [71]. Individual FCMs can be aggregated to produce a combined overall FCM that will incorporate the knowledge from all the different experts and/or stakeholders involved in the FCM construction process. The main objective behind aggregating individual FCMs is to improve the reliability of the overall model and make it less susceptible to potentially inaccurate knowledge of a single expert and/or stakeholders or knowledge inconsistency among the participants.

A significant issue that is common in the aggregation process is the fact that experts and/or stakeholders usually provide individual FCM models of different number of concepts for a given system and consequently the corresponding weight matrices differ in terms of dimension. This can be tackled by equalizing the size of all matrices by adding extra columns and rows, filled with elements that take a null value. Thus, for every individual FCM model augmented to have N number of concepts, there is a corresponding matrix of NxN size, which can now participate in the aggregation process.

Regarding the combination of multiple FCMs into a single collective model, among the techniques that can be found in the related literature, two methods are widely used in real-life problems [72]—the Weighted Average method introduced by Kosko [4] and the Ordered Weighted Average (OWA) method introduced by Yager [73].

- *Weighted Average* – Initially, the average aggregation method was proposed by [4] for aggregating a large number of FCMs consisting of the same or different concepts (representing different variables, status, parameters, etc.). Considering the case that *n* Experts assign a weight value w_{ij}, between the nodes C_i and C_j on individual FCMs with the same number of concepts, then the aggregated weight $w_{ij}^{(ave)}$ between these nodes can be defined as the average value of the *n* weights w_{ij}:

$$w_{ij}^{(ave)} = \frac{w_{ij}^{(1)} + w_{ij}^{(2)} + \cdots + w_{ij}^{(n)}}{n} \tag{2.3}$$

This basic approach has been extended to take into consideration the credibility factors of individual maps [4]. In this weighted average method, a weight w_k is assigned to the k^{th} expert representing the degree of his reliability that takes values in the interval [0,1]. The aggregated matrix is calculated using the following formula:

$$w_{ij}^{(ave)} = \frac{1}{\sum_{k=1}^{K} w_k}\left(w_1 w_{ij}^{(1)} + w_2 w_{ij}^{(2)} + \cdots + w_k w_{ij}^{(\mathrm{k})}\right) \tag{2.4}$$

The weighted average method is used by experts after they describe the causal interrelation between two concepts of the fuzzy cognitive map with linguistic rules. Using this procedure, these rules are aggregated, and the final overall rule is created. The overall output is taken as the weighted average of each rule's output. Taking one step further, Mazzuto et al. [74] developed a method which combines the technique of the Aggregation of Individual Evaluations and the structured credibility evaluation method, that can aggregate individual's knowledge and beliefs according to the expertise areas of each expert. In fact, each concept has been classified in specific expertise areas, according to the experts' experience and skills. Thus, the experts' credibility is evaluated according to these areas. However, there are certain limitations to implementing this methodology. For example, when a large number of stakeholders/participants are asked to assign values on the relationships of a given system, significant deviations can arise between these values. This fact shows an inconsistency of knowledge among the participants that leads to an inaccurate overall FCM. Moreover, the applicability of this method is limited by difficulties in estimating the credibility coefficients [54].

- *OWA* - Considering aggregation methodologies based on OWA, the conjunctive and disjunctive behavior of the investigated system is unified in one parameterized operator. OWA operators allow the representations of sophisticated relationships between the arguments and can provide a parameterized family of aggregation operators which are suitable for handling the various AND/OR relationships of the arguments from pure ANDs to pure ORs [75]. Two characterizing measures, the orness measure and the dispersion measure were further introduced by Yager [73] and they are associated with the weighting vector W of an OWA operator.

The application of OWA operators in the aggregation of individual FCMs has a limited presence in the literature. In particular, OWA operators in an FCM framework were introduced by Zhenbang and Lihua [75], who highlighted the ability of OWA operators to simulate the various AND/OR relationships between the concepts and studied the OWA aggregation under different conditions. An OWA operator of dimension n is a mapping:

$$f: R^n \to R$$

that includes a correlated vector of weights W

$$W = [w_1 \ w_2 \ \dots \ w_n]^T \tag{2.5}$$

so that

$$\sum_i w_i = 1; \quad w_i \in [0, 1] \tag{2.6}$$

and

$$f(a_1, \dots, a_n) = \sum_{j=1}^{n} w_j \ b_j, \tag{2.7}$$

where, b_j is the j[th] largest object of the collection of the aggregated elements $a_1, a_2 \ \dots, a_n$. The function value $f(a_1, \dots, a_n)$ determines the aggregated value of arguments $a_1, a_2 \ \dots, a_n$.

It has been shown that the re-ordering step is a basic characteristic with respect to the OWA operator, in particular, an argument a_i is not associated with a particular weight w_i but rather a weight w_i is associated with the ordered position i of the arguments. An essential characteristic of the OWA operators is that, in order to properly select the vector W, the Max, Min and arithmetic average operators need to be defined:

i. For $W = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$, $f(a_1, \dots, a_n) = \operatorname*{Max}_i a_i$

ii. For $W = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}$, $f(a_1, \dots, a_n) = \operatorname*{Min}_i a_i$

iii. For $W = \begin{bmatrix} 1/n \\ 1/n \\ \vdots \\ 1/n \end{bmatrix}$, $f(a_1, \dots, a_n) = \frac{1}{n}\sum_{i=1}^{n} a_i$

Brown [76] emphasized that the OWA operators were basically aggregation operators, inheriting the characteristics of the *Max* and *Min* operators regarding the commutatively, monotonicity, and idempotency:

$$\operatorname*{Min}_{i} a_i \leq f(a_1, \ldots, a_n) \leq \operatorname*{Max}_{i} a_i \tag{2.8}$$

As this category of operators runs between the $Max\ (or)$ and the $Min\ (and)$, Yager [73] introduced a measurement function to define the type of the aggregation performed with respect to a particular value, namely the $orness\ measure$ of the aggregation, which is calculated by Equation 2.9:

$$Orness\ (W) = \frac{1}{n-1} \sum_{i=1}^{n} (n-1) w_i \tag{2.9}$$

As suggested by Yager [73], this measure determines whether the aggregation works as an $or\ (Max)$ operation; it is described by the following equations:

$$orness\ ([1\ 0 \ldots 0]^T) = 1, \tag{2.10}$$

$$orness\ ([0\ 0 \ldots 1]^T) = 0, \tag{2.11}$$

$$orness\ \left(\left[\frac{1}{n}\ \frac{1}{n} \ldots \frac{1}{n}\right]^T\right) = 0.5. \tag{2.12}$$

Consequently, the *Max*, *Min*, and arithmetic average operators are considered as OWA operators, whose degree of *orness* takes the values 1, 0, and 0.5, respectively.

Yager [73] introduced a second measure, namely *dispersion* or *entropy* connected with a weighting vector. The degree of information used, based on W, throughout the aggregation process can be calculated by the following equation (Equation 2.13).

$$Disp\ (W) = \sum_{i=1}^{n} w_i \ln w_i \tag{2.13}$$

O'Hagan [77] generated the OWA weights, which have a predefined degree of *orness* a and maximise the entropy, with a certain method that uses these elements. He called them MEOWA operators. This procedure is defined by the following constrained optimisation problem. However, the desired degree of *orness* a needs to be specified.

$$Maximize \sum_{i=1}^{n} w_i \ln w_i \tag{2.14}$$

$$subject\ to\ a = \frac{1}{n-1} \sum_{i=1}^{n} (n-1) w_i \tag{2.15}$$

$$\sum_{i=1}^{n} w_i = 1,\ \ w_i \in [0,1], i = (1,\dots,n). \tag{2.16}$$

2.6 New OWA-based aggregation method for Fuzzy Cognitive Maps

Yager has previously suggested a method for obtaining the weights associated with the OWA aggregation in the situation where observed data on the arguments have been provided [73]. However, there is a gap in the relevant literature concerning the existence of an algorithm which can be used for aggregating weights assigned by experts/stakeholders' opinion in designing FCMs. In this direction, a new OWA-based aggregation algorithm is proposed so that it can learn the weights associated with a particular use of the OWA operator from a group of experts and stakeholders of the specific scientific domain. This work focuses on developing an alternative aggregation methodology for the FCM modelling, in order to fill the absence of learning OWA operators in aggregation of weights in FCMs, considering that FCMs have been proposed as a unique methodology able to aggregate diverse sources of knowledge to represent a "scaled-up" version of individuals' knowledge and beliefs [12, 78]. Moreover, learning operators are used in this study for defining weights among the concepts so the studying OWA aggregation approach will be strengthened in terms of performance. This method particularly meets wide applicability and has great effectiveness when a large number of participants/ stakeholders are present.

The OWA weights can be obtained through the following process. Initially, it can be assumed that a collection of m links is given which are the weighted interconnections among concepts (samples), each comprised of an n-tuple of values, as well as an associated single value, called the aggregated value is also given, which is denoted as d_k.

It is further assumed that a set of m links/edges exists in an FCM model and a set of n experts/stakeholders are involved in the process of assigning values to each of the links/edges. Experts' opinions (scores) are indicated as $\mathrm{a}_{\mathrm{k}1}, \mathrm{a}_{\mathrm{k}2} \dots, \mathrm{a}_{\mathrm{kn}}$ for any $k = 1, \dots, m$ (see Table 2.1). Finally, an expert with deep knowledge of the specific domain reviews the numerical values of the scores for each weighted link and afterwards he provides an aggregated score, denoted as d_k for that alternative.

Table 2.1: Experts' opinions for each link and the aggregated score.

Weighted link	**Exp.1**	**Exp.2**	**…**	**Exp.n**	**Aggregated Value**
w_1	a_{11}	a_{12}		$\mathrm{a}_{1\mathrm{n}}$	d_1
w_2					
…	…	…	…	…	…
w_k	$\mathrm{a}_{\mathrm{k}1}$	$\mathrm{a}_{\mathrm{k}2}$	…	a_{kn}	d_k

The main goal of this process is to obtain an OWA operator, represented as a weighting vector W which models the aggregation task regarding the specific data set, which should also satisfy the following condition for any k.

$$f(\mathrm{a_{k1}}, \mathrm{a_{k2}} \dots, \mathrm{a_{kn}}) = d_k$$

Considering the linearity of the OWA aggregation method with respect to the ordered arguments, the reordered objects of the k_{th} sample are $b_{k1}, b_{k2}, \dots, b_{kn}$, where b_{kn} is the *n-th* largest element of the argument collection $\mathrm{a_{k1}}, \mathrm{a_{k2}} \dots, \mathrm{a_{kn}}$. Hence, the modelling process of aggregation lies in the determination of the OWA weights vector W:

$$W = [w_1 \ w_2 \ \dots \ w_n]^T$$

such that

$$\mathrm{b_{k1}w_1 + b_{k2}w_2 + \cdots + b_{kn}w_n = d_k}$$

for any $k = 1, \dots, m$.

In the next step, an OWA weights vector $W = [w_1 \ w_2 \ \dots \ w_n]^T$ is sought to approximate the aggregation operator by minimizing the instantaneous errors e_k:

$$e_k = \frac{1}{2}(b_{k1}w_1 + b_{k2}w_2 + \cdots + b_{kn}w_n - d_k)^2 \tag{2.17}$$

regarding the weights w_i .

This seems to be a constrained optimization problem, where the OWA weights w_i need to comply with the following conditions:

$$\sum_{i=1}^{n} w_i = 1, \ \ w_i \in [0,1], \qquad i = (1, \dots, n).$$

Next the following assumption is considered with respect to the OWA weights in order to avoid the constraints on w_i :

$$w_i = \frac{e^{\lambda_i}}{\sum_{j=1}^{n} e^{\lambda_j}}, \qquad i = (1, \dots, n) \tag{2.18}$$

The weights w_i are positive and equal to 1 for all the λ_i parameters. Hence, the optimization problem is converted to the unconstrained nonlinear problem which minimizes the instantaneous errors e_k, as follows:

$$e_k = \frac{1}{2}\left(b_{k1}\frac{e^{\lambda_1}}{\sum_{j=1}^{n} e^{\lambda_j}} + b_{k2}\frac{e^{\lambda_2}}{\sum_{j=1}^{n} e^{\lambda_j}} + \cdots + b_{kn}\frac{e^{\lambda_n}}{\sum_{j=1}^{n} e^{\lambda_j}} - d_k\right)^2 \tag{2.19}$$

with respect to the parameters λ_i.

This task can be addressed with the use of the gradient descent technique, in which the parameters λ_i, $i = (1, \ldots, n)$ are updated through the following rule:

$$\lambda_i(l+1) = \lambda_i(l) - \beta \frac{\partial e_k}{\partial \lambda_i} |\lambda_i = \lambda_i(l) \tag{2.20}$$

where β represents the learning rate $(0 \leq \beta \leq 1)$.

For simplification purposes, $\hat{d}_k$ denotes the estimate of the aggregated value d_k:

$$\hat{d}_k = b_{k1} \frac{e^{\lambda_1}}{\sum_{j=1}^{n} e^{\lambda_j}} + b_{k2} \frac{e^{\lambda_2}}{\sum_{j=1}^{n} e^{\lambda_j}} + \cdots + b_{kn} \frac{e^{\lambda_n}}{\sum_{j=1}^{n} e^{\lambda_j}} \tag{2.21}$$

In this context, the steps of the proposed algorithms for learning OWA weights are described as follows, considering experts' opinions as the argument values $(\mathrm{a_{k1}}, \mathrm{a_{k2}} \ldots, \mathrm{a_{kn}})$:

- Step 1: Create a slightly different parameter ρ for each argument that indicates the optimism of the decision-maker,$0 \leq \rho \leq 1$.
- Step 2: Compute the aggregated values for each sample with the Hurwics method, where the aggregated value *d* obtained from a tuple of *n* arguments, $a_1, a_2, \ldots, a_n$, is defined as a weighted average of the *Max* and *Min* values of that tuple.

$$\rho \operatorname*{Max}_i a_i + (1-\rho) \operatorname*{Min}_i a_i = d \tag{2.22}$$

- Step 3: Reorder the objects $\mathrm{a_{k1}}, \mathrm{a_{k2}} \ldots, \mathrm{a_{kn}}$.
- Step 4: Compute the current estimation of the aggregated values d_k

$$\mathrm{\hat{d}_k = b_{k1}w_1 + b_{k2}w_2 + \cdots + b_{kn}w_n} \tag{2.23}$$

  through initial values of the OWA weights $w_1 = 1/n$.

- Step 5: Calculate the total $\hat{d}_k$, d_k, b_{ki} for each *i*. The parameters λ_i determine the weights of OWA and are updated with the propagation of the error $\hat{d}_k - d_k$ between the current estimated aggregated value and the actual aggregated value (see Equation 2.20).
- Step 6: Compute the current estimations of the λ_i.

$$\mathrm{\lambda_i(l+1) = \lambda_i(l) - \beta w_i(l)(b_{ki} - \hat{d}_k)(\hat{d}_k - d_k)} \tag{2.24}$$

  through initial values $\lambda_i(0)=0$, $i = (1, \ldots, n)$, and a learning rate of β=0.35.

- Step 7: Use λ_i, $i = (1, \ldots, n)$, for providing latest estimate of the weights.

$$w_i = \frac{e^{\lambda_i(l)}}{\sum_{j=1}^{n} e^{\lambda_i(l)}}, i = (1, n) \quad (2.25)$$

- Step 8: Update w_i and $\hat{d}_k$ at each iteration until the estimations for all the λ_i converge to, that is $\Delta = |\lambda(l+1) - \lambda(l)|$ are small.

2.6.1 Indicative example using 3 experts

In what follows, an explanatory paradigm considering three (3) experts who assign numerical values to weights, will better illustrate the proposed FCM aggregation approach in the environmental domain.

As mentioned above, the Experts' opinions are considered as argument values $a_{k1}, a_{k2} \dots, a_{kn}$, and the weight between two concepts as a link (sample). Zero values for weights were not considered in the aggregation process. An FCM model investigated in a previous work of [79], that consists of 7 concepts and 14 weighted connections among concepts, was selected to show how the above steps are implemented.

Table 2.2: Explanatory paradigm in agriculture for the aggregation of experts' opinions

Sample Weight	**Exp.1**	**Exp.2**	**Exp.3**	**Aggregated Value**
C1-C7	0.43	0.50	0.58	0.45
C2-C1	0.57	0.60	0.68	0.58
C2-C7	0.57	0.60	0.68	0.58
C3-C2	−0.30	-0.35	-0.25	-0.32
C3-C7	-0.39	-0.25	-0.30	-0.32
C4-C5	-0.32	-0.40	-0.47	-0.38
C4-C7	-0.43	-0.30	-0.30	-0.35
C5-C4	-0.37	-0.40	-0.45	-0.37
C5-C7	0.68	0.60	0.50	0.53
C6-C2	0.58	0.55	0.70	0.56
C6-C7	0.55	0.50	0.65	0.53
C7-C1	0.22	0.37	0.33	0.23
C7-C2	0.67	0.70	0.75	0.67
C7-C5	0.54	0.58	0.47	0.48

We calculated the aggregated values using various values for parameter ρ within $[0.01, 0.2]$. For example, ρ = 0.153; 0.131; 0.181; 0.075; 0.055;

Using min and max values of ρ, the aggregated value of weight was calculated as follows.

$$0.153(0.58) + (1 - 0.153)(0.43) = 0.45$$

We initialized $\lambda_i(0) = 0$, $i = (1, n), \beta = 0.35$ and $w_1 = w_2 = w_3 = 0.33$. The estimated values of λ_i after 108 iterations were:

$$\lambda_1 = 0.63, \qquad \lambda_2 = -0.19, \qquad \lambda_3 = 0.82$$

The following OWA weights have been calculated considering the above λ_i:

$$w_1 = 0.146, \qquad w_2 = 0.227, \qquad w_3 = 0.626$$

We followed the same process for parameter ρ for $0.3 < \rho < 0.5$ and $0.5 < \rho < 0.7$.

Table 2.3 gathers the calculated values for OWA aggregated weights for all interrelationships among FCM concepts, as well as the deviations between the benchmark weight Wb (average method) and the Wowa, weight produced by learning OWA operators.

Table 2.3: Weights produced by learning OWA operators

Weight	**Average weight (Wb)**	**Weight by 0.01 < ρ < 0.2**	**Weight by 0.3 < ρ < 0.5**	**Weight by 0.5 < ρ < 0.7**	**ΔW (Deviation in aggregated Value)**
C1-C7	0.50	0.47	0.53	0.58	0.03
C2-C1	0.38	0.33	0.40	0.45	0.05
C2-C7	0.62	0.59	0.64	0.68	0.03
C3-C2	-0.30	-0.32	-0.28	-0.25	0.02
C3-C7	-0.31	-0.35	-0.29	-0.25	0.04
C4-C5	-0.40	-0.43	-0.37	-0.32	0.03
C4-C7	-0.34	-0.38	-0.32	-0.30	0.04
C5-C4	-0.41	-0.43	-0.39	-0.37	0.02
C5-C7	0.59	0.55	0.62	0.68	0.04
C6-C2	0.61	0.58	0.57	0.70	0.03
C6-C7	0.57	0.53	0.59	0.65	0.04
C7-C1	0.31	0.27	0.33	0.37	0.04
C7-C2	0.71	0.69	0.72	0.75	0.02
C7-C5	0.53	0.5	0.55	0.58	0.03

It is observed that the produced weights of the links among concepts calculated with the proposed OWA aggregation method do not emerge significant deviations against the corresponding average weights in most of the cases in this example. Moreover, having performed a larger number of experiments with different weights values and various numbers of experts and or stakeholders as well as using datasets previously published in the works of [15, 20], it emerges that this approach is reliable producing sufficient results. As a conclusion to the above, exploring different ρ values can help decision makers to successfully and safely aggregate opinions from a large number of experts/stakeholders.

2.7 Inference and Simulation process

After the design of the FCM, which is usually carried out with the help of experts and/or stakeholders, causality is traced through simulations [15]. In particular, data are inserted through the input concepts, so as FCM performs reasoning inferring decisions which are produced in a numerical form the output concepts [8, 14]. As the system evolves over time, every concept has a new value at every step of interaction. The value of each concept is influenced by the values of the connected concepts multiplied by the corresponding causal weights and/or by its previous value, driving the system into reaching to an equilibrium point. The value for each concept is calculated using one of the following calculation rules (Equations 2.26 - 2.28):

Kosko:

$$A_i^{(\kappa+1)} = f\left(\sum_{j=1, j\neq i}^{n} w_{ji} \times A_j^{\kappa}\right) \tag{2.26}$$

Modified Kosko:

$$A_i^{(\kappa+1)} = f\left(A_i^{(\kappa)} + \sum_{j=1, j\neq i}^{n} w_{ji} \times A_j^{\kappa}\right) \tag{2.27}$$

Rescale:

$$A_i^{(\kappa+1)} = f\left((2A_i^{(\kappa)} - 1) + \sum_{j=1, j\neq i}^{n} w_{ji} \times (2A_j^{\kappa} - 1)\right) \tag{2.28}$$

where $A_i^{(\kappa+1)}$ is the value of concept C_i at simulation step k + 1, A_j^{κ} is the value of concept C_j at step k, w_{ji} is the weight of the interconnection between concept C_j and concept C_i, and f is a threshold (transformation) function that squashes the result of the multiplication in the interval [0, 1]. The Kosko's activation rule (see Equation 2.26) that was initially introduced to calculate the value of each concept, considers only the influence of the interconnected concepts. Overall, the selection of the proper rule depends mainly on the examined domain whereas the distinctive key features of the system under investigation need to be considered in this direction.

Several transformation functions can be used during the beforementioned process for producing each concept's value. Though, the following four are the most used transformation functions, namely bivalent (Equation 2.29), trivalent (Equation 2.30), Sigmoid (Equation 2.31) and hyperbolic tangent (Equation 2.32):

Bivalent:

$$f(x) = \begin{cases} 1, & x < 0 \\ 0, & x \geq 0 \end{cases} \tag{2.29}$$

Trivalent:

$$f(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases} \tag{2.30}$$

Sigmoid:

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{2.31}$$

Hyperbolic tangent: $$f(x) = \tanh(\lambda x) \tag{2.32}$$

where λ is a real positive number ($\lambda > 0$), which determines the steepness of the continuous function f and x is the value A_i^κ on the equilibrium point. At each step, the value A_i of a concept is influenced by the values of concepts connected to it and it is updated according to the inference rule. This process continues until the system converges which indicates that the difference between two subsequent value of the outputs values must be equal or lower to ε (epsilon, ε = 0.001).

2.8 Proposed tools for Fuzzy Cognitive Map modeling and scenario analysis

Inheriting the main characteristics of Fuzzy Logic and recurrent Neural Networks, FCMs can model any real-world system as a collection of concepts and causal relationships among them. From an Artificial Intelligence perspective, FCMs are dynamic networks with learning capabilities, which make FCMs essential for modeling and decision-making tasks. In addition, the more data is available for modelling the problem at stake, the better the system becomes at adapting itself and reaching a solution [2]. To tackle this vast amount of data, various parameters, modelling, learning and simulation tasks of complex systems, researchers need a simple but powerful software tool that could help them in this direction.

As found in the related literature, several tries occurred by researchers for developing software products with simple or advanced functions that could perform either designing and analyzing tasks or even more complex like learning, aggregation and simulation on FCM-based systems. In particular, FCMapper which is based on MS Excel, is one of the first FCM analysis tools available online, whereas additional social-network software like Pajek or Visone is needed for FCMs visualization. Also, FCM TOOL along with its extension were proposed to offer a learning algorithm for estimating the causal weights, designing, learning and simulating FCM-based systems, especially in pattern classification problems, whereas a later version was renamed as FCM Expert [80]. In the form of libraries, JFCM was developed as a small and simple open source library that can be used to create a variety of cognitive networks, also loading networks from XML files [81]. An open source FCM library in R language named “fcm” has been recently proposed under the Comprehensive R Archive Network (CRAN) [82], which provides users with a selection of six different inference methods and four threshold functions. On the other hand, Mental Modeler is a quite interesting approach which facilitates the aggregation and analysis of group models by combining FCMs created by different individuals or stakeholders, using a web-based interface [83]. Also, FuzzyDANCES is a tool to draw and analyze FCMs by calculating network graph indices, also containing algorithms for sensitivity analysis (Winding Stairs) and map learning using Differential Evolution [84]. Aguilar and Contreras developed the FCM designer tool with a Spanish interface, which offers a variety of ways to describe causal links in a static or dynamic way, employing logic rules, mathematical equations, or Fuzzy Logic [85].

Another software product that entails FCM-based decision-making capabilities is ISEMK [86] and is mainly devoted to forecasting tasks. The main features of ISEMK are:

- the population-based learning of FCM with the use of RCGA and SOGA based on real multivariate time series,
- the multi-step supervised learning with the use of gradient method and real multivariate time series,
- the visualization of structure of the analyzed FCM and the results of learning, as well as the testing of the learned FCMs operation.

The ISEMK tool was particularly used in this thesis to perform predictions using evolutionary FCMs and ANNs, supporting a comparative analysis conducted between the proposed ensemble forecasting approach with other individual models, as is presented in chapter 5.

However, a gap is noticed in the relevant literature, regarding the existence of a more user-friendly tool that can provide extra capabilities such as aggregating FCM models and learning them using supervised and unsupervised algorithms. In this direction, a new web-based tool called FCMwizard, (available at http://fcmwizard.com) [87] was developed, which incorporates these functionalities for helping research community to freely experiment with them and exploit all the capabilities offered. Furthermore, a Java-based tool called OWA FCM, was also used for the purposes of this dissertation for implementing the OWA operators in the process of aggregating individual FCM models. Both new software products are thoroughly described in the following sections, whereas a more detailed presentation of the FCMWizard tool can be found in the web link provided.

2.8.1 OWA FCM aggregation tool

OWA FCM is a flexible and user-friendly tool developed to provide the research community with an automated method for aggregating a large number of individual FCMs, thus producing a combined FCM, enriched with knowledge from experts and stakeholders involved in this task. More specifically, the OWA FCM software tool was developed to deal with the proposed approaches for experts' credibility and weight aggregation using OWA operators. The tool was developed in Java programming language. An overview snapshot of the user interface can be seen in Figure 2.6.

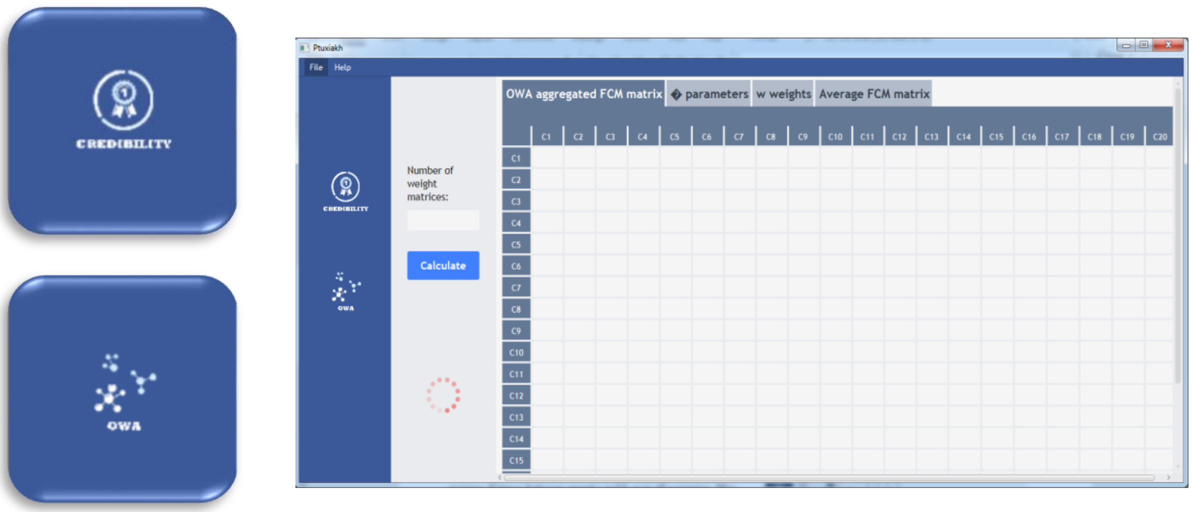


Figure 2.6: Screenshot of the FCM-OWA tool for aggregation

On the left side of the main panel lie the “OWA aggregation” and the “Credibility” functions. The user has access to a main menu where the “import” and “export” buttons are placed.

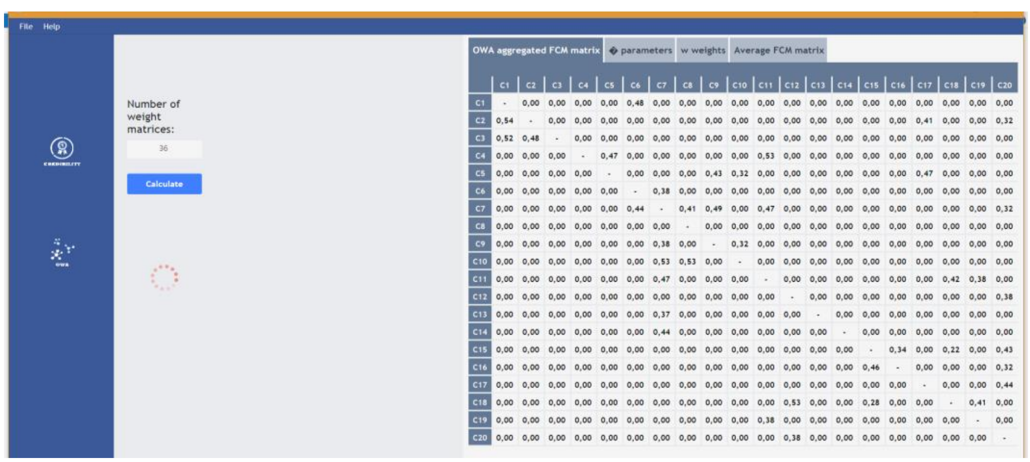
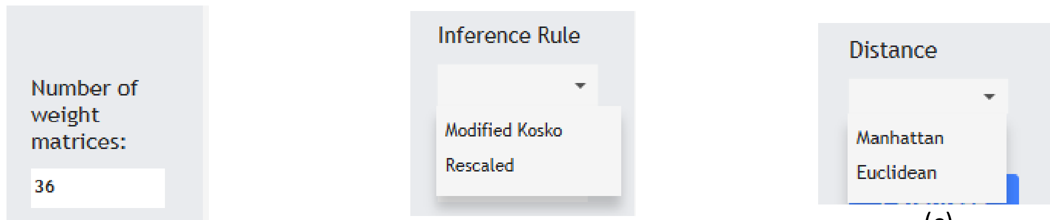


Figure 2.7: Screenshot of “OWA” tab

As far as the “OWA aggregation” function is concerned, the user needs first to define the number of input weight matrices as shown in Figure 2.7, for example 36, and next to insert an excel file with the weight matrices, one in each sheet, defined by each expert. After the user clicks the “Calculate” button, the OWA aggregated FCM matrix appears in the first tab (see Figure 2.7). Also, the average aggregated FCM can be displayed on the “Average FCM” tab.

Regarding the “Credibility” function of the tool, this can be reached through the side menu by clicking on the corresponding button. This option allows users to select the wanted Inference Rule (Figure 2.8(b)) and the Distance (Figure 2.8(c)) for the calculation of credibility weights after first specifying the number of input weight matrices (Figure 2.8(a)).



(a) (b) (c)

Figure 2.8: (a) The “number of weight matrices” tab, (b) “The inference Rule” tab and the (c) “Distance” tab.

By clicking on “Calculate”, the credibility results appear in the first tab (see Figure 2.6).

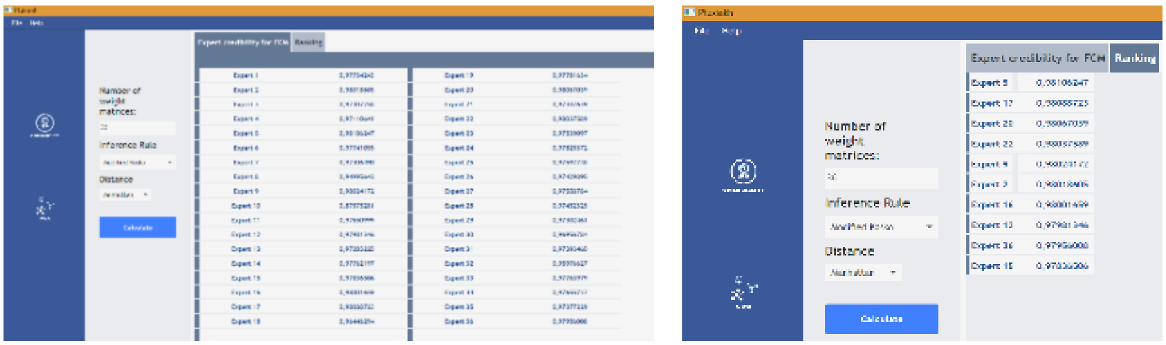


Figure 2.9: Left: “Credibility” results tab for the SHG group. Right: Ranking of Experts (SHG group) with the highest credibility.

In the second tab, we rank the experts’ credibility according to the consensus endpoint of the weighted interconnections among concepts. The first 10 experts with the highest credibility in weights are displayed in Figure 2.9 (right).

The user is also given the option, from the main menu of the Tool, to export the OWA aggregated FCM matrix and the Credibility results table, saving them as an excel file.

2.8.2 FCM WIZARD tool for designing and analyzing FCMs

FCMWizard (www.fcmwizard.com) is a new web-based software tool that has the special ability to construct an FCM model using data that come from experts’ or stakeholders’ knowledge. Using a very intuitive Graphical User Interface [87], the tool can also analyze the behavior of the FCM model by performing simulations for different possible scenarios, in different scientific domains.

The FCMWizard tool can be seen as having four main functionality categories. Any type of users can use the first category without a thorough knowledge of the mathematical foundations of the FCM methodology. They can design new FCMs independently from the type of the application by adding new concepts and causal relationships between them using influence weights. Moreover, when group modeling is used, the different individuals’ cognitive maps can be combined in an easy and meaningful way to produce a collective FCM, which in general might help reaching consensus, promote learning and reduce conflicts [17]. FCM Wizard offers the possibility to aggregate different FCMs by augmenting their adjacency matrices in order to reflect all proposed concepts from the different participants, then averaging is used to produce the group map.

Among the functionalities that site on the main menu (see Figure 2.10), there are three main modes for constructing an FCM, namely: (i) Expert mode, wherein experts and/or stakeholders can construct manually an FCM for a real problem, (ii) Data-based Learning mode, wherein the FCM model is constructed automatically using given data, and (iii) Merge mode, where different individual FCMs can be combined to provide an augmented and collective FCM, model in order to generate aggregated system complexities.

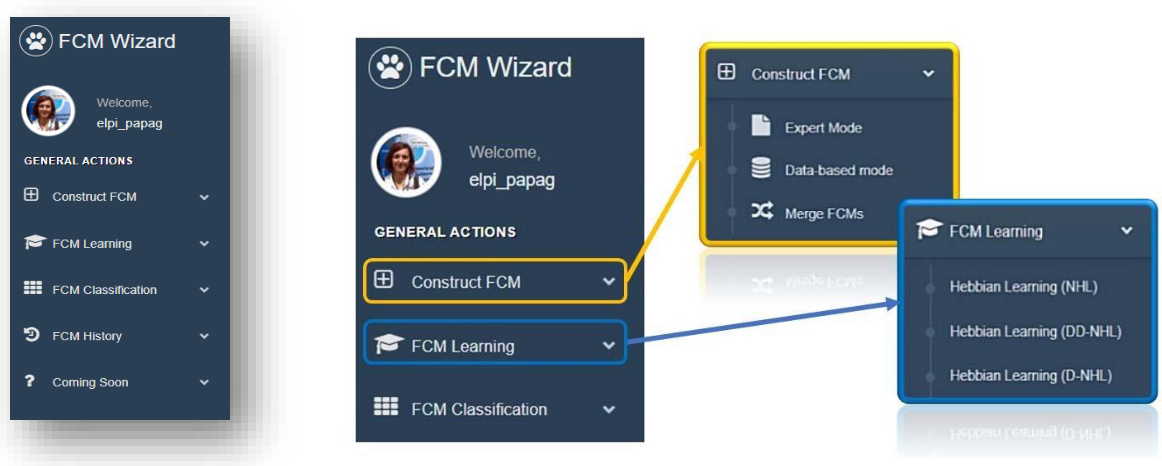


Figure 2.10: Main menu of FCMWizard

Regarding the FCM Learning Mode, FCMWizard offers three main modes (see Figure 2.10): (i) Hebbian Learning (NHL): weights are fine-tuned by data assuming that all the concepts are synchronously triggered at each iteration and they synchronously change their values. Constraints on concepts and weights can be considered for updating weighted connections. (ii) Data-driven Hebbian Learning (DD-NHL): an extended NHL method through historical data for the input concepts to fine-tune weights, and (iii) Differential Hebbian Learning (D-NHL): This algorithm correlates the changes in the concepts to modify their weights.

For the model development, users have the advantage of generating new concepts and causal relationships between them, with no need to know the mathematical foundations of the methodology and regardless the type of application domain. Selecting the "Expert Mode" under the main menu "Construct FCM", users can easily design an FCM model by adding new nodes and new directed lines that represent the causal relationships between nodes (see Figure 2.11). Green direct lines denote positive weights whereas red inverse relationships denote negative weights. Moreover, the FCMWizard tool has the ability to automatically design an FCM model only by properly importing the model's adjacency matrix.

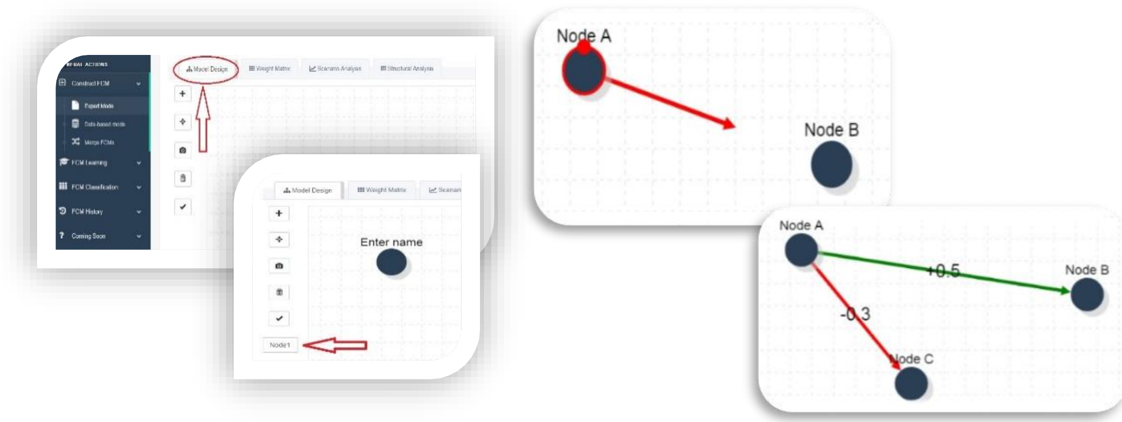


Figure 2.11: FCM model development process

In order to describe certain specifications and different aspects of the behavior of the examined model, structural analysis is needed, as a necessary step for determining the dynamics of the system. Considering that the construction of FCM maps relies heavily on expert and human perceptions, a way to compare is by analyzing the map structure using graph theory indices [12, 17]. The FCMWizard online module is designed to provide calculations over such graph theory indices, including the total number of concepts and connections, connection to concept ratio, the type of variables (receiver, transmitter or ordinary), indegree, outdegree, degree centrality, betweenness centrality, closeness centrality, complexity ratio, density and hierarchy index (see Figure 2.12). Centrality is considered an index of importance for a concept. That is, a concept with a high degree of centrality plays an important role in the cognitive map [12]. Also, complexity, density and hierarchy index are among significant structural indices for analyzing the graphical structure of FCMs.

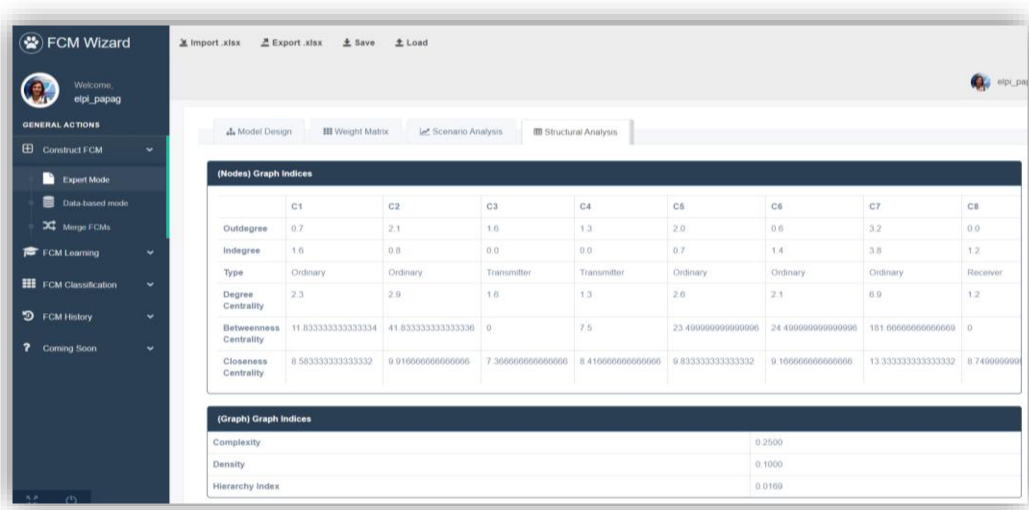
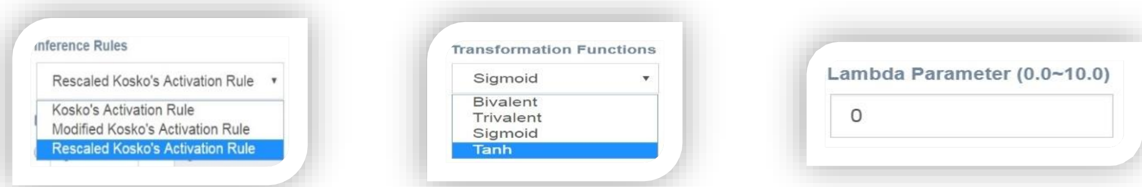


Figure 2.12: The “Structural Analysis” tab of FCMWizard

FCMWizard entails also the ability to perform "what-if" scenario analysis, allowing users with more expertise like FCM analysts that are familiar with the method's mechanics, to simulate a FCM model by specifying the desired parameters for this task. The objective of this process is to determine the feasibility of scheduled simulations and anticipate contingent situations. In the case of the FCM model, various parameters need to be properly defined. These are: the initial stimulus state vector, the inference rule's type, the transfer function with its learning parameter along with the number of iterations or the convergence step (see Figure 2.13). The provided tool also offers users with the open/closed lock option, which can keep the value of a concept unchained throughout iterations, as being "clamped" (see Figure 2.14). This category can be somewhat challenging to other types of users like stakeholders or policy analysts and will necessitate a learning curve.



a) b) c)

Figure 2.13: Selection of (a) Inference Rule, (b) Transformation function and (c) lambda parameter of the transformation function

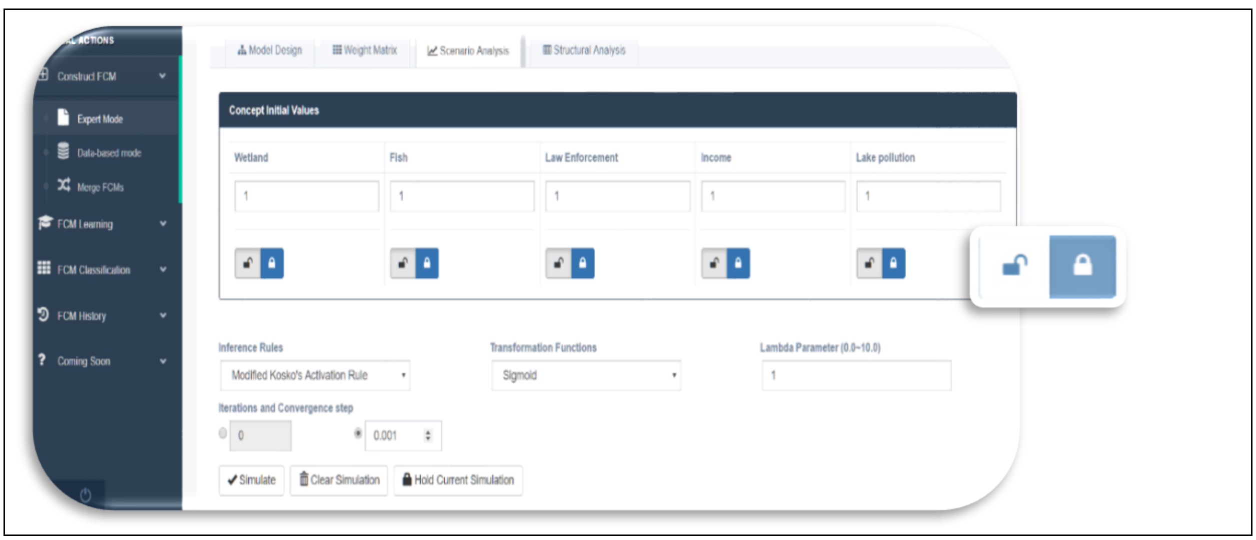


Figure 2.14: Screenshot of the "scenario analysis" mode.

A major shortcoming of FCMs is the potential convergence to undesired steady states or unacceptable decisions according to problem constraints and a critical dependence on experts. In order to overcome these shortcomings, learning algorithms have been investigated and proposed for FCMs by using historical data, contributing hence to adaptive FCMs and improving the robustness and accuracy of FCM output, especially in prediction tasks. To that end, another category of functionalities was integrated in this software product to allow FCM models to be constructed and calibrated using observed historical data. More specifically, FCMWizard contains a package of Hebbian-based learning algorithms such as non-linear hebbian, differential hebbian, data-driven hebbian and active hebbian learning [57].

2.9 Conclusions

This chapter presents the FCM methodology which highly contributes on modelling and analyzing complex and dynamic systems. FCMs are fuzzy structures that combine the advantageous characteristics of both fuzzy logic and Neural Networks, which incorporate knowledge acquisition and indicate the causality among concepts of complex systems characterized by uncertainty. In fact, FCM has the ability to capture and describe a system’s behavior encapsulating and analyzing the accumulated knowledge and experiences of human experts on complex systems in various scientific domains.

On the other hand, developing an FCM model is a challenging task since it usually involves individual knowledge acquisition from numerous and multiple experts and/or stakeholders from the application domains. Thus, an aggregation procedure is further needed to produce an overall single FCM which will be less susceptible to potentially erroneous beliefs of a single expert, and improve as well the credibility of modelling with FCMs. Only a few aggregation methods can be found in the related literature, such as the weighted average and the OWA method as the ones that are the most commonly used in this context. However, they either entail certain limitations over their implementation in the aggregation process or have been applied in a limited number of studies concerning a small group of experts and/or stakeholders.

A new alternative aggregation methodology for FCM modeling is developed to properly aggregate FCM connections/links defined by multiple experts and/or stakeholders using learning OWA operator weights, also calculating credibility weights for a large number of experts and/or stakeholders. In this direction, a Java-based tool was developed to provide the research community with an automated method of aggregating a large number of individual FCMs designed by experts and/or stakeholders, applying also the credibility weight methodology in ranking experts for most efficient FCM models for scenario analysis and policy making. Furthermore, a new software tool, called FCM Wizard, is presented to automatically construct FCM models by either using experts’ knowledge or by using data when available. It also serves as a necessary simulation tool that allows researchers and the FCM community to make decisions and perform policy simulations on their own case studies through a very intuitive Graphical User Interface, whereas it incorporates numerous simulation and inference options, as well as Hebbian-based learning algorithms that can significantly improve the system’s performance.

Chapter 3

Socio-Economic Sustainability: Modeling and Planning Using FCMs

3.1 Introduction

Modelling and more specifically the participatory approach to modelling has been emerged as a key prerequisite in the decision-making process through which stakeholders contribute to the representation of the perceived causal linkages of a complex system. The use of fuzzy cognitive maps (FCMs) for participatory modelling helps policy-makers develop dynamic semi-quantitative models for strategizing development interventions, whereas the aggregation of knowledge from multiple stakeholders provides consolidated and more reliable results. In the context of formulating suitable strategies, policy-makers and governments seek to investigate the interconnection between the environmental, social and economic pillars of sustainable development. Sustainable development has become a question of growing importance as it is considered as the essential element for improving the quality of life on earth of both current and future generations.

It is a common view that worldwide, the impacts of various anthropogenic activities such as increased industrialization, pollution, deforestation, and overconsumption, are causing destruction and overexploitation of natural resources. They have been recognized as the most significant risk not only for the environment but also for human health and well-being [88, 89]. The overexploitation of natural resources has grown rapidly in the last two decades, and global resource supply chains have become extremely complex. This has resulted in the increase of environmental pressures and impacts [89]. If humankind continues to live on the edge of or outside the ecological limits, it will be much more difficult to achieve equity, justice, prosperity, well-being and healthy quality of life for everyone, both on global and local levels [32]. The need for humanity to remain within the safe operating space of planetary boundaries and the need to eradicate poverty and accelerate sustainable socio-economic development are linked by the concept of “safe and just space for humanity” [90]. Therefore, a global shift from a linear economy towards a circular economy is needed. Hence, socio-institutional change along with resource efficiency and innovative product design [91] can contribute to economic development and human well-being, with reduced pressures and impacts on the environment. The circular economy approach aims at continuous economic development to achieve waste minimization, energy efficiency, and environmental conservation, without posing significant challenges to the environment and natural resources [92]. Circular economy is a competitive environmental strategy to production processes and economic activities, that allows resources to maintain their highest value. It also benefits businesses and society as a whole, with better supply chain, low volatility of resource prices, better customer relations, improved services, and new employment opportunities [92]. The key considerations in the implementation of circular economy are to refuse, reduce, rethink, repair, restore, remanufacture and reuse resources [91, 93]. They also include the pursue of longevity, renewability, replaceability, and upgradability for resources and products that are used.

The sustainable development goal "One" of the United Nations seeks to eradicate poverty and subsequent inequalities in all forms, leaving no one behind. The multi-dimensional nature of poverty involves the lack of income or consumption, food insecurity, high vulnerability to risks, low human capital, unequal social relations, and powerlessness [94]. On the other side, its eradication involves complex interactions within socio-economic systems. Across the world, several development projects [95] and poverty alleviation programmes [94, 96] have been implemented, which are primarily aimed at socio-economic development and poverty reduction of poor and vulnerable communities. Understanding such complex interactions requires a participatory modelling approach that can be implemented by FCMs.

In participatory modelling, stakeholders allow decision-makers to understand meaningful interactions occurring inside a complex system and contribute valuable first-hand knowledge for supporting decision-making, policy formulation, regulation, and management purposes [23]. FCM is a common participatory modelling methodology which has the capability to model any real-world system, easily integrate diverse human knowledge and adapt to a particular domain [55]. In recent years, FCMs have been applied extensively in multiple domains due to their simple model structure and ease of use [71, 97]. It is no wonder that they have become a powerful soft-computing modelling tool [8]. In all cases, the FCM-based particip atory modelling approach attempts to capture the causal relationships within complex systems exploiting the views and perceptions of stakeholders. Doing so, can reduce conflicts among stakeholders by capturing different inter-sectorial synergies and tradeoffs, helping them to reach consensus in a complex policymaking environment.

Furthermore, the aggregation of individual FCM models must be taken into account when a variety of sources need to be included in the modelling procedure of a given system [71]. Individual FCMs, constructed by experts and/or stakeholders, can be aggregated to produce a combined FCM that will incorporate the knowledge from all the different experts and/or stakeholders involved in the FCM construction process. The main objective behind aggregating individual FCMs is to improve the reliability of the final FCM model. That is, the FCM model becomes less susceptible to potentially erroneous beliefs of a particular expert, helping to bridge knowledge discrepancies among the participants. Regarding the combination of multiple FCMs into a single collective model, among the techniques that can be found in the related literature, two methods are widely used in real-life problems [72]: the weighted average and the OWA method introduced by Yager [73]. The weighted average method is considered as the benchmark method for FCM aggregation purposes, in which the final FCM model is built by averaging numerical values for a given interconnection [98]. Its rules are aggregated with the help of fuzzy operators, while the overall output is elaborated using the weighted average of the output of each rule [8]. However, there are certain limitations towards the implementation of this methodology. For example, when a large number of stakeholders/participants are asked to assign values on the relationships of a given system, significant deviations can arise between these values. This fact shows an inconsistency of knowledge among the participants that leads to an inaccurate overall FCM. On the other hand, the application of OWA operators in the aggregation of individual FCMs has a limited presence in the literature. In particular, OWA operators in an FCM framework were introduced by Zhenbang and Lihua [75], who highlighted the ability of OWA operators to simulate the various AND/OR relationships between the concepts. They also studied the OWA aggregation under different conditions. An OWA operator based on distance was examined by Leyva-Vazquez et al. [99] to rank the scenarios depending on the decision-makers' risk preferences.

In the context of the two cases, as they will be described in the following sections, the new method for aggregating individual FCMs, using the application of the OWA operators, is explored. Both cases originate from the same examined problem which is based on the DAY-NRLM (Deendayal Antyodaya Yojana-National Rural Livelihoods Mission) poverty eradication program in India but constitute two different approaches in terms of FCM development and scenario analysis. They both follow the participatory approach, whereas different modules of knowledge, such as participants' confidentiality and different interpretations regarding model's conceptualization, are involved in the FCM development process. Also, the two cases incorporate different combinations of concepts for scenario planning. The objective behind the presentation of two similar approaches under the same case study is: a) to extensively illustrate the functionalities of the OWA-based aggregation methodology and b) shed light on how the application of different scenarios can offer different dimensions in efficiently addressing the problem of socio-economic and environmental sustainability. Thus, it can help policy-makers and governments to tailor suitable strategies in the domain.

3.2 Proposed FCM-based framework

A mixed-concept design approach is adopted for obtaining cognitive maps from the participants, which involves an open-concept design followed by a closed-concept design. The methodology used to develop FCMs is conducted in seven distinct steps that are thoroughly described below. This multi-step FCM development process is visually illustrated in Figure 3.1.

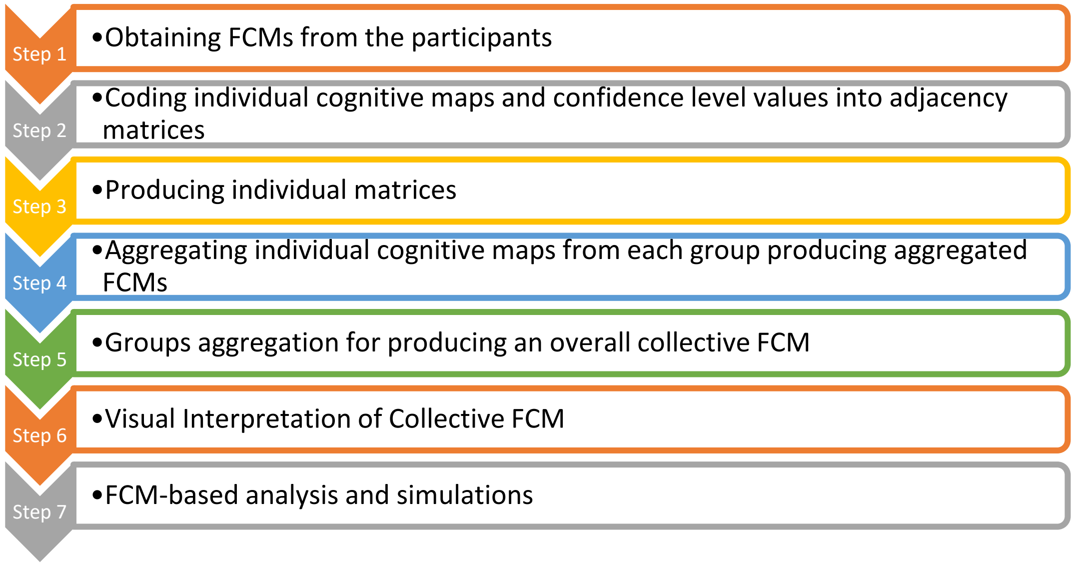


Figure 3.1: Visual illustration of the FCM development process.

Step 1: Obtaining cognitive maps from the participants

i. Expert-based FCM using an open-concept design.

The first step starts with a group discussion involving national and state-level implementers who identify factors responsible for achieving the outcomes of the given real-life problem, described by the DAY-NRLM programme. Next, a group of concepts and sub-concepts are identified, being available for further analysis. In the current case study, 20 categories of main concepts and 129 sub-concepts were identified so as they contribute to the FCM development process. The participants are demonstrated on how to draw a fuzzy cognitive map for a simple system that serves as an example. Once the participants understand the process of constructing a cognitive map, they are asked to draw fuzzy cognitive maps by providing causal links to each main concept. They are further requested to assign weights for the relationships between the concepts (see Step 1(iii)).

ii. Preparation of study protocol based on the expert-based model.

A protocol (see Figure 3.2) generated by the experts (national and state-level programme implementers), depicting all the 20 categories of main concepts and 129 sub concepts, is prepared, which also includes the links identified by the experts. This protocol was approved by the Research Ethics Committee of the Institute of Rural Management Anand (IRMA). The Expert-based FCM model deriving from the implementation of this protocol, is going to be further compared with the FCM models, produced from the aggregation processes, to help this study meet its objectives.

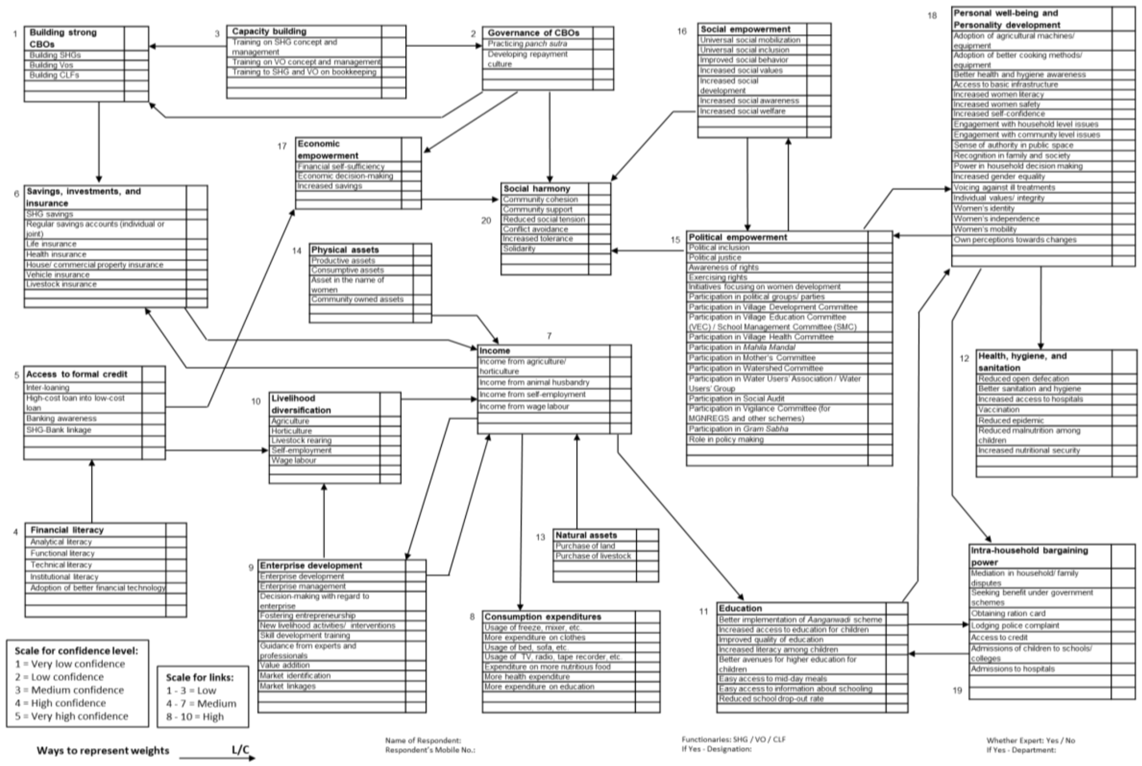


Figure 3.2: The FCM protocol used for data collection from the participants.

iii. Closed-concept design from the community-level stakeholders.

The protocol is administered to four different groups of stakeholders from the DAY-NRLM programme, who are asked to construct FCMs. These are functionaries of Self-Help Groups (SHGs), their federations [Village Organisations (VOs) and Cluster Level Federations (CLFs)], and Community Resource Persons (CRPs). All the community stakeholders are women. A total of 179 FCMs were obtained from over 600 participants during the FCM exercise. These participants were selected randomly between the programme participants. SHG and VO functionaries were divided into smaller sub-groups, with each sub-group comprising four to five members, to construct FCMs. On the other hand, the CLF functionaries and CRPs drew the FCMs individually.

In this step, every community group/ individual stakeholder provides weights to the individual links on a scale of 1–10 and in the case that the level of confidence for such weights is required, then such confidence degree is given on a scale of 1–5, as discussed earlier. Ten (10) denotes the highest strength and one (1) the lowest [12]. The participants are also asked to draw new links between the categories, depending on what they believe. However, in this case, none of them created any additional link. Each group made a presentation to the researchers after having concluded in the construction of the FCM.

Step 2: Coding individual cognitive maps and confidence level values into adjacency matrices

Each fuzzy cognitive map constructed is coded into separate Excel sheets with concepts listed in vertical (*Ci*) and horizontal (*Cj*) axes; this forms a square adjacency matrix [12, 13]. The positive wording of all the concepts warrants only positive values for the relationships. Accordingly, the weight values are coded into the adjacency matrix only when there is a connection between two given concepts [12]. The weights given to each link are normalized between 0 and +1 (if a value is +5, then it is normalized to +0.5) while coding into the adjacency matrix [13]. Similarly, the confidence level values, when they are present, are also normalized between 0 and 1 (for example, value 1 corresponds to 0.2, value 2 to 0.4, and value 5 corresponds to 1).

Step 3: Producing individual matrices

Each adjacency matrix consists of the normalized weights of the individual cognitive map named as adjacency links matrix. The corresponding individual FCM model is called FCM model.

Table 3.1: Adjacency matrix with links (L)

	C1	**C2**	**C3**	**…**	**C20**
C1	0	0.00	0.00	…	0.00
C2	$w_{1,2}^{(l)}$	0.00	0.00	…	$w_{20,2}^{(l)}$
C3	$w_{1,3}^{(l)}$	$w_{2,3}^{(l)}$	0.00	…	0.00
⋮	⋮	⋮	⋮	$w_{i,j}^{(l)}$	⋮
C20	0.00	0.00	0.00		0.00

In the case where the level of confidence is involved in the FCM development process, the normalized weight value of every existing link is multiplied with its normalized confidence level value. So, it produces the adjacency confidence and links matrix that correspond to the individual confidence and links FCM model. Doing so, a new FCM model is being built that seems to represent participants' opinions with high reliability. In this case, two FCM models are created based on each map: one for links (see Table 3.1) and another for confidences and links (see Table 3.2).

Table 3.2: Adjacency matrix with links (L) and confidences (C)

	C1	**C2**	**C3**	**…**	**C20**
C1	0	0.00	0.00	…	0.00
C2	$w_{1,2}^{(l)}, w_{1,2}^{(c)}$	0.00	0.00	…	$w_{20,2}^{(l)}, w_{20,2}^{(c)}$
C3	$w_{1,3}^{(l)}, w_{1,3}^{(c)}$	$w_{2,3}^{(l)}, w_{2,3}^{(c)}$	0.00	…	0.00
⋮	⋮	⋮	⋮	$w_{i,j}^{(l)}, w_{i,j}^{(c)}$	⋮
C20	0.00	0.00	0.00		0.00

Step 4: Aggregating individual cognitive maps from each group producing aggregated FCMs.

In this step, all individually coded cognitive maps are aggregated and additively superimposed using the two aggregation methods (the Average and the OWA) [100]. Two collective FCMs are created for every group of participants for each aggregation method, named as the average-FCM and OWA-FCM. An overall group FCM (Collective-FCM) is produced separately from each of these methods. The obtained Collective-FCM represents the perception of all the stakeholders (SHG, VO, CLF, and CRP) and includes all the concepts from all individual cognitive maps. Thus, two collective-FCMs are created for every group of participants for each aggregation method; the Average-FCM and OWA-FCM, referring to the FCMs that include the weight value for every single link. In the case where there is a demand for confidence values, then two more collective-FCMs, the Average-FCM and OWA-FCM, are created. Every link value between two nodes is the result of the multiplication of its weight value with its corresponding confidence level value.

i. Average aggregation

The average aggregation method suggested by Kosko [4] is used for aggregating a large number of FCMs consisting of the same or different concepts (representing different variables, status, parameters, among other things). Considering the case that *n* Experts assign a weight value w_{ij}, between the nodes C_i and C_j on individual FCMs with the same number of concepts, then the aggregated weight $w_{ij}^{(ave)}$ between these nodes can be defined as the average value of the n weights w_{ij}.

$$w_{ij}^{(ave)} = \frac{w_{ij}^{(1)} + w_{ij}^{(2)} + \cdots + w_{ij}^{(n)}}{n} \tag{3.1}$$

A more detailed description of the Average aggregation method can be found in section 2.3.

ii. OWA aggregation

The proposed algorithm for aggregating the weights assigned by the experts and stakeholders during the FCMs' designing process learns the weights linked with a specific use of the OWA operator from the experts and stakeholders. More specifically, the OWA weights can be obtained through the following process:

Table 3.3: The proposed algorithmic steps for the aggregation of weights

Steps	Description
Step 1:	Create a slightly different parameter ρ for each argument that indicates the optimism of the decision-maker, $0 \leq \rho \leq 1$.
Step 2:	Compute the aggregated values for each sample with the Hurwics method, where the aggregated value d obtained from a tuple of n arguments, $a_1, a_2, \ldots, a_n$, is defined as the weighted average of the *Max* and *Min* values of that tuple.

$$\rho \operatorname*{Max}_{i} a_i + (1-\rho) \operatorname*{Min}_{i} a_i = d \quad (3.2)$$

Step 3: Reorder the objects $a_{k1}, a_{k2} \dots, a_{kn}$.

Step 4: Compute the current estimation of the aggregated values d_k

$$\hat{d}_k = b_{k1}w_1 + b_{k2}w_2 + \cdots + b_{kn}w_n \quad (3.3)$$

through initial values of the OWA weights w_1=1/n.

Step 5: Calculate the total $\hat{d}_k$, d_k, b_{ki} for each i. The parameters λ_i determine the weights of OWA and are updated with the propagation of the error $\hat{d}_k - d_k$ between the current estimated aggregated value and the actual aggregated value (see Equation (3.3)).

Step 6: Compute the current estimations of the λ_i

$$\lambda_i(l+1) = \lambda_i(l) - \beta w_i(l)(b_{ki} - \hat{d}_k)(\hat{d}_k - d_k) \quad (3.4)$$

through initial values $\lambda_i(0) = 0$, $i = (1, \dots, n)$, and a learning rate of β=0.35.

Step 7: Use λ_i, $i = (1, \dots, n)$, for providing latest estimate of the weights.

$$w_i = \frac{e^{\lambda_i(l)}}{\sum_{j=1}^{n} e^{\lambda_i(l)}}, i = (1, n) \quad (3.5)$$

Step 8: Update w_i and $\hat{d}_k$ at each iteration until the estimations for all the λ_i converge to, that is Δ = $|\lambda(l+1) - \lambda(l)|$ are small.

Initially, experts' opinions are considered as argument values ($a_{k1}, a_{k2} \dots, a_{kn}$). The OWA aggregation method is analytically described in Section 2.6.

Step 5: Groups aggregation for producing an overall collective FCM

Next, two Collective-FCMs are produced from each one of the four groups (SHG-FCM, VO-FCM, CLF-FCM and CRP-FCM), using the weighted average aggregation method as well as the OWA-based aggregation method. Thus, a Collective-FCM is produced from the implementation of each aggregation method. The Collective-FCM is enriched with the knowledge of all stakeholders involved.

Step 6: Visual Interpretation of Collective FCM

The collective FCMs are analyzed using the FCMWizard software tool (www.fcmwizard.com) [101]. The tool includes modelling and visualization capabilities for the consensus FCM models, depicting the connections among the factors and also reflecting the importance of different concepts within various asset classes [13]. Thus, four average-FCM models designed by each group (SHG, VO, CLF, CRP) are produced by the FCMWizard tool which remarkably contributes to the success of the FCM development process.

Step 7: Fuzzy cognitive map-based analysis and simulations

The FCM-based analysis is divided into three discreet sub-steps including the structural analysis, the development of input vectors for conducting policy scenarios and the simulation process, which are individually described below in further details.

i. Structural analysis

The structural analysis provides a description of FCM models with the help of indices including in-degree (weight of inbound links), out-degree (weight of outbound links), degree of centrality (sum of the corresponding absolute weights of in-degree and out-degree), complexity, density and the hierarchy index [12, 17]. Centrality is considered a significant index, so that a concept with a high degree of centrality has an important role in the cognitive map [12, 101]. Complexity, density and hierarchy index are among significant structural indices for analyzing the graphical structure of FCMs [12, 101]. The structural analysis is conducted with the aim of the FCMWizard tool.

ii. Development of input vectors for policy scenarios

In this step, the influence that certain variables have on the examined system is assessed. Taking into consideration the number of each concept's substantial connections, the existence of their strong and direct connection to the objective concept along with the structural analysis as described in the previous step, can guide researchers to select the proper concepts to become the base of the scenarios since they can strongly affect the behavior of the system. Overall, suitable input vector concepts that could well influence the dynamics of the system are properly selected to form the scenarios. The simulation results of the above scenarios help us to understand the critical factors to achieve the desired programme outcomes.

iii. Simulation process

FCM-based simulations can offer a deeper understanding of the concepts behavior and their relations in terms of how one concept affects others. The FCM-based simulations are carried out using the FCMWizard tool [101]. Each concept in the FCM model has a state variable that varies from |0| to |1| and is associated with an activation variable. In other words, |0| means 'non-activated' and |1| means 'activated' [13, 38, 38, 102]. When one or more concepts are 'activated' by inputting an initial non-zero value, this activation spreads through the matrix following the weighted relationships. Each iteration produces a new state vector with 'activated' and 'non-activated' concepts. Feedback loops cause repeated activation of a concept, introducing non-linearity to the model [2, 28, 38]. The activation of concepts is iterated, using a 'squashing function' to rescale concept values towards |1|, until the model reaches the equilibrium or the steady-state [38]. The simulation process culminates with the attainment of a steady-state of the system. To determine the steady-state, we ran a simulation process starting with an initial state vector X_0, with the input vectors identified in each scenario clamped to 1. An equilibrium or steady-state vector is obtained after the FCM convergence [2, 38, 38, 102]. This outcome is compared against a baseline scenario where the system (output vector) reaches the steady-state with clamping all the initial values to zero. Exploring the dynamic change of concepts values between the baseline steady-state and the outcome of the clamping procedure enables quantitative interpretation of the impact of the key concepts on the system. The simulation process entails the application of a sigmoid function with lambda = 1, as a threshold function, on the adjacency matrix after it was multiplied with the input vector. The process is iterated until the system reaches a steady-state. We apply the modified Kosko activation rule proposed by Stylios and Groumpos [8] to run simulations, because of its memory capabilities, along with the Sigmoid transfer function (Equation 2.26), as the concepts only have positive values. The resulting concept values can be used to interpret the outcomes of a particular scenario and to study the dynamics of the modelled system [13, 38].

FCMWizard is used for simulation purposes as it has the unique ability to automatically construct an FCM using the knowledge of experts or stakeholders and can perform simulations for possible scenarios in diverse scientific domains [101]. The impact of the conducted scenarios on the selected decision concepts is examined, further identifying which key concepts affect the final deliverables of the program.

3.3 Case A: Sustainable socio-economic planning for rural communities

3.3.1 Problem statement

This case study tries to identify an ideal strategy for sustainable socio-economic development planning for rural communities in developing economies by evaluating the Deendayal Antyodaya Yojana–National Rural Livelihoods Mission (DAY-NRLM) programme. DAY-NRLM, a centrally sponsored programme of the Government of India, is one of the world's largest poverty eradication programmes that aims to eliminate rural poverty in the country through the promotion of multiple livelihoods for each rural poor household. It follows a participatory and community-demand-driven approach that focusses largely on the eradication of poverty and pays special attention to the development of social resilience and sustainable socio-economic development. It predominantly focuses on livelihood enhancement through building self-managed and sustainable community institutions of "the rural poor women". These community institutions are expected to overcome their social, financial, and economic exclusion. The broader objectives of the programme involve social mobilization, institution building, enrolment of women in social security schemes and entitlements, socio-economic inclusion, sustainable livelihoods, capacity building, promotion of economic stability, improvement of social resilience, and skill development, aiming at the elimination of rural poverty. Ultimately, these outcomes will lead to reduced socio-economic poverty and improved quality of life.

This case study adopted a mixed-concept design approach for obtaining cognitive maps, involving open-concept design followed by closed-concept design. A total of 31 national and state-level implementers identified 20 categories of main concepts and 129 sub-concepts. Every key concept was formed from a list of certain sub-concepts that define it well. The sub-concepts were introduced by the experts and policymakers to offer a deeper understanding of the examined problem, making it clear to the participants.

Table 3.4: The list of concepts and sub-concepts for the examined case study

Key Concept	SUB-CONCEPTS	
C1: Building strong CBOs	Building SHGs Building VOs	Building CLFs
C2: Governance of CBOs	Practicing panch sutra	Developing repayment culture
C3: Capacity building	Training on SHG concept and management Training on VO concept and management	Training to SHG and VO on bookkeeping
C4: Financial literacy	Analytical literacy Functional literacy Technical literacy	Institutional literacy Adoption of better financial technology
C5: Access to formal credit	Inter-loaning High-cost loan into low-cost loan	Banking awareness SHG-Bank linkage

C6: Savings, investments and insurance	SHG savings Regular savings accounts (individual or joint) Life insurance	Health insurance Vehicle insurance Livestock insurance
C7: Income	Income from agriculture/ horticulture Income from animal husbandry	Income from self-employment Income from wage labour
C8: Consumption expenditures	Usage of freeze, mixer, etc. More expenditure on clothes Usage of bed, sofa, etc. Usage of TV, radio, tape recorder, etc.	Expenditure on more nutritious food More expenditure on health More expenditure on education
C9: Enterprise development	Enterprise development Enterprise management Decision-making with regard to enterprise Fostering entrepreneurship New livelihood activities/interventions	Skill development training Guidance from experts / professionals Value addition Market identification Market linkages
C10: Livelihood diversification	Agriculture Horticulture Livestock rearing	Self-employment Wage labour
C11: Education	Better implementation of Aanganwadi scheme Increased access to education for children Improved quality of education Increased literacy among children Reduced school drop-out rate	Better avenues for higher education for children Easy access to mid-day meals Easy access to information about schooling
C12: Health, hygiene, and sanitation	Reduced open defecation Better sanitation and hygiene Increased access to hospitals Vaccination	Reduced epidemic Reduced malnutrition among children Increased nutritional security
C13: Natural assets	Purchase of land	Purchase of livestock
C14: Physical assets	Productive assets Consumptive assets	Asset in the name of women Community owned assets
C15: Political empowerment	Political inclusion Political justice Awareness of rights Exercising rights Initiatives focusing on women development Participation in political groups/ parties Participation in Village Development Committee Participation in Village Education Committee	Participation in Mahila Mandal Participation in Mother's Committee Participation in Watershed Committee Approaching to higher officials in block and district for exercising rights Participation in Social Audit Participation in Vigilance Committee

	Participation in Village Health Committee	Participation in Gram Sabha Role in policy making
C16: Social empowerment	Universal social mobilization Universal social inclusion Improved social behavior Increased social values	Increased social development Increased social awareness Increased social welfare
C17: Economic empowerment	Financial self-sufficiency Economic decision-making	Increased savings
C18: Personal well-being and Personality development	Adoption of agricultural machines/ equipment Adoption of better cooking methods/ equipment Better health and hygiene awareness Access to basic infrastructure Increased women literacy Increased women safety Increased self-confidence Engagement with household level issues Engagement with community level issues	Sense of authority in public space Recognition in family and society Power in household decision making Increased gender equality Voicing against ill treatments Individual values/ integrity Women's identity Women's independence Women's mobility Own perceptions towards changes
C19: Intra-household bargaining power	Mediation in household/ family disputes Seeking benefit under government scheme Obtaining ration card Lodging police complaint	Access to credit Admissions to schools/ colleges Admissions to hospitals
C20: Social harmony	Community cohesion Community support Reduced social tension	Conflict avoidance Increased tolerance Solidarity

Four different groups of women functionaries of DAY-NRLM of Jammu and Kashmir state of India—The Self-Help Groups (SHGs), the Village Organization (VOs), the Cluster Level Federations (CLFs) and the Community Resource Persons (CRPs) constructed FCMs in groups of 4–5 members. The SHGs group consists of 36 participants, the VOs have 52 participants, the CLFs comprise 60 participants, whereas the CRPs include 31 participants. A list of SHGs, VOs, and CLFs was generated who would be interviewed for the FCM exercise, using "Microsoft Excel RAND function" from the 10 districts of Jammu and Kashmir, 5 districts from each region.

The following section presents the process of FCM modelling using participants' perceptions and scenario analysis regarding the examined approach which is focused on economic sustainability and livelihood diversification of poor women in rural areas. In particular, the proposed generic methodology, whose steps were thoroughly described in section 3.2, is applied in the current case study, followed by the corresponding results so as the specific objectives of this work are met.

3.3.2 Application of the Proposed FCM-based Framework

In this section, the process of FCM modelling using participants' perceptions followed by a scenario analysis are illustrated in separate comprehensive steps as follows, with respect to the examined approach which is focused on economic sustainability and livelihood diversification of poor women in rural areas.

Step 1: Obtaining fuzzy cognitive maps from the participants.

As described earlier, 20 categories of main concepts and 129 sub-concepts were properly identified by national and state-level implementers, producing the Expert-based FCM. The visual representation of this model, which is depicted in Figure 3.3, will be compared with the FCM models derived from the aggregation processes, helping this study to meet its goals.

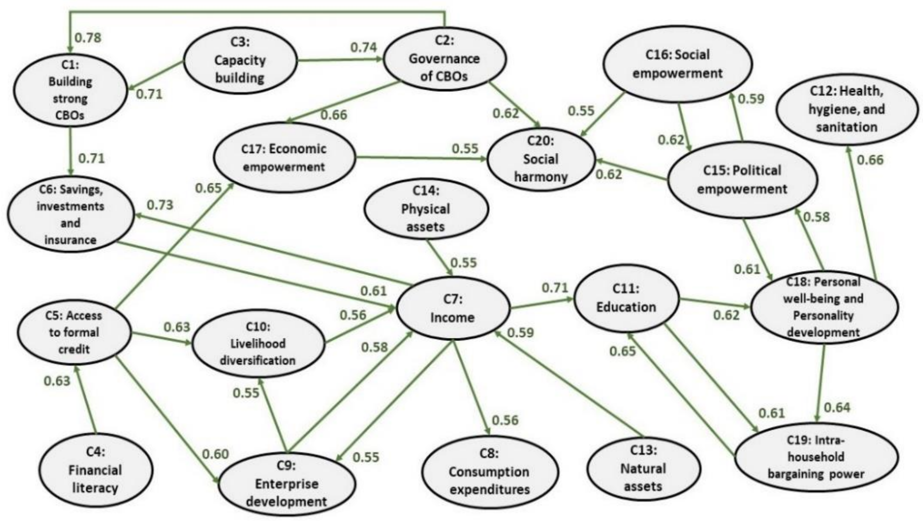


Figure 3.3: Expert-based FCM model

Furthermore, 179 individual fuzzy cognitive maps in total, were collected during the FCM exercise from approximately 600 participants coming from 10 districts of the state of Jammu and Kashmir in India. Participants of all the four groups (SHG, VO, CLF, and CRP) were also asked to assign a numerical value (degree of significance) to every sub-concept on a scale of 1–10 in order to assess the impact of each sub-concept to the corresponding key concept. An overall average degree of significance was calculated for every key concept to estimate the significance of each concept in the examined FCM model. This process helped with the selection of the most important concepts for policy-making.

Step 2: Coding individual cognitive maps into adjacency matrices

Fuzzy cognitive maps individually produced by the participants were coded into separate Excel sheets to form adjacency matrices. When a connection exists between two concepts, then the corresponding weight value is coded into the square matrix. Weights given to each link were then normalized between 0 and +1 (the value 7 is normalized to 0.7) for coding into the adjacency matrix [38, 76], providing a number of adjacency matrices equal to the number of participants of each one of the four groups.

Next, all participants of all four groups (SHG, VO, CLF, and CRP) were asked to assign a numerical value (degree of significance) to every sub-concept on a scale of 1–10 in order to assess the impact each sub-concept has to the corresponding key concept. An overall average degree of significance is calculated for every key concept to estimate the significance of each concept in the examined FCM model.

Table 3.5 illustrates an example regarding the mean values of the degree of significance for the three sub-concepts of the key concept C1, from each group of the Kashmir region, along with the calculated average value (degree of significance) that corresponds to the key concept C1. The complete Tables with the degree of significance for all sub-concepts for both Kashmir and Jammu regions are sited on Tables B.1 and B.2 in Appendix B.

Table 3.5: Degree of significance for the sub-concepts of C1, for Kashmir. CRP: Community Resource Persons.

Key Concept	Sub-Concept	SHG	VO	CLF	CRP	Average
C1: Building Strong CBOs						8.87
	Building SHGs	8.3	8.5	9.1	9.6	8.875
	Building VOs	8.0	8.4	8.6	9.8	8.70
	Building CLFs	7.9	9.1	9.3	9.8	9.025

Step 3: Producing individual matrices.

In this step and for every individual model concerning all four groups of participants, the developed matrix of normalized weight values and that of confidence level values for the corresponding existing links, as described in the previous step, are multiplied. A new composite individual matrix is created for each individual cognitive map. In particular, the normalized weight value of every existing link is multiplied with its normalized confidence level value producing an overall value (strength) of every connection. This leads to the building of a new adjacency matrix for every FCM model that seems to represent participants' opinions with high reliability.

Step 4: Aggregating individual cognitive maps from each group producing aggregated FCMs.

All coded maps from each group that were produced from the procedure described above, were aggregated using the two aggregation methods, the weighted Average and the OWA, to make collective FCMs. Two collective FCMs are created for every group of participants for each aggregation method, named Average-FCM and OWA-FCM.

Specifically, the process of learning OWA operators' weights was implemented using the proposed OWA aggregation methodology (as described in section 2.6), which aggregates FCM connections/links defined by multiple experts and/or stakeholders. This process is accomplished with the help of FCM-OWA aggregation tool whose functions and characteristics were described in section 2.8.1. The relevant matrices for each group regarding both aggregation methods are depicted in the following Figures.

Figure 3.4:OWA FCM and Average FCM matrices for the SHG group

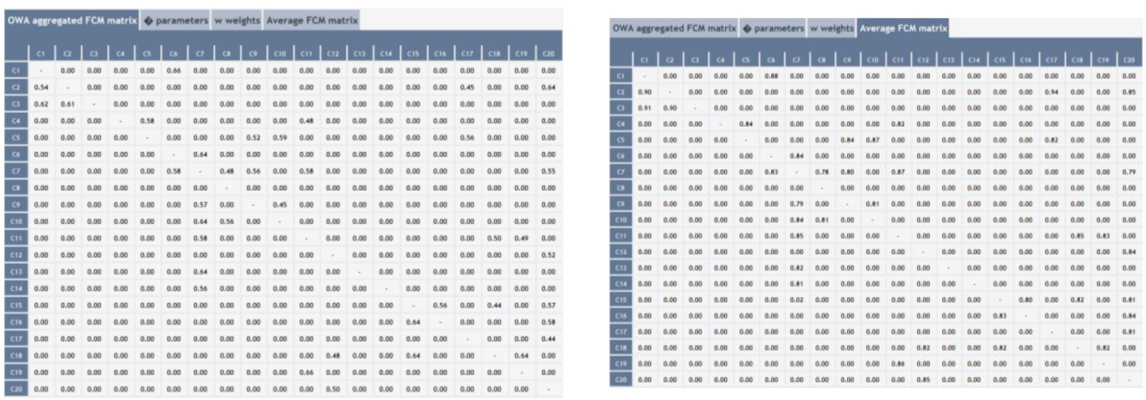


Figure 3.5: OWA FCM and Average FCM matrices for the VO group

Figure 3.6: OWA FCM and Average FCM matrices for the CLF group

OWA aggregated FCM matrix | ◆ parameters | w weights | Average FCM matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	-	0.00	0.00	0.00	0.00	0.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C2	0.48	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	0.00	0.00	0.34
C3	0.48	0.47	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C4	0.00	0.00	0.00	-	0.44	0.00	0.00	0.00	0.00	0.00	0.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C5	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.32	0.44	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00
C6	0.00	0.00	0.00	0.00	0.00	-	0.35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C7	0.00	0.00	0.00	0.00	0.00	0.39	-	0.21	0.29	0.00	0.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23
C8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C9	0.00	0.00	0.00	0.00	0.00	0.00	0.19	0.00	-	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C10	0.00	0.00	0.00	0.00	0.00	0.00	0.31	0.20	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C11	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.32	0.00
C12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.37
C13	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C14	0.00	0.00	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00
C15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.23	0.00	0.43	0.00	0.29
C16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21	-	0.00	0.00	0.00	0.36
C17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.33
C18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.21	0.00	0.00	-	0.35	0.00
C19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.37	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00
C20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-

OWA aggregated FCM matrix | ◆ parameters | w weights | Average FCM matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	-	0.00	0.00	0.00	0.00	0.78	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C2	0.81	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.71	0.00	0.00	0.69
C3	0.84	0.79	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C4	0.00	0.00	0.00	-	0.73	0.00	0.00	0.00	0.00	0.00	0.75	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C5	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.71	0.75	0.00	0.00	0.00	0.00	0.00	0.00	0.76	0.00	0.00	0.00
C6	0.00	0.00	0.00	0.00	0.00	-	0.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C7	0.00	0.00	0.00	0.00	0.00	0.76	-	0.70	0.69	0.00	0.76	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.66
C8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C9	0.00	0.00	0.00	0.00	0.00	0.00	0.67	0.00	-	0.68	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C10	0.00	0.00	0.00	0.00	0.00	0.00	0.74	0.64	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C11	0.00	0.00	0.00	0.00	0.00	0.00	0.73	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.77	0.71	0.00
C12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.70
C13	0.00	0.00	0.00	0.00	0.00	0.00	0.70	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C14	0.00	0.00	0.00	0.00	0.00	0.00	0.70	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00
C15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.69	0.00	0.71	0.00	0.65
C16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.68	-	0.00	0.00	0.00	0.71
C17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.65
C18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.73	0.00	0.00	0.63	0.00	0.00	-	0.74	0.00
C19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00
C20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-

Figure 3.7: OWA FCM and Average FCM matrices for the CRP group

Step 5: Groups aggregation for producing an overall collective FCM.

In this step, two collective FCMs are produced for each group (SHG-FCM, VO-FCM, CLF-FCM, and CRP-FCM) by deploying the weighted average and the OWA aggregation approaches. More specifically, an Average FCM and an OWA FCM are formed for every group of the participants, whereas an overall Collective FCM is created for both aggregation methods, namely Average FCM Collective and OWA FCM Collective. This process is visually illustrated in the next diagram so as a clearer view and better understanding of this case study is provided.

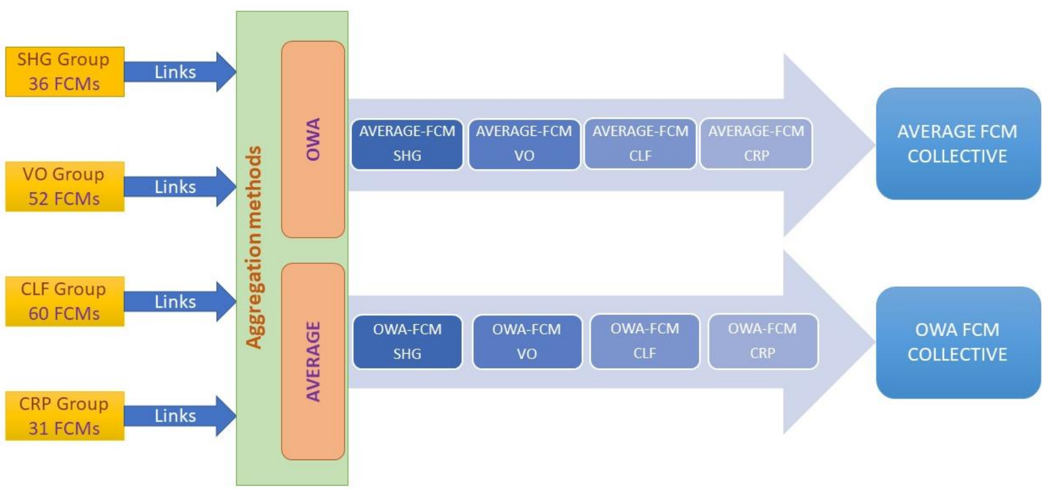


Figure 3.8: The aggregation process diagram

Step 6: Visual Interpretation of Collective FCM for each group.

This step as described in the proposed methodology, includes the visualization of the consensus FCM models which depicts the connections among the existing concepts. The collective FCMs were properly visualized and further analyzed using the FCMWizard software (www.fcmwizard.com) [101], which includes modelling and visualization capabilities. The

Average-FCM models produced from each group (SHG, VO, CLF, CRP) and designed by the FCMWizard tool are illustrated in the Figures below (see Figures 3.9, 3.10, 3.11 and 3.12).

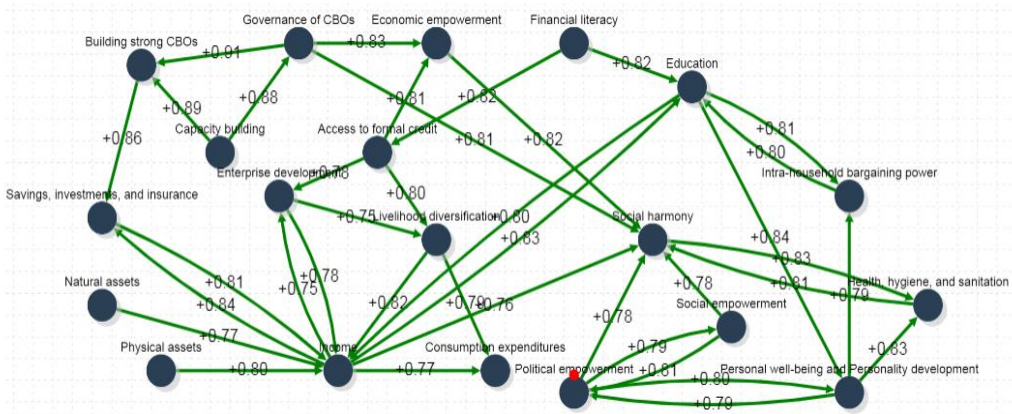


Figure 3.9**:** Fuzzy cognitive map of SHG group of JK-NRLM programme

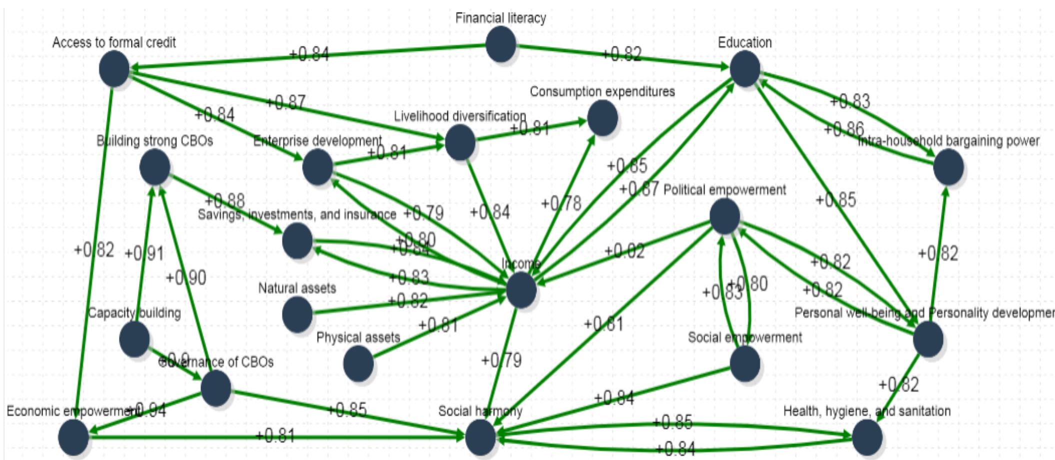


Figure 3.10: Fuzzy cognitive map of VO group of JK-NRLM programme

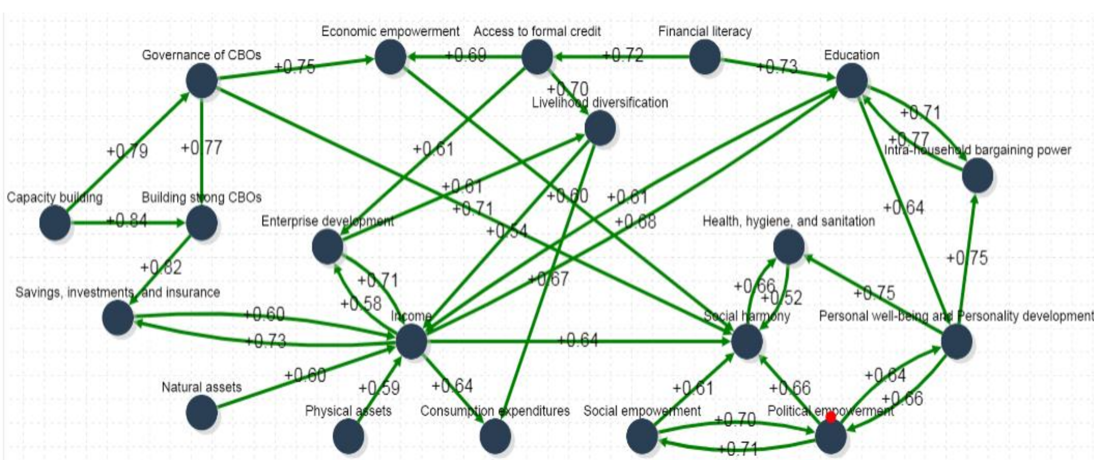


Figure 3.11: Fuzzy cognitive map of CLF group of JK-NRLM programme

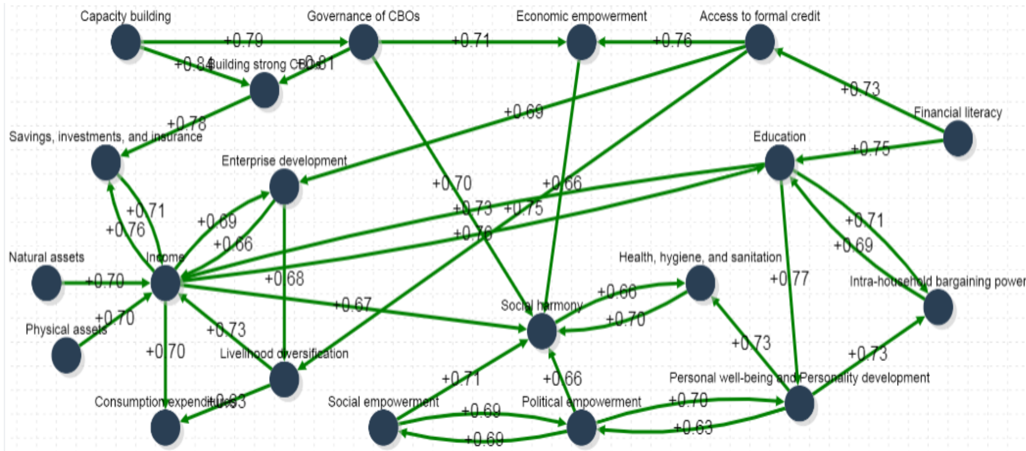


Figure 3.12: Fuzzy cognitive map of CRP group of JK-NRLM programme

Step 7: Fuzzy cognitive map-based analysis and simulations

i. Structural analysis

According to the structural analysis as described in the proposed methodology, the most influential concepts need to be identified as those that can have an important role in the cognitive map. The filtering technique of key concepts is common in scenario planning and helps linking storylines to the quantitative model, as well as to pay attention to pivotal concepts that can influence, directly or not, the outcome of the examined system, or even significantly change its balance [103].

The key concepts of this case study were mainly emerged by certain characteristics of the studied model such as indegree (weight of inbound links), outdegree (weight of outbound links) and degree centrality, which actually helped researchers to recognize the most important key concepts of the system. The first two indicate to what extent a concept is a transmitter (influential) or receiver (dependent). This is similar to the bi-dimensional categorization of influence-dependence axes in cross-impact analysis [17]. Degree centrality is the relative importance of a concept within the FCM structure, which is calculated by the sum of the corresponding absolute indegree and outdegree causal weights [17]. These calculated indices for the collective average-FCM, along with the concepts identified previously, are summarized in Table 3.6. Additionally, the overall specifications of the above FCM model are presented in Table 3.7.

Table 3.6: Finalized concepts, their description, and type with three major indices values (indegree, outdegree, and centrality). Average-FCM (L)

Concepts	Description	Indegree	Outdegree	Centrality	Betweenness Centrality	Closeness Centrality	Type
C1: Building strong CBOs	Build competence and confidence	0.90	1.80	2.60	11.83	8.58	Ordinary
C2: Governance of CBOs	Organize the goals, roles and responsibilities of CBOs	2.60	0.90	3.40	40.50	9.91	Ordinary
C3: Capacity building	Obtain, improve, and retain skills, knowledge and other resources for their jobs	1.80	0.00	1.80	0.00	7.36	Transmitter
C4: Financial literacy	Possession of skills and knowledge to make effective decisions with all the financial resources	1.60	0.00	1.60	7.50	8.41	Transmitter
C5: Access to formal credit	Demand for Loans provided by formal banking institution	2.40	0.80	3.20	23.33	9.83	Ordinary
C6: Savings, investments, and insurance	Increasing income, reducing expenses, protection from financial loss	0.80	1.70	2.50	25.83	9.33	Ordinary
C7: Income	Wages, salaries, profits, and other forms of earnings	4.00	4.80	8.80	201.3	13.83	Ordinary
C8: Consumption expenditures	Spending by households on goods and services	0.00	1.60	1.60	0.00	8.91	Receiver
C9: Enterprise development	Provide contributions to develop business sustainability	1.50	1.50	3.10	4.66	9.75	Ordinary
C10: Livelihood diversification	Construct a diverse portfolio of social activities to improve the standards of living	1.60	1.60	3.20	9.66	10.25	Ordinary
C11: Education	Acquisition of knowledge, skills, values, beliefs, and habits	2.50	2.50	4.90	53.58	10.58	Ordinary
C12: Health, hygiene, and sanitation	Practices that contribute to good health and keep our environment healthy	0.80	1.60	2.40	6.83	8.83	Ordinary
C13: Natural assets	Augmentation of natural resources, etc.	0.80	0.00	0.80	0.00	8.24	Transmitter

C14: Physical assets	Water supply and irrigation, infrastructure development	0.80	0.00	0.80	0.00	8.24	Transmitter
C15: Political empowerment	Political inclusion, political justice	2.40	1.60	3.90	29.33	10.83	Ordinary
C16: Social empowerment	Participation in various village-level committees, universal social mobilization, social inclusion	1.60	0.80	2.40	0.00	8.41	Ordinary
C17: Economic empowerment	Savings, financial self-sufficiency, etc.	0.80	1.70	2.50	22.49	9.75	Ordinary
C18: Personal well-being and Personality development	Experience of health, happiness, and prosperity. Improving a person's behavior and attitude	2.40	1.60	4.00	21.16	9.50	Ordinary
C19: Intra-household bargaining power	Decisions about household unit, like whether to spend or save, to study or work	0.80	1.60	2.40	0.00	7.94	Ordinary
C20: Social harmony	The promotion of ethnic cohesion and peace	0.80	4.80	5.50	101.6	12.16	Ordinary

Table 3.7: Specifications of the FCM model.

Index	Value
POSITIVE (NEGATIVE) CONNECTIONS	59 (76)
DENSITY	0.1026
HIERARCHY INDEX	0.0256
AVERAGE DEGREE CENTRALITY	3.07
AVERAGE BETWEENESS CENTRALITY	27.9875
AVERAGE CLOSENESS CENTRALITY	9.5366

ii. Development of input vectors for policy scenarios

For the scenario analysis, the researchers identified the most significant concepts (called decision concepts) that affect the status of the system being examined. During the FCM exercise, the degree of significance of every key concept was also recorded taking into consideration the perception of over 600 participants of SHGs, VOs, CLFs, and CRPs. On the basis of the FCM models prepared by the participants, social harmony (C20), women's socio-economic empowerment

(C16 and C17) as well as personal well-being and personality development (C18) were emerged to be the most significant concepts, which are likely to have considerable impacts on the system. The results for this type of analysis are presented in Figure 3.13. When it comes to scenario planning, the first established approach is the selection of the most important concepts that will formulate the scenarios. The seven concepts that were selected are C1—"Building strong CBOs", C2—"Governance of CBOs", C3—"Capacity building", C5—"Access to formal credit", C15—"Political empowerment", C16—"Social empowerment", and C17—"Economic empowerment". These concepts, assigned by the programme participants and implementers, were selected properly as they were among concepts with the highest degree of centrality, having both in/out-degree values, whereas their degree of significance was the highest among all key concepts (see section 3.3.3.1). Thus, they could significantly influence the dynamics of the system. The selected scenarios with their concepts are briefly presented in the following Table 3.8.

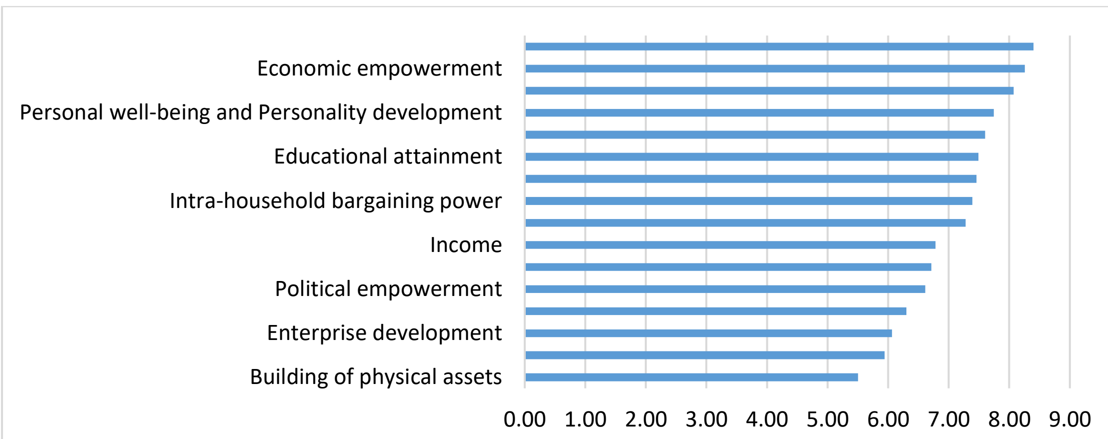


Figure 3.13: Impacts of NRLM based on perception of Stakeholders

Table 3.8: The key concepts of each scenario

Scenarios	Concepts	
Scenario 1 (S1)	C1: Building strong CBOs	
Scenario 2 (S2)	C2: Governance of CBOs	
Scenario 3 (S3)	C3: Capacity building	
Scenario 4 (S4)	C3: Capacity building	C5: Access to formal credit
Scenario 5 (S5)	C2: Governance of CBOs	C3: Capacity building
Scenario 6 (S6)	C1: Building strong CBOs	C3: Capacity building
Scenario 7 (S7)	C15: Political empowerment	
Scenario 8 (S8)	C16: Social empowerment	
Scenario 9 (S9)	C17: Economic empowerment	

- Scenario 1 examines the effects of building CBOs (C1), whereas scenario 2 presents the effects of governance of CBOs (C2) in terms of SHGs, VO, and CLFs.
- Scenario 3 presents the effects of capacity building of the CBOs (C3) in terms of governance and management.
- Scenario 4 highlights the effects of capacity building of the CBOs (C3) in terms of governance and management, along with access to formal credit (C5) in terms of micro-finance and SHG-bank linkage.
- Scenario 5 shows the effects of governance of CBOs (C2) in terms of SHGs, VO, and CLFs, along with the capacity building of the CBOs (C3) in terms of governance and management.
- Scenario 6 illustrates the effects of building strong CBOs (C1) in terms of SHGs, VO, and CLFs, and capacity building of the CBOs (C3) in terms of governance and management.
- Scenarios 7 to 9 highlight the effects of political (C15), social (C16), and economic (C17) empowerment of women, respectively. These empowerments represent political inclusion, political justice, participation in various village-level committees, savings, financial self-sufficiency, universal social mobilization, and social inclusion, among others.

iii. FCM Simulation process

The scenarios defined above will contribute to the understanding of all the critical factors that affect the system dynamics, through a simulation process. In particular, the values that will be produced through this process for each conducted scenario will be properly interpreted providing certain assumptions regarding the system's behavior. For the scenario analysis, the software tool "FCMWizard" is employed to carry out the FCM-based simulations and the corresponding results are presented in detail in the following section.

3.3.3 Results

3.3.3.1 Characteristics of the key concepts

In terms of degree centrality and degree of significance, they both emerge as being the highest for the concepts C1, C2, C3, C15, C17, C18, and C20, justifying the selection of these concepts to be the main components of this case study scenarios. To strengthen this decision, these values are further compared with the corresponding degree centrality of the aggregated and the Expert-based FCM model, as presented in Table 3.9. The analysis shows that the foresaid concepts can be indeed selected as the most significant ones and will be further used in the scenario analysis.

Table 3.9: Average degree of significance and centrality values for all key concepts

Key Concept	Degree of Significance (average value)	Centrality (Expert-based)	Centrality (Aggregated)
C1: Building strong CBOs	9.11	2.2	2.60
C2: Governance of CBOs	9.16	2.7	3.40
C3: Capacity building	8.82	1.5	1.80
C4: Financial literacy	7.35	0.6	1.60
C5: Access to formal credit	8.46	2.5	3.20
C6: Savings, investments, and insurance	7.00	2.0	2.50
C7: Income	6.84	5.4	8.80
C8: Consumption expenditures	6.13	0.6	1.60
C9: Enterprise development	6.18	2.3	3.10
C10: Livelihood diversification	7.38	1.7	3.20
C11: Education	7.61	2.5	4.90
C12: Health, hygiene, and sanitation	7.71	0.7	2.40
C13: Natural assets	6.40	0.6	0.80
C14: Physical assets	5.66	0.6	0.80
C15: Political empowerment	6.74	3.0	3.90
C16: Social empowerment	8.00	1.8	2.40
C17: Economic empowerment	8.21	1.9	2.50
C18: Personal well-being and Personality development	7.80	3.1	4.00
C19: Intra-household bargaining power	7.46	1.9	2.40
C20: Social harmony	8.45	2.3	5.50

Concerning the degree of significance reported in the above table, this was calculated as a summation of all corresponding values of significance, assigned by the participants of all four groups for each sub-concept as described in section 3.3.2.

The next table includes the key concepts with the respective mean values for both regions, as well as the overall average value of the degree of significance. The following Figure (Figure 3.14) illustrates these values in a graph for a better visual interpretation of the results.

Table 3.10: Mean values of significance for two regions and the average degree of significance.

Key Concepts	Degree of significance (Mean value) with respect to the region		Average Degree of significance
	Kashmir	Jammu	
C1: Building strong CBOs	8.79	9.43	9.11
C2: Governance of CBOs	8.92	9.41	9.16
C3: Capacity building	8.69	8.95	8.82
C4: Financial literacy	7.73	6.98	7.35
C5: Access to formal credit	8.18	8.74	8.46
C6: Savings, investments, and insurance	5.97	8.03	7.00
C7: Income	6.62	7.07	6.84
C8: Consumption expenditures	5.47	6.79	6.13
C9: Enterprise development	5.76	6.61	6.18
C10: Livelihood diversification	7.03	7.72	7.38
C11: Education	7.17	8.05	7.61
C12: Health, hygiene, and sanitation	7.32	8.10	7.71
C13: Natural assets	6.05	6.75	6.40
C14: Physical assets	5.11	6.20	5.66
C15: Political empowerment	6.27	7.21	6.74
C16: Social empowerment	8.25	7.76	8.00
C17: Economic empowerment	8.37	8.06	8.21
C18: Personal well-being and Personality development	7.60	8.00	7.80
C19: Intra-household bargaining power	7.20	7.73	7.46
C20: Social harmony	8.26	8.64	8.45

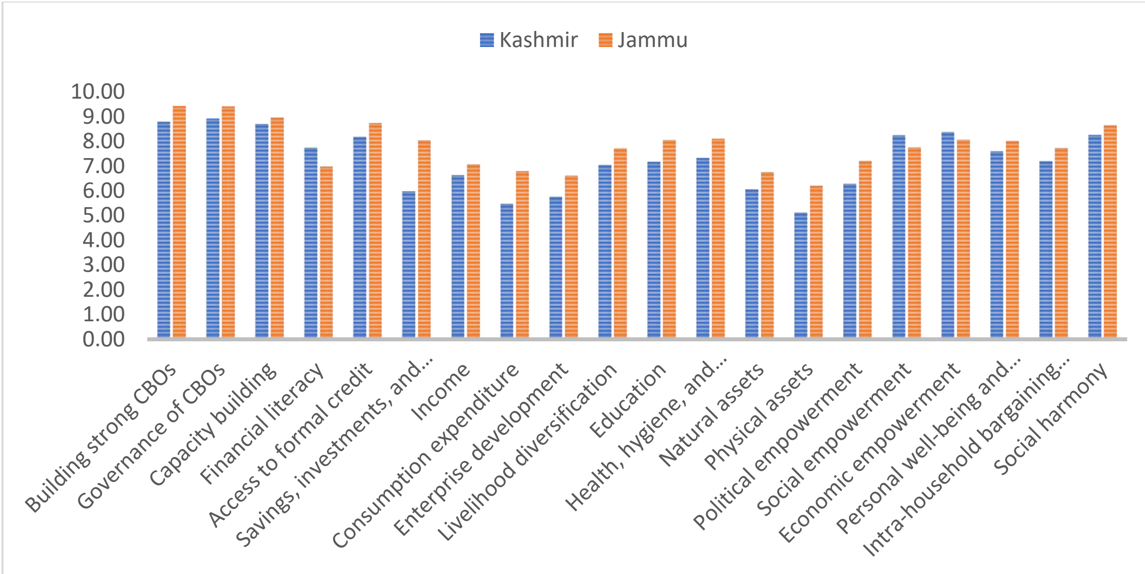


Figure 3.14**:** Mean values of significance for the regions of Jammu and Kashmir

3.3.3.2 Aggregation Results

This section presents the results produced from the application of the two aggregation methods on the FCM models. The FCM models constructed by each participant group (SHG, VO, CLF, and CRP) were aggregated using the two aggregation methods, the average and the OWA. A collective FCM was produced for each of these two methods. The aggregation process was delivered with the help of the OWA FCM tool that was developed for this purpose. The relevant tool screenshots of the two weight matrices produced regarding the collective Average-FCM and OWA-FCM models are illustrated in Figure 3.15 and Figure 3.16.

Weight Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	0	0	0	0	0	0.86	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C2	0.89	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.85	0	0	0.82
C3	0.9	0.88	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C4	0	0	0	0	0.82	0	0	0	0	0	0.82	0	0	0	0	0	0	0	0	0
C5	0	0	0	0	0	0	0	0	0.78	0.83	0	0	0	0	0	0	0.81	0	0	0
C6	0	0	0	0	0	0	0.8	0	0	0	0	0	0	0	0	0	0	0	0	0
C7	0	0	0	0	0	0.83	0	0.78	0.76	0	0.83	0	0	0	0	0	0	0	0	0.77
C8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C9	0	0	0	0	0	0	0.78	0	0	0.76	0	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0.81	0.77	0	0	0	0	0	0	0	0	0	0	0	0
C11	0	0	0	0	0	0	0.8	0	0	0	0	0	0	0	0	0	0	0.84	0.81	0
C12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.8
C13	0	0	0	0	0	0	0.79	0	0	0	0	0	0	0	0	0	0	0	0	0
C14	0	0	0	0	0	0	0.79	0	0	0	0	0	0	0	0	0	0	0	0	0
C15	0	0	0	0	0	0	0.01	0	0	0	0	0	0	0	0	0.79	0	0.79	0	0.78
C16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.79	0	0	0	0	0.79
C16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.79	0	0	0	0	0.79
C17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.79
C18	0	0	0	0	0	0	0	0	0	0	0	0.82	0	0	0.77	0	0	0	0.81	0
C19	0	0	0	0	0	0	0	0	0	0	0.81	0	0	0	0	0	0	0	0	0
C20	0	0	0	0	0	0	0	0	0	0	0	0.8	0	0	0	0	0	0	0	0

Figure 3.15: Weight matrix for the Average FCM

Weight Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	0	0	0	0	0	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C2	0.533	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.505	0	0	0.508
C3	0.57	0.595	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C4	0	0	0	0	0.535	0	0	0	0	0	0.483	0	0	0	0	0	0	0	0	0
C5	0	0	0	0	0	0	0	0	0.47	0.498	0	0	0	0	0	0	0.463	0	0	0
C6	0	0	0	0	0	0	0.463	0	0	0	0	0	0	0	0	0	0	0	0	0
C7	0	0	0	0	0	0.515	0	0.413	0.433	0	0.45	0	0	0	0	0	0	0	0	0.438
C8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C9	0	0	0	0	0	0	0.445	0	0	0.415	0	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0.53	0.463	0	0	0	0	0	0	0	0	0	0	0	0
C11	0	0	0	0	0	0	0.39	0	0	0	0	0	0	0	0	0	0	0.51	0.478	0
C12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.458
C13	0	0	0	0	0	0	0.475	0	0	0	0	0	0	0	0	0	0	0	0	0
C14	0	0	0	0	0	0	0.483	0	0	0	0	0	0	0	0	0	0	0	0	0
C15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.445	0	0.433	0	0.5
C16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.508	0	0	0	0	0.493
C17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.468
C18	0	0	0	0	0	0	0	0	0	0	0	0.498	0	0	0.44	0	0	0	0.533	0
C19	0	0	0	0	0	0	0	0	0	0	0.533	0	0	0	0	0	0	0	0	0
C20	0	0	0	0	0	0	0	0	0	0	0	0.398	0	0	0	0	0	0	0	0

Figure 3.16: Weight matrix for the OWA FCM

These two collective FCM models derived from each one of the aggregation processes, were further compared to the Expert-based FCM (see Figure 3.3 in section 3.3.2: step1) produced by national and state-level implementers. This process will assess the performance of both aggregation approach. From the comparative analysis that was conducted among the aggregated average-FCM, OWA-FCM, and Expert-based FCM, it is observed that a slight divergence emerges between the OWA-FCM and the Expert-based FCM. This means that the OWA-FCM model resembles the structure of the Expert-based FCM and consequently can present a similar performance to the model constructed by the experts.

3.3.3.3 Scenario Results

FCM-based simulations can offer a deeper understanding of the concepts behavior and their relations in terms of how one concept affects others. In the respective case study, an FCM-based simulation process was performed by "clamping" the initial values of the key concepts one-by-one. This outcome was compared against a baseline scenario where the system (output vector) reached the steady-state through clamping all the initial values to zero. The exploration of the dynamic change of concepts values between the baseline steady-state and outcome of the clamping procedure enables a quantitative interpretation of the impact of the key concepts on the system. The simulation process entails the application of a sigmoid function with lambda = 1 as a threshold function on the adjacency matrix after it was multiplied by the input vector. The process was iterated until the system reached a steady-state. The FCMWizard tool, presented in 2.8.2, was used for the simulation purposes, as it has the unique ability to construct an FCM using data that come from experts or stakeholders' knowledge and can perform simulations for different possible scenarios, in different scientific domains, using a very intuitive graphical user interface [101]. The impact of the conducted scenarios on the selected decision concepts was examined, further identifying which key concepts affect the final deliverables of the program.

The scenario analysis performed simulations for the selected nine scenarios (Table 3.8). For example, scenario 1 (S1) was devoted to increasing the concept C1—"Building strong CBOs by "clamping" it to one, whereas scenarios 2 (S2) and 3 (S3) studied the effects of the concepts C2—"Governance of CBOs" and C3—"Capacity building" by clamping the values of these concepts to one. The nine scenarios were conducted with the two aggregated collective FCMs, average-FCM and OWA-FCM. The Expert-based FCM, which was constructed by the experts, was considered as the benchmark model that would help the researchers to further investigate the usefulness, importance and superiority of the proposed OWA aggregation method against the average aggregation method.

The following Table and Figures gather the overall results produced from the scenario analysis involving the two aggregated FCM models, the average-FCM and the OWA-FCM, as well as the Expert-based FCM. More specifically, Table 3.11 represents the scenario results for the Expert-based FCM model, with respect to the initial and final value of each concept for every scenario, whereas the Figures that follow graphically illustrate concepts deviations from the steady state and the percentage of change of the decision concepts for each scenario.

Table 3.11: Scenario results (initial and final value) for each concept, for the Expert-based FCM.

	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5		Scenario 6		Scenario 7		Scenario 8		Scenario 9	
Key Concept	Initial value	Final value	Initial value	Final value	Initial value	Final value	Initial value	Final value	Initial value	Final value	Initial value	Final value	Initial value	Final value	Initial value	Final value	Initial value	Final value
C1	1	1	0	0.7764	0	0.9072	0	0.9072	0	0.9072	1	1	0	0.7763	0	0.776	0	0.7763
C2	0	0.659	1	1	0	0.8281	0	0.8281	1	1	0	0.828	0	0.659	0	0.659	0	0.659
C3	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0
C4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C5	0	0.659	0	0.659	0	0.659	1	1	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C6	0	0.8959	0	0.8959	0	0.9051	0	0.9052	0	0.9051	0	0.905	0	0.8959	0	0.896	0	0.8959
C7	0	0.9537	0	0.9537	0	0.954	0	0.954	0	0.954	0	0.954	0	0.9537	0	0.954	0	0.9537
C8	0	0.8718	0	0.8718	0	0.8718	0	0.8719	0	0.8718	0	0.872	0	0.8718	0	0.872	0	0.8718
C9	0	0.8562	0	0.8562	0	0.8563	0	0.8563	0	0.8563	0	0.856	0	0.8562	0	0.856	0	0.8562
C10	0	0.8516	0	0.8516	0	0.8516	0	0.8517	0	0.8516	0	0.852	0	0.8516	0	0.852	0	0.8516
C11	0	0.8908	0	0.8908	0	0.8908	0	0.8908	0	0.8908	0	0.891	0	0.8908	0	0.891	0	0.8908
C12	0	0.8912	0	0.8912	0	0.8914	0	0.8914	0	0.8914	0	0.891	0	0.8912	0	0.891	0	0.8912
C13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C15	0	0.8663	0	0.8663	0	0.8663	0	0.8663	0	0.8663	0	0.866	1	1	0	0.866	0	0.8663
C16	0	0.7851	0	0.7851	0	0.7851	0	0.7851	0	0.7851	0	0.785	0	0.7852	1	1	0	0.7851
C17	0	0.8483	0	0.8483	0	0.8641	0	0.8641	0	0.8641	0	0.864	0	0.8483	0	0.848	1	1
C18	0	0.877	0	0.877	0	0.877	0	0.877	0	0.877	0	0.877	0	0.877	0	0.877	0	0.877
C19	0	0.8806	0	0.8805	0	0.8806	0	0.8806	0	0.8806	0	0.881	0	0.8806	0	0.881	0	0.8805
C20	0	0.9769	0	0.9769	0	0.9794	0	0.9794	0	0.9794	0	0.979	0	0.9769	0	0.977	0	0.9769

For all three FCMs (average, OWA, and expert-based), Figure 3.17 illustrates the deviations from the steady-state for all concepts values produced from the simulation process. Figures 3.18 and 3.19 gather the outcomes regarding the percentage of change for the values of certain key concepts, for all performed scenarios, with respect to FCMs. It should be noted that in the relevant Figures, AVE is the abbreviation for Average, whereas EB is for Expert-based.

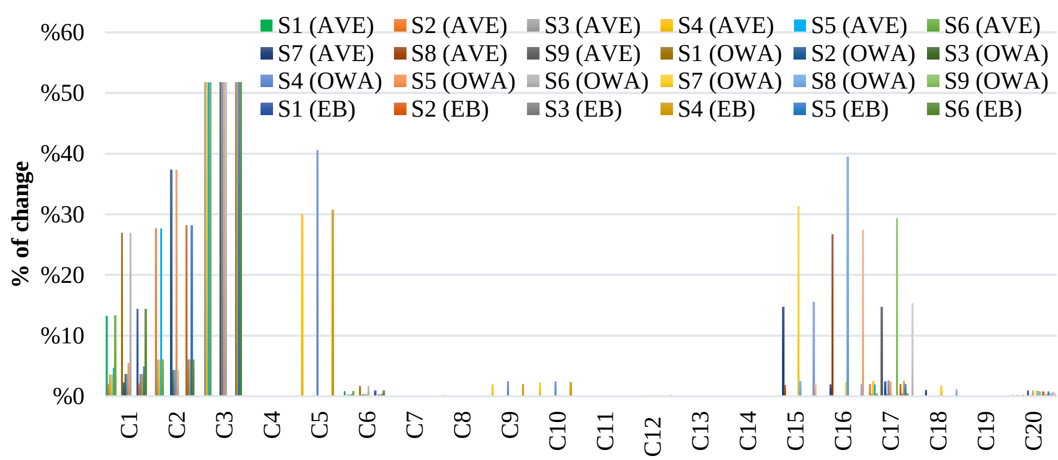


Figure 3.17: Deviations of concepts values from the steady state for all FCMs, considering the degree of significance.

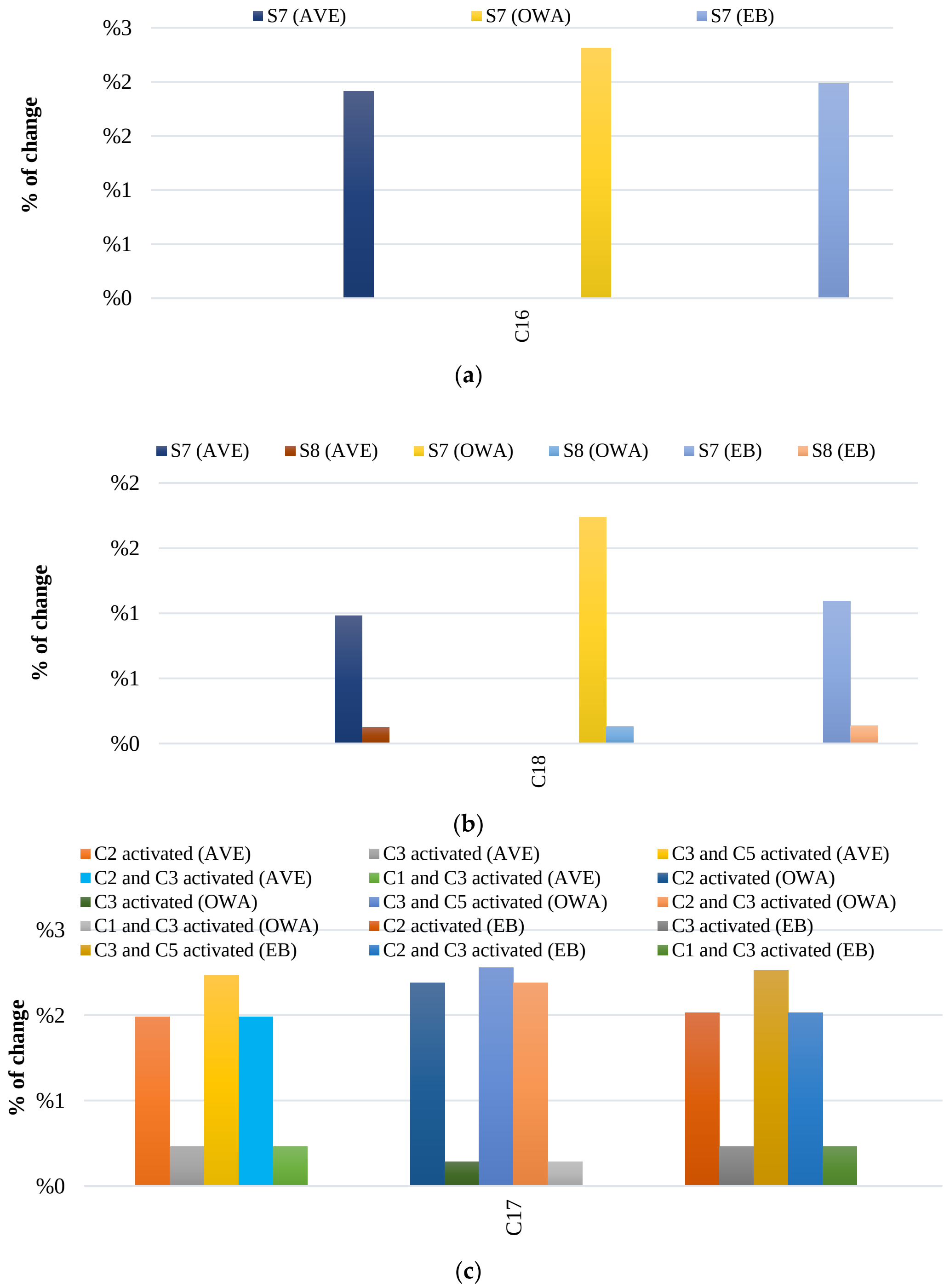


Figure 3.18: Percentage of change for decision concepts (**a**) C16, (**b**) C18, and (**c**) C17 when all scenario concepts were clamped to one for the Expert-based FCM.

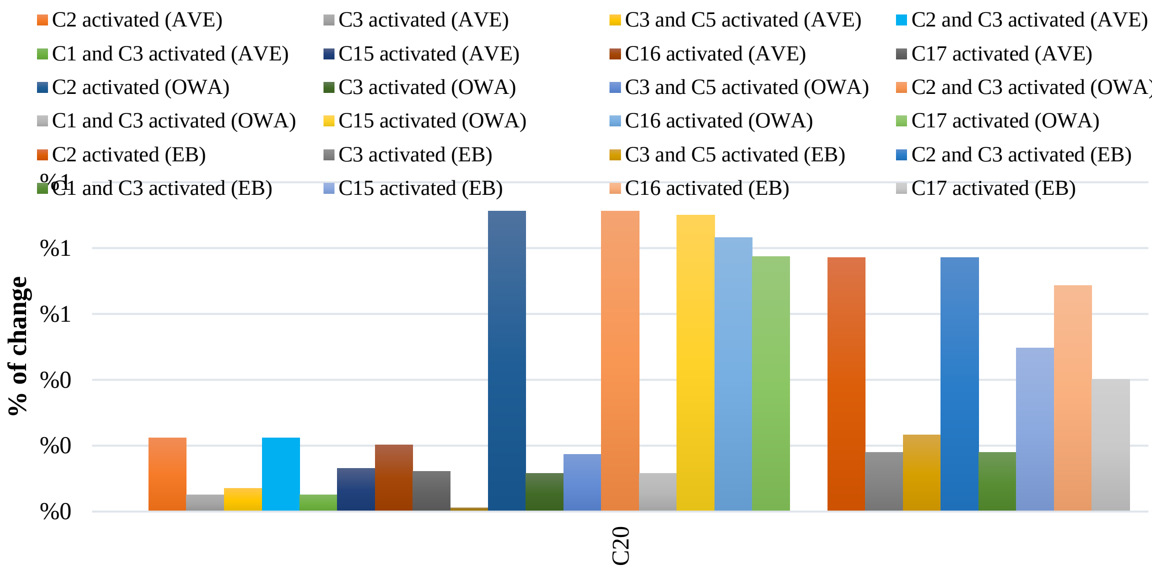


Figure 3.19: Percentage of change for decision concept C20 (social harmony) when the key concepts of each devoted scenario were clamped to one.

The following Table briefly presents the impact that the examined scenarios have on the four decision concepts of the system.

Table 3.12: Scenarios mainly affecting decision concepts.

Decision Concepts	**Scenarios Mainly Affecting Decision Concepts**
C16	C15 activated (S7).
C17	C2 activated (S2), C2 and C3 activated (S5), C3 and C5 activated (S5).
C18	C15 activated (S7), C16 activated (S8).
C20	C2 activated (S2), C2 and C3 activated (S5), C15 activated (S7), C16 activated (S8), C17 activated (S9).

3.3.3.4 Sensitivity analysis

To further assess the degree of impact that certain concepts have on the decision concept C20, a sensitivity analysis was performed and noteworthy observations were emerged. Sensitivity analysis is a tool that can analyze how the different values of a set of independent variables affect a specific dependent variable under certain specific conditions. This analysis is useful because it studies qualitatively and/or quantitatively the model response to changes in input variables and interprets the behavior of the system studied by the analysis of interactions between variables. For example, the expected values of various parameters involved can be used to evaluate the robustness, i.e., 'sensitivity' of the results from these changes and identify the values beyond which the results change significantly, thus taking the right decisions about the phenomenon under investigation.

The following sensitivity analysis conducted for this case study, reveals the relative changes in social harmony (C20) under different values of key concepts (see Figures 3.20, 3.21 and 3.22). It was observed that there was a strong influence from the absence of political and social empowerment, as well as from the absence of governance of CBOs. This conveyed the notion that the key factors affecting social harmony were C2 and C15–C17. Sensitivity analysis was also performed for the key concepts C11 and C12, but no influences were observed from their deviations. This means that they were reluctant in playing a significant role in the decision concept of social harmony.

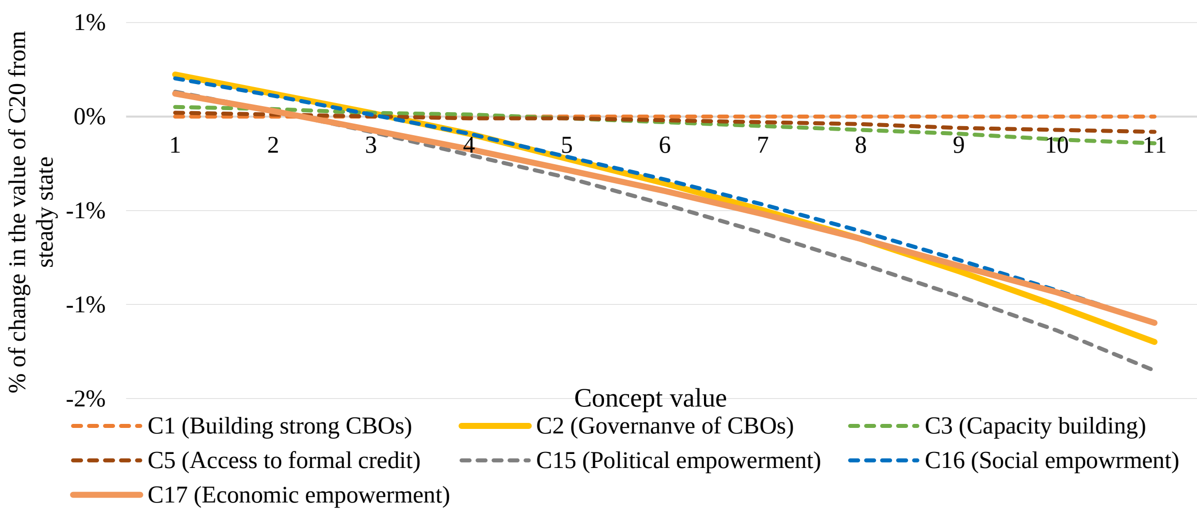


Figure 3.20: Sensitivity analysis for the concept C20 regarding the average FCM.

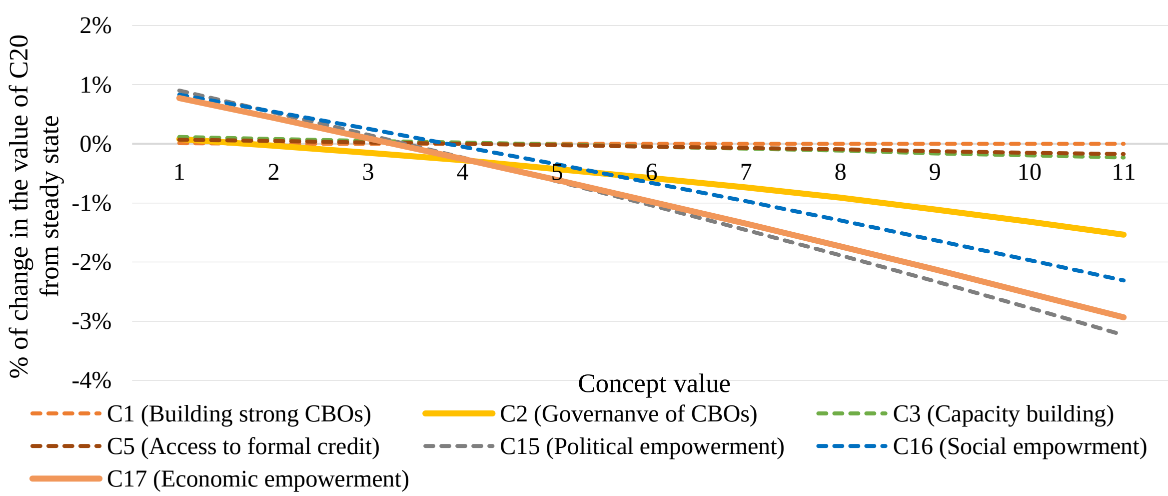


Figure 3.21: Sensitivity analysis for the concept C20 regarding the OWA-FCM.

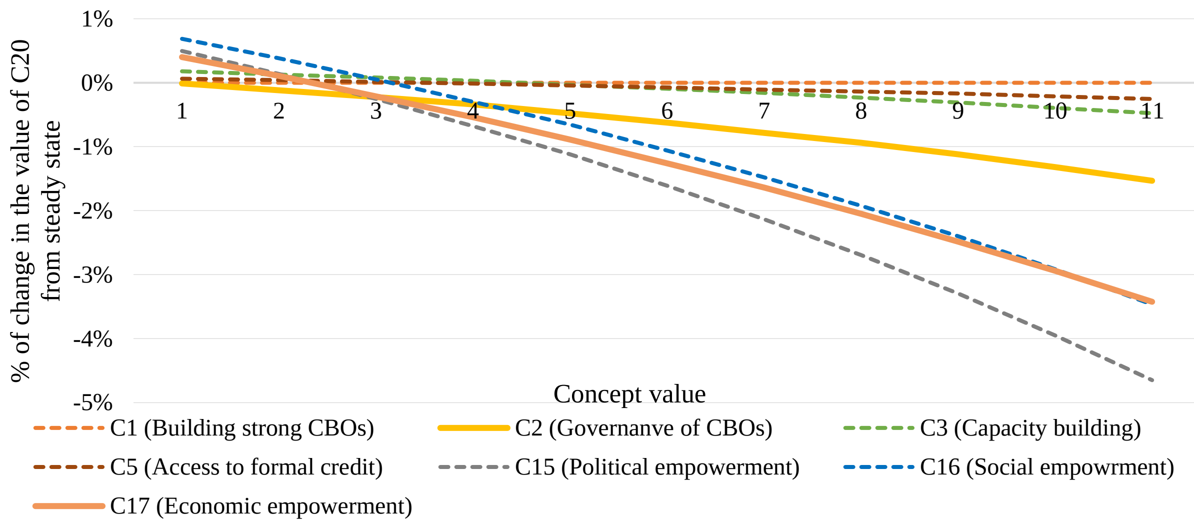


Figure 3.22: Sensitivity analysis for the concept C20 regarding the initial Expert-based FCM.

3.3.4 Discussion of results

This case study identified the key-concepts and their respective sub-concepts aiming towards the elimination of rural poverty in the developing economy, on the basis of socio-economic sustainable development. It also deals with the contribution of the OWA-FCM aggregation method by learning OWA operator weights in the participatory modelling domain. The innovation of this approach lies in the fact that the strengths of the relationship were calculated with the proposed aggregation technique and further compared with the weights of the average method and those assigned by the experts. The observations that were drawn from the above figures and tables focus on the following two main points:

- The impact that certain key concepts have on other concepts and how they could affect the examined system.
- The performance of both the average and the OWA aggregation methods, comparing their outcomes with the Expert-based FCM model. With respect to concepts potential in affecting the state of the system, the following considerable observations emerged:

i. The decision concept C16—"Social empowerment" was solely affected by C15—"Political empowerment" for all FCMs (average, OWA, and expert). Moreover, women's personal well-being and personality development (decision concept C18) increased when more political and social empowerment (decision concepts C15 and C16) was offered to them.

ii. Furthermore, it was observed that the key concept C2 (Governance of CBOs), as well as the combinations C2 (Governance of CBOs) and C3 (Capacity building), and C3 (Capacity building) and C5 (Access to formal credit), had the highest impact in the decision concept C17—"Economic empowerment" for all collective FCMs. A significant increase in C17 was emerged, particularly when the OWA aggregation method was applied.

iii. It also emerged from the above Figures and Table 3.10, that the increase of social harmony (C20) was directly connected to the increase of the following key concepts: C2—"Governance of CBOs", the combination of C2—"Governance of CBOs" and C3—"Capacity building", as well as the concepts C15—" Political empowerment", C16—"Social empowerment" and C17—"Economic empowerment". Results of FCM-based simulations revealed that impacts of the DAY-NRLM programme could be realized better if strong institutions are built.

iv. Overall, the concepts C2, C3, C5, C15, C16, and C17 had a significant impact in the policy-making and strategic planning of socio-economic sustainability of poor rural communities because they presented considerably higher deviations from the steady-state than the rest of the concepts (see Figures 3.17 and 3.19). To further check the validity of the outcomes, a sensitivity analysis regarding the impact that these key concepts had on decision concept C20, for all three FCMs (average, OWA, and expert-based), was conducted, and the corresponding results are presented in Figures 3.20, 3.21 and 3.22. There seems to be an influence from the absence of political, social, and economic empowerment, as well as from the absence of governance of CBOs, which corresponded to the concepts C2, C15, C16, and C17, affecting the community's social harmony (C20).

Concerning the performance of the two examined aggregation methods, the following important observations were extracted, after a careful analysis of the Tables and Figures above.

i. The OWA aggregation method seemed to be superior against the average aggregation method, in terms of participatory modelling, when a large number of participants were involved. After a thorough view of Figures 3.17 to 3.19, where the scenario analysis of the three different FCMs was conducted, it can be concluded that in most cases, the deviations were higher when the OWA aggregation method was applied, compared with those resulting from the average aggregation method.

ii. As mentioned before, the Expert-based FCM model is considered as the benchmark model, as it was produced by experts' opinions. When the OWA-FCM model was compared to the Expert-based FCM model, it emerged that the results on decision making were better or similar to those regarding the experts' FCM model. Thus, it can be concluded that the OWA-FCM model resembles the structure of the Expert-based FCM model.

iii. Overall, for the purpose of analysis and decision-making, the OWA aggregation method was proven to be suitable for policy-making and strategic decision planning considering many participants, outperforming the average aggregation method.

3.3.5 Policy Implications of the Scenario Results

The scenarios 1 to 6 examine how certain key concepts of the DAY-NRLM programme such as strong CBOs, good governance within CBOs, better capacity building of communities and CBOs, as well as access to formal credit, would help to achieve the final objectives of the programme, that is, alleviation of socio-economic poverty and better quality of life. In particular, increased access to formal credit and good governance would empower the SHG women economically, politically, and socially, as well as increase social harmony in the community. Consequently, income and savings would increase, and that would lead to an increase in consumption expenditure, livelihood diversification, and enterprise development. Higher income will lead to better access to education for women and their children, consequently developing their personality, personal well-being, and overall socio-economic status.

Scenarios 7 to 9 highlight the effects of political (C15), social (C16), and economic (C17) empowerment of women, respectively. These empowerments represent political inclusion, political justice, participation in various village-level committees, savings, financial self-sufficiency, universal social mobilization, and social inclusion, among others. These scenarios also show an increase in income and savings, which would further lead to a rise in consumption expenditure, livelihood diversification, and enterprise development. Increased income will lead to better access to education for SHG women and their children; it would consequently develop the personality and personal well-being of SHG women. Better education will improve their intra-household bargaining power and health, hygiene, and sanitation. However, the result showed that empowerment alone is inadequate, and hence building strong CBOs and better access to formal credit are essential.

The outcomes of the scenario analysis highlight the importance of the simultaneous implementation of multiple concepts for the development of SHG members. Enhancing the capacities of SHG members, good governance within the CBOs and micro-finance through high-quality CBOs comprise the main aspects that should be taken into consideration in the examined case. Access to micro-finance and higher income will help community members to diversify their livelihood options and develop small enterprises. As a result, women empowerment and social safety nets will emerge, and women will improve their education, health, and develop their personality. All the above factors will help poor rural communities and their members to decrease socio-economic poverty while improving social resilience and promoting economic stability.

However, there is a need to incorporate resource efficiency in local businesses and mainstream industries, which can reduce pressures and impacts on the environment while contributing to socio-economic development and human well-being [91]. A shift towards the circular economy could translate into significant changes in people's lives [93]. Worldwide, small and medium enterprises are trying to move towards circular business models and solutions; however, the lack of consumer interest and awareness along with the lack of support from demand networks prevent the implementation of green innovations and act as the main obstacle for a transition towards the circular economy [93].

Several concepts identified in this study have the potential to incorporate the circular economy approach. The characteristics of those concepts that can influence communities' perceptions and attitudes towards circular solutions could include (C8) consumption—encouraging a non-materialistic environment among households and communities, supporting decisions to buy refurbished products over new ones, and increasing longevity of purchased products; (C9) enterprise development—building green enterprises, reusing/repairing/recycling resources at various levels, and more focus on product quality and service offering; (C10) livelihood diversification—a shift towards green livelihoods, and building farm and non-farm livelihood portfolios; (C12) natural assets—sustainable use and management of water and land resources, soil nutrient management through organic fertilizers, composting, and mulching, among others, and sustainable livestock management; and (C13) health, hygiene, and sanitation—changing consumer behavior, waste management at various levels, that is, households and industries, through reduction, reusing, and recycling, and wastewater treatment.

3.4 Case B: Poverty alleviation analysis based on "Theory of Change"

3.4.1 Problem statement

The current case (case B) extends the previously reported study (case A), while particularly emphasizes on the alleviation of poverty, which is considered a crucial socio-economic phenomenon that torments rural communities in a great extent. The general objective of this approach is to address the issue of socio-economic sustainability planning through the development of an FCM framework which implements system modelling and scenario planning. At the same time, the suggested framework proposes a new aggregation method using learning OWA (ordered weighted averaging) operators for aggregating FCM weights assigned by numerous stakeholders. Additionally, the level of confidence of stakeholders which is integrated in the aggregation process, along with the sophisticated and 'to the point' scenarios developed, provide an added value to this work. The applicability of the proposed methodology is demonstrated through a complex real-life development intervention with a large number of participants being involved in the construction of the FCM model. More specifically, researchers are given the chance to evaluate the theory of change for the world's most extensive poverty alleviation programme in India. Concurrently, the proposed method provides an opportunity to policy-makers to evaluate the outcomes of proposed policies while addressing social resilience and economic mobility. National and state level implementers and representatives of community-based organizations (CBOs) of the DAY-NRLM (*Deendayal Antyodaya Yojana*-National Rural Livelihoods Mission), the world's most extensive poverty alleviation programme, participated in this study.

The DAY-NRLM is a community institutions-based poverty alleviation programme sponsored by the Government of India. The predominant focus of the DAY-NRLM is to reduce socioeconomic poverty and improve the quality of life of the vulnerable and poor rural communities. The Jammu and Kashmir State Rural Livelihood Mission (JKSRLM) implemented the programme in the State under the name '*Umeed*', which means 'hope'.

Influential community-based organizations (CBOs), capacity building exercises involving CBOs and their members, access provision to financial resources to CBOs and their members, and livelihood diversification and enterprise development form the pillars of the programme, as illustrated in Figure 3.23. The successful execution of these building blocks of the programme is likely to make the CBOs effective in programme delivery. Building strong CBOs for universal social mobilization and the improvement of the governance of CBOs is expected to ensure access to financial resources in terms of a revolving fund, a community investment fund and an SHG-bank linkage. The capacity building of community members and CBOs is conducted through community service providers. Diversification of livelihoods of the communities and enterprise development through skill development, value addition, and value chain infrastructure are other vital pieces of the programme. The institutional effectiveness of the CBOs successfully delivers its different set of interventions.

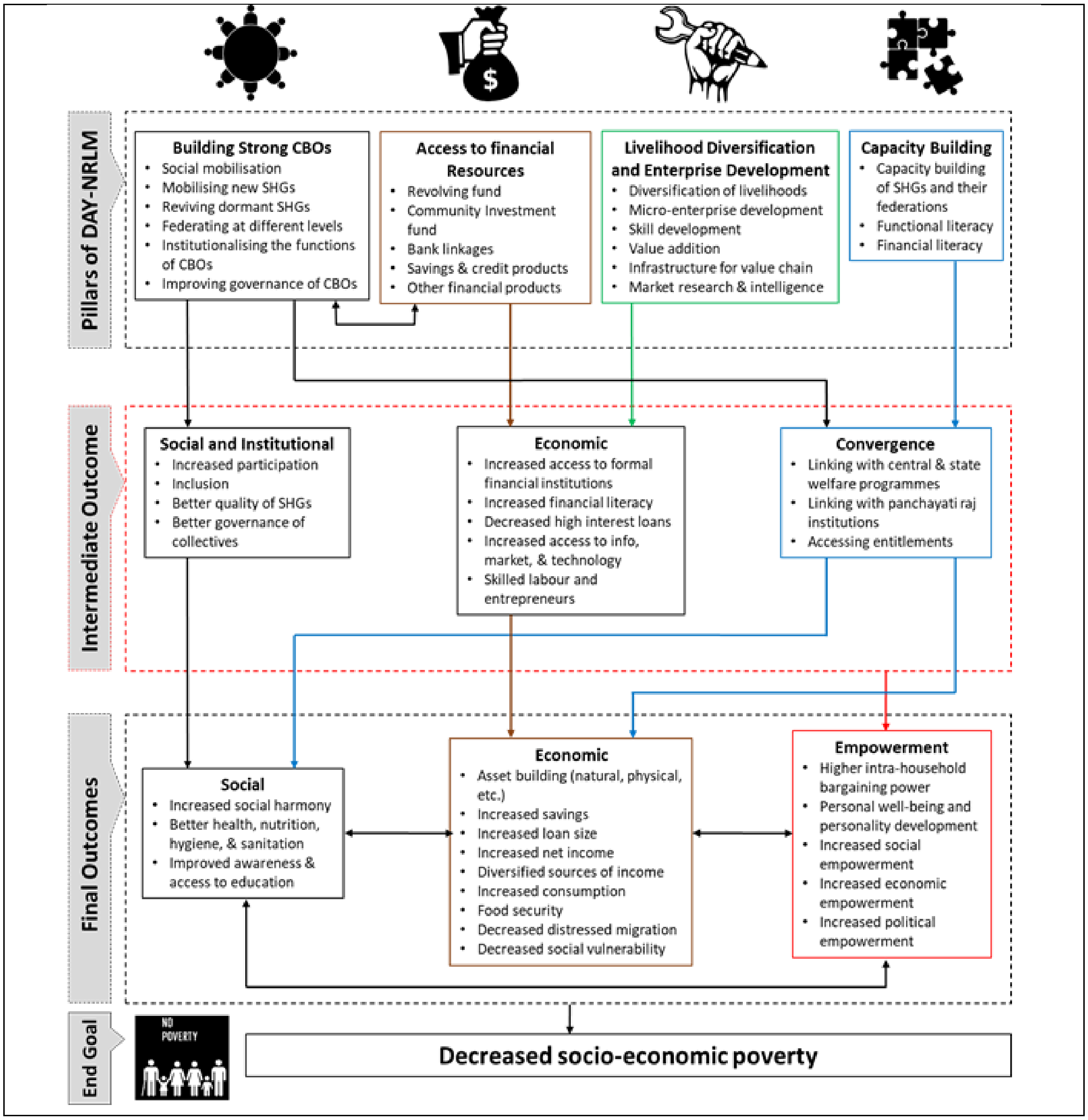


Figure 3.23: Theory of change for alleviation of socio-economic poverty in Jammu and Kashmir.

The principal intermediate outcomes of the programme include socio-economic inclusion, better governance, greater access to formal financial institutions, information, technology, market, and entitlements, among other things. The final outcomes of the programme include greater social harmony, asset creation, higher-income, better health, hygiene and sanitation, better awareness and access to education, and less vulnerability, among other things, in conjunction with greater social, economic, and political empowerment of women. These outcomes are interconnected and provide feedback to each other. Ultimately, these outcomes will lead to the final delivery of the programme, i.e. decrease in socio-economic poverty and improvement in the quality of life. The theory of change helps us to develop input vectors for policy scenarios.

3.4.2 Application of the proposed FCM-based Framework

In what follows, the proposed FCM framework describes in specific steps the processes of FCM-based participatory modelling and OWA learning aggregation, as well as the implementation of a policy making approach to alleviating poverty and achieving social resilience under a socio-economic perspective.

Step 1: Obtaining cognitive maps from the participants

A mixed-concept design approach was adopted for obtaining cognitive maps from the participants, which involves an open-concept design followed by a closed-concept design.

i. Expert-based FCM using an open-concept design.

31 national and state-level implementers were involved in a group discussion regarding the impacts of DAY-NRLM interventions. It prompted them to identify factors responsible for achieving the outcomes of the programme. They identified 20 categories of main concepts and 129 sub-concepts that were then displayed over a whiteboard. After that, the participants were shown how to draw a fuzzy cognitive map citing impacts of deforestation, a neutral problem domain, as an example. Once the participants understood the process of constructing a cognitive map, they were requested to draw fuzzy cognitive maps by providing causal links to each main concept. Figure 3.24 represents the main concepts and their causal links identified by the experts. The participants were also requested to assign weights for the relationships between the concepts on a scale of 1–10 for each link. Ten (10) denoted the highest strength and one (1) the lowest [12]. They were also asked to assign a level of confidence in the weights on a scale of 1–5 (1 = Very low confidence; 2 = Low confidence; 3 = Medium confidence; 4 = High confidence; and 5 = Very high confidence) for each link.

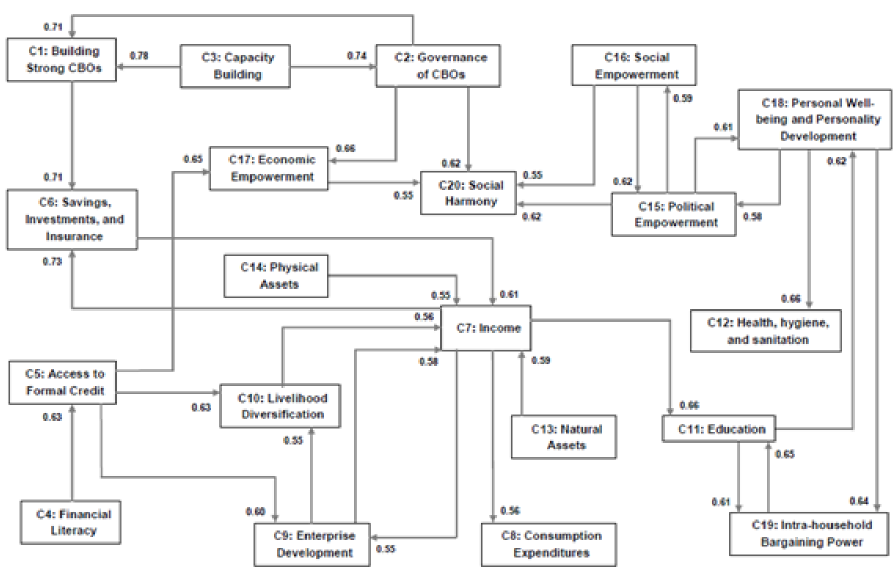


Figure 3.24: Expert-based FCM model.

ii. Preparation of study protocol based on the Expert-based model

A protocol (see Figure 3.2) was prepared depicting all the 20 categories of main concepts and 129 sub-concepts generated by the experts (national and state-level programme implementers). The links identified by the experts were also illustrated in the protocol. The Research Ethics Committee of the Institute of Rural Management Anand (IRMA) approved this protocol. The Expert-based FCM model as shown in Figure 3.24, based on this protocol, is going to be compared with the FCM models, derived from the aggregation processes, to help this study meet its objectives.

iii. Closed-concept design from the community-level stakeholders.

The protocol was next administered to four different groups of stakeholders from DAY-NRLM. They were asked to construct FCMs, i.e., functionaries of Self-Help Groups (SHGs), their federations [Village Organisations (VOs) and Cluster Level Federations (CLFs)], and Community Resource Persons (CRPs). All the community stakeholders were women. A total of 179 fuzzy cognitive maps were obtained from over 600 participants during the FCM exercise. These participants were selected randomly from the programme participants. SHG and VO functionaries were divided into smaller sub-groups, with each sub-group comprising four to five members, to construct FCMs. On the other hand, the CLF functionaries and CRPs drew the FCMs individually.

During this exercise, every community group/ individual stakeholder provided weights to the individual links on a scale of 1–10 and the level of confidence for such weights on a scale of 1–5 as discussed earlier. The participants were also asked to draw new links between the categories, depending on what they believed. However, none of them created any additional link. Each group made a presentation to the researchers after having concluded construction of the FCM.

Step 2: Coding individual cognitive maps and confidence level values into adjacency matrices

Each fuzzy cognitive map was then coded into separate Excel sheets with concepts listed in vertical C_i and horizontal C_j axes; this formed a square adjacency matrix [12, 13, 38]. The positive wording of all the concepts warranted only positive values for the relationships. Accordingly, the weight values were coded into the adjacency matrix only when there was a connection between two given concepts [12]. The weights given to each link were normalized between 0 and +1 (if the values +5, then they are normalized +0.5) while coding into the adjacency matrix [13, 104]. Similarly, the confidence level values were also normalized between 0 and 1 (for example, value 1 corresponds to 0.2, value 2 to 0.4, and value 5 corresponds to 1).

Step 3: Producing individual links (L) and confidences and links (C) matrices.

Each adjacency matrix consists of the normalized weights of the individual cognitive map named as adjacency links (L) matrix, and the corresponding individual FCM model called as FCM (L) model. Taking one step further from the adjacency matrices related to each group or individual participants, the normalized weight value of every existing link was multiplied with its normalized confidence level value producing the adjacency confidence and links (C) matrix that corresponds to the individual FCM (C) model.

As a result, two FCM models were developed based on each map: one for links (L) and another for confidences and links (C). For the second FCM model, the final value (strength) of every connection was produced through the multiplication of the weight of every connection with the value of the confidence level assigned by the participants to the corresponding links. Hence, a new FCM model is built that seems to represent participants' opinions with high reliability.

Step 4: Aggregating individual cognitive maps from each group producing aggregated links (L) and confidences and links (C) FCMs

In this step, all individually coded cognitive maps were aggregated and additively superimposed using the two aggregation methods (the Average and the OWA) [100]. Thus, two collective-FCMs were created for every group of participants for each aggregation method; the Average-FCM (L) and OWA-FCM (L), referring to the FCMs that include the weight value for every single link, and the Average-FCM (C) and OWA-FCM (C) where every link value between two nodes was the result of the multiplication of its weight value with its corresponding confidence level value. Figure 3.25 depicts a visual representation of the aggregation process.

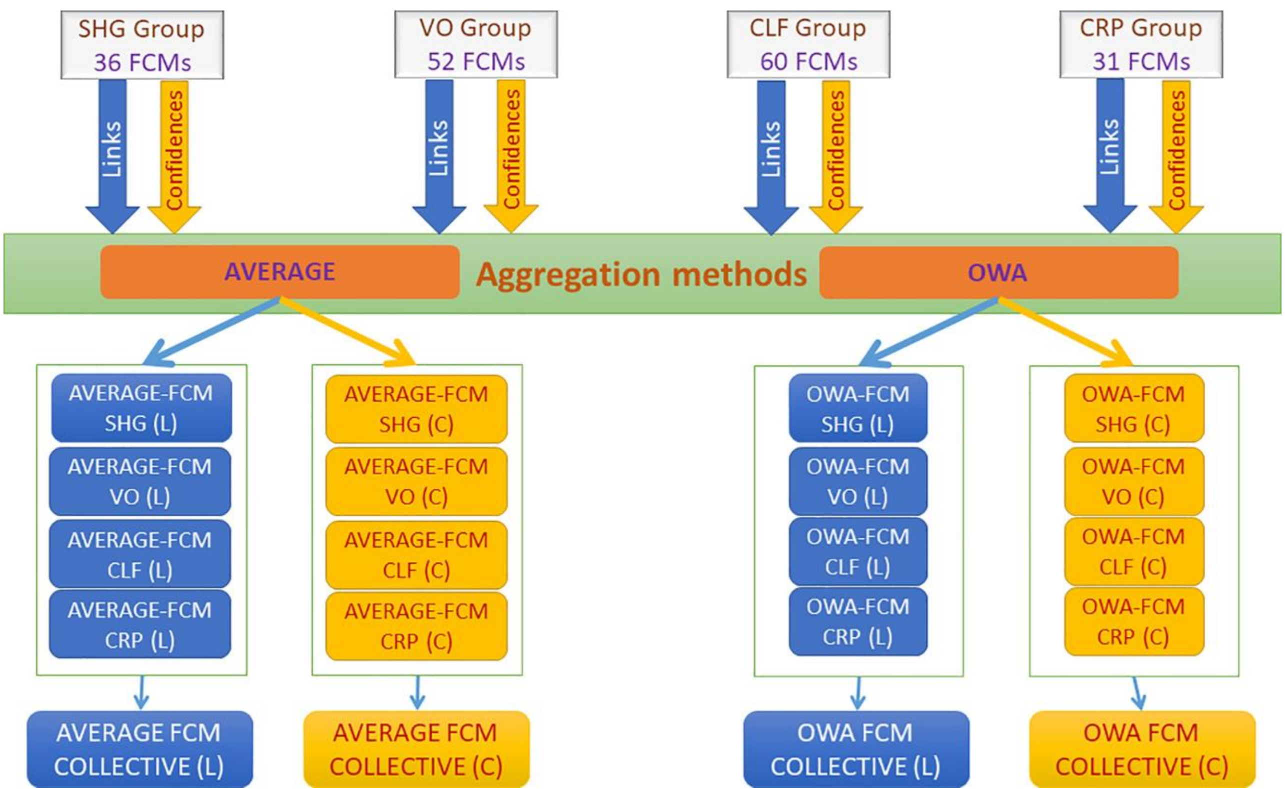


Figure 3.25: The steps of the aggregation process.

Step 5: Groups aggregation for producing an overall collective FCM

Following the process described in step 4, four Collective-FCMs were produced from each one of the four groups (SHG-FCM, VO-FCM, CLF-FCM, and CRP-FCM) using both aggregation methods. In particular, an overall Collective FCM is created for both aggregation methods, regarding links (L) and confidences and links (C). As shown in Figure 3.25, a Collective-FCM is produced from the implementation of each aggregation method for both links (L) and confidences and links (C). The FCM models produced are: Average-FCM Collective (L), OWA-FCM Collective (L), Average-FCM Collective (C) and OWA-FCM Collective (C). These Collective-FCMs are enriched with the knowledge of all stakeholders involved. The matrices that correspond to the two collective-FCMs regarding both aggregation methods considering links (L), are illustrated in the following Figures. The adjacency weights matrices for the other two collective-FCMs, Average-FCM and OWA-FCM, regarding confidence and links (C) are provided in Appendix B.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	0	0	0	0	0	0.86	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C2	0.89	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.85	0	0	0.815
C3	0.9025	0.88	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C4	0	0	0	0	0.82	0	0	0	0	0	0.8225	0	0	0	0	0	0	0	0	0
C5	0	0	0	0	0	0	0	0	0.785	0.825	0	0	0	0	0	0	0.81	0	0	0
C6	0	0	0	0	0	0	0.7975	0	0	0	0	0	0	0	0	0	0	0	0	0
C7	0	0	0	0	0	0.825	0	0.7775	0.7575	0	0.83	0	0	0	0	0	0	0	0	0.7725
C8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C9	0	0	0	0	0	0	0.775	0	0	0.76	0	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0.805	0.7725	0	0	0	0	0	0	0	0	0	0	0	0
C11	0	0	0	0	0	0	0.8	0	0	0	0	0	0	0	0	0	0	0.835	0.8075	0
C12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.8
C13	0	0	0	0	0	0	0.7875	0	0	0	0	0	0	0	0	0	0	0	0	0
C14	0	0	0	0	0	0	0.785	0	0	0	0	0	0	0	0	0	0	0	0	0
C15	0	0	0	0	0	0	0.005	0	0	0	0	0	0	0	0	0.7875	0	0.7875	0	0.775
C16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.7925	0	0	0	0	0.7925
C17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.7875
C18	0	0	0	0	0	0	0	0	0	0	0	0.815	0	0	0.7725	0	0	0	0.8075	0
C19	0	0	0	0	0	0	0	0	0	0	0.805	0	0	0	0	0	0	0	0	0
C20	0	0	0	0	0	0	0	0	0	0	0	0.8	0	0	0	0	0	0	0	0

Figure 3.26: Adjacency weights matrix for Average-FCM (L) model

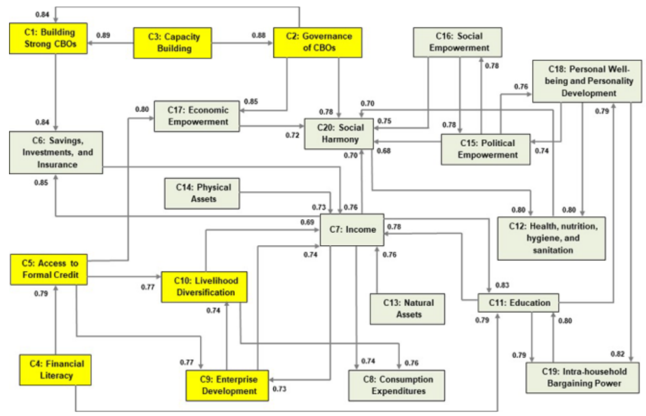
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	0	0	0	0	0	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C2	0.5325	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.505	0	0	0.5075
C3	0.57	0.595	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C4	0	0	0	0	0.535	0	0	0	0	0	0.4825	0	0	0	0	0	0	0	0	0
C5	0	0	0	0	0	0	0	0	0.47	0.4975	0	0	0	0	0	0	0.4625	0	0	0
C6	0	0	0	0	0	0	0.4625	0	0	0	0	0	0	0	0	0	0	0	0	0
C7	0	0	0	0	0	0.515	0	0.4125	0.4325	0	0.45	0	0	0	0	0	0	0	0	0.4375
C8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C9	0	0	0	0	0	0	0.445	0	0	0.415	0	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0.53	0.4625	0	0	0	0	0	0	0	0	0	0	0	0
C11	0	0	0	0	0	0	0.39	0	0	0	0	0	0	0	0	0	0	0.51	0.4775	0
C12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4575
C13	0	0	0	0	0	0	0.475	0	0	0	0	0	0	0	0	0	0	0	0	0
C14	0	0	0	0	0	0	0.4825	0	0	0	0	0	0	0	0	0	0	0	0	0
C15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.445	0	0.4325	0	0.5
C16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5075	0	0	0	0	0.4925
C17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4675
C18	0	0	0	0	0	0	0	0	0	0	0	0.4975	0	0	0.44	0	0	0	0.5325	0
C19	0	0	0	0	0	0	0	0	0	0	0.5325	0	0	0	0	0	0	0	0	0
C20	0	0	0	0	0	0	0	0	0	0	0	0.3975	0	0	0	0	0	0	0	0

Figure 3.27: Adjacency weights matrix for OWA-FCM (L) model

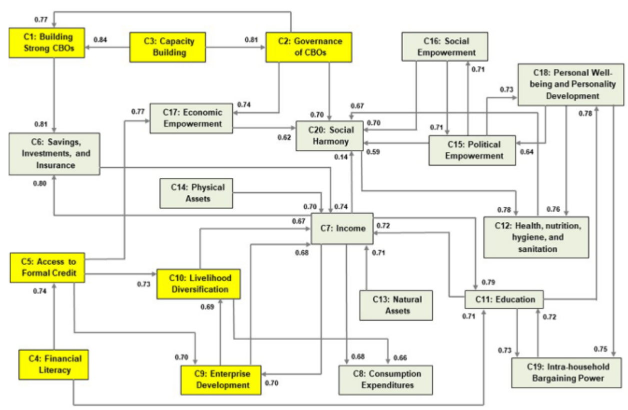
Step 6: Visual Interpretation of Collective FCM

According to the proposed methodology, as presented in section 3.2, this step visualizes the consensus FCM models along with the connections among the existing concepts. The collective

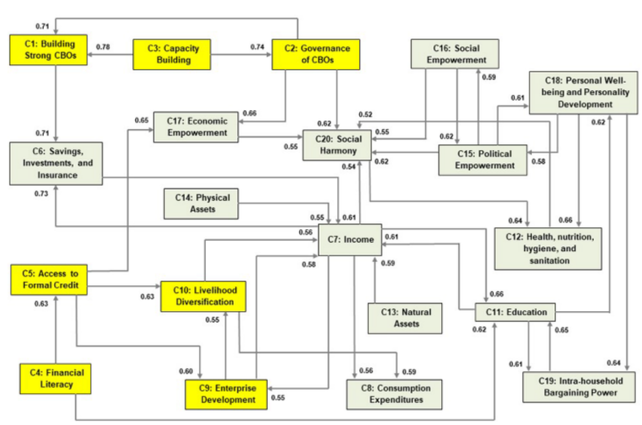
FCM models for each group (SHG, VO, CLF, CRP) were produced by the FCMWizard tool which is characterized by modelling and visualization capabilities. The four Collective-FCM models considering links (L) and confidences and links (C), for both methods, are presented in Figures 3.28(a), 3.28(b), 3.28(c), and 3.28(d).



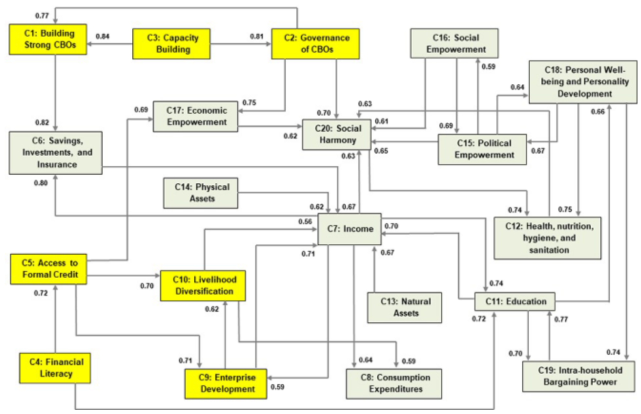
(a)



(b)



(c)



(d)

Figure 3.28: Collective-FCM models for a) Average-FCM (L), b) OWA-FCM (L), c) Average-FCM (C) and d) OWA-FCM (C).

Step 7: Fuzzy cognitive map-based analysis and simulations

i. Structural analysis

Structural analysis provides a description of FCM models with the help of indices including in-degree (weight of inbound links), out-degree (weight of outbound links), degree centrality (sum of the corresponding absolute weights of in-degree and out-degree), complexity, density, and the hierarchy index [12, 17]. The structural analysis for this case study is conduct with the use of the FCMWizard tool. The values calculated, regarding the degree centrality, complexity, density and hierarchy index, are 3.07, 0.25, 0.103 and 0.035 respectively, for the overall OWA aggregated FCM. These structural indices help in analyzing the graphical structure of FCMs [12, 101, 104].

ii. Development of input vectors for policy scenarios

As discussed in the 'Theory of change' in Section 3.4.1, the institutional effectiveness of CBOs is critical for effective operation and for achieving the end goal of the programme. Thus, considering the effectiveness of CBOs, the following concepts of the FCM model from the four elements of the programme were selected for the FCM-based simulations: C1-"Building strong CBOs", C2-"Governance of CBOs", C3-"Capacity Building", C5-"Access to formal credit", C9-"Enterprise development", and C10-"Livelihood diversification". These concepts were selected as they describe the four elements of the programme, while being among the concepts with the highest degree centrality so that they could well influence the dynamics of the system. The scenarios selected with their input vector concepts are briefly presented in Table 3.13.

Table 3.13: The input vector concepts of each scenario.

Scenarios	Input vector concepts					
Scenario 1	C1: Building strong CBOs	C2: Governance of CBOs				
Scenario 2	C3: Capacity building					
Scenario 3	C5: Access to formal credit					
Scenario 4	C9: Enterprise development	C10: Livelihood diversification				
Scenario 5	C1: Building strong CBOs	C2: Governance of CBOs	C3: Capacity building			
Scenario 6	C1: Building strong CBOs	C2: Governance of CBOs	C5: Access to formal credit			
Scenario 7	C1: Building strong CBOs	C2: Governance of CBOs	C9: Enterprise development	C10: Livelihood diversification		
Scenario 8	C5: Access to formal credit	C9: Enterprise development	C10: Livelihood diversification			
Scenario 9	C1: Building strong CBOs	C2: Governance of CBOs	C3: Capacity building	C5: Access to formal credit	C9: Enterprise development	C10: Livelihood diversification

• *Scenario 1* examines the effects of building strong CBOs (C1) and the governance of CBOs (C2) in terms of SHGs, VO, and CLFs, while *Scenario 2* presents the effects of capacity building of the CBOs (C3) in terms of governance and management.

• *Scenario 3* studies the effects of access to formal credit (C5) in terms of micro-finance and SHG-bank linkage.

• *Scenario 4* highlights the effects of enterprise development of the CBOs (C9) in terms of business sustainability, along with livelihood diversification (C10) in terms of living standards.

• The rest of the scenarios examined are combinations of the above four scenarios. In particular, *Scenario 5* shows the effects of building strong CBOs (C1) along with the governance of CBOs (C2) and the capacity building of the CBOs (C3).

• *Scenario 6* illustrates the combination of the effects of building strong CBOs (C1) in terms of SHGs, VOs, and CLFs, the governance of CBOs (C2), and the access to formal credit (C5).

• *Scenario 7* considers the effects of building strong CBOs (C1) and the governance of CBOs (C2) along with enterprise development (C9) and livelihood diversification (C10) of the CBOs.

• *Scenario 8* examines the effects of access to formal credit (C5), enterprise development (C9) and livelihood diversification (C10) of the CBOs.

- *Scenario 9* highlights the effects of all the pre-selected vital concepts: building strong CBOs (C1), governance of CBOs (C2), capacity building of the CBOs (C3), access to formal credit (C5), enterprise development (C9), and livelihood diversification (C10) of the CBOs.

The simulation results of the above scenarios help in understanding the critical factors that will lead to the achievement of the desired programme outcomes.

iii. Simulation process

This process involves the implementation of the FCM-based simulations with respect to 9 scenarios as they were formed above. For each scenario, certain concepts are activated according to Table 3.13, and the system reaches an equilibrium point after a number of iterations are conducted using a 'squashing function' to rescale concept values towards |1|. The FCMWizard tool will help the simulation process be accomplished and the outcomes be interpreted towards the exploration of the modelled system's dynamics. The results produced are thoroughly provided in the following section.

3.4.3 Results

3.4.3.1 Characteristics of the key concepts

It is necessary to limit the concepts to the most influential and uncertain while dealing with a large number of concepts, which are challenging to analyze individually. Some independent concepts are disconnected from the system, while some dependent concepts have a relatively low degree of influence but strong dependence. Filtering key concepts from the FCM system is a traditional approach in scenario planning that helps link narratives to the quantitative model while focusing on the critical concepts with strong direct or indirect effects on the scenario objectives, which can significantly change the balance of the entire system [103]. In the FCM-based scenario analysis, the identification of key concepts mainly relies on the perception of the experts. However, some characteristics obtained from the model facilitate the process.

The weights of the links reveal three useful structural indices for this matter: in-degree, outdegree, and degree centrality [12, 17]. Degree centrality is considered as the relative importance of a concept within the FCM structure [17]. The calculated values of degree centrality for the Collective Average-FCM (L), for each concept, are summarized in Figure 3.29.

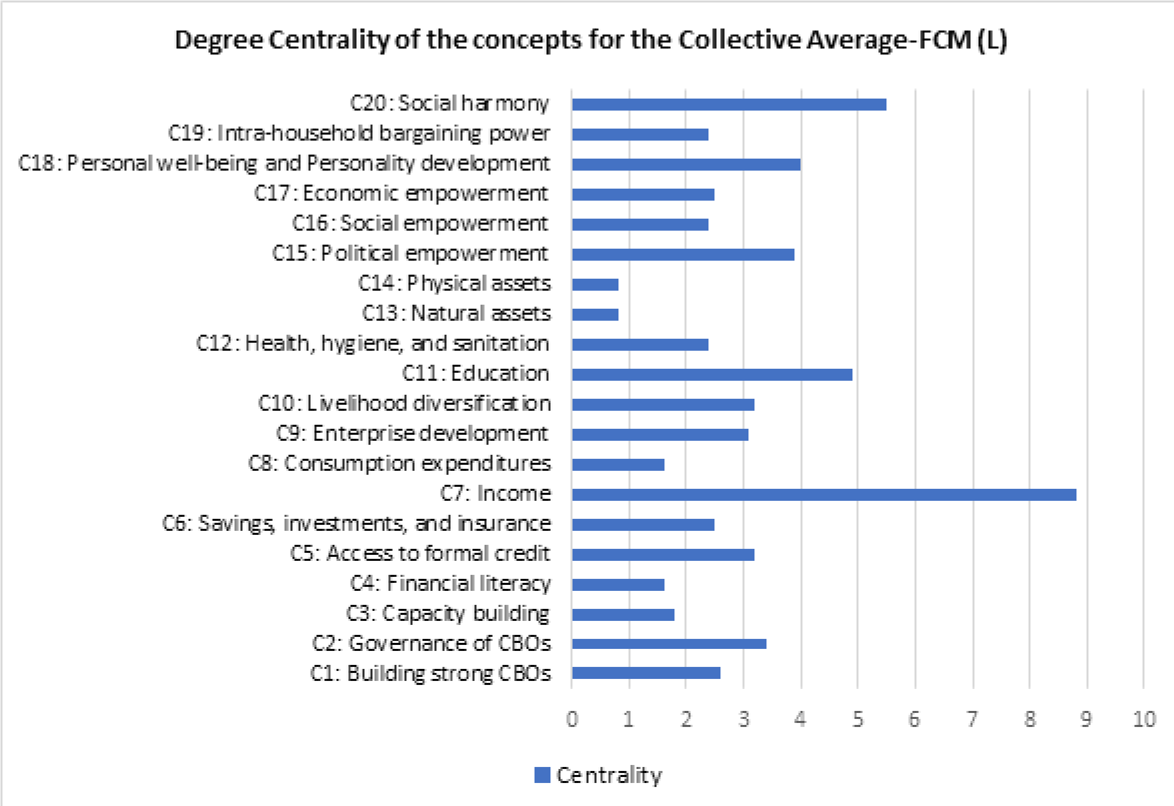


Figure 3.29: Finalized concepts and their centrality for the Collective Average-FCM (L)

3.4.3.2 Aggregation results

This section illustrates the results produced from the application of the two aggregation methods on the FCM models. As described in section 3.4.2: step 5, after the application of the Average and OWA aggregation processes, four matrices were produced containing the calculated values of weights. These are the two Collective-FCMs with confidences and links (C), namely the Average-FCM (C) and the OWA-FCM (C), and the two Collective-FCMs considering links (L), namely the Average-FCM (L) and the OWA-FCM (L). The aggregated matrices considering Links (L) are provided in section 3.4.2 (see Figures 3.26 and 3.27) whereas those considering Confidence and Links (C) are presented in the Appendix B (see Figures B.3 and B.4).

In order to proceed with the comparison analysis, mean deviations among the aggregated Average-FCM and OWA-FCM, for both links (L) and confidences and links (C), were calculated. The results are shown in Table 3.14. Before that, the deviations between the weights among all the above FCMs (in pairs) had also been calculated.

Table 3.14: Mean deviations among the aggregated FCMs

Comparing FCMs		**Mean Deviation**
OWA-FCM (L)	Average-FCM (L)	0.32
OWA-FCM (C)	Average-FCM (C)	0.37
Experts' FCM	Average-FCM (L)	0.27
Experts' FCM	Average-FCM (C)	0.24
Experts' FCM	OWA-FCM (C)	0.12

When evaluating the values produced from the results presented in Table 3.14, it is observed that the minimum mean deviation value (= 0.12) is located between the OWA-FCM with confidence and links (C) and the Experts' FCM, while the next smallest value lies in between Average-FCM with confidence and links (C) and the Experts' FCM. It can be concluded that the OWA-FCM model resembles the structure of the Expert-based FCM and consequently, can present a similar performance to the model constructed by the experts. Therefore, the superiority of the OWA-FCM model against the Average-FCM may be inferred after an adequate evaluation and interpretation of the results produced.

3.4.3.3 Scenario results

This section details out the results of the FCM-based simulations where scenario analysis is conducted. Simulating the FCM model provides a profound understanding of the concepts' behavior, their relationships, and the magnitude of impacts on other concepts. The scenario analysis was performed by multiplying the input vectors with the adjacency matrix while applying the Sigmoid threshold function with $\lambda = 1$ after every multiplication. The process was iterated until the system (output vectors) reached the steady-state.

Before the simulation process takes place, a baseline scenario needs to be conducted. The next step provides a comparison between the results of the scenarios and those resulting from the state of the model where all the initial values of concepts are zero (baseline scenario). Figures 3.30 and 3.31 present the results of simulations of the baseline scenarios for both aggregated methods, considering the FCM models with links (Average-FCM (L) and OWA-FCM (L)).

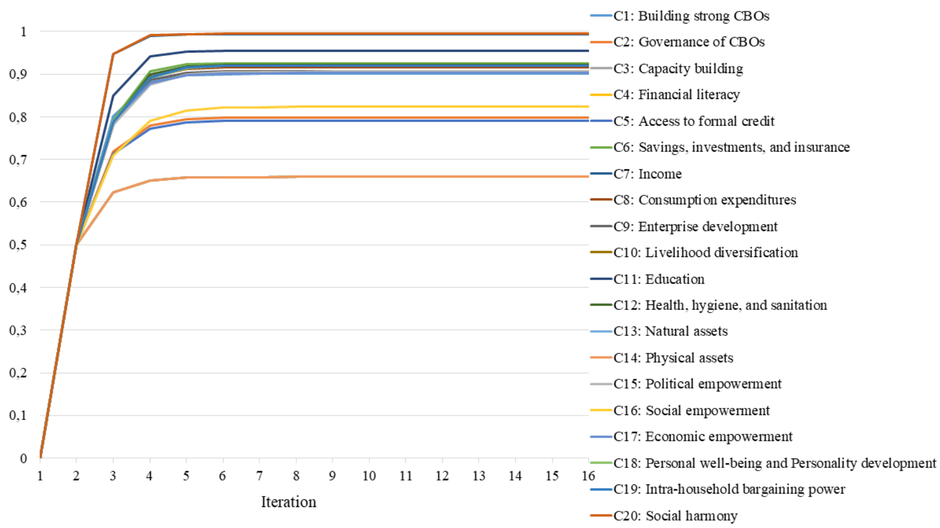


Figure 3.30: The baseline scenario for overall Average-FCM (L) model

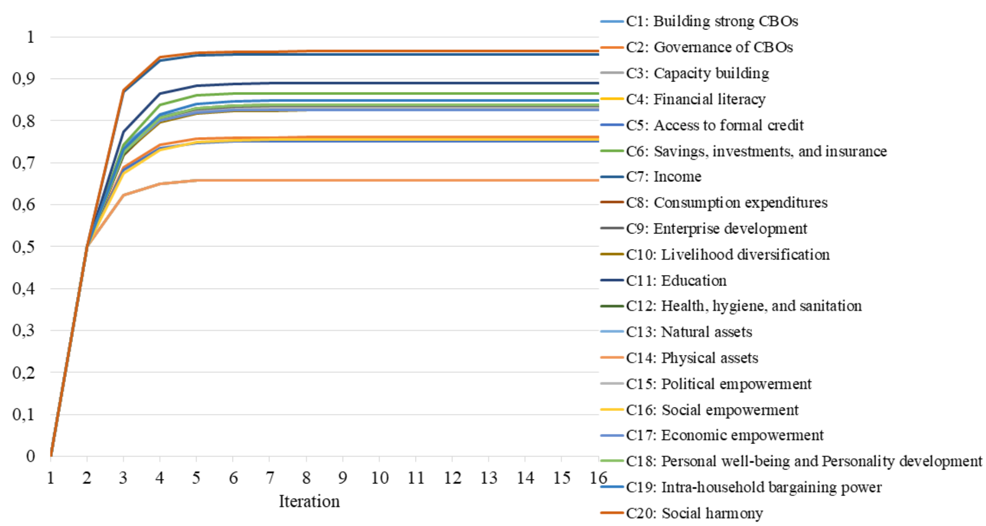


Figure 3.31: The baseline scenario for overall OWA-FCM (L) model

Subsequently, the simulation process is performed by “clamping” the initial values of the input vector concepts one-by-one. The results are compared against the baseline scenario where the system reaches the steady-state by clamping all the initial values to zero. Exploring the dynamic change of the values of the concepts between the baseline steady-state and the results of the clamping procedure enables quantitative interpretation of the impact of the key concepts on the system.

Concerning the Expert-based FCM model, the results of the scenarios are shown in Table 3.15. The results of the scenarios for the other aggregated FCMs (the Average and the OWA, for links (L) and confidences and links (C)) are depicted in Tables 3.16, 3.17, 3.18 and 3.19.

Table 3.15: Scenario results (initial and final value) for each concept, for the Expert-based FCM

	Scenario 1		*Scenario 2*		*Scenario 3*		*Scenario 4*		*Scenario 5*		*Scenario 6*		*Scenario 7*		*Scenario 8*		*Scenario 9*	
Key Concept	*Initial value*	*Final value*	*Initial value*	*Final value*	*Initial value*	*Final value*	*Initial value*	*Final value*	*Initial value*	*Final value*	*Initial value*	*Final value*	*Initial value*	*Final value*	*Initial value*	*Final value*	*Initial value*	*Final value*
C1	1	1	0	0.906	0	0.874	0	0.874	1	1	1	1	1	1	0	0.874	1	1
C2	1	1	0	0.827	0	0.780	0	0.780	1	1	1	1	1	1	0	0.780	1	1
C3	0	0.659	1	1	0	0.659	0	0.659	1	1	0	0.659	0	0.659	0	0.659	1	1
C4	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C5	0	0.765	0	0.765	1	1	0	0.765	0	0.765	1	1	0	0.765	1	1	1	1
C6	0	0.910	0	0.904	0	0.902	0	0.903	0	0.910	0	0.910	0	0.911	0	0.903	0	0.911
C7	0	0.962	0	0.962	0	0.963	0	0.968	0	0.962	0	0.963	0	0.968	0	0.968	0	0.968
C8	0	0.790	0	0.790	0	0.790	0	0.791	0	0.790	0	0.790	0	0.791	0	0.791	0	0.791
C9	0	0.864	0	0.864	0	0.882	1	1	0	0.864	0	0.882	1	1	1	1	1	1
C10	0	0.860	0	0.860	0	0.880	1	1	0	0.860	0	0.880	1	1	1	1	1	1
C11	0	0.890	0	0.890	0	0.890	0	0.891	0	0.890	0	0.890	0	0.891	0	0.891	0	0.891
C12	0	0.798	0	0.798	0	0.798	0	0.798	0	0.798	0	0.798	0	0.798	0	0.798	0	0.798
C13	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C14	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C15	0	0.865	0	0.865	0	0.865	0	0.865	0	0.865	0	0.865	0	0.865	0	0.865	0	0.865
C16	0	0.785	0	0.785	0	0.785	0	0.785	0	0.785	0	0.785	0	0.785	0	0.785	0	0.785
C17	0	0.885	0	0.871	0	0.886	0	0.867	0	0.885	0	0.901	0	0.885	0	0.886	0	0.901
C18	0	0.876	0	0.876	0	0.876	0	0.876	0	0.876	0	0.876	0	0.876	0	0.876	0	0.876
C19	0	0.879	0	0.879	0	0.879	0	0.879	0	0.879	0	0.879	0	0.879	0	0.879	0	0.879
C20	0	0.953	0	0.948	0	0.947	0	0.946	0	0.953	0	0.954	0	0.953	0	0.947	0	0.954

Table 3.16: Scenario results (initial and final value) for each concept, for the Average-FCM (L)

	Scenario 1		***Scenario 2***		***Scenario 3***		***Scenario 4***		***Scenario 5***		***Scenario 6***		***Scenario 7***		***Scenario 8***		***Scenario 9***	
Key Concept	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**
C1	1	1	0	0.929	0	0.900	0	0.900	1	1	1	1	1	1	0	0.900	1	1
C2	1	1	0	0.849	0	0.798	0	0.798	1	1	1	1	1	1	0	0.798	1	1
C3	0	0.659	1	1	0	0.659	0	0.659	1	1	0	0.659	0	0.659	0	0.659	1	1
C4	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C5	0	0.791	0	0.791	1		0	0.791	0	0.791	1	1	0	0.791	1	1	1	1
C6	0	0.931	0	0.927	0	0.925	0	0.925	0	0.931	0	0.931	0	0.932	0	0.925	0	0.932
C7	0	0.993	0	0.993	0	0.993	0	0.994	0	0.993	0	0.993	0	0.994	0	0.994	0	0.994
C8	0	0.915	0	0.915	0	0.916	0	0.921	0	0.915	0	0.916	0	0.921	0	0.921	0	0.921
C9	0	0.907	0	0.907	0	0.921	1	1	0	0.907	0	0.921	1	1	1	1	1	1
C10	0	0.904	0	0.904	0	0.920	1	1	0	0.904	0	0.920	1	1	1	1	1	1
C11	0	0.955	0	0.955	0	0.955	0	0.955	0	0.955	0	0.955	0	0.955	0	0.955	0	0.955
C12	0	0.922	0	0.922	0	0.922	0	0.922	0	0.922	0	0.922	0	0.922	0	0.922	0	0.922
C13	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C14	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C15	0	0.905	0	0.905	0	0.905	0	0.905	0	0.905	0	0.905	0	0.905	0	0.905	0	0.905
C16	0	0.823	0	0.823	0	0.823	0	0.823	0	0.823	0	0.823	0	0.823	0	0.823	0	0.823
C17	0	0.917	0	0.906	0	0.917	0	0.902	0	0.917	0	0.930	0	0.917	0	0.917	0	0.930
C18	0	0.919	0	0.919	0	0.919	0	0.919	0	0.919	0	0.919	0	0.919	0	0.919	0	0.919
C19	0	0.919	0	0.919	0	0.919	0	0.919	0	0.919	0	0.919	0	0.919	0	0.919	0	0.919
C20	0	0.995	0	0.994	0	0.994	0	0.994	0	0.995	0	0.995	0	0.995	0	0.994	0	0.995

Table 3.17: Scenario results (initial and final value) for each concept, for the Average-FCM (C)

	Scenario 1		***Scenario 2***		***Scenario 3***		***Scenario 4***		***Scenario 5***		***Scenario 6***		***Scenario 7***		***Scenario 8***		***Scenario 9***	
Key Concept	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**
C1	1	1	0	0.914	0	0.882	0	0.882	1	1	1	1	1	1	0	0.882	1	1
C2	1	1	0	0.830	0	0.783	0	0.783	1	1	1	1	1	1	0	0.783	1	1
C3	0	0.659	1	1	0	0.659	0	0.659	1	1	0	0.659	0	0.659	0	0.659	1	1
C4	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659

C5	0	0.769	0	0.769	1	1	0	0.769	0	0.769	1	1	0	0.769	1	1	1	1
C6	0	0.912	0	0.906	0	0.904	0	0.904	0	0.912	0	0.912	0	0.912	0	0.904	0	0.912
C7	0	0.983	0	0.982	0	0.983	0	0.985	0	0.983	0	0.983	0	0.985	0	0.985	0	0.985
C8	0	0.882	0	0.882	0	0.883	0	0.891	0	0.882	0	0.883	0	0.891	0	0.891	0	0.891
C9	0	0.873	0	0.873	0	0.889	1	1	0	0.873	0	0.889	1	1	1	1	1	1
C10	0	0.871	0	0.871	0	0.891	1	1	0	0.871	0	0.891	1	1	1	1	1	1
C11	0	0.933	0	0.933	0	0.933	0	0.933	0	0.933	0	0.933	0	0.933	0	0.933	0	0.933
C12	0	0.894	0	0.894	0	0.894	0	0.894	0	0.894	0	0.894	0	0.894	0	0.894	0	0.894
C13	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C14	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C15	0	0.872	0	0.872	0	0.872	0	0.872	0	0.872	0	0.872	0	0.872	0	0.872	0	0.872
C16	0	0.789	0	0.789	0	0.789	0	0.789	0	0.789	0	0.789	0	0.789	0	0.789	0	0.789
C17	0	0.889	0	0.876	0	0.890	0	0.872	0	0.889	0	0.905	0	0.889	0	0.890	0	0.905
C18	0	0.888	0	0.888	0	0.888	0	0.888	0	0.888	0	0.888	0	0.888	0	0.888	0	0.888
C19	0	0.888	0	0.888	0	0.888	0	0.888	0	0.888	0	0.888	0	0.888	0	0.888	0	0.888
C20	0	0.986	0	0.984	0	0.984	0	0.984	0	0.986	0	0.986	0	0.986	0	0.984	0	0.986

Table 3.18: Scenario results (initial and final value) for each concept, for the OWA-FCM (L)

	Scenario 1		***Scenario 2***		***Scenario 3***		***Scenario 4***		***Scenario 5***		***Scenario 6***		***Scenario 7***		***Scenario 8***		***Scenario 9***	
Key Concept	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**
C1	1	1	0	0.865	0	0.833	0	0.833	1	1	1	1	1	1	0	0.833	1	1
C2	1	1	0	0.802	0	0.760	0	0.760	1	1	1	1	1	1	0	0.760	1	1
C3	0	0.659	1	1	0	0.659	0	0.659	1	1	0	0.659	0	0.659	0	0.659	1	1
C4	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C5	0	0.751	0	0.751	1	1	0	0.751	0	0.751	1	1	0	0.751	1	1	1	1
C6	0	0.878	0	0.868	0	0.865	0	0.866	0	0.878	0	0.878	0	0.878	0	0.866	0	0.878
C7	0	0.958	0	0.958	0	0.959	0	0.964	0	0.958	0	0.959	0	0.965	0	0.964	0	0.965
C8	0	0.832	0	0.832	0	0.834	0	0.845	0	0.832	0	0.834	0	0.845	0	0.845	0	0.845
C9	0	0.831	0	0.831	0	0.849	1	1	0	0.831	0	0.849	1	1	1	1	1	1
C10	0	0.824	0	0.824	0	0.845	1	1	0	0.824	0	0.845	1	1	1	1	1	1
C11	0	0.889	0	0.889	0	0.889	0	0.889	0	0.889	0	0.889	0	0.889	0	0.889	0	0.889
C12	0	0.838	0	0.838	0	0.838	0	0.838	0	0.838	0	0.838	0	0.838	0	0.838	0	0.838
C13	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C14	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C15	0	0.829	0	0.829	0	0.829	0	0.829	0	0.829	0	0.829	0	0.829	0	0.829	0	0.829

C16	0	0.755	0	0.755	0	0.755	0	0.755	0	0.755	0	0.755	0	0.755	0	0.755	0	0.755
C17	0	0.845	0	0.829	0	0.844	0	0.826	0	0.845	0	0.862	0	0.845	0	0.844	0	0.862
C18	0	0.838	0	0.838	0	0.838	0	0.838	0	0.838	0	0.838	0	0.838	0	0.838	0	0.838
C19	0	0.848	0	0.848	0	0.848	0	0.848	0	0.848	0	0.848	0	0.848	0	0.848	0	0.848
C20	0	0.969	0	0.966	0	0.965	0	0.965	0	0.969	0	0.970	0	0.969	0	0.966	0	0.970

Table 3.19: Scenario results (initial and final value) for each concept, for the OWA-FCM (C)

	Scenario 1		***Scenario 2***		***Scenario 3***		***Scenario 4***		***Scenario 5***		***Scenario 6***		***Scenario 7***		***Scenario 8***		***Scenario 9***	
Key Concept	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**	**Initial value**	**Final value**
C1	1	1	0	0.816	0	0.787	0	0.787	1	1	1	1	1	1	0	0.787	1	1
C2	1	1	0	0.759	0	0.728	0	0.728	1	1	1	1	1	1	0	0.728	1	1
C3	0	0.659	1	1	0	0.659	0	0.659	1	1	0	0.659	0	0.659	0	0.659	1	1
C4	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C5	0	0.711	0	0.711	1	1	0	0.711	0	0.711	1	1	0	0.711	1	1	1	1
C6	0	0.810	0	0.798	0	0.796	0	0.797	0	0.810	0	0.810	0	0.811	0	0.797	0	0.811
C7	0	0.887	0	0.886	0	0.887	0	0.900	0	0.887	0	0.888	0	0.900	0	0.900	0	0.900
C8	0	0.763	0	0.763	0	0.764	0	0.778	0	0.763	0	0.764	0	0.778	0	0.778	0	0.778
C9	0	0.770	0	0.770	0	0.789	1	1	0	0.770	0	0.789	1	1	1	1	1	1
C10	0	0.753	0	0.753	0	0.771	1	1	0	0.753	0	0.771	1	1	1	1	1	1
C11	0	0.829	0	0.829	0	0.829	0	0.83	0	0.829	0	0.829	0	0.83	0	0.83	0	0.83
C12	0	0.778	0	0.778	0	0.778	0	0.778	0	0.778	0	0.778	0	0.778	0	0.778	0	0.778
C13	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C14	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659	0	0.659
C15	0	0.761	0	0.761	0	0.761	0	0.761	0	0.761	0	0.761	0	0.761	0	0.761	0	0.761
C16	0	0.717	0	0.717	0	0.717	0	0.717	0	0.717	0	0.717	0	0.717	0	0.717	0	0.717
C17	0	0.791	0	0.775	0	0.791	0	0.773	0	0.791	0	0.808	0	0.791	0	0.791	0	0.808
C18	0	0.771	0	0.771	0	0.771	0	0.771	0	0.771	0	0.771	0	0.771	0	0.771	0	0.771
C19	0	0.778	0	0.778	0	0.778	0	0.778	0	0.778	0	0.778	0	0.778	0	0.778	0	0.778
C20	0	0.873	0	0.866	0	0.866	0	0.866	0	0.873	0	0.874	0	0.874	0	0.866	0	0.874

The scenario analysis performs simulations for the 9 scenarios that were formed in Section 3.4.2. Scenario 1 is dedicated to increasing the concepts C1-“Building strong CBOs” and C2-“Governance of CBOs” by “clamping” them to one, while scenarios 2 and 3 increase the concepts C3-“Capacity Building” and C5-“Access to formal credit” by “clamping” them to one, respectively. Scenario 4 refers to the increase of the concepts C9-“Enterprise development” and C10-“Livelihood diversification” by “clamping” them to one.

In Scenario 5, the key concepts C1-“Building strong CBOs”, C2-“Governance of CBOs”, and C3-“Capacity Building” are all clamped to one. The same procedure is followed for Scenario 6 where the key concepts C1-“Building strong CBOs, C2-“Governance of CBOs”, and C5-“Access to formal credit” are clamped to one, while Scenario 7 refers to the concepts C1-“Building strong CBOs, C2-“Governance of CBOs”, C9-“Enterprise development”, and C10-“Livelihood diversification” clamped to one. Scenario 8 considers “clamping” the key concepts C5-“Access to formal credit”, C9-“Enterprise development”, and C10-“Livelihood diversification” to one. In the end, Scenario 9 is conducted by “clamping” all the key concepts (C1-“Building strong CBOs”, C2-“Governance of CBOs”, C3-“Capacity Building”, C5-“Access to formal credit”, C9-“Enterprise development”, and C10-“Livelihood diversification”) to one.

The four aggregated FCMs (Average-FCM (L), Average-FCM (C), OWA-FCM (L) and OWA-FCM (C)), have been exerted to test nine plausible scenarios as mentioned above. Thus, the scenarios developed have been generalized to the poverty alleviation programme of India, with the poverty alleviation change scenarios extracted.

The results for scenario analysis are illustrated in Figures 3.32 and 3.33, in the form of spider graphs. For the specific case study, the Expert-based FCM is considered as the benchmark model that helped the researchers to further investigate the usefulness, importance and superiority of the proposed OWA aggregation method against the Average aggregation method.

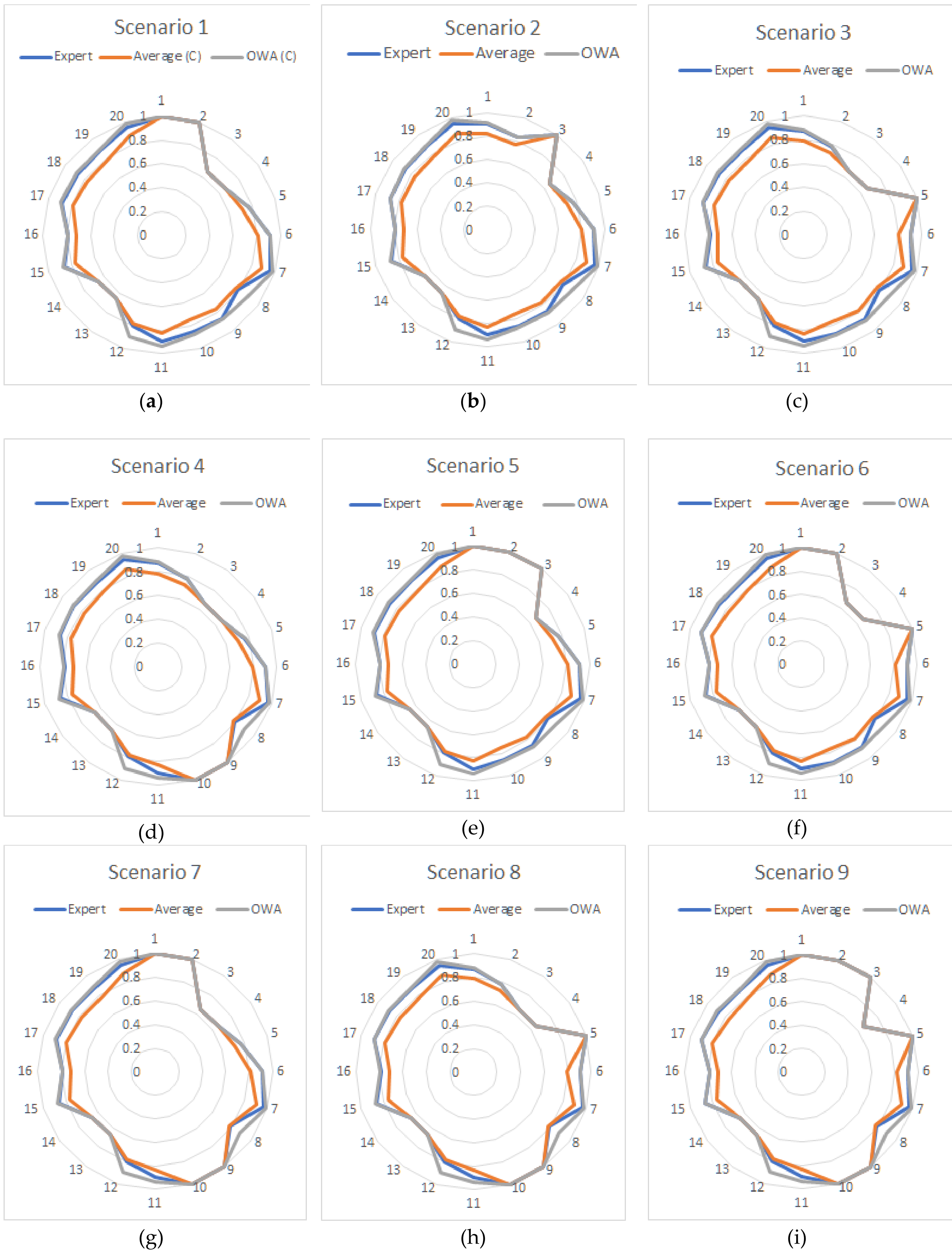


Figure 3.32: Spider graphs for the Expert-based, Average, and OWA-FCMs (C)

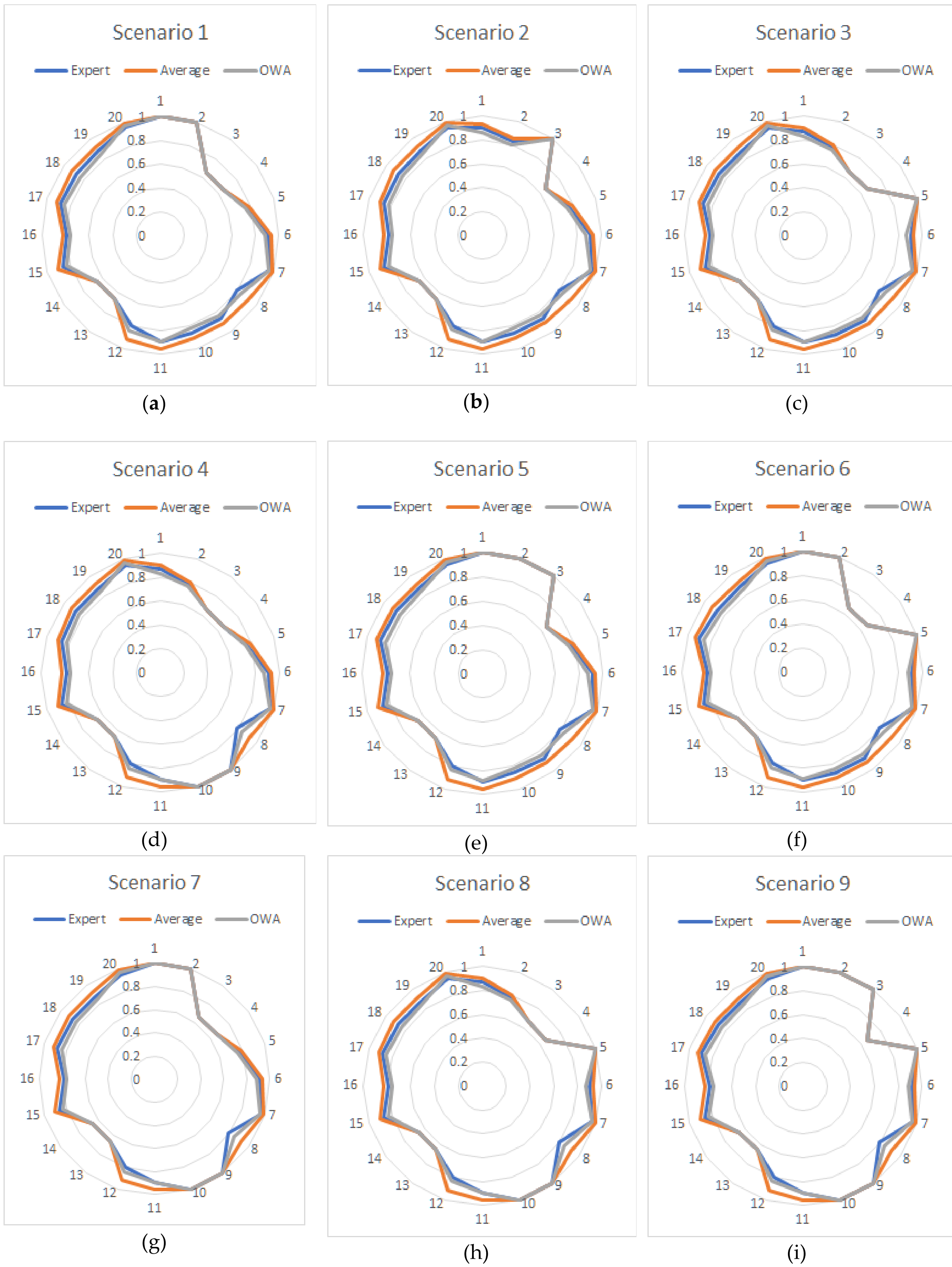


Figure 3.33: Spider graphs for the Expert-based, Average, and OWA-FCMs (L)

To begin with, Figure 3.32 and Figure 3.33 illustrate spider charts for all three FCMs (Average, OWA and Expert-based) depicting the deviation for all concepts after the nine scenarios were conducted while considering links (L), plus confidences and links (C), correspondingly.

All the examined scenarios presented in the above two Figures, for both cases (for links and for confidences and links), reveal that the produced analysis results for the OWA FCM are in high consistency with those for the Expert-based FCM. The OWA method seems to resemble the Expert-based FCM in terms of performance as the chart lines of the OWA and the Expert-based FCMs coincide in most of the cases of the scenarios produced, as presented in Figure 3.35 and Figure 3.36. The results work as indicators to verify the superiority of the OWA-FCM aggregation over the Average-FCM, making OWA a trustworthy method with regard to FCMs' aggregation.

The following Figure gathers all the outcomes after the execution of the scenarios, with respect to the percentage of change for each concept, for all FCMs considering Confidences and Links (Average, OWA, and Expert-based).

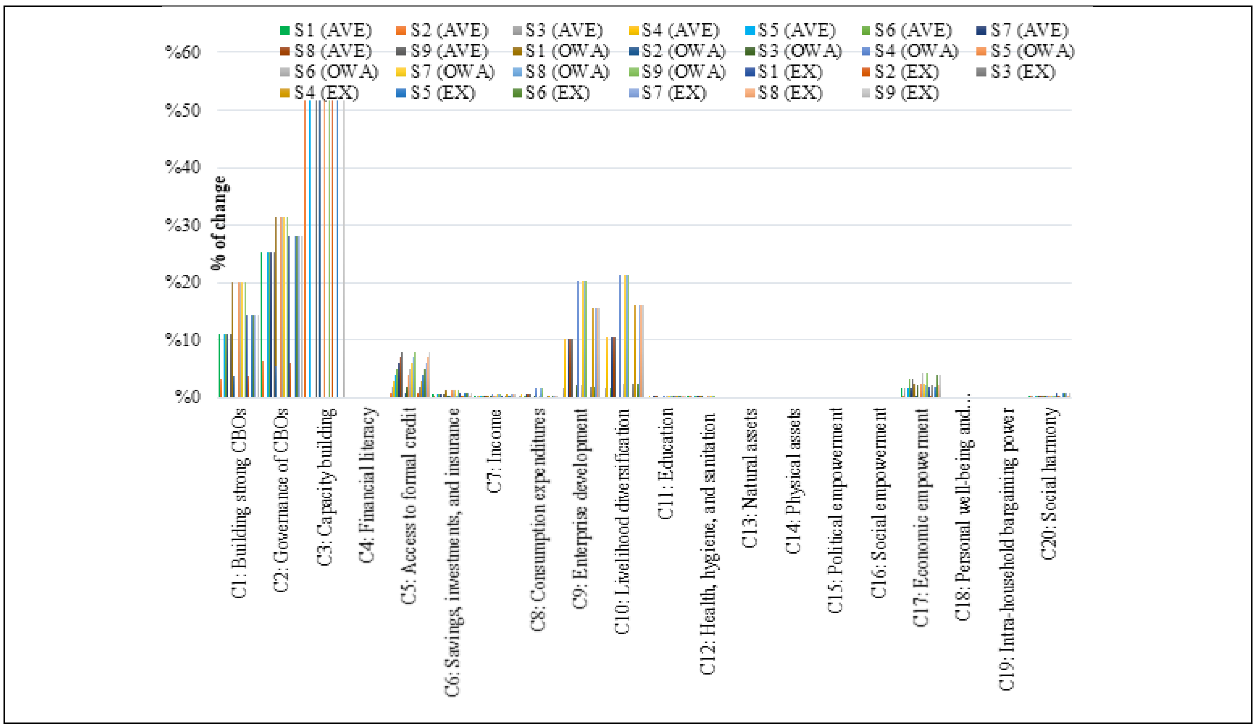
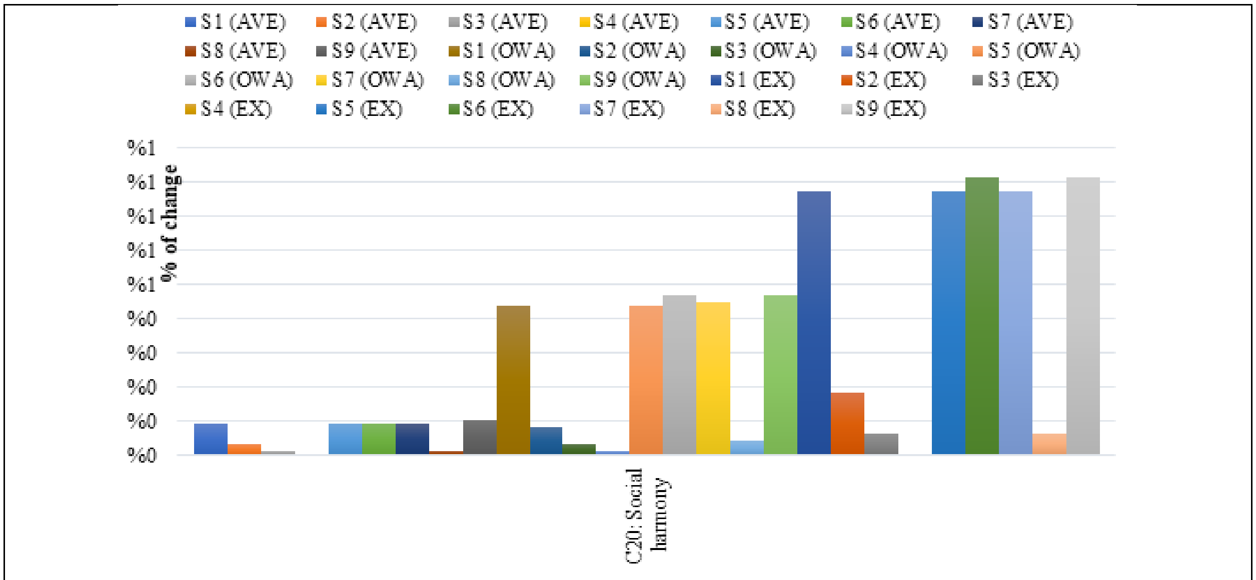


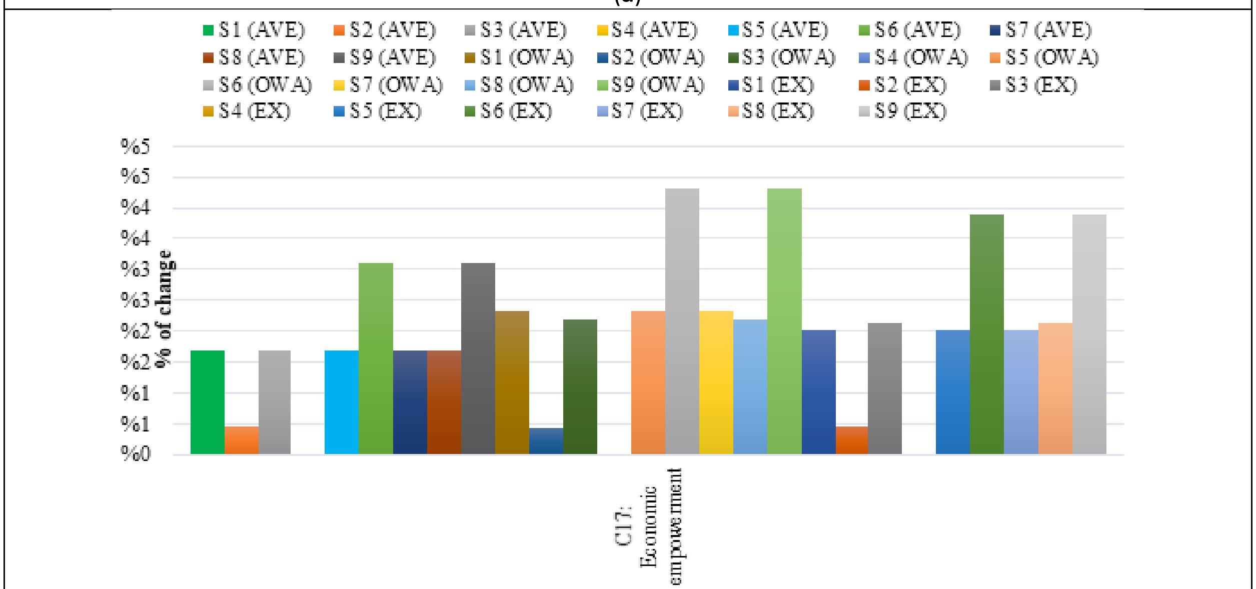
Figure 3.34: Scenario analysis for all FCMs considering confidences and links (C)

Among the concepts identified in the final outcomes of 'Theory of Change' that could affect the end goal in terms of decreased socio-economic poverty, concepts C17 and C20 seem to have emerged as notable deviations from the initial states after the implementation of scenario analysis (see Figure 3.34). Therefore, the scenario analysis mainly focusses on the impact that the key concepts have on these two output concepts C17-"Economic Empowerment" and C20-"Social Harmony", which researchers consider as the outcome concepts that need to be improved by the DAY-NRLM programme interventions.

Thus, the deviations for these outcome concepts for all three FCMs are calculated, considering only confidences and links (C). The results for concepts C20 and C17 are depicted in Figure 3.35.



(a)



(b)

Figure 3.35: Deviations for concepts (a) C20 and (b) C17 for aggregated FCMs considering confidences and links (C).

After having conducted a detailed analysis of the results presented above, it can be concluded that the percentage of change for both outcome concepts C20 and C17 is notable only for six out of the nine scenarios (S1, S5, S6, S7, S8, and S9) performed. Results of the scenarios S2, S3, and S4 seem to be less significant, on the other hand. Therefore, only these six scenarios are taken into consideration, hereafter.

Figure 3.36 reveals that between the two applied aggregation methods, the Average and the OWA, the latter is more efficient with respect to the accuracy of the results compared to the Expert-based FCM model, which is considered as a benchmark model for the purposes of this case study.

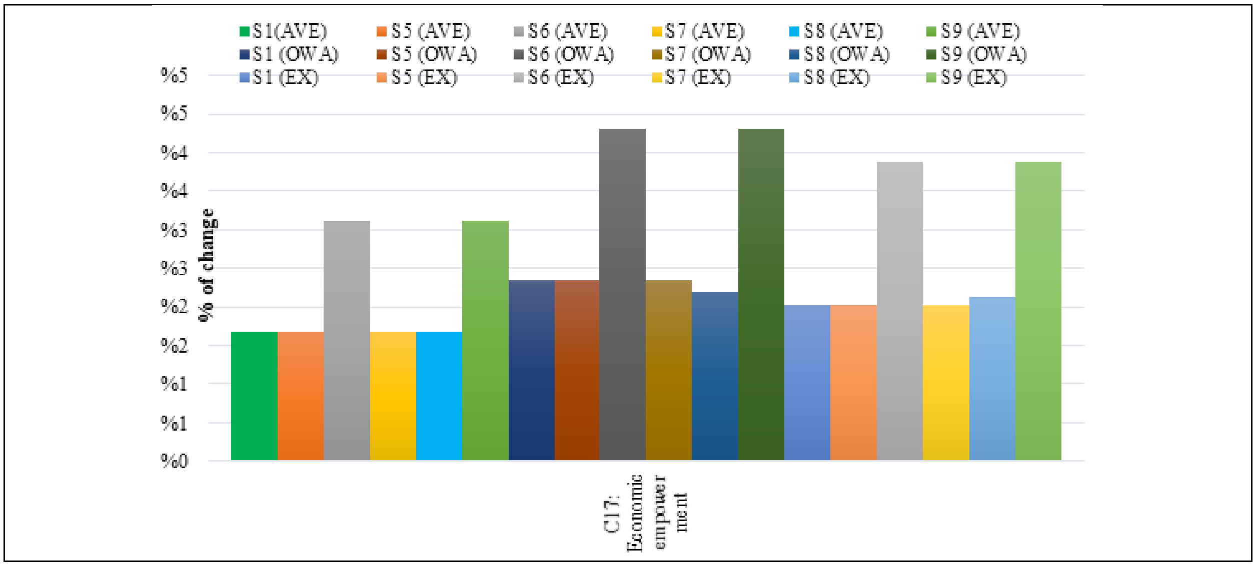


Figure 3.36: Percentage of change for concept C17, considering confidences and links (C).

In Figure 3.36, the change in percentage of the outcome concept C17, compared to the initial steady-state, is presented for all three approaches (Average, OWA, and Expert-based) for confidences and links (C). The respective deviations calculated for the outcome concept C20, for all three FCMs, are depicted in Figure 3.37.

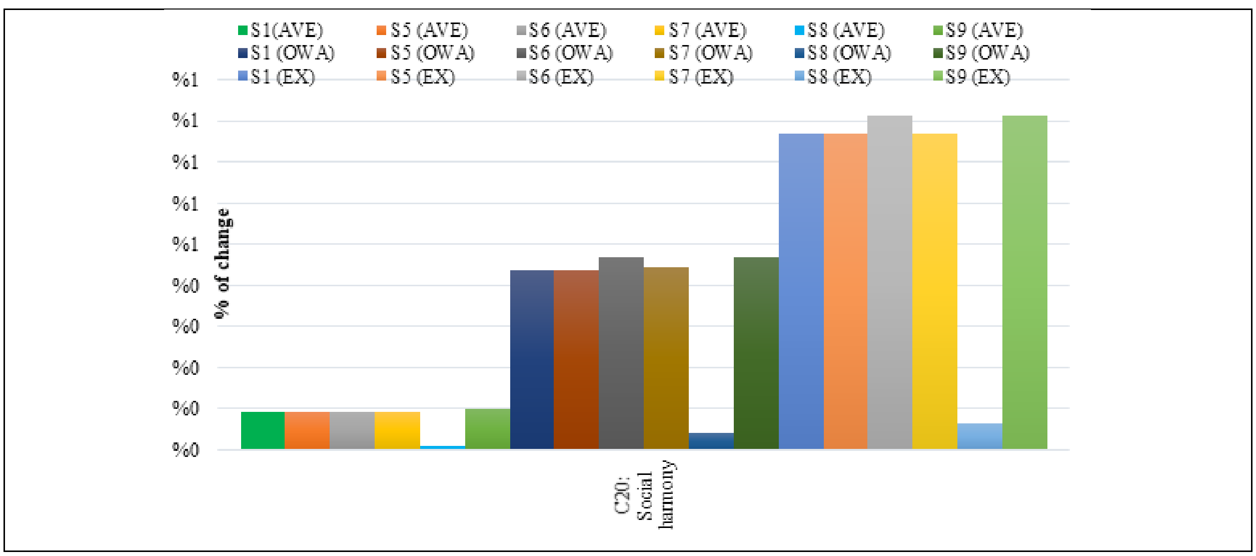


Figure 3.37: Percentage of change for concept C20, considering confidences and links (C)

3.4.4 Discussion of Results

The dimensions of poverty eradication in the rural area of India present a complex system. Figure 3.35 reveals that the concepts of the scenarios S2, S3, S4 with respect to all three FCM approaches (Average, OWA and Expert-based) for confidences and links (C), have a small impact on the final outcomes C17 (Economic empowerment) and C20 (Social Harmony) since the percentage of change from the initial steady-state for the concepts C17 and C20 seems to be insignificant when the concepts of the scenarios implemented are “clamped” to one. For this reason, this case study ignored these scenarios and focused on the rest of scenarios (S1, S5, S6, S7, S8 and S9) to further investigate their impact on poverty alleviation.

From Figures 3.36 and 3.37, it emerges that the combination of key concepts C1, C2, C3, C5, C9 and C10 (Scenario 9) has the highest impact on key concepts C17 and C20 for all aggregated FCMs, showing a significant increase in these concepts, particularly when OWA aggregation method is applied, considering confidences and links. With respect to the performance of the two aggregation methods examined, the following key remarks are drawn after a careful investigation of Tables and Figures above:

i. In the participatory modelling, when a large number of participants are involved, the OWA aggregation method appears superior against the Average aggregation method. After a detailed observation of Figures 3.36 and 3.37, where scenario analysis of the three different FCMs, considering confidences and links (C), is conducted, it is observed that deviations from the initial state are higher when the OWA aggregation method is applied. In both cases, the OWA method performs better in the decision-making process, compared to the Average aggregation method.

ii. The proposed OWA aggregation method exhibits outstanding performance while performing scenario analysis for the concepts examined. This may emanate from the fact that the results produced from the application of the OWA aggregation method (when referring to the FCMs either with links (L) or confidences and links (C)) are closer to those deriving from the Expert-based FCM model, which is considered as the benchmark model. Therefore, they surpass those of the Average aggregation method (Figures 3.36 and 3.37). The group of experts as stated above, can create an accurate model that could well describe the problem examined in order to make appropriate strategic decisions.

iii. On the other hand, for all the possible cases examined, the Average aggregation method appears less important in decision-making when its outcomes are matched with the FCM model created by the experts.

iv. The proposed OWA aggregation method exhibits better performance compared to the Expert-based, considering the case of the FCMs with confidences and links (C) with respect to key concepts C17 and C20. As can be seen in Figures 3.34, 3.36, and 3.37, the results derived from the application of the OWA aggregation method are better than those from the experts.

v. The performance of the OWA aggregated FCM model is similar to that of the Expert-based FCM model in terms of consistency of results produced between the two approaches (Figures 3.36 and 3.37).

In general, it is validated that the OWA aggregation method outperforms the Average aggregation method and is suitable for scenario analysis, strategic decision-making, and policy-planning, especially when a large number of participants is involved.

3.4.5 Policy implications of the scenario results

The scenarios S1 to S4, previously analyzed, illustrate the importance of strong CBOs, good governance within CBOs, better capacity building of communities and CBOs, access to formal credit, livelihood diversification, and enterprise development to achieve the end goal of the programme, i.e. decrease in socio-economic poverty. The results show that if CBOs habitually mainstream financial institutions, offer support through SHG-bank linkages, help livelihood diversification, and develop livelihood enterprises, then one can expect the following: better capacity building of communities and CBOs along with good governance within CBOs. This will help shape strong CBOs. Good governance reflects adherence to the *Panchsutra* (regular meetings, regular savings, regular inter-loaning, timely repayments, and up-to-date books of accounts). Better access to formal credit could lead to the provisioning of savings and investments to stakeholders. Insurance, alongside, is also likely to increase. Besides, an increase in natural and physical assets is likely to increase household incomes. A better income is likely to increase the expenditure on consumer goods, healthcare, and education. Increased income and savings could as well lead to increased livelihood diversification and enterprise development. Further, greater access to formal credit and good governance within the CBOs is likely to result in economic, political, and social empowerment of SHG women besides improving social harmony within the community. Better education is likely to develop the personality and personal well-being of SHG women besides improving their intra-household bargaining power along with health, hygiene, and sanitation.

The scenarios S5 to S9 show different combinations of input vector concepts used in previous scenarios. The outcomes show a result similar to that of the previous scenarios. The building of CBOs and providing them with access to formal credit will probably enhance the economic, social, and political empowerment of women. Also, increasing income and savings could lead to higher consumer spending, diversification of livelihoods, and development of livelihood enterprises. Higher incomes could lead to a better access to education for women and their children, helping develop their personality and personal well-being while improving their overall socio-economic status. Better education is also likely to improve their intra-household bargaining power and health, hygiene, and sanitation.

In general, the results confirm that several concepts are complementary and should be implemented simultaneously for the overall development of SHG members. It is necessary to improve the capacities of SHG members while ensuring good governance within the CBOs and providing micro-finance through high-quality CBOs. Access to micro-finance and higher income will help them to diversify their livelihood options and develop micro-enterprises. This will result in socio-economic empowerment of women, provide them with social safety nets while improving their education, health and hygiene and developing their personalities. Thus, the findings reveal that the creation of strong community-based institutions through capacity building and access to formal credits will help the alleviation of socio-economic poverty.

3.5 Concluding Remarks

The main goal of this chapter is to provide the research community and policymakers with a methodological framework to address the problem of socio-economic and environmental sustainability incorporating a participatory modelling approach implemented by fuzzy cognitive maps. In the context of formulating the right strategies, policy-makers and governments seek to investigate the interconnection between the environmental, social and economic pillars of sustainable development. On this basis, performing aggregation tasks, this chapter examined the contribution of the OWA-based FCM aggregation method which learns the OWA operator weights integrating data that represent participants' perceptions. This methodology was applied in two different approaches (Case A and Case B) of the same problem which regards the DAY-NRLM poverty alleviation programme, that aims at socio-economic growth, economic sustainability, and livelihood diversification of poor women in rural areas in India.

For both cases, the relationship strengths between the participant concepts were calculated with the proposed aggregation approach and compared with the benchmark weights (average) along with those assigned by the experts. The results show that in both cases, the OWA-FCM resembles the structure of the expert-based FCM and, in most instances, showcase an improved performance compared to the model constructed by the experts. The scenarios carried out which are based on different FCMs, tried to model the circumstances relevant to improving livelihoods by creating sustainable and self-managed institutional platforms, together with the promotion of social resilience and economic empowerment of the poor rural women.

The overall findings in terms of socio-economic sustainability, focus on the fact that using a combination of interventions – building strong CBOs, good governance within CBOs, better capacity building of communities and CBOs, access to formal credit to the community, livelihood diversification, and enterprise development — extreme poverty can be reduced. In this context, policy-makers are provided with an opportunity to have a clear view of all the existing interconnections within social, economic and environmental systems and further propose suitable and efficient policies in this direction. Moreover, decision-makers can apply the proposed FCM-based framework along with the new software tools for policy-making in various domains, proving its generic applicability and convenience when a significantly large number of participants are involved in designing FCMs. This FCM-based framework can facilitate the preparation of more appropriate, equitable and effective policy scenarios and responses, including shifting investment, production, distribution and consumption towards more sustainable approaches, and for the development of better governance capacities at multiple scales.

Chapter 4

Economic-Environmental Sustainability: Modeling and Scenario Analysis in Energy Sector using FCMs

4.1 Introduction

Energy sector has sparked great interest from governments over the last decade towards diminution of world's dependency to fossil fuels, greenhouse gas emissions reduction and global warming mitigation. Realizing the imminent energy crisis worldwide, countries' energy policies and development plans mainly focus on sustainable development in socio-economic and environmental terms. However, this development that is based on delivering basic environmental, social and economic services should consider the reassurance of the viability of natural, built and social systems upon which these services depend [105].

Under these circumstances, it emerges that the development and harnessing of the available renewable energy resources seems to be the only option for social, economic and environmental sustainability. In this direction, Photovoltaic Solar Energy (PSE) holds a significant role in the transition to sustainable energy systems. These systems and their optimal exploitation require an effective supply chain management system, such as design of the network, collection, storage, or transportation of this energy resource, without disregarding a country's certain socio-economic and political conditions. In the case of Brazil, which constitutes the case study in this chapter, the adoption of photovoltaic solar energy has been motivated not only by the energy matrix diversification but also from the shortages, problems, and barriers that the Brazilian energy sector has faced, lately. However, PSE development is affected by various factors with high uncertainty, such as political, social, economic, and environmental, that include critical operational sustainability issues. Thus, an elaborate modelling of energy management and a well-structured decision support process are needed to enhance the performance efficiency of PSE supply chain management. Overall, the following social, economic and environmental aspects must be considered when exploring the photovoltaic solar energy planning [105]:

i) Resource management (environmental),
ii) infrastructure and service development guaranteeing affordability for rural populations (economic), and
iii) social resilience and income reassurance (social)

This chapter focuses on the investigation of certain factors and their influence on the development of the Brazilian PSE with the help of Fuzzy Cognitive Maps. Fuzzy Cognitive Map is an established methodology for scenario analysis and management in diverse domains, inheriting the advancements of fuzzy logic and neural networks. In this context, a semi-quantitative model was designed with the help of various stakeholders from the specific energy domain and three plausible scenarios were conducted in order to support a decision-making process on PSE sector development and the country's economic potential. The outcome of this analysis reveals that the development of the PSE sector in Brazil is mainly affected by economic and political factors.

This chapter is explicitly devoted to the following tasks: (i) to apply the quasi-qualitative method of Fuzzy Cognitive Mapping for modelling the complex Renewable Energy system through stakeholders' perceptions, and (ii) to perform an FCM-based simulation process by investigating various scenarios regarding the Brazilian PSE development with the use of the FCMWizard tool.

4.2 Related work

Over the last two decades, renewable energy has been considered as a vital candidate in global power demand [106], and thus, its exploitation needed to be well explored and studied. However, due to several limitations, such as environmental problems and because of the high uncertainty that these kinds of systems present, the renewable energy sector is considered highly non-linear and complex. In this context, Fuzzy Cognitive Map is a method that can illustrate the uncertainty causality [107] and becomes a powerful tool to model such complex systems that involve many factors [57]. Due to this fact, FCMs have been recently deployed in a renewable energy domain with great perspectives.

Due to their modelling and simulation capabilities, along with their ability to predict a system's behavior, FCMs have gained wide acceptance and popularity [57] during the last decades. A noteworthy characteristic is that they can promote learning as they can combine experts' knowledge and historical data to improve their performance on modelling and prediction, thus, overcoming the subjectivity of experts' opinions [15], [108]. Moreover, FCMs were recently exploited for scenario planning, even though they were not introduced for such tasks [109]. A number of FCM-based scenarios have been explored in [28] where the robustness of scenario planning was significantly enhanced.

In this context, exploiting their advantageous capabilities of handling the uncertainty causality [107] and modelling complex systems with many parameters [57], FCMs have been successfully involved in the renewable energy domain. In the related literature, there are several studies regarding the integration of FCMs in Energy sector dealing with modelling, management and decision-making tasks [109–111], due to their ability to cope with inherent uncertainties in vast domains and to model human reasoning processes [57]. Particularly, FCMs have been employed to model the total energy behavior of intelligent buildings and increase their energy efficiency [112]. Regarding the renewable energy domain, a socio-economic analysis was conducted in [113], in which FCMs were employed to identify potential consequences over the mix of fossil fuel and renewable energy power sectors, as well as how certain policies that regard the energy domain can affect a country's economic growth. We also need to report on [114], in which an FCM methodology was applied for assessing energy efficiency strategies, electricity demand prediction and policy-making in the Renewable Energy sector, employing a stakeholder-driven approach based on FCMs. Furthermore, the modelling methodology of FCMs was also proposed in [111] to address and investigate the energy efficiency in buildings, using a proper mix of renewable energy resources, efficiently meeting the total energy demand of a region.

In the field of photovoltaic solar energy, a number of studies can be found in the literature [115–119]. Alipour et al., in a recent study, explored the FCM capabilities on identifying and analyzing unpredictable factors that have a direct impact on solar photovoltaics in an uncertain socio-economic, political and technological environment [87]. It is worth mentioning that this is the first research study that implements FCM-based scenario analysis in the renewable energy field.

The FCM technique is applied in this chapter to perform a decision-making process for PSE sector development, providing at the same time the researchers and the FCM community with an efficient simulation tool called FCMWizard, to conduct policy making simulations in their own case studies. In particular, relevant FCM-based scenarios for the Brazilian Photovoltaic Solar Energy Sector (PSE) are explored employing the FCMWizard tool. The PSE arises as one of the most promising renewable energy sources to replace fossil fuels [46], since climate and environmental changes, described by the scientific community, are increasing continuously. This happens as a result of the increasing energy demand that stems from technological progress and other advancements in human development. Scenario planning has proven to be the appropriate technique for institutions that are immersed in this PSE sector and need to make complex decisions, taking into account various uncertainties and risks, such as socio-political, environmental and technological.

4.3 Problem Statement

Environmental degradation caused by deforestation, gas emission, and environmental pollution, has caused countries to rethink their electric systems. As a solution to the problems caused by the unsustainable exploration of fossil fuels, renewable energies have become the focus of attention of a broad range of agents. However, in Brazil, unlike other countries, the investment in photovoltaic solar energy was driven by different reasons, such as the increase in the cost of energy produced in thermoelectric plants and the emission of greenhouse gases by burning of fossil fuels [120, 121].

Among other solutions, PSE shows up as a viable and necessary source of electrical energy. Given that it is located mostly in the intertropical region and has excellent potential for solar energy utilization throughout the year, the Brazilian solar radiation is higher than the European for almost its entire territory [122]. Based on Renewable Energy Country Attractiveness Index [123], Brazil is eighth in the raking of attractiveness when speaking of photovoltaic solar energy. In 2014, Brazil had its total installed to power up to 15 MW, and in 2015, the same number surpassed 32 MW. Statistics of the Mines and Energy Ministry [124] indicated that by 2018 Brazil should be between the 20 countries with the most prominent generation of solar energy.

On the other hand, the high cost of acquisition of photovoltaic and their low conversion efficiency from solar irradiation to electrical energy are the main impediments to the large-scale diffusion of these systems [125]. As a solution, the government can understand the dynamic of PSE development from other countries and propose policies that improve the use of solar energy in an urban environment. Given that the future of the PES depends on several issues, it needs to be planned and controlled. For this purpose, scenario planning constitutes a fundamental tool.

4.4 Proposed Methodology for FCM model development

In order to provide a quasi-quantitative model for scenario planning, regarding the studied problem of PSE growth in Brazil, the FCM development process was conducted in six steps, as shown in Table 4.1, below. Figure 4.1 offers a visual representation of these steps for better understanding of the procedure and for the convenience of the readers.

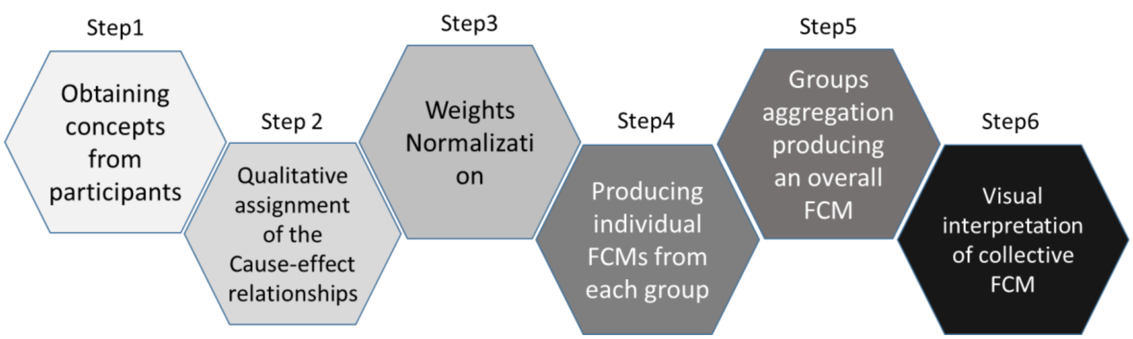


Figure 4.1: The steps of FCM development process.

Table 4.1: Steps of the proposed FCM development process

Steps	Description
Step 1: Obtaining concepts from participants.	The first step deals with the determination of the most essential independent variables that define the examined problem and affect the dependent variable. Participants are asked to determine the concepts of the system but only the most important in order to avoid designing a system with a vast number of variables that would be difficult to study.
Step 2: Qualitative assignment of cause-effect relationships between concepts.	In the second step, participants are asked to assign values on the scale of 1–10 and to determine whether there is a positive or negative cause-effect relationship for the weighted interconnections among the depended and most significant variables that constitute the FCM model. Ten (10) denotes the highest strength and one (1) the lowest.

	The sign + (plus) denotes a positive influence, whereas the sign – (minus) denotes a negative influence that one node has to another.
Step 3: Weights Normalization (coding into an adjacency matrix).	Weights given to each link were then normalized between 0 and 1 (as described in Table 4.1), considering positive and negative values for coding into the adjacency matrix [76]. So, we substitute the qualitative values assigned by the stakeholders for expressing the degree of influence with the corresponding quantitative values, in order to define the weight matrix of each stakeholder, as presented in Table 4.2. For example, the qualitative value 10 (that denotes the highest strength) is substituted by the quantitative weight value 1.
Step 4: Producing individual FCMs from each group.	In this step, every group of the participants was asked to construct an individual FCM by defining the primary variables and determining the weights values of all causal relationships. This process also includes the identification of the decision concept, which is a dependent variable for the problem under investigation. As we aim to analyze the Brazilian Solar Photovoltaic Energy Sector, the dependent variable was set to be the “Development of PSE in Brazil”. The procedure that was followed, is described below in detail, as there is a need to highlight the importance of all the steps taken for the success of this study.
Step 5: Groups Aggregation producing an Overall FCM.	In this step, all individually coded cognitive maps from the three groups were aggregated and an overall group FCM (Collective-FCM) was produced that includes all the concepts from all individual cognitive maps. This collective FCM represents the perception of all the stakeholders and is enriched with the knowledge of all stakeholders involved.
Step 6: Visualization of collective FCM.	After the aggregation process, that was based on the weighted average method, the Collective-FCM was analyzed using the FCMWizard software tool (version 1.0, E.I. Papageorgiou, Larissa, Greece). Since the tool includes modelling and visualization capabilities, a visual representation of the condensed FCM model was created by FCMWizard, which specifically illustrates the concepts and all the connections between them. The graphical representation of the collective FCM is presented in section 4.4.1, where an overview of the FCMWizard tool is presented.

Following the steps defined in Table 4.1, the project was carried out with the help of researchers of the University of São Paulo (USP) and University of Brasília (UNB) specialized in the solar photovoltaic energy. Along with other specialized stakeholders (such as specialists from the National Electric Energy Agency (government) and the Brazilian Solar Energy Association (professionals)), they were the primary sources of data and information for the development of this research.

Interviews were conducted individually or with pairs of specialists from the National Electric Energy Agency (government), the World Wildlife Fund (NGO), Brazilian Solar Energy Association (professionals), and researchers from the University of São Paulo and Brasília (specialists). A workshop was also carried out with a group of eight graduate students at the Institute of Energy and Environment of the University of São Paulo, IEE/USP, to consolidate the FCMs.

Specifically, a pretest was first carried out with a potential consumer with a business background, through an individual interview, during which the dynamics of FCMs and the proposed method were explained. The respondent had trouble defining the primary variables (concepts) and establishing the exact weights (from -1 to 1) of the causal relations. After proper guidance and following the contents of Table 4.2, he managed to develop a potential FCM in the end.

Table 4.2: Normalizing qualitative (linguistic) to quantitative values for the weighted interconnections.

Qualitative Opinion (Linguistic Values)	**Weight Value (Quantitative)**	**Qualitative Opinion (Linguistic Values)**	**Weight Value (Quantitative)**
1 - Extremely low	0.1	6 - Medium high	0.6
2 - Very low	0.2	7 - High	0.7
3 - Low	0.3	8 - Very High	0.8
4 - Medium low	0.4	9 - Extremely high	0.9
5 - Medium	0.5	10 - Highest strength	1

The second FCM was constructed after interviewing a specialist in SPE from the University of Brasília (UNB). He responded with great enthusiasm and a consensus was reached for 12 interrelated concepts, establishing at the same time the causal relations and respective weights.

In the next FCM, the proposed method was investigated with the help of a group of SPE specialists from IEE/USP. In a workshop with eight participants, the dynamics of FCMs and the proposed method were explained. These specialists identified 13 concepts and established their connections and weights. In this type of approach (workshop), the most prominent advantage came from the debate among the participants. Instead of creating individual FCMs, a collaborative process for scenario planning was suggested where the participants cooperated to produce a more productive and accurate knowledge in the form of a consolidated FCM. The weight value for each interconnection is calculated as the average of all values that each participant gave for the corresponding interconnection, taking into consideration Table 4.2. However, the FCM achieved by the group of specialists from USP, was not a significant improvement regarding complexity and robustness in comparison with the others.

The FCMs elaborated from the information of the specialists, and stakeholders were integrated into a single FCM. Table 4.3 presents the list of the concepts contained in this collective FCM, with a short description of them. They identified 29 concepts in total and established the connections and weights among these concepts. Also, they determined the 10 most central concepts (concepts in bold in Table 4.3) in terms of significance in the decision-making process through scenario analysis. Moreover, the weights of the connections were equal to the average of the weights established by the specialists and stakeholders.

Table 4.3: List of concepts integrating the collective FCM.

Concept	ID	Description
Development of solar photovoltaic energy	**C1**	Possible evolution of the Photovoltaic Solar Energy Sector in Brazil
Potential generating jobs	C2	Refers to the capacity to create employment.
Market competition	C3	Rivalry between companies selling similar products and services.

Public knowledge of SPE	**C4**	Society's understanding and awareness of the functioning and role of PS energy in energy systems and everyday use.
Public opinion (ecological and social consciousness)	C5	Public awareness regarding the importance of environmental protection
Purchase cost	**C6**	The price of energy product or services that are available for purchase by suppliers or consumers.
Maintenance costs	C7	The expenses incurred to keep an item in good condition or good working order
Energy demand	**C8**	The quantity of energy that consumers wish to acquire for a set price in a market.
Energy availability	C9	The amount of energy from various energy recourses that is available for consumption
Decentralized energy creation	C10	Energy production facilities closer to the site of energy consumption that allow for more optimal use of renewable energy
Government incentives	**C11**	They are benefits granted by governments to foster the progress of the sector (tax exemptions, financing lines, demand creation).
Private sector involvement	**C12**	The participation of the private sector in energy projects of the government.
Geographical location	C13	Geographic location refers to a position of the country on Earth. Defined by longitude and latitude.
Energy dependence concerns	**C14**	Energy source dependence. Need to diversify the energy matrix.
ABNT (Brazilian Technical Standards)	C15	A private non-profit organization which is responsible for technical standards in Brazil, and intends to promote technological development in the country
Payback Period	**C16**	The length of time required for an investment to recover its initial outlay in terms of profits or savings.
Environmental pollution	C17	The addition of any substance or any form of energy to the environment at a rate faster than it can be dispersed, diluted or decomposed.
Energy price	**C18**	The value of the energy expressed in monetary terms.
National production equipment	C19	Production equipment that belongs to a country and its purpose is to produce goods of a wanted quality when provided with production resources of a required quality
Equipment performance	C20	Effectiveness of output of a given piece of equipment.
Companies' qualifications	C21	Certain requirements or certificates for specific occupational needs.
Professional technical qualifications	C22	Associated with how excellent the professionals' skills are. It means the attributes and characteristics of a worker.
Availability of alternative energies	C23	The amount of energy from alternative energy recourses that is available for consumption
Market regulations	C24	Government regulations to ensure that markets function effectively and efficiently.
Economic situation	**C25**	It is the capacity of an economy to produce goods and services. In Brazil, the most common proxy used is a Gross domestic product (GDP).
Global treaties	C26	A formal agreement between two or more independent governments that impact the energy sector (Kyoto Protocol, Montreal Protocol).
Taxation	C27	Taxes account for a significant share of the final prices consumers pay for energy and can have a significant impact on consumption and investment patterns.
Political situation	C28	The way power is achieved and used in a country
Technological maturity	C29	Technological progress or growth

In this context, a 29-nodes FCM model was produced from the experts/stakeholders and its adjacency matrix (see Figure 4.2) was created accordingly, including the causal relationships between the concepts and their weight.

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0
0.5	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	-0.25	0	0	0	0	0	0	0	0	0	0	0	0	0
0.63	0	0	0	0.75	0	0	0	0	0	0	0	0	0	0	0	0	-0.25	0	1	0	0.75	0	0	0	0	0	0	0
0.38	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	-0.5	0	0	0	0	0	0	0	0	0	0	0	0
-0.92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.83	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0
0.5	0	0	0	0	0	0	0	0.5	0	0	0	0	0.88	0	0	0	0.25	0	0	0	0.25	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0.75	0	0	0	0	0	0.75	0	0	0	-1	0	0	0	0	0	0	0.75	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.67	0.75	0	0	0	-0.63	0	0	0	0	0	0.63	0	0	0	-0.5	0	-0.25	-0.5	0	0	0	0	1	0	0	0	0	0.5
0.5	0	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.25	1	0	0	0	0	0	0	0	0	0	0.5
0.38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.75	0	0.5	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0
0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
-0.63	0	0	0	0	0	0	0	0	0	0	0	-0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0.75	0	0	0
0.75	0	0	0.5	0	0	0	0	0	0	0	0	0	0	0	-0.8	0	0	0	0	0	0	0	1	-0.5	0	0	0	0
0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
0.5	0	0	0	0	-0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.75	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.75	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	-0.5	0	0	0.25	0	0	0	0	0	0	0	0	0	0
1	0.25	0	0	0	0	0	0.5	0	0	0	0.5	0	0	0	0	0	-0.25	0	0.5	0	0	0	0	0	0	0	0	0
0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0.25	0	0	0	0	0	0	0	0	0	0.5	0	0	-0.5	0	0	0	0	0	0	0	0	0	0
0.25	0	0	0	0	0	0	0	0	0	0.63	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0

Figure 4.2: Adjacency matrix.

4.5 Applying FCMWizard tool for FCM construction and scenario analysis

This section describes the way to construct an FCM model and visualize its results for the given problem of PSE in Brazil, using the FCM Wizard tool. Moreover, the structural analysis, the Hebbian-based Learning and the scenario analysis are further described, along with relevant figures and tables, produced by the tool.

4.5.1 Expert-Based Construction

Without a deeper knowledge of the mathematical foundations of the methodology and regardless of the type of application domain, users can create new concepts and causal relationships between them, using influence weights, to design a new model. Users are provided with the ability to easily design an FCM model by adding new nodes whereas, new directed lines can be drawn representing the causal relationships between nodes. A green direct relationship denotes a positive weight and a red inverse relationship denotes a negative weight.

So, the FCM model that was proposed and designed by the stakeholders can be easily constructed using the FCMWizard tool, as illustrated in Figure 4.3. This consensus FCM model comprises concepts in the form of nodes (C1, C2, .., C29) and directed lines (green or red) with a positive or negative weight. Moreover, this FCM model can be directly designed by the FCMWizard, after properly importing the adjacency matrix (see Figure 4.2), as provided by the Stakeholders. The weight matrix, as illustrated in the tab “weight matrix” of the tool, is presented in Figure 4.4. Each number of this weight matrix represents the causal relationship between the concepts that are sited in the corresponding row and column of this matrix.

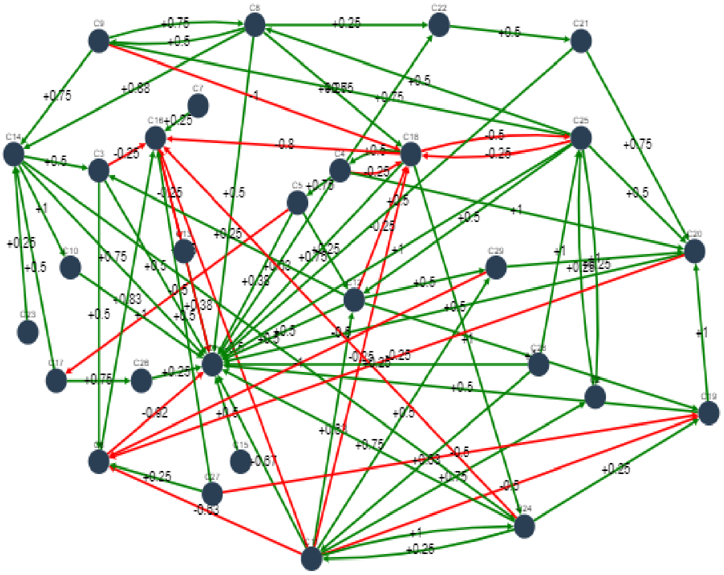


Figure 4.3: Consensus FCM model for PSE in Brazil designed in FCMwizard tool.

Model Design | Weight Matrix | Scenario Analysis | Structural Analysis

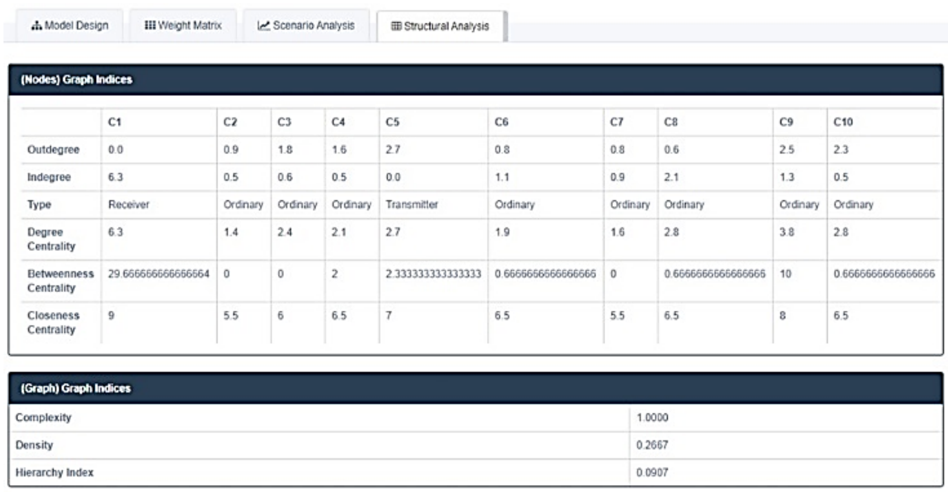
Weight Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29
C1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0
C3	0.5	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	-0.25	0	0	0	0	0	0	0	0	0	0	0	0	0
C4	0.63	0	0	0	0.75	0	0	0	0	0	0	0	0	0	0	0	0	-0.25	0	1	0	0.75	0	0	0	0	0	0	0
C5	0.38	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	-0.5	0	0	0	0	0	0	0	0	0	0	0	0
C6	-0.92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.83	0	0	0	0	0	0	0	0	0	0	0	0	0
C7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0
C8	0.5	0	0	0	0	0	0	0	0.5	0	0	0	0	0.88	0	0	0	0.25	0	0	0	0.25	0	0	0	0	0	0	0
C9	0	0	0	0	0	0	0	0.75	0	0	0	0	0	0.75	0	0	0	-1	0	0	0	0	0	0	0.75	0	0	0	0
C10	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C11	0.67	0.75	0	0	0	-0.63	0	0	0	0	0	0.63	0	0	0	-0.5	0	-0.25	-0.5	0	0	0	0	1	0	0	0	0	0.5
C12	0.5	0	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.25	1	0	0	0	0	0	0	0	0	0	0.5
C13	0.38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C14	0.75	0	0.5	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0
C15	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C16	-0.63	0	0	0	0	0	0	0	0	0	0	0	-0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C17	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0.75	0	0	0
C18	0.75	0	0	0.5	0	0	0	0	0	0	0	0	0	0	0	-0.8	0	0	0	0	0	0	0	1	-0.5	0	0	0	0
C19	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
C20	0.5	0	0	0	0	-0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C21	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.75	0	0	0	0	0	0	0	0	0
C22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0
C23	0	0	0	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C24	0.75	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	-0.5	0	0	0.25	0	0	0	0	0	0	0	0	0	0
C25	1	0.25	0	0	0	0	0	0.5	0	0	0	0.5	0	0	0	0	0	-0.25	0	0.5	0	0	0	0	0	0	0	0	0
C26	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C27	0	0	0	0	0	0.25	0	0	0	0	0	0	0	0	0	0.5	0	0	-0.5	0	0	0	0	0	0	0	0	0	0
C28	0.25	0	0	0	0	0	0	0	0	0	0.63	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
C29	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0

Figure 4.4: Screenshot of weight matrix of the final consensus FCM model produced in FCMWizard.

4.5.2 Structural Analysis

This software module encapsulates the ability to calculate various graph theory indices like the total number of concepts, number of connections, connection-to-concept ratio, outdegree, indegree, type of variables (receiver, transmitter or ordinary), degree centrality, betweenness centrality, closeness centrality, complexity ratio, density, and hierarchy index [12]. In Figure 4.5, a snapshot of the first ten concepts' graph indices is illustrated. Centrality is considered a significant index, so that a concept with a high degree of centrality has an important role in the cognitive map [12, 101]. Centrality is calculated by the sum of the corresponding absolute indegree and outdegree causal weights [98]. Table 4.4 gathers the two most important indices of centrality (Degree and Betweenness) for all 29 concepts, as calculated by the tool. As observed from Figure 4.5 and Table 4.4, the concepts C1, C4, C6, C8, C11, C14, C16, C18, C24, and C25 present a higher degree of centrality than the rest of the concepts, so they can have a significant role on the examined energy system. Complexity, density and hierarchy index too, are among significant structural indices for analyzing the graphical structure of FCMs.


Model Design | Weight Matrix | Scenario Analysis | Structural Analysis

(Nodes) Graph Indices

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Outdegree	0.0	0.9	1.8	1.6	2.7	0.8	0.8	0.6	2.5	2.3
Indegree	6.3	0.5	0.6	0.5	0.0	1.1	0.9	2.1	1.3	0.5
Type	Receiver	Ordinary	Ordinary	Ordinary	Transmitter	Ordinary	Ordinary	Ordinary	Ordinary	Ordinary
Degree Centrality	6.3	1.4	2.4	2.1	2.7	1.9	1.6	2.8	3.8	2.8
Betweenness Centrality	29.666666666666664	0	0	2	2.333333333333333	0.6666666666666666	0	0.6666666666666666	10	0.6666666666666666
Closeness Centrality	9	5.5	6	6.5	7	6.5	5.5	6.5	8	6.5

(Graph) Graph Indices

Complexity	1.0000
Density	0.2667
Hierarchy Index	0.0907

Figure 4.5: Screenshot of the "Structural Analysis" tab.

Table 4.4: Centrality indices for all concepts, calculated in FCMWizard.

Concept	Centrality		Concept	Centrality		Concept	Centrality	
	Degree	Betweenness		Degree	Betweenness		Degree	Betweenness
C1	11.9	441.4	**C11**	6.3	63.6	**C21**	1.8	11.3
C2	1.3	0.4	**C12**	3.9	30.8	**C22**	1.5	2.6
C3	2.0	13.5	**C13**	0.6	0	**C23**	0.3	0
C4	3.9	23.8	**C14**	5.1	125.0	**C24**	4.3	15.3
C5	1.9	20.9	**C15**	0.5	0	**C25**	5.5	49.7
C6	4.4	28.9	**C16**	4.5	106.9	**C26**	1.0	7.3
C7	0.3	0	**C17**	1.8	5.6	**C27**	1.3	1.5
C8	3.6	35.4	**C18**	5.8	45.5	**C28**	1.9	0.4
C9	3.8	3.8	**C19**	3.8	21.5	**C29**	3.0	1.5
C10	2.0	0	**C20**	5.0	29.6			

From the constructed FCM model (Figure 4.3), it emerges that concepts with the most substantial number of connections are: Public knowledge on SPE (C4), Public opinion (C5), Energy demand (C8), Government incentives (C11), Private sector involvement (C12), Environmental pollution (C17), Energy price (C18), and Economic situation (C25). These key concepts are also directly and strongly connected to the objective concept C1 (development of solar photovoltaic energy). Hence, in terms of their degree of centrality and connectedness (see Figure 4.5 and Table 4.4), concepts C4, C5, C11, C17, and C18 were chosen by the researchers to become the base of the scenarios since they can strongly affect the behavior of the system.

4.5.3 Scenario Development

The first established approach in scenario planning is the selection of the most important concepts (called decision concepts). Among the concepts selected to construct the studied FCM model (see Table 4.3), five concepts were identified that could well affect the behavior of the system. These concepts (C4, C5, C11, C17, and C18), given by the programme participants and implementers, were selected as they were among the concepts with the highest centrality, having both in/out-degree values, while they are strongly connected with the objective of this scenario planning, which is the development of PSE (concept C1).

For the purposes of this chapter, three scenarios were developed through plausible combinations of the aforementioned decision concepts. To check the behavior of the system, a set of concepts combinations were tested in which the concepts values were activated and clamped to one. Thus, three scenarios were finally scheduled: “Instability”, “Disastrous” and “Government Incentives”. The selected scenarios with their concepts are briefly presented in the following table.

Table 4.5: The key concepts of each scenario.

Scenarios	Concepts	
Scenario 1 (S1)	C18: Energy Price	
Scenario 2 (S2)	C4: Public Knowledge on PSE	C11: Government Incentives
	C5: Public opinion	C17: Environmental pollution
Scenario 3 (S3)	C11: Government Incentives	

- Scenario 1 (S1) examines the effects of energy price (C18) in monetary terms.
- Scenario 2 (S2) presents the effects of public knowledge on SPE (C4) in terms of general awareness of the role and significance of PSE, public opinion (C5) considering the awareness of the society about the importance of environmental protection, government incentives (C11) in terms of taxation and financial grants, along with environmental pollution (C17) in terms of energy substances affecting the environment.
- Scenario 3 (S3) highlights the effects of government incentives (C11) in terms of taxation and other financial benefits, granted by the government.

The first scenario, namely "Instability", reflects the recent history of Brazil, in which the country is undergoing economic and political instability. The current economic crisis in Brazil began in mid-2014, and this economic crisis was accompanied and intensified by a political crisis [126]. As a result of these crises, Dilma Rousseff, president of the time, suffered impeachment in 2016. The crisis also generated unemployment, which reached its peak in 2017 [127]. In response, the price of energy has risen dramatically. Consecutively, the concept "Energy price" was chosen to be the only concept examined in this scenario and so, its value is clamped to 1.

The "Disastrous" scenario reflects the shortage of electricity in Brazil, the blackouts, as well as some other environmental disasters, namely Mariana and Brumadinho. Brazil has had to activate thermoelectric plants regularly, but this backup capacity was insufficient, and rationing had to be imposed. To avoid another "blackout crisis," the government decided to create a set of initiatives to encourage the growth of PSE, through the establishment of subsidized credit lines and tax exemptions. In 2015 and 2019, the mining dams named Brumadinho and Mariana, collapsed. Part of the demand for energy migrated to the PSE and the price of electricity provided by the government decreased. This scenario examines the impact the concepts "Public knowledge on PSE" and "Government incentives" have on the system dynamics and were accordingly activated and clamped to 1.

In the third, "Government Incentives" scenario, Government offers financial assistance to private businesses making investments through the use of economic incentives. Incentives can include tax abatements, tax revenue sharing, grants, infrastructure assistance, no or low-interest financing, free land, tax credits, and other financial resources. Thus, there seems to be more private sector involvement leading to a greater market competition, resulting in an overall energy price decrease. This could make the public feel more comfortable to consume more energy. In this scenario, the concept "Government Incentives" was clamped to 1, so the researchers can estimate through the simulation process the degree this concept affects the examined energy system.

4.5.4 Scenario analysis/simulation

The simulation process as thoroughly described in section 2.7, involves the FCM-based model simulation [14] following the scheduled "what-if" scenario analysis. This process can be performed by the FCMWizard tool after the desired parameters, such as the initial stimulus state vector, the inference rule's type, the transfer function, its learning parameter, and the number of iterations or the convergence step need to be specified and properly defined. Users are also offered the open/closed lock option to set and keep the value of a concept unchained throughout iterations, as being "clamped" [87].

In what follows, a detailed example of scenario analysis using FCMWizard is presented to exhibit in details the process of model simulation. This example is included in the study of [128] which was published as part of the proceedings book of abstracts in the IEEE-WCCI2020 conference. In particular, the simulation model for this exemplary case study is part of the full version of the examined model presented in this chapter. More specifically, this model considers only 10 out of the 29 concepts assigned by the experts, as the most significant concepts for a preliminary decision-making analysis. These 10 concepts are C1-"Development of solar photovoltaic energy", C2-"Public knowledge of PSE", C3-"Purchase cost", C4-"Energy demand", C5-"Government incentives", C6-"Private sector involvement", C7-"Energy dependence concerns", C8-"Payback Period", C9-"Energy price" and C10-"Economic situation". The produced FCM model is illustrated in Figure 4.6, whereas a screenshot of the corresponding adjacency matrix, as produced by the tool, is depicted in Figure 4.7.

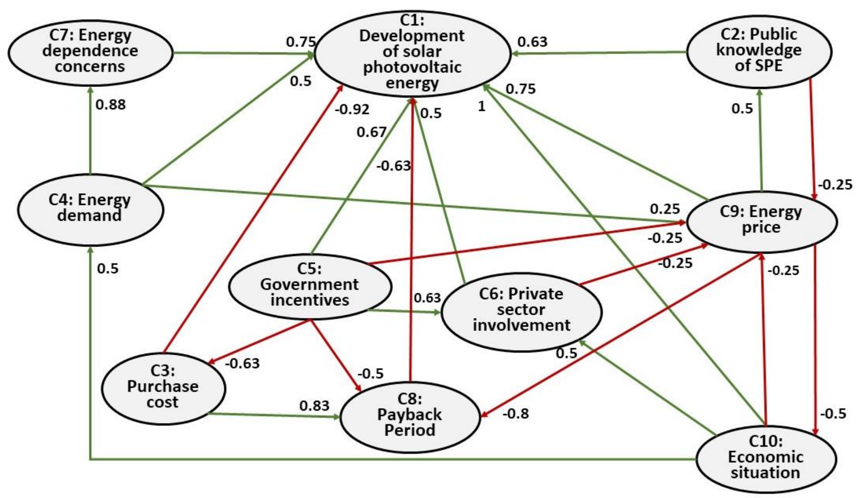


Figure 4.6: 10-nodes FCM model produced by stakeholders

Weight Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0	0	0	0	0	0	0	0	0	0
C2	0.63	0	0	0	0	0	0	0	-0.25	0
C3	-0.92	0	0	0	0	0	0	0.83	0	0
C4	0.5	0	0	0	0	0	0.88	0	0.25	0
C5	0.67	0	-0.63	0	0	0.63	0	-0.5	-0.25	0
C6	0.5	0	0	0	0	0	0	0	-0.25	0
C7	0.75	0	0	0	0	0	0	0	0	0
C8	-0.63	0	0	0	0	0	0	0	0	0
C9	0.75	0.5	0	0	0	0	0	-0.8	0	-0.5
C10	1	0	0	0.5	0	0.5	0	0	-0.25	0

Figure 4.7: Screenshot of weight matrix.

For the examined case, the simulation example is devoted to the investigation of the impact of concept C5-“Government incentives” on the other concepts and the examined system, too. The first step of this process deals with the investigation of a baseline scenario, where all the initial values of concepts are zero. In the next step, a comparison between the results of the conducted scenarios and those of the baseline scenario is performed. The Table with concepts values produced in the baseline scenario for all iterations steps, is presented below.

Table 4.6: FCM iterations steps in the baseline scenario

Concepts	***Iterations***								
	0	1	2	3	4	5	6	7	8
C1	0.5	0.893	0.956	0.965	0.966	0.966	0.966	0.966	0.966
C2	0.5	0.679	0.720	0.726	0.726	0.726	0.726	0.726	0.726
C3	0.5	0.546	0.538	0.532	0.529	0.529	0.528	0.528	0.528
C4	0.5	0.679	0.723	0.733	0.735	0.736	0.736	0.736	0.736
C5	0.5	0.622	0.651	0.657	0.657	0.659	0.659	0.659	0.659
C6	0.5	0.744	0.805	0.818	0.821	0.821	0.822	0.822	0.822
C7	0.5	0.719	0.789	0.806	0.810	0.811	0.811	0.811	0.811
C8	0.5	0.566	0.570	0.57	0.57	0.570	0.570	0.570	0.570
C9	0.5	0.531	0.512	0.501	0.497	0.496	0.496	0.496	0.496
C10	0.5	0.562	0.574	0.579	0.581	0.582	0.583	0.583	0.583

Let us now consider the concept “Government Incentives” (C5) for the considered PSE problem, and investigate how it affects the other concepts. In the scenario analysis, where this concept is “activated”, users need to set up the tool by defining various parameters for the simulation process, such as the inference rule, the transformation function, the Lambda parameter and either the number of iterations or the convergence step. The screenshot in Figure 4.8 illustrates the options offered by FCMWizard, concerning the parameters configuration for the simulation process.

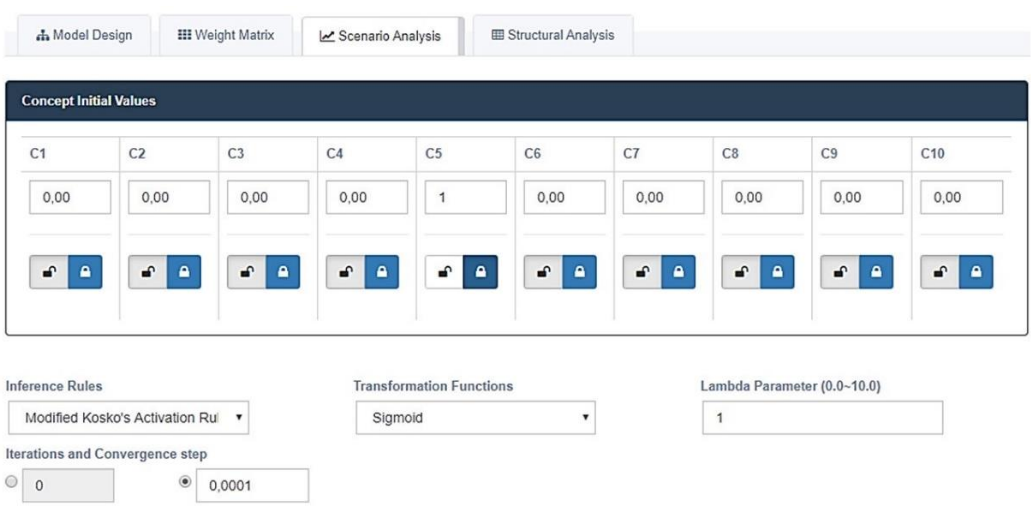
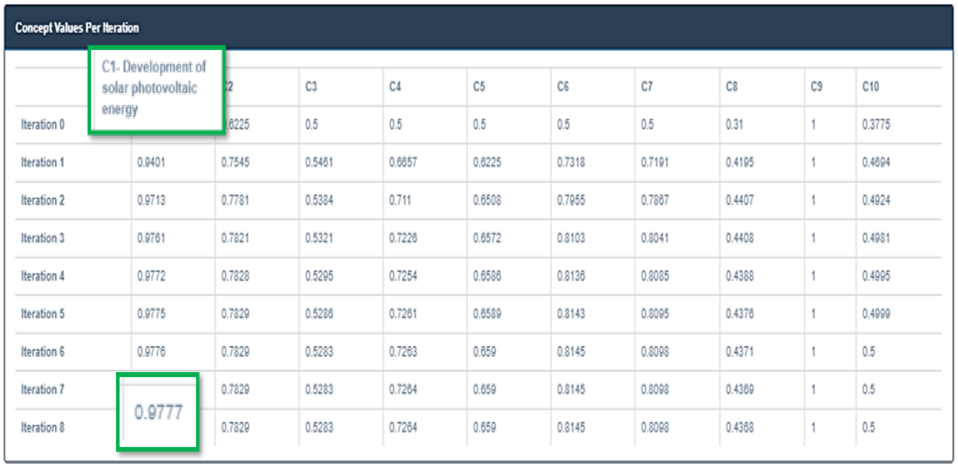


Figure 4.8: Screenshot of the Scenario analysis mode by FCM Wizard.

The produced results of this scenario analysis example, in the form of tables and graphs, are depicted in Table 4.7, Figure 4.9 and Figure 4.10, and can reveal the variety of functionalities and capabilities of the FCMWizard tool.



Concept Values Per Iteration

	C1- Development of solar photovoltaic energy	C2	C3	C4	C5	C6	C7	C8	C9	C10
Iteration 0		.6225	0.5	0.5	0.5	0.5	0.5	0.31	1	0.3775
Iteration 1	0.9401	0.7545	0.5461	0.6657	0.6225	0.7318	0.7191	0.4195	1	0.4694
Iteration 2	0.9713	0.7781	0.5384	0.711	0.6508	0.7955	0.7867	0.4407	1	0.4924
Iteration 3	0.9761	0.7821	0.5321	0.7226	0.6572	0.8103	0.8041	0.4408	1	0.4981
Iteration 4	0.9772	0.7828	0.5295	0.7254	0.6586	0.8136	0.8085	0.4388	1	0.4995
Iteration 5	0.9775	0.7829	0.5286	0.7261	0.6589	0.8143	0.8095	0.4376	1	0.4999
Iteration 6	0.9776	0.7829	0.5283	0.7263	0.659	0.8145	0.8098	0.4371	1	0.5
Iteration 7	0.9777	0.7829	0.5283	0.7264	0.659	0.8145	0.8098	0.4369	1	0.5
Iteration 8		0.7829	0.5283	0.7264	0.659	0.8145	0.8098	0.4368	1	0.5

Figure 4.9: Screenshot of the Table with concepts' values for each iteration from FCMwizard.

Table 4.7: Concepts' values for the examined scenario

Concepts	***Iterations***								
	0	1	2	3	4	5	6	7	8
C1	0.661	0.946	0.973	0.976	0.976	0.976	0.976	0.976	0.976
C2	0.5	0.672	0.713	0.721	0.722	0.722	0.722	0.722	0.722
C3	0.347	0.429	0.450	0.455	0.456	0.457	0.457	0.457	0.457
C4	0.5	0.679	0.724	0.734	0.736	0.737	0.737	0.737	0.737
C5	1	1	1	1	1	1	1	1	1
C6	0.652	0.822	0.850	0.855	0.855	0.856	0.856	0.856	0.856
C7	0.5	0.719	0.789	0.806	0.810	0.811	0.811	0.812	0.812
C8	0.377	0.454	0.483	0.495	0.5	0.502	0.502	0.502	0.502
C9	0.438	0.475	0.469	0.466	0.465	0.464	0.464	0.464	0.464
C10	0.5	0.569	0.582	0.586	0.587	0.588	0.588	0.588	0.588

Figure 4.10: Graphical plot of convergence performed by FCMWizard

As observed in Table 4.7, the value of the examined concept C5 remains unchanged, while the final value of concept C1 in the examined scenario has changed compared to that of the Baseline scenario, after same number of iterations have been completed. Thus, it can be concluded that concept C5-"Government Incentives" affects the concept C1-"development of solar photovoltaic energy". Figure 4.11 illustrates the deviations from the steady state (Baseline scenario) for all key concepts of the studied PSE problem.

From this exemplary scenario analysis, it is clearly observed that concept C5 has a negative effect on concepts C2, C3, C8 and C9, whereas a relatively minor positive influence can be seen on concepts C1, C4, C6 and C7.

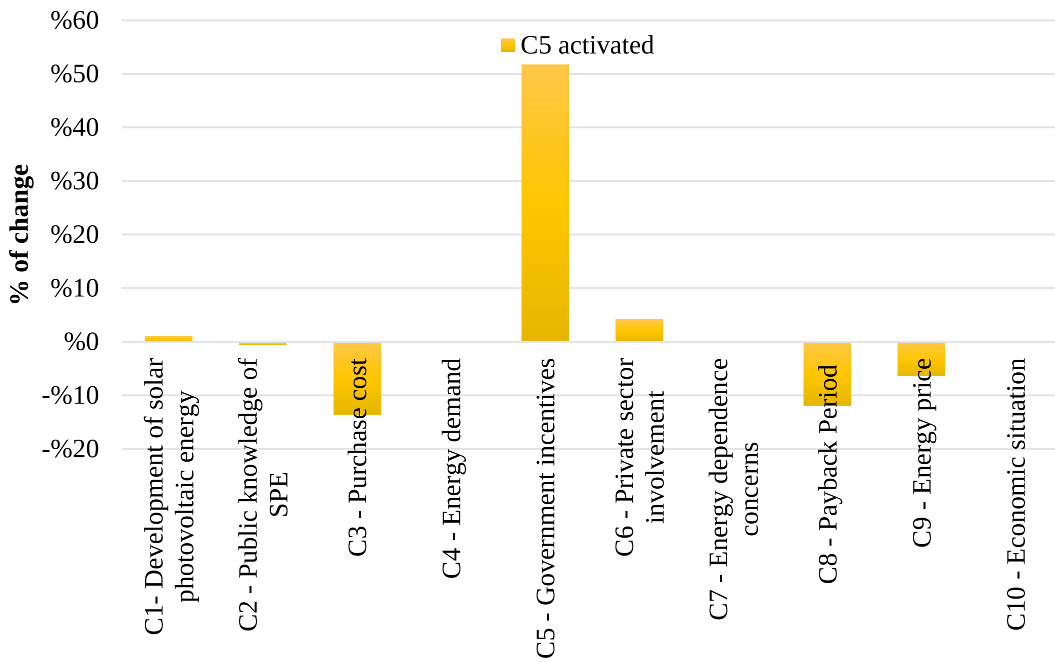


Figure 4.11: Percentage of change for key concepts when concept C5 is activated.

4.6 Results

For a deeper understanding of the examined problem, such as the concepts behavior, their relations and the extent to which one concept affects others, an FCM simulation process is needed. This process entails the multiplication of the input vector with the adjacency matrix, and in the output vector a transfer function (Equation (2.31)) is applied each time as a threshold function, until the system reaches a stable state. This study employs the FCMWizard tool to simulate and analyze the problem [87].

The process of FCM-based simulation is performed by "clamping" the initial value of certain key concepts each time. This outcome is compared against a baseline scenario where the system reaches the steady state. After analyzing the deviations of concepts values between the baseline steady state and the outcome of the simulation process, researchers can interpret the impact of the key concepts on the system on a quantitative basis.

Before the simulation process takes place, a baseline scenario needs to be conducted, so in the next step there will be a comparison between the results of the three scenarios and those resulting from the state of the model where all the initial values of concepts are zero (baseline scenario). In Figure 4.12, an exemplary table with the first 20 concepts values in all iterations steps, regarding the baseline scenario, is presented, while Figure 4.13 depicts the corresponding graph showing the steady state of every concept comprising this FCM model.

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
0.9925	0.7311	0.7058	0.6792	0.7058	0.4838	0.6225	0.7549	0.6792	0.7311	0.7191	0.7667	0.5927	0.8442	0.6225	0.5659	0.5622	0.4073	0.6514	0.9325
0.9995	0.8123	0.7891	0.7074	0.7712	0.3953	0.6508	0.8393	0.742	0.8285	0.7899	0.8563	0.6109	0.9209	0.6508	0.5366	0.5521	0.306	0.7232	0.98
0.9997	0.8351	0.8121	0.7027	0.7861	0.3535	0.6572	0.8618	0.7616	0.8519	0.8068	0.8788	0.617	0.9343	0.6572	0.5143	0.5415	0.2627	0.7481	0.9854
0.9998	0.8407	0.8174	0.6972	0.788	0.339	0.6586	0.8676	0.7672	0.8565	0.8102	0.8839	0.6197	0.937	0.6586	0.5057	0.537	0.249	0.755	0.9865
0.9998	0.842	0.8186	0.6946	0.7877	0.3346	0.6589	0.8691	0.7687	0.8574	0.8108	0.8851	0.6209	0.9376	0.6589	0.5029	0.5357	0.2452	0.7567	0.9867
0.9998	0.8423	0.8189	0.6936	0.7873	0.3334	0.659	0.8695	0.7691	0.8575	0.8109	0.8853	0.6213	0.9377	0.659	0.5021	0.5354	0.2443	0.7571	0.9867
0.9998	0.8424	0.8189	0.6933	0.7871	0.333	0.659	0.8696	0.7692	0.8576	0.8109	0.8854	0.6215	0.9377	0.659	0.5018	0.5354	0.2441	0.7572	0.9867
0.9998	0.8424	0.8189	0.6932	0.787	0.3329	0.659	0.8696	0.7692	0.8576	0.8109	0.8854	0.6215	0.9377	0.659	0.5017	0.5354	0.244	0.7573	0.9867
0.9998	0.8424	0.8189	0.6932	0.787	0.3329	0.659	0.8696	0.7692	0.8576	0.8109	0.8854	0.6215	0.9377	0.659	0.5017	0.5354	0.244	0.7573	0.9867

Figure 4.12: Screenshot of the FCM iterations steps in the baseline scenario (FCMWizard tool).

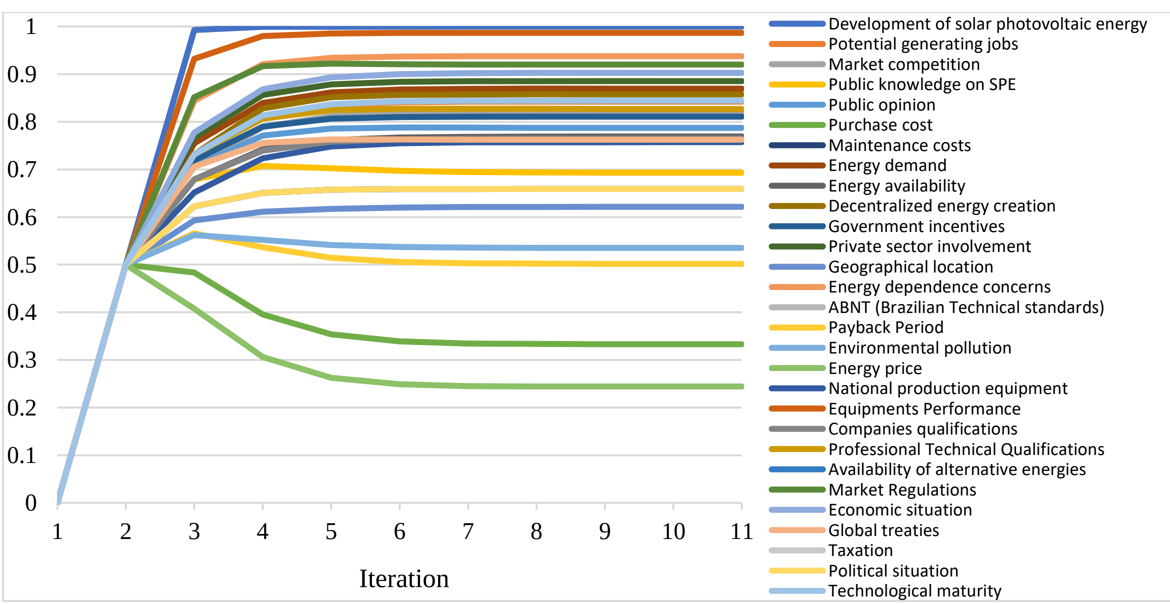


Figure 4 13: Screenshot of the graph regarding concepts' values in the Baseline scenario.

As it was reported in the "Scenario Analysis" section, the simulation process started after the baseline scenario had been performed. Then, scenario analysis performed simulations for the selected three scenarios (Table 4.5). In this context, scenario 1 (S1) was devoted to increasing the decision concept C18—"Energy price" by "clamping" it to one. Scenario 2 (S2) studied the effects of the decision concepts C4—"Public Knowledge on PSE", C5—"Public opinion", C11—"Government Incentives" and C17—"Environmental pollution" by clamping the values of these concepts to one. In the end, Scenario 3 (S3) investigated how the increase of decision concept C11—"Government Incentives" affects the examined system, when "clamping" its values to one. The results for scenario analysis are illustrated in the following figures. The results are interpreted by comparing the relative change between this baseline scenario and the new steady state.

Let us now consider the Scenario S3, that concept "Government Incentives" (C11) is activated for the considered PSE problem, and the process of how this concept affects the other concepts needs to be investigated. For performing the scenario analysis, a number of parameters need to be defined such as the inference rule, the transformation function, Lambda parameter, and either the number of iterations or the convergence step. All these simulation options and learning parameters are offered by the tool. In particular, it supports three FCM inference rules, four threshold functions, besides the possibility of customizing other parameters too [101].

In Figure 4.14, a screenshot of the options provided by "FCMWizard" is provided, regarding the parameters' configuration for the simulation process. Specifically, the initial value of the concept C11 was clamped to 1, the Modified Kosko's activation rule and the Sigmoid transformation function were selected, as well as the Lambda parameter and the convergence step were set to 1 and 0.0001 respectively. The produced values for every concept of this scenario analysis example are depicted in Table 4.8 and Figure 4.15, as follows.

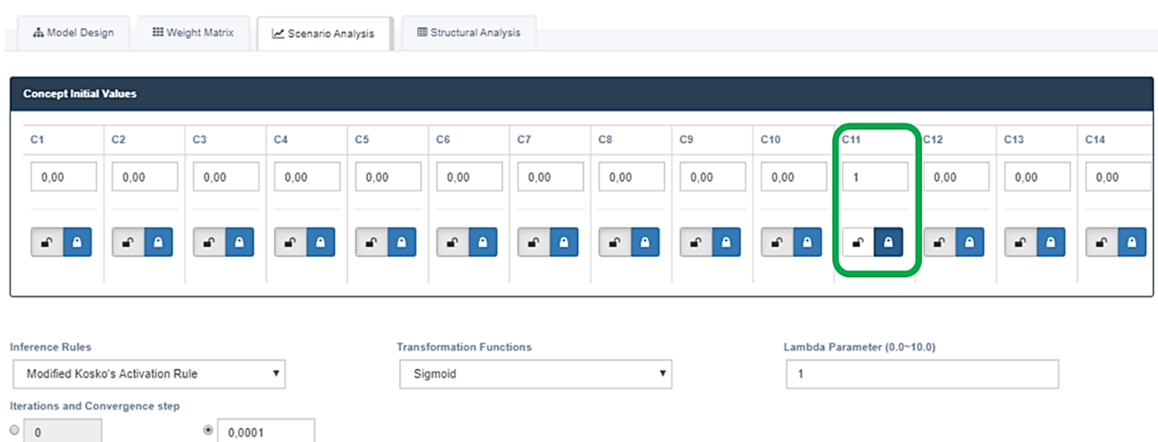


Figure 4.14: Screenshot of the Scenario analysis mode by FCM Wizard.

Table 4.8: Table with concepts' values for each iteration, produced from FCMwizard.

Runs	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Iteration 0	0.661	0.679	0.5	0.5	0.5	0.347	0.5	0.5	0.5	0.5	1
Iteration 1	0.996	0.825	0.713	0.672	0.705	0.341	0.622	0.759	0.679	0.731	1
Iteration 2	0.999	0.854	0.793	0.700	0.770	0.306	0.650	0.840	0.742	0.828	1
Iteration 3	0.999	0.861	0.813	0.698	0.785	0.297	0.657	0.862	0.761	0.851	1
Iteration 4	0.999	0.862	0.818	0.694	0.787	0.296	0.658	0.867	0.767	0.856	1
Iteration 5	0.999	0.862	0.819	0.692	0.787	0.296	0.658	0.869	0.768	0.857	1
Iteration 6	0.999	0.862	0.819	0.69	0.787	0.296	0.659	0.869	0.769	0.857	1
Iteration 7	0.999	0.862	0.819	0.691	0.786	0.296	0.659	0.869	0.769	0.857	1
Iteration 8	0.999	0.862	0.819	0.691	0.786	0.296	0.659	0.869	0.769	0.857	1
Iteration 9	0.999	0.862	0.819	0.691	0.786	0.296	0.659	0.869	0.769	0.857	1

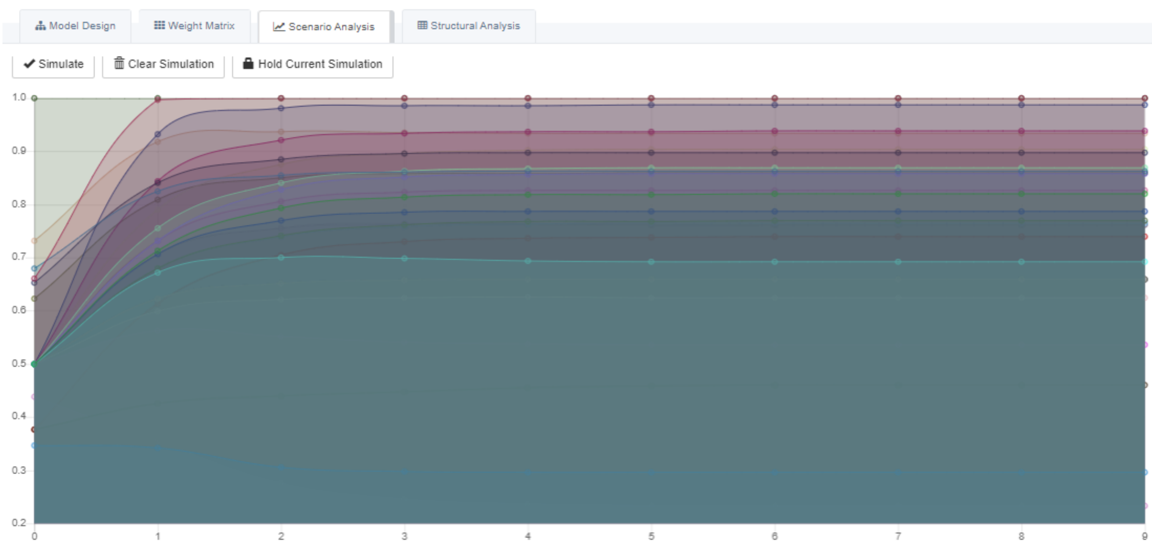


Figure 4.15: Graphical plot of convergence performed by FCMWizard.

Figures 4.16, 4.17 and 4.18 illustrate separately the outcomes of the three scenarios performed (S1, S2 and S3 respectively) for each concept whereas, Figure 4.19 gathers all the outcomes after the three scenarios were performed with respect to the percentage of change (deviations from the steady state). Thus, through the analysis and further interpretation of the results produced for the examined renewable energy system scenario, policy makers will be allowed to select the right strategies in this direction. Negative values mean that the concepts have negative acceleration, whereas positive values imply that the concepts have positive acceleration. Worth mentioning is the fact that a negative change in the value of development of solar energy (C1) is regarded as a deceleration in deployment and diffusion of solar energy compared to the current state.

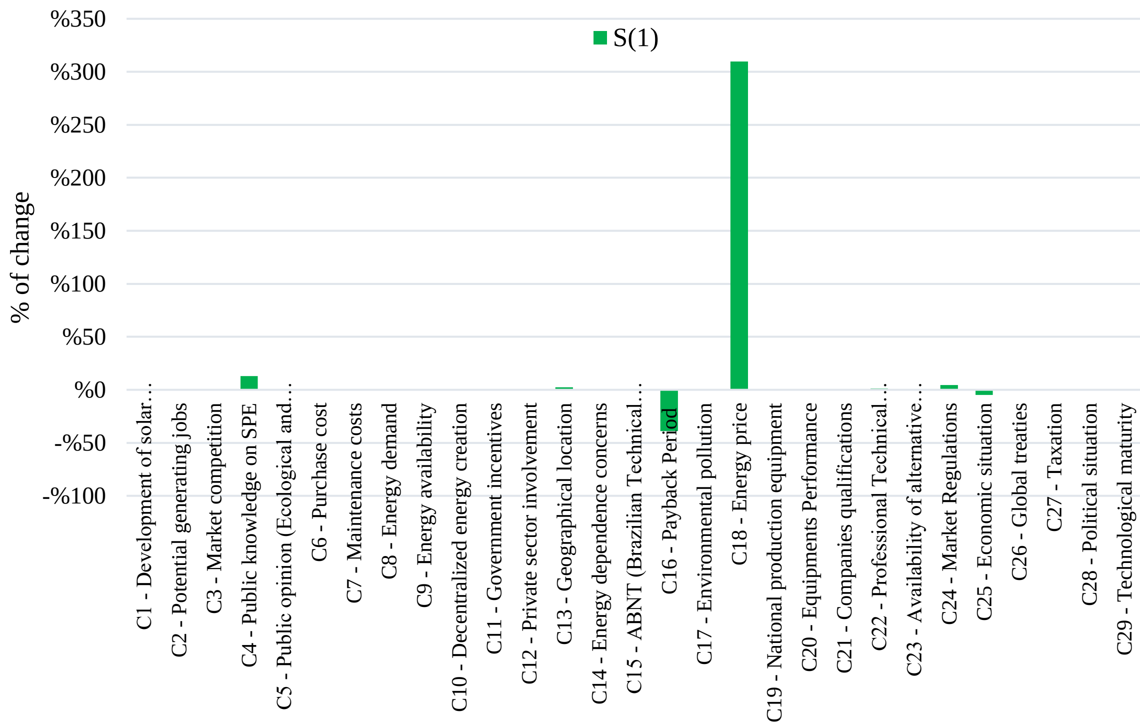


Figure 4.16: Percentage of change (deviation) for all key concepts when concept C18 is activated (S1).

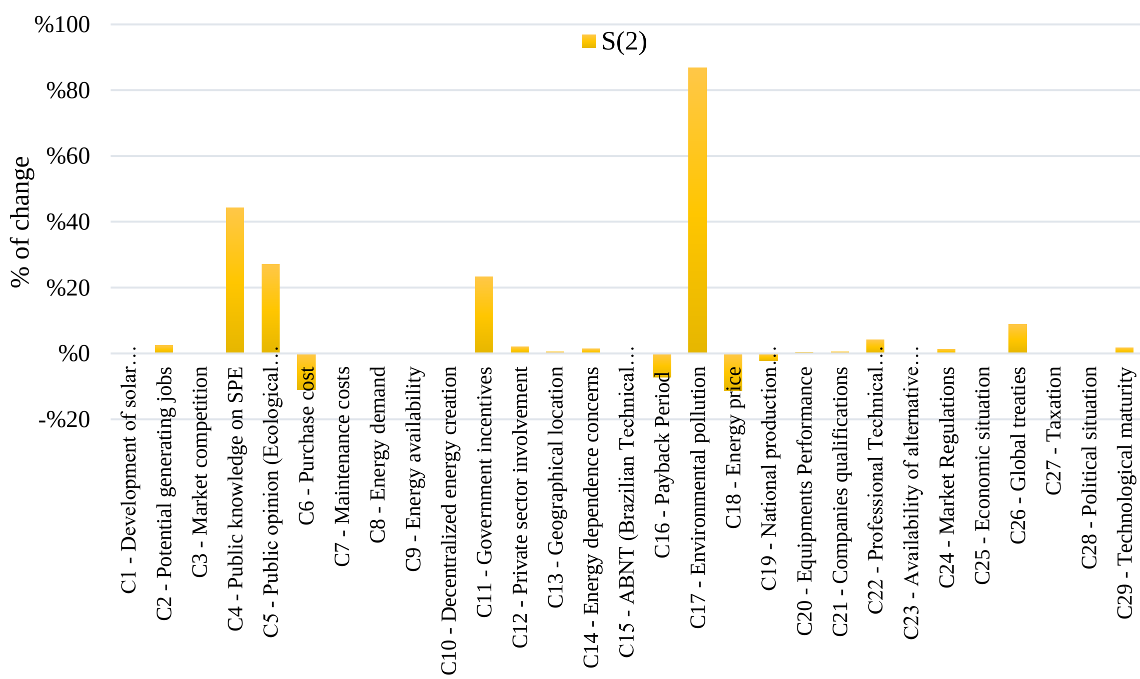


Figure 4.17: Percentage of change (deviation) for all key concepts when concepts C4, C5, C11, and C17 are activated (S2).

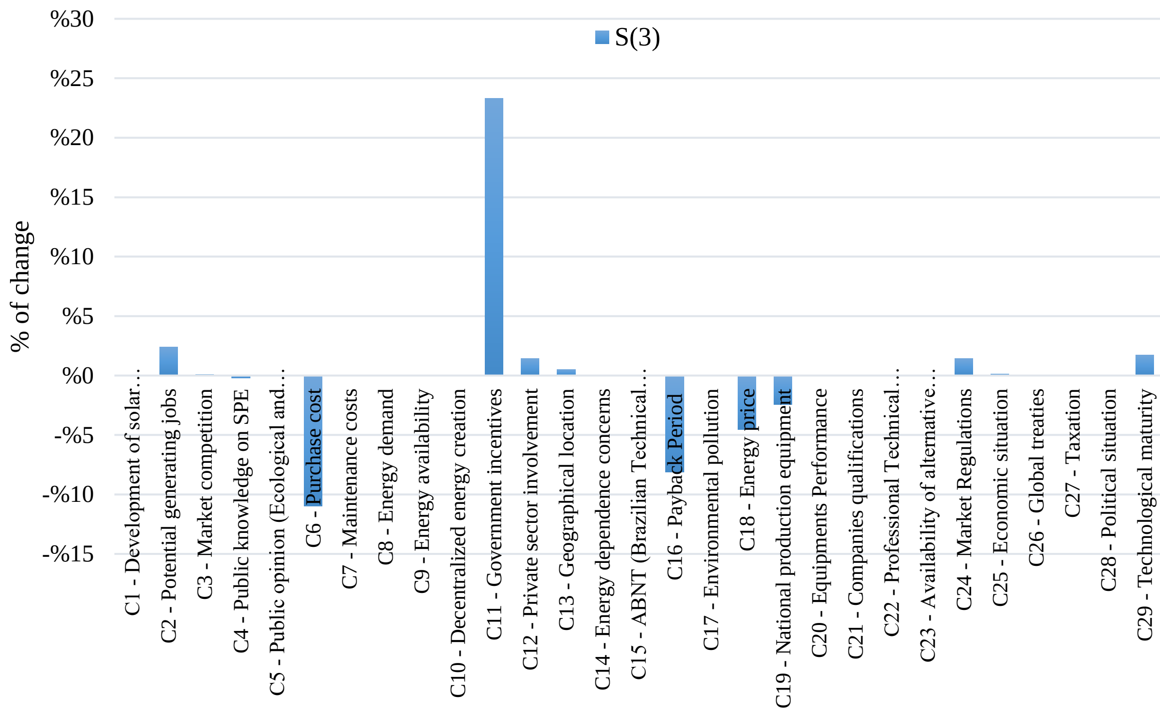


Figure 4.18: Percentage of change (deviation) for all key concepts when concept C11 is activated (S3).

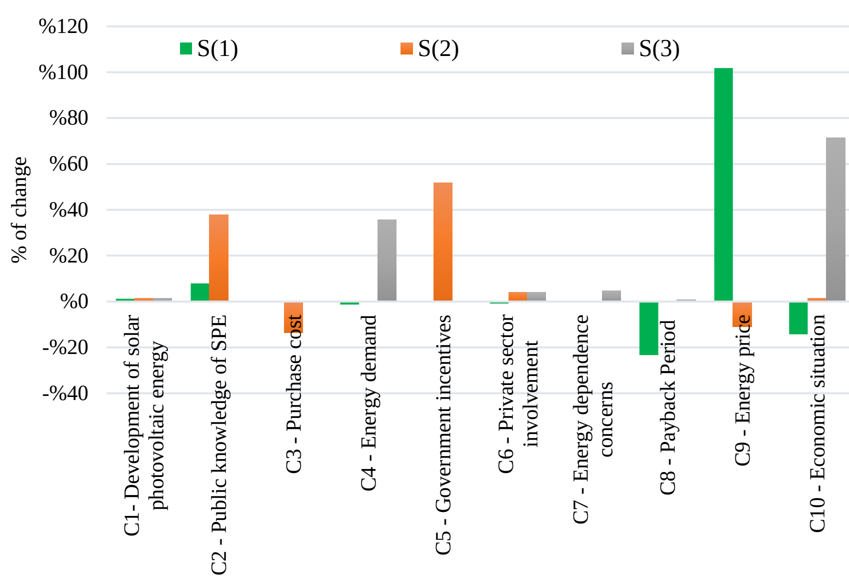


Figure 4.19: Scenario Analysis graph that illustrates the deviations for all key concepts, compared to the initial steady-state (baseline scenario).

The end goal of the examined case study was set to be the development of solar photovoltaic energy sector in Brazil, which is represented by the concept C1. Therefore, the scenario analysis mainly focuses on the impact that the decision concepts have on this output concept C1-

"Development of solar photovoltaic energy", which is considered by the researchers as the main objective of this project.

Accordingly, the deviations for this concept (C1) are properly calculated after performing all three different scenarios. The results regarding the deviations of concept C1, compared to the initial state, after the three scenarios were performed, are depicted in Figure 4.20. It is observed that C1 is the most affected output concept when the third scenario (S3) is performed.

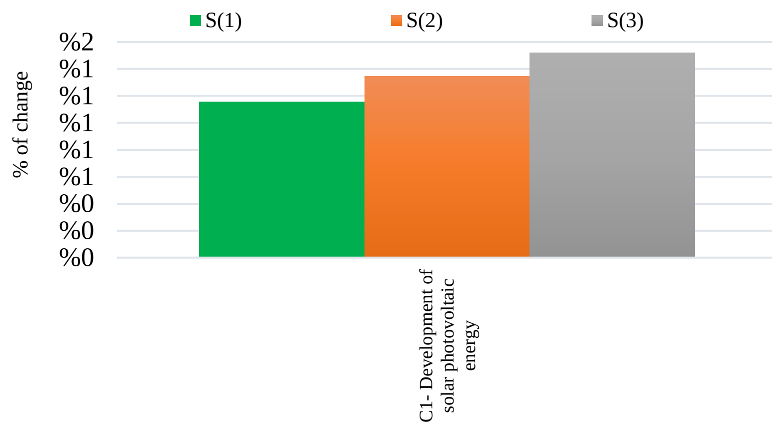


Figure 4.20: Decision concept C1 percentage of change, compared to the initial steady-state.

4.7 Discussion of Results

The problem of Brazilian PSE sector development is tackled with the FCMs methodology using FCMWizard's powerful simulation environment for policy making in the renewable energy domain. Users have the ability to form certain scenarios with the help of energy specialists and stakeholders from the specific domain and conduct simulations in order to observe how the examined system responds to changes of certain concepts values. Casting a thorough look on the results presented in the figures above (Figures 4.16, 4.17 and 4.18), certain conclusions can emerge for each scenario conducted.

The overall observations that were drawn from the figures above, focus on the following points:

- Considering the first conducted scenario (S1) and the "clamped" decision concept C18—"Energy price", the final values of decision concepts C1, C4, C13, C16, C24, and C25 have changed (increased or decreased) compared to those of the baseline scenario, for the same number of iterations. Thus, it can be concluded that concept C18—"Energy price" mainly affects positively decision concepts C1, C4, C13, and C24, whereas concepts C16 and C25 are negatively affected.
- Following the same direction, the results of scenario S2 (see Figure 4.17) reveal that an overall increase in decision concepts C4, C5, C11, and C17 leads to a slight increase in the

values of most concepts, while concepts C1, C2, C12, C22, and C25 seem to be positively affected to a greater extent. On the other hand, there is a noteworthy decrease in the final values of concepts C6, C16, C18, and C19.

- In the case of the third scenario and the clamped concept C11—"Government Incentives", the increase of its value is directly connected to an increase of the values of key concepts C2, C12, C13, C24, and C29. On the contrary, concept C11 affects inverse concepts C6, C16, C18, and C19.
- The participant concepts of Scenarios S1 and S2 have a significant positive impact on decision concept C1, which is the main outcome of this study, whereas Scenario 3 does not present any impact on that concept.
- When concept C11—"Government Incentives" is combined with other concepts, as participant concepts of the same scenario (S2), then it contributes to the increase of the decision concept C1 and the overall change of the examined system's state. When it performs individually, as a single concept of Scenario S3, then no impact on concept C1-"Development on PSE" and the overall system status are noticed.

Focusing on the first scenario (S1), the outcomes showed that an increase in energy price led people to seek new energy sources alternatives and thus, energy demand was decreased, while public awareness of the SPE was increased, given that the payback period decreased. Furthermore, since the companies might have identified a very turbulent and disadvantageous market to exploit, a reduction in the private sector involvement is observed. Without the participation of the private sector, the purchase cost increased.

The conclusions for the second scenario (S2) are briefly presented as follows. Since environmental pollution has sharpened people's ecological awareness and knowledge on PSE, the Brazilian government creates various initiatives and programs to foster the growth of this sector, reducing the payback time of the investment. Part of the demand for energy migrated to the PSE and the price of electricity provided by the government, decreased. The purchase cost decreased accordingly.

In response to the third scenario (S3), where government incentives are considered, economic incentives and other financial resources, given by the government, can possibly cause a significant increase in private sector involvement and greater competition in the PSE market, resulting in a bigger employment capacity. A decrease in energy price is possible and consequently, the country's own inhabitants will feel more confident to consume more energy in their daily life.

Considering the key concepts of the three conducted scenarios, it emerges that government incentives are mostly able to change the stability of Brazil's Renewable Energy system. After a critical overview of the overall results, it is unlikely the PSE sector develops much, unless there are noteworthy political and economic changes in the status of the country. Moreover, the FCM-based simulation process has shown that Brazil's PSE development is dependent on economic parameters such as the incentives given by the government and is influenced by uncertain factors like public ecological awareness. In addition, the penetration of the private sector in the PSE can affect the dynamics of the system as well as have an impact on the everyday life of Brazilian citizens.

The conducted scenarios highlight the system's uncertainty and show to the policy makers how they can develop effective strategies for creating a more robust system that is free from possible future instabilities. The tool settings that are offered, can help users to conduct further scenarios and try different configurations by activating different variables, individually or in a set, as well as by changing the weighted interconnections among them, in order to see how the model reacts in different circumstances.

4.8 Concluding remarks

This chapter explores the contribution of the Fuzzy Cognitive Map methodology by means of an efficient simulation tool called FCMWizard. This software has been developed to implement certain tasks such as modeling experts' knowledge, learning and simulating FCM-based complex systems, in participatory domains. The basic idea behind this effort was to provide experts, stakeholders or both, that belong to various scientific areas, with a free under request, user-friendly and flexible, as regards the number of variables and weights, tool, which can be used anytime and in any discipline or domain without time or memory restrictions. This efficient software that uses certain learning algorithms, offers to users the ability to easily and intuitively design models for a wide range of problems, as well as perform scenario planning for making strategic decisions and policy making in a simple, user-friendly environment, without any computational cost.

The innovation in this work is based on the fact that, decision-makers can apply the Fuzzy Cognitive Map technique along with the proposed software tool to model experts' and stakeholders' perceptions and further conduct different scenarios implemented by the FCMWizard tool. In this context, policy-making can be carried out in various domains and with different configurations of the tool, regarding the type of inference rules, the number of variables, and the weights values or concepts selection in the scenario planning, thus highlighting the generic applicability and usefulness of the new tool.

To show the functionalities and examine the performance of this flexible and interactive web-based software, a case study was elaborately investigated concerning the development of Brazil's Photovoltaic Solar energy sector and a relevant scenario analysis was conducted. The main outcomes of this research can surely assist regulatory authorities of Renewable Energy in deciding about efficient strategies with respect to optimal exploitation of the PSE sector and Brazil's overall socio-economic growth.

Chapter 5

Demand Forecasting Using Fuzzy Methods

5.1 Introduction

Demand forecasting has been a highly important and dynamic research domain, having wide applicability to many diverse scientific fields, ranging from ecological modeling to energy [49], finance [50], tourism [51], and electricity load [52]. A summary of applications regarding forecasting in various areas can be found in a plethora of review papers published in the relevant literature [129–133]. To Energy, demand forecasting has a vital role in terms of supply and demand management for private companies and governments [134]. Especially in the last decades, there has been a remarkable increase in energy consumption all over the world due to the increasing technological advancements and the rapid global population growth. For this reason, the need for energy demand management became crucial for achieving economic success, thus resulting in self-sufficiency and economic development [135]. Accordingly, energy consumption forecasting is essential, as it predicates an energy efficient policy, optimization of usage and energy supplies optimum management. Even though a variety of methods have been investigated for energy demand forecasting, this is not an easy task, as it is affected by uncertain exogenous factors such as weather, technological development and government policies [136].

Among all energy resources, Natural Gas (NG) has particularly received the largest increase in consumption lately [137], mostly due to its popularity as a clean energy source, with respect to environmental concerns. This energy source is characterized by low-level emissions of greenhouse gases in comparison with other non-renewable energy sources [48, 138] and is considered as the cleanest-burning fossil fuel [139]. One fifth of the world's primary energy demand is covered by NG [48] and is linked to industrial production, transportation, health, agricultural output and household use. Natural gas demand seems to increase considerably due to several socio-economic and political reasons, while price and environmental concerns are significant regulatory factors affecting natural gas demand. Therefore, the prediction of natural gas consumption, as a time series forecasting problem, is becoming important in contemporary energy systems, allowing energy policymakers to apply effective strategies in order to guarantee sufficient natural gas supplies.

5.2 Related Research Work in Energy Domain

So far, many research papers have tried to give a clear insight regarding energy forecasting by suggesting models for predicting energy consumption. Various models have also been proposed in the field of NG forecasting, as a non-renewable source of energy. A summary of both energy and NG consumption forecasting regarding prediction methods, input variables used for modelling, as well prediction area, can be found in many review papers in the relevant literature. For example, and as far as NG forecasting is concerned, there is a thorough literature survey of published papers [48, 138, 140] that classifies various models and techniques that have been recently applied in. There has been also an attempt by researchers to classify all models applied in this area according to their performance characteristics, as well as to offer some future research directions. The models presented, were developed by researchers with the aim to predict NG consumption on hourly, daily, weekly, monthly or yearly basis with an acceptable degree of accuracy. Overall, the current section encapsulates the related literature that regards the application of traditional AI techniques along with soft computing methods such as neural networks, fuzzy logic and other hybrid methods developed, to predict the energy consumption with a particular focus on NG demand.

5.2.1 AI in Energy Demand Forecasting

ANN, Genetic Algorithm (GA) and fuzzy inference systems (FIS), as Artificial Intelligence (AI) techniques, are among those methods that are often used in energy domain and specifically for energy demand forecasting, due to their high flexibility, reasonable estimation and prediction ability. From the relevant literature, there have been several attempts in energy forecasting by ANN, like those in [141–143]. ANN has been applied to forecast electric energy consumption in Saudi Arabia [144], energy consumption of a passive solar building [145], energy consumption of the Canadian residential sector [146], the peak load of Taiwan [147], while ANNs have been further explored in [148–150] for short-term load forecasting. An Abductive network machine learning for predicting monthly electric energy consumption in domestic sector of Eastern Saudi Arabia was proposed in [151]. Moreover, Support Vector Machines (SVMs) and Genetic Algorithms (GA) were explored in [141, 152] to predict electricity load. In [153], SVMs coupled with empirical mode decomposition were used to perform long term load forecasting. GAs have been used in [154] to estimate Turkey's energy demand and electricity demand in industrial sector, respectively. In addition, Azadeh et al. have proposed the integration of GAs and ANNs to estimate and predict electrical energy consumption [155]. A number of literature reviews have also been performed regarding various energy fields. For example, in [156] a review of the conventional methods and AI methods for electricity consumption forecasting is provided, while in [157] the strengths, shortcomings, and purpose of numerous AI-based approaches in the energy consumption forecasting of urban and rural-level buildings are discussed. In [158], a review about conventional models, including time series models, regression models and gray models has been conducted with respect to energy consumption forecasting. Moreover, an overview of AI methods in short term electric load forecasting area have been discussed in [159].

5.2.2 AI applied in Natural Gas consumption forecasting

On the other hand, there are many studies where different AI methods like Neural Networks, Neuro-Fuzzy and other ANN topologies have been investigated and applied in NG demand forecasting [160–167]. In this context, ANNs have been extensively used in [162, 165, 167–172] to investigate short-term NG forecasts, while in [164], different types of ANN algorithm were explored to forecast gas consumption for residential and commercial consumers in Istanbul, Turkey. ANN was also used in [173] for daily and weekly prediction of NG consumption of Siber, using historical temperature and NG consumption data, in [174] for NG output prediction of USA until 2020, as well as in [175] for prediction of NG consumption and production in China from 2008 to 2015, applying the grey theory along with NNs. Furthermore, a combination of ANNs was applied in [162, 163] for the prediction of NG consumption at a citywide distribution level.

More recent studies present numerous techniques for NG demand forecasting, including computational intelligence-based models (ANNs), fuzzy logic and support vector machines [47, 176–178]. In this sense, a combination of recurrent neural network and linear regression model is used in [179] to generate forecasts for future gas demand, whereas a Multi Layered Perceptron (MLP) neural network was deployed in [180] to estimate the next day gas consumption. A day-ahead forecast was also examined in [181] by developing a Functional AutoRegressive model with eXogenous variables (FARX). Moreover, machine learning tools such as Multiple Linear Regression (MLR), ANN and Support Vector Regression (SVR) were devised in [182] to project NG consumption in the province of Istanbul, as well as in [179] to forecast the residential NG demand in the city of Ljubljana, Slovenia. When considering AI methods, self-adapting intelligent grey models were also deployed for forecasting NG demand, as in [183].

Regarding neural network algorithms, the multilayer perceptron and the radial basis function network with different activation functions were trained and tested in [168–170], while the authors in [171] used a multilayer perceptron algorithm for neural network and compared this model with two timeseries models. In addition, Taspinar et al. explored daily gas consumption forecasting through different methods including the seasonal autoregressive integrated moving average model with exogenous inputs (SARIMAX), multi-layer perceptron ANN (ANN-MLP), ANN with Radial Basis Functions (ANN-RBF), and multivariate Ordinary Least Squares (OLS) [169]. Different sets of AI methods were also implemented in the following studies regarding NG consumption. ANN with linear regression models were used in [184] for daily prediction, while ANN and Fuzzy ANN models were investigated in [185] regarding consumption in a certain region of Poland. Finally, it is worth mentioning that there has been a similar research in [47], which proposes the hybrid wavelet-ANFIS/NN model to compute day-ahead forecasts for 40 distribution nodes in the national NG system of Greece.

5.2.3 ANFIS in Energy Consumption Forecasting

There are plenty of works in the relevant literature regarding the application of the ANFIS model in forecasting energy consumption. As regards the electricity domain, ANFIS model was applied to forecast annual regional load in Taiwan [186] and annual demand in Turkey [187]. In both cases, the results were good and the ANFIS model performed better than regression, neural network and fuzzy hybrid systems. ANFIS was also used in [188] for short term electricity demand forecasting, using weekly electricity load data, as well as in [155], to estimate possible improvement of electricity consumption. Also, for electricity loads forecasting, ANFIS was used in [189] to highlight its superiority to ANN model, while it was furthermore applied in the field of transportation, forecasting the corresponding energy demand for the years 2010 to 2030, in the country of Jordan, revealing the efficiency of the examined model. Another study regarding the energy domain, where the ANFIS model was applied, is that of [190]. A long-term prediction of oil consumption is studied, which further examines the interrelationship between oil consumption and economic growth in Turkey, for the years 2012 to 2030.

5.2.4 ANFIS applied in Natural Gas Consumption Forecasting

Casting a view on the literature that refers to NG consumption forecast, only one study that devises solely an ANFIS model was found. Specifically, ANFIS was used in [191] to estimate the daily NG demand in Iran, which actually used an extremely small dataset of historical data for both testing and training (December 2007 – June 2008). Models trained on a small dataset attend to overfit, which results in high variance and very high error on a test set, producing inaccurate results. In this case, the predicting error decreases monotonically with the size of training set. The rest of the studies deal with approaches that combine ANFIS with other methods. For example in [168], statistical time series analysis along with ANN and ANFIS methods are applied in order to predict weekly NG consumption in Turkey. Moreover, an ANFIS-Fuzzy Data Envelopment Analysis (FDEA) was developed in [192] for long-term NG consumption forecasting and analysis. In this study, 104 ANFIS were constructed and tested and 6 models were proposed to forecast annual NG consumption. The same approach was proposed in [191] for accurate gas consumption estimation. 3 patterns of the hybrid ARIMA–ANFIS model were tested in [135], to predict the annual energy consumption in Iran, using a set of data like population, GDP, export and import. Finally, a hybrid model of adaptive neuro fuzzy inference system and computer simulation for the prediction of NG consumption, was developed in [193].

5.2.5 FCMs in Energy and Natural Gas Consumption Forecasting

Other soft computing techniques, like evolutionary FCMs, have also been applied for modeling and prediction of time series problems. The dynamic modeling structure of FCMs inheriting the learning capabilities of recurrent neural networks, works properly for modeling and time series prediction. Regarding the task of multivariate time series prediction, Froelich and Salmeron proposed a nonlinear predictive model based on evolutionary algorithm for learning fuzzy grey cognitive maps [194], while Papageorgiou et al. [195] and Poczeta et al. [196] applied a new type of evolutionary FCMs enhanced with the Structure Optimization Genetic Algorithm (SOGA) in energy for electricity load forecasting. Through the SOGA algorithm, an FCM model can automatically be constructed by taking into consideration any available historical data. A two-stage prediction model for multivariate time series prediction, based on the efficient capabilities of evolutionary FCMs and enhanced by structure optimization algorithms and ANNs, was introduced in [197]. In the first stage of the prediction model, SOGA-FCM was applied for selecting the most significant concepts and defining the relationships between them. Next, that model was fed into the second stage to define the initial features and weights of the training ANN. This generic prediction approach was applied in four common prediction problems, one of them dealt with electric power consumption.

In [198], Poczeta and Papageorgiou conducted a preliminary study on implementing FCMs with ANNs for NG prediction, showing for first time the capabilities of evolutionary FCMs in this domain. Furthermore, the research team in [53] recently contacted a study for time series analysis devoted to NG demand prediction in three Greek cities, implementing an efficient ensemble forecasting approach through combining ANN, Real Coded Genetic Algorithm (RCGA)-FCM, SOGA-FCM, and hybrid FCM-ANN. In this research study the advantageous features of intelligent methods through an ensemble to multivariate time series prediction in NG demand forecasting are emerged.

5.3 Case Study and Dataset: Natural gas Demand

The dataset covers ten different prediction datasets of historical data referring to ten cities all over Greece (Alexandroupoli, Athens, Drama, Karditsa, Larissa, Markopoulo, Serres, Thessaloniki, Trikala and Volos) and was linked to the values of gas demand for eight (8) previous years, in total. It should be mentioned that the time period for each dataset (city) is not the same in duration and does not correspond to the same years of data with all the other datasets collected. Table 5.1 depicts the duration in years that is linked to each dataset collected and used in this case study. The historical datasets for 15 Greek cities were initially provided by NG Grid company of Greece, DESFA, which is responsible for the operation, management, exploitation and development of the Greek NG system and its interconnections. However, after a thorough review of the available datasets, only 10 out of 15 cities was decided to be included in the case study, since these datasets contained less outliers and missing values than the rest 5 datasets that were finally rejected, for data consistency purposes. For the datasets that were finally included in this work, a preliminary preprocessing phase was performed, where the insignificant outliers were removed, and any missing values were substituted with the average real value of the previous two days demand. The real data that have been used for ANFIS modeling, performance evaluation and comparison with other popular forecasting methods, were then split into training and testing samples. For all cities, the last year of each dataset (from November

2017 up to October 2018) was devoted to testing, whereas the rest of the years were used for training the developed ANFIS model.

Table 5.1: Time Period referred to each time-series dataset for all cities

City	Time period of the examined data	City	Time period of the examined data
Alexandroupoli	2/2013 - 10/2018	Markopoulo	3/2010 - 10/2018
Athens	3/2010 - 10/2018	Serres	6/2013 - 10/2018
Drama	9/2011 - 10/2018	Thessaloniki	3/2012 - 10/2018
Karditsa	5/2014 - 10/2018	Trikala	9/2012 - 10/2018
Larissa	3/2010 - 10/2018	Volos	3/2010 - 10/2018

In order to properly forecast day-ahead NG consumption demand for Greece, proper number and type of input parameters should be selected. Therefore, five factors have been carefully considered as input parameters and the amount of one day ahead NG consumption demand of each distribution point, as the output parameter. The prediction model is based on observations of past NG consumption, weather data, and calendar indicators, which are all among the most important input variables for prediction of NG consumption [140]. In particular, the dataset contains historical data of NG consumption of each city's distribution point, the daily average temperature of the area in Celsius degrees, a month indicator and a day indicator. As regards the previous NG consumption data, these are linked to two different input variables: demand of a day before and current day demand. The temperature data are obtained by the nearest to the distribution gas point meteorological station. Concerning the calendar indicators (month and day), they need to undergo certain data form preprocessing before their use. Specifically, two different input indicators need to be considered for each one of the two variables. That is, k=1,2,…,12 as month index (1-January, 2-February,…,12-December) and l=1,2,..,7 as day index (1-Monday, 2-Tuesday, …7-Sunday). Following the coding procedure as presented in [199], the index for month is scaled to the range [1/12, 1] in which the months of the year from January to December take successive values of the scaled index. That is, January has the value of 1/12 and December the value of 1. Similarly, the days of the week take successive values in the scaled range [1/7, 1], in which Monday and Sunday take the values of 1/7 and 1, respectively. All these parameters who constitute actual recorded data are briefly presented in Table 5.2.

Table 5.2: Input and Output parameters

TYPE	PARAMETER	UNIT
INPUT	demand of a day before	MWh
INPUT	current day demand	MWh
INPUT	daily average temperature	Celsius degrees
INPUT	Month indicator	k=1/12, 2/12, …, 1
INPUT	Day indicator	l=1/7, 2/7, ..., 1
OUTPUT	A day ahead NG demand	MWh

All data that compose the investigated dataset have undergone a normalization process. This was necessary because all entries need to have the same, limited range of values so the model produces meaningful results.

The algorithm that was used for data normalization is the Min-Max, which scales the values of the dataset linearly over a specific range. As described in previous works [53], each variable is normalized in the range [0, 1] before the forecasting model is applied. The normalized variable is taking again its original value when the testing phase is implemented. Data normalization is carried out mathematically, as follows:

$$x_i^{(new)} = \frac{x_i - x^{(min)}}{x^{(max)} - x^{(min)}}, \qquad \forall i = 1, 2, \dots, N \tag{5.1}$$

where, $x^{(new)}$ is the normalized value of the variable x, $x^{(min)}$ and $x^{(max)}$ are respectively, the minimum and maximum values of the concerned variable x.

The features gathered and used in this chapter for the FCM model construction were adequate as well as properly selected following the relevant literature regarding the prediction of natural gas consumption. In particular, from a recent literature review [140], past gas consumption combined with meteorological data (especially temperature) are the most common input variables for prediction of natural gas consumption. Another recent study [47] has used past consumption, temperature, months and days of week, while in [191], day of week and demand of the same day in previous year were used as input variables for NG forecasting. Hence, the selection of the specific features for the purposes of this chapter is in line with the practices described in the reported literature, and sufficient to predict the consumption of the examined energy domain.

5.4 Methods

5.4.1 Ensemble forecasting method

Prior to the presentation of the proposed ensemble of methods, the popular and efficient FCM-based evolutionary approaches for forecasting, called RCGA and SOGA, are presented in this section along with their hybrid combination with ANNs, (SOGA FCM-ANN), and the popular ANN architecture, as well. Also, the two most popular and commonly used ensemble methods, the AVG and the EB methods, are both described below, as they are applied to the ensemble forecasts to improve the prediction accuracy.

5.4.1.1 Individual forecasting methods based on FCMs and ANNs

Evolutionary algorithms are popular techniques for FCMs learning. In this section, we explore two effective techniques: Real-Coded Genetic Algorithm (RCGA) [54] and Structure Optimization Genetic Algorithm (SOGA) [197].

- *Real Coded Genetic Algorithm (RCGA)*

The RCGA algorithm defines individual in the population as follows [54]:

$$W' = \left[w_{1,2}, w_{1,3}, w_{1,4}, \dots, w_{j,i}, \dots, w_{n,n-1}\right]^T \tag{5.2}$$

where, $w_{j,i}$ is the weight of the relationship between the j-th concept and the i-th concept.

Individual in the population is evaluated with the use of a fitness function based on data error [196]:

$$fitness_p(MSE_{tr}(l)) = \frac{1}{aMSE_{tr}(l) + 1} \tag{5.3}$$

where, a is a parameter, l is the number of generation, $l = 1, \dots, L$, L is the maximum number of generations, p is the number of individual, $p = 1, \dots, P$, P is the population size and $MSE_{tr}(l)$ is the data error, described as follows:

$$MSE_{tr}(l) = \frac{1}{N_{tr}} \sum_{t=1}^{N_{tr}} {e_t}^2 \tag{5.4}$$

where, $t = 1, \dots, N_{tr}$, N_{tr} is the number of training records and e_t is the one-step ahead prediction error at the t-th iteration, described as follows:

$$e_t = Z(t) - X(t) \tag{5.5}$$

where, $X(t)$ is the predicted value of the output concept and $Z(t)$ is the desired value of the output concept.

When the maximum number of generations L is reached, or the condition (5.6) is met, which means that the learning process is successful, then the RCGA stops.

$$fitness_p\big(MSE_{tr}(l)\big) > fitness_{max} \tag{5.6}$$

where, $fitness_p\big(MSE_{tr}(l)\big)$ is the fitness function value for the best individual and $fitness_{max}$ is a parameter.

- *Structure Optimization Genetic Algorithm (SOGA)*

The SOGA algorithm is an extension of the RCGA algorithm [195, 196] that allows the decision-maker to determine the most significant concepts and the relationships between them.

Individual is evaluated based on the fitness function based on new data error, described as follows [196]:

$$MSE'_{tr}(l) = MSE_{tr}(l) + b_1 \frac{n_r}{n^2} MSE_{tr}(l) + b_2 \frac{n_c}{n} MSE_{tr}(l) \tag{5.7}$$

where, b_1, b_2 are the parameters of the fitness function, n_r is the number of the non-zero relationships, n_c is the number of the concepts in the analyzed model, n is the number of all possible concepts, l is the number of generation, $l = 1, \dots, L$, L is the maximum number of generations.

The fitness function that follows (5.8), calculates the quality of each population.

$$fitness_p(MSE'_{tr}(l)) = \frac{1}{aMSE'_{tr}(l) + 1} \tag{5.8}$$

where, α is an experimentally defined parameter, p is the number of the individual, $p = 1, \dots, P$, P is the population size and $MSE'_{tr}(l)$ is the new error measure.

A less complex time series prediction model could be constructed by removing the redundant concepts and connections between them with the use of a binary vector C and the proposed error function.

The algorithmic steps of the learning and analysis of the FCM in modeling prediction systems with the use of population-based algorithms (SOGA and RCGA) were analytically presented in [197].

For the experiments, the evolutionary operators, a) ranking selection, b) uniform crossover, and c) random mutation were used [200, 201]. An elite strategy selection was additionally applied, while a probability of crossover Pc and mutation Pm was assigned to each population.

- *Artificial Neural Networks*

An artificial neural network (ANN) is a collection of artificial neurons organized in the form of layers. Neurons are connected by weighted connections to form a NN. The most widely used ANNs in time series prediction are the multilayer perceptrons with an input layer, an output layer, and a single hidden layer that lies between the input and output layer. The most common structure is an ANN that uses one or two hidden layers, since a feed-forward neural network with one hidden layer is able to approximate any continuous function. Supervised learning algorithms and historical data can be used for the learning process of ANNs. The output of each neuron can be calculated based on the following formula:

$$\mathrm{X(t)} = F\left(\sum_{j=1}^{m} X_j(t) \cdot w_j + b\right) \tag{5.9}$$

where, $X_j(t)$ is the value of the j-th input signal, $t = 1, \dots, N_{tr}$, N_{tr} is the number of training records, w_j is the synaptic weight, m is the number of input signals, b is the bias and F is the sigmoid activation function. Training a neural network needs the values of the connection weights and the biases of the neurons to be determined. There are many neural network learning algorithms. The most popular algorithm for ANN learning is the back-propagation method. In this learning method, the weights change their values according to the learning records, until one epoch (an entire learning dataset) is reached. The aim of this method is to minimize the error function, described as follows:

$$MSE_{tr}(l) = \frac{1}{2N_{tr}} \sum_{t=1}^{N_{tr}} {e_t}^2 \tag{5.10}$$

where, $t = 1, \dots, N_{tr}$, N_{tr} is the number of training records, l is the number of epoch, $l = 1, \dots, L$, L is the maximum number of epochs and e_t is the one-step ahead prediction error at the t-th iteration which is equal to:

$$e_t = Z(t) - X(t) \tag{5.11}$$

where, $X(t)$ is the output value of the ANN and $Z(t)$ is the desired value.

The modification of the weights in the back-propagation algorithm can be calculated by the formula:

$$\Delta_{w_{kj}}(l) = -\gamma \frac{\partial J(l)}{\partial w_{kj}(l)} \tag{5.12}$$

where, $\Delta_{w_{kj}}(l)$ is a change of the weight w_{kj} at the l-th epoch, γ is a learning coefficient.

Back propagation algorithm with momentum modifies the weights according to the formula:

$$\Delta_{w_{kj}}(l) = -\gamma \frac{\partial J(l)}{\partial w_{kj}(l)} + \alpha \Delta_{w_{kj}}(l-1) \tag{5.13}$$

where, α is a momentum parameter.

- *Hybrid approach based on FCMs, SOGA and ANNs*

The hybrid approach for time series prediction is based on FCMs, the SOGA algorithm, and ANNs [54]. This approach consists of two stages:

1. Construction of the FCM model based on the SOGA algorithm to reduce the concepts that have no significant influence on data error.
2. Considering the selected concepts (data attributes) as the inputs for the ANN and ANN learning with the use of backpropagation method with momentum.

This hybrid structure allows the decision-maker to select the most significant concepts for an FCM model using the SOGA algorithm. These concepts are used as inputs for the ANN model. Such a hybrid approach aims to find the most accurate model for time series prediction problems.

5.4.1.2 Forecasting aggregation methods

The most intuitive and popular way of forecasts aggregation is to linearly combine the constituent forecasts [202]. There are various methods proposed in literature for selecting the combining weights [203]. The most popular and widely used ensemble methods are the error-based and the simple average [204]. The easiest among them is the simple average in which all forecasts are weighted equally, often remarkably improving overall forecasting accuracy [204].

Considering that $\mathrm{Y} = [\mathrm{y}_1, \mathrm{y}_2, \mathrm{y}_3, \dots, \mathrm{y}_\mathrm{N}]^\mathrm{T}$ is the actual out-of-sample testing dataset of a time series and $\hat{Y}^i = \left[\hat{y}_1^i, \hat{y}_2^i, \dots, \hat{y}_n^i\right]^T$ is the forecast for the i_{th} model, the linear combination of n forecasts is produced by [205]:

$$\hat{y}_k = w_1\hat{y}_k^{(1)} + w_2\hat{y}_k^{(2)} + \dots + w_n\hat{y}_k^{(n)} = \sum_{i=1}^{n} w_i\hat{y}_k^{(i)}, \qquad \forall k = 1, 2, \dots, N \tag{5.14}$$

Hereby, the analysis is based on these most popular ensemble methods. A brief discussion follows for each one.

- The *simple average (AVG)* method [204] is an unambiguous technique which assigns the same weight to each single forecast. Based on empirical studies in the literature, it has been observed that the AVG method is robust and able to generate reliable predictions while it can be characterized as remarkably accurate and impartial. Being applied in a number of models, with respect to effectiveness, the AVG improved the average accuracy when increasing the number of combined single methods [204]. Comparing the referent method with the weighted combination techniques, in terms of forecasting performance, the researchers in [206] concluded that a simple average combination may be more robust than weighted average combinations. In the simple average combination, the weights can be specified as follows:

$$w_i = \frac{1}{n}, \qquad \forall i = 1, 2, \dots, n \tag{5.15}$$

- The *Error Based (EB)* method [207] consists of component forecasts which are given weights that are inversely proportional to their in-sample forecasting errors. For instance, researchers may give a higher weight to a model with lower error, while they may assign a less weight value to a model that presents more error, respectively. Most of the cases, the forecasting error is calculated using total absolute error statistic, such as the Sum of Squared Error (SSE) [202]. The combining weight to each individual prediction is mathematically given by:

$$w_i = e_i^{-1} \Big/ \sum_{i=1}^{n} e_i^{-1}, \qquad \forall i = 1, 2, \dots, n \tag{5.16}$$

5.4.1.3 The proposed ensemble forecasting methodology

In this section, a new advanced forecasting approach is explored by introducing a different split of dataset in the case of daily, weekly or monthly forecasting. Furthermore, a combination of forecasts from multiple structurally different models, like ANN and FCM with various efficient learning algorithms and hybrid configurations of them, is investigated. Also, the two most popular and usually used ensemble methods, the AVG and the EB methods are applied to the ensemble forecasts, aiming to improve the prediction accuracy.

In the described ensemble scheme, the selection of the appropriate validation set, i.e. the selection of the parameter N_{vd} and the group size N_{tr}, is very important. The validation set should reflect the characteristics of the testing dataset that is practically unknown in advance. As such, in this study, the process of data split was set as follows. The data split take place by removing 15% of the total dataset N and saving for later use as testing data. The remaining 85% of the dataset is then split again into an 82/18 ratio, resulting in the following portions: 70% for training and 15% for validation. Also, the group size N_{tr} (i.e. the training data) should be appropriately selected so that it is neither too small nor too large.

Due to the nature of the problem, and since time series data are involved, the most efficient method for resampling is the boosting/bootstrapping method [208]. In boosting, resampling is strategically geared to provide the most informative training data for each consecutive predictor. Therefore, an appropriate bootstrapping method is applied, so that the training dataset should have the same size at each resampling set, and the validation and testing sets should keep the same size (after excluding the k-values from the in-sample dataset).

The proposed effective forecast combination methodology for time series forecasting presented in the chapter, includes three main processing steps: (i) Data pre-processing, for handling the missing values, normalizing the collected time series data and splitting the dataset, (ii) the various forecasting methods of ANNs, RCGA-FCMs, SOGA-FCMs and Hybrid SOGA FCM-ANN with their ensembles, and (iii) evaluation of the prediction results implementing the two most popular and used ensemble methods of simple average (AVG) and error-based (EB). Figure 5.1 visually illustrates in flowchart steps the suggested methodology.

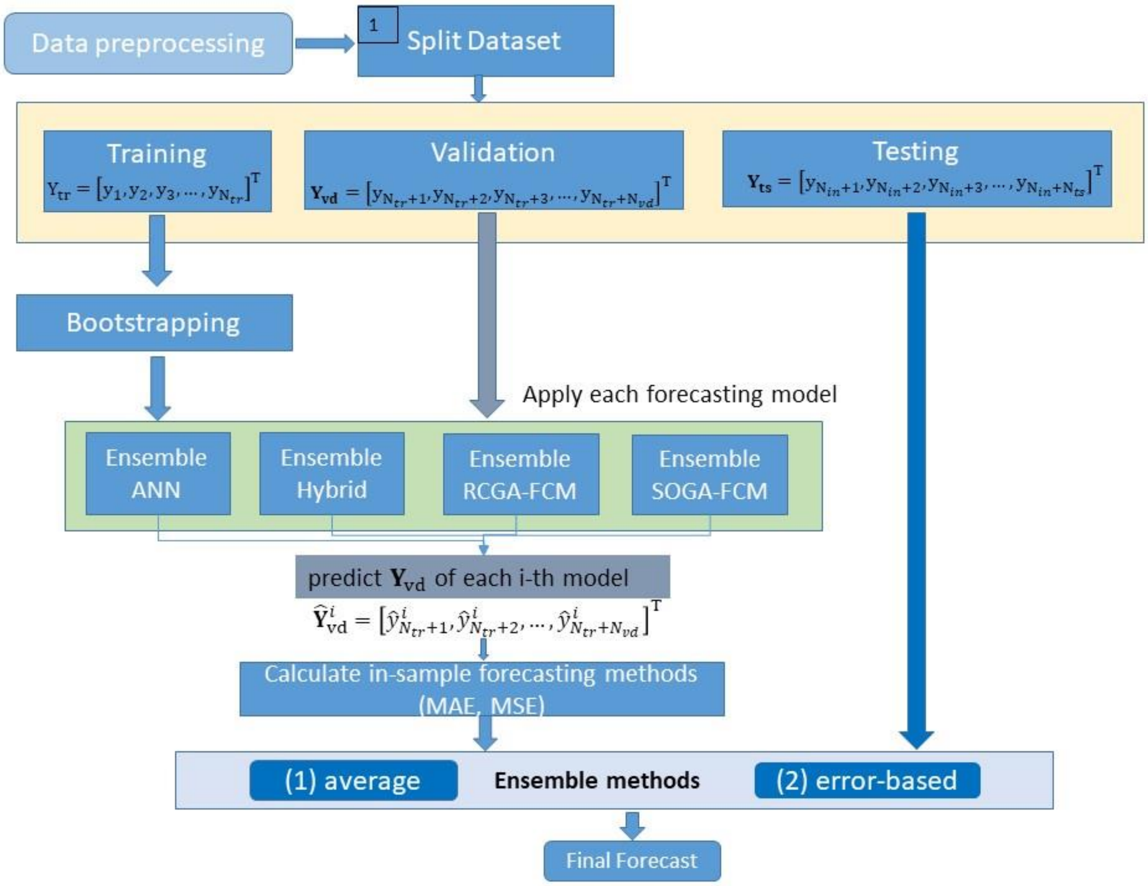


Figure 5.1: Flowchart of the proposed forecasting combination approach.

In the followed approach, data preprocessing includes outliers detection and removal, as well as handling missing data and data normalization, which are all in accordance with the principles of Data Science practices described in corresponding literature. For outliers detection, the Z-score was first calculated for each sample on the data set using the standard deviation value that is presented in the descriptive statistics (see Tables C.1 and C.2 in Appendix C). Then, a threshold was specified and the data points that lied beyond this threshold were classified as outliers and were removed. Mean imputation was performed to handle missing values. Specifically, for numerical features missing values were replaced by the mean feature value.

Each dataset is normalized to [0, 1] before the forecasting models are applied. The normalized datasets are taking again their original values, while the testing phase is implemented. The data normalizations are carried out mathematically, as follows:

$$y_i^{(new)} = \frac{y_i - y^{(min)}}{y^{(max)} - y^{(min)}}, \qquad \forall i = 1, 2, \dots, N \tag{5.17}$$

where, $\mathrm{Y} = \left[\mathrm{y}_1, \mathrm{y}_2, \mathrm{y}_3, \dots, \mathrm{y}_{\mathrm{N}_{train}}\right]^{\mathrm{T}}$ is the training dataset and $\mathrm{Y}^{(new)} = \left[y_1^{(new)}, y_1^{(new)}, \dots, y_N^{(new)}\right]^{\mathrm{T}}$ is the normalized dataset. $y^{(min)}$ and $y^{(max)}$ are respectively the minimum and maximum values of the training dataset Y.

The Min-Max normalization method [209] was selected as being one of the most popular and comprehensible methods, in terms of performance of the examined systems, while several researchers showed that it produces better (if not equally good) results with high accuracy, comparing to other normalization methods [210]. In [210] the Min-Max was valued as the second-best normalization method in the back propagation NN model, justifying the selection of this method for data normalization. Moreover, since the FCM concepts use values within the range [0, 1] for the conducted simulations and do not deal with real values, the selected method seemed to be proper for this case-study. Also, this normalization approach has been previously used in [196, 197].

The implementation of a generic forecasting combination approach (with ANNs, FCMs and their hybrid structures) which is able to be applied in any time series dataset, entails the execution of the following steps as thoroughly presented below.

Step 1. (Split Dataset). The original time series $\mathrm{Y} = [\mathrm{y}_1, \mathrm{y}_2, \mathrm{y}_3, \dots, \mathrm{y}_{\mathrm{N}}]^{\mathrm{T}}$ is divided into the in-sample training dataset $\mathrm{Y}_{\mathrm{tr}} = \left[\mathrm{y}_1, \mathrm{y}_2, \mathrm{y}_3, \dots, \mathrm{y}_{\mathrm{N}_{tr}}\right]^{\mathrm{T}}$, the in-sample validation dataset $\mathrm{Y}_{\mathrm{vd}} = \left[\mathrm{y}_{\mathrm{N}_{tr}+1}, \mathrm{y}_{\mathrm{N}_{tr}+2}, \mathrm{y}_{\mathrm{N}_{tr}+3}, \dots, \mathrm{y}_{\mathrm{N}_{tr}+\mathrm{N}_{vd}}\right]^{\mathrm{T}}$, and the out-of-sample testing dataset $\mathrm{Y}_{\mathrm{ts}} = \left[\mathrm{y}_{\mathrm{N}_{in}+1}, \mathrm{y}_{\mathrm{N}_{in}+2}, \mathrm{y}_{\mathrm{N}_{in}+3}, \dots, \mathrm{y}_{\mathrm{N}_{in}+\mathrm{N}_{ts}}\right]^{\mathrm{T}}$, so that $N_{in} = N_{tr} + N_{vd}$ is the size of the total in-sample dataset and $N_{in} + N_{ts} = N$, where N is the number of days, or weeks, or months, according to the short or long term prediction based on the time series horizon.

Step 2. (Resampling method/Bootstrapping). Let consider k as the training sets from the whole dataset, each time. For example, in monthly forecasting, one month is excluded every time from the initial in-sample dataset, starting from the first month of the time series values, and proceeding with next month until k=12, (i.e. this means that 1 to 12 months are excluded from the initial in-sample dataset). Therefore, k subsets of training data are created and used for training. The remaining values of the in-sample dataset are used for validation, whereas the testing set remains the same. Figure 5.2 shows an example of this bootstrapping method for the ensemble SOGA-FCM approach. In particular, Figure 5.2(a) represents the individual forecasters' prediction values and their average error calculation, whereas in Figure 5.2(b) the proposed forecasting combination approach for SOGA-FCM is depicted for both ensemble methods.

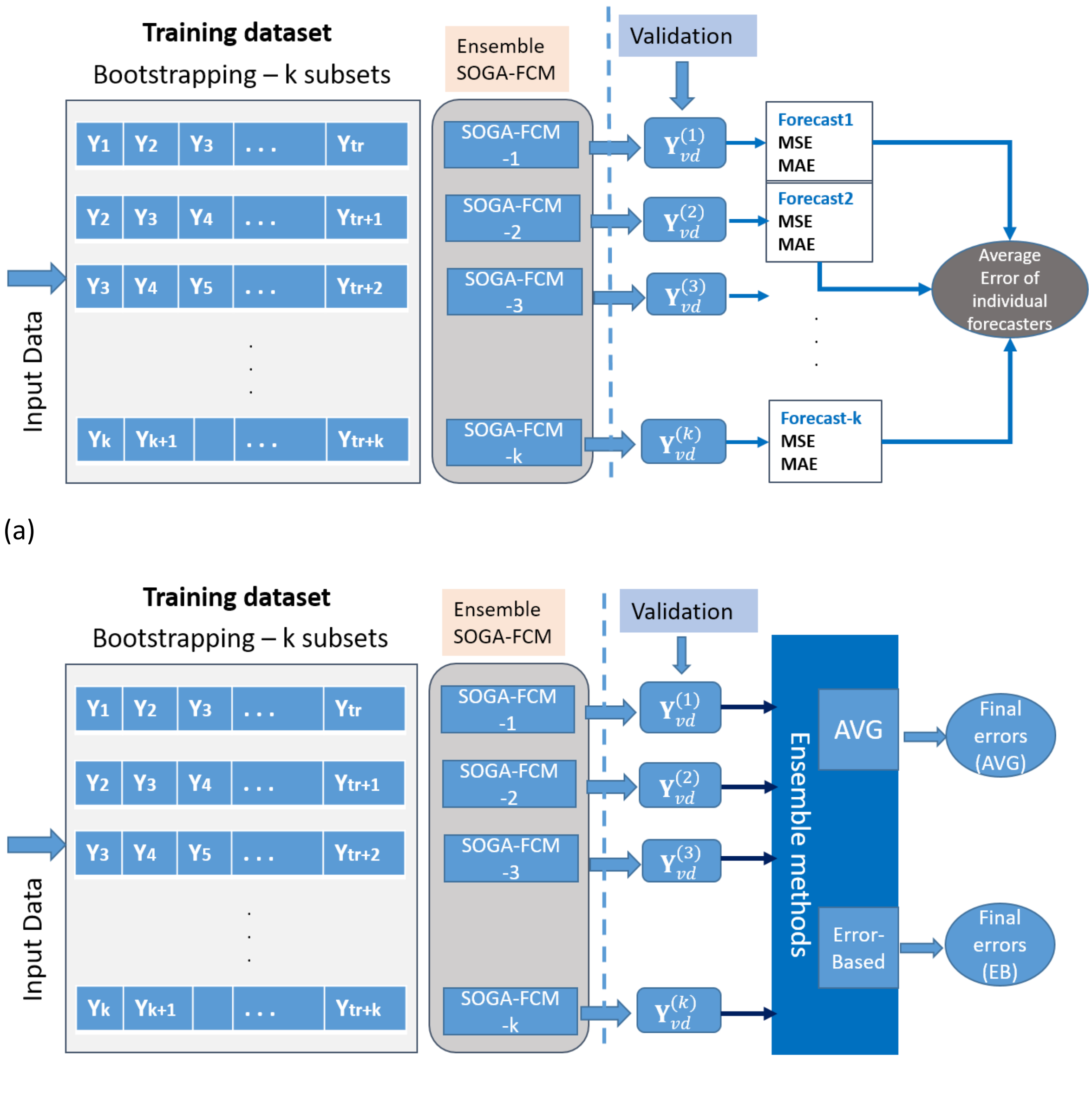


Figure 5.2: (a) Forecasting approach using individual forecasters of SOGA-FCM and mean average (b) Example of the proposed forecasting combination approach for SOGA-FCM using ensemble methods.

To accomplish daily forecasting, the number of days excluded at each subset k needs to be selected in advance. For the sake of simplicity (as in the case of monthly forecasting), one day can be excluded at each sub-set from the initial in-sample dataset. The overall approach including ANN, FCMs and hybrid configurations of them is illustrated in Figure 5.3. The four ensemble forecasters are produced after validation process and used for testing through the proposed approach.

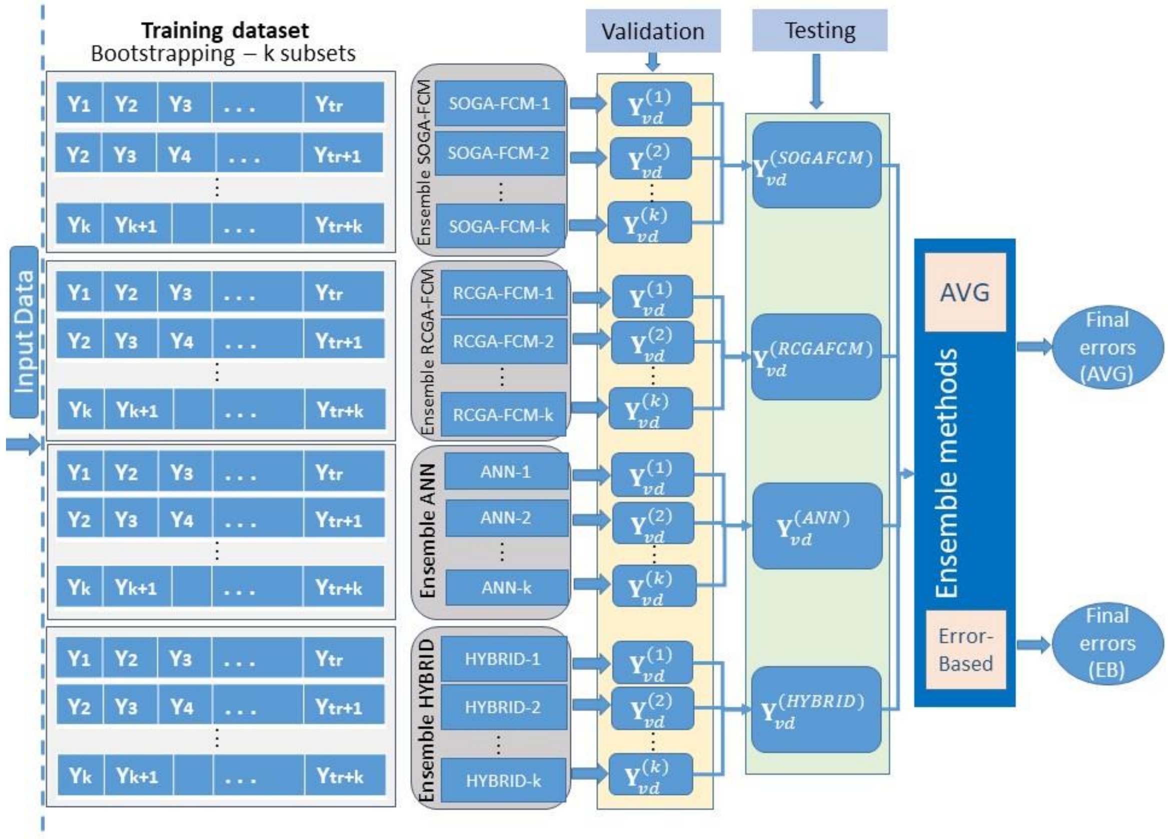


Figure 5.3: The proposed forecasting combination approach using ensemble methods and ensemble forecasters.

Step 3. n component forecasting models appear and $\widehat{\mathrm{Y}}_{\mathrm{ts}}^{i} = \left[\hat{y}_{N_{in}+1}^{i}, \hat{y}_{N_{in}+2}^{i}, \dots, \hat{y}_{N_{in}+N_{ts}}^{i}\right]^{\mathrm{T}}$ are obtained as the forecast of Y_{ts} through the i^{th} model.

Step 4. Each model is implemented on Y_{tr} and is used to predict Y_{vd}. Let $\widehat{\mathrm{Y}}_{\mathrm{vd}}^{i} = \left[\hat{y}_{N_{tr}+1}^{i}, \hat{y}_{N_{tr}+2}^{i}, \dots, \hat{y}_{N_{tr}+N_{vd}}^{i}\right]^{\mathrm{T}}$ be the prediction of Y_{vd} through the i^{th} model.

Step 5. The in-sample forecasting error of each model is calculated through suitable error measure. Mean Absolute Error (MAE) and Mean Squared Error (MSE) are popular error statistics [54] and are used in this case-study to find the in-sample forecasting errors of the component models.

Step 6. Based on the obtained in-sample forecasting errors, a score is assigned to each component model as $\gamma_i = \frac{1}{MSE\ Y_{vd}, \hat{Y}_{vd}^{i}}$, $\forall i = 1, 2, \dots, n$. The scores are assigned to be inversely proportional to the respective errors, so that a model with comparatively smaller in-sample error receives more score and vice versa.

Step 7. A rank $r_i \epsilon 1, 2, \ldots, n$ is assigned to the i^{th} model, on the basis of its score, so that $r_i \geq r_j$, if $\gamma_i \leq \gamma_j$, $\forall i, j = 1, 2, \ldots, n$. The minimum, i.e. the best rank is equal to 1 and the maximum, i.e. the worst rank is at most equal to n.

Step 8. A number n_r is chosen so that $1 \leq n_r \leq n$ whereas $I = i_1, i_2, \ldots, i_{n_r}$ is the index set of the n_r component models, whose ranks are in the range [1, n_r]. So, a subgroup of n_r smallest ranked component models is properly selected.

Step 9. Finally, the weighted linear combination of these selected n_r component forecasts is obtained, as follows:

$$\hat{y}_k = w_{i_1} \hat{y}_k^{i_1} + w_{i_2} \hat{y}_k^{i_2} + \cdots + w_{i_{n_r}} \hat{y}_k^{i_{n_r}} = \sum_{i \epsilon I} w_i \, \hat{y}_k^i, \qquad \forall i = 1, 2, \ldots, n \tag{5.18}$$

Here, $w_{i_k} = {}^{\gamma_{i_k}}\!\big/_{\sum_{k=1}^{n_r} \gamma_{i_k}}$ is the normalized weight to the selected component model, so that $\sum_{k=1}^{n_r} w_{i_k} = 1$.

Step 10. The simple average method can be also adopted, as alternative to Step 6-9, to calculate the forecasted value.

The validation set is used during the training process for updating the algorithm weights appropriately and, thus, improving its performance and avoiding overfitting. After model training, a new run is performed on the testing data, so as it can be verified if they have been predicted correctly and, if it has been so, the validation set keeps being hidden.

5.4.2 Demand forecasting using Adaptive Neuro-Fuzzy Inference System (ANFIS)

5.4.2.1 Main aspects of ANFIS

Adapted Neuro-Fuzzy Inference System (ANFIS) uses an architecture that is based on both ANN and Fuzzy Logic principles and takes advantage of the benefits of both in a single framework. It can be described by the fuzzy “IF-THEN” rules from the Takagi and Sugeno (TS) type [211] as follows:

$$\begin{gathered} R_i\!: if\ x_1 = A_{i,1}\ and\ \ldots and\ x_k = A_{i,k} \\ then\ y_i = b_{i,0} + b_{i,1} x_1 + b_{i,2} x_2 + \cdots + b_{i,k} x_k \end{gathered} \tag{5.19}$$

where, $A_{i,k}$ is the membership function associated with input variables x_k and n is the number of inputs.

A typical ANFIS network is a five-layer structure consisting of the fuzzy layer, the product layer, the normalized layer, the de-fuzzy layer and the total output layer [212–214].

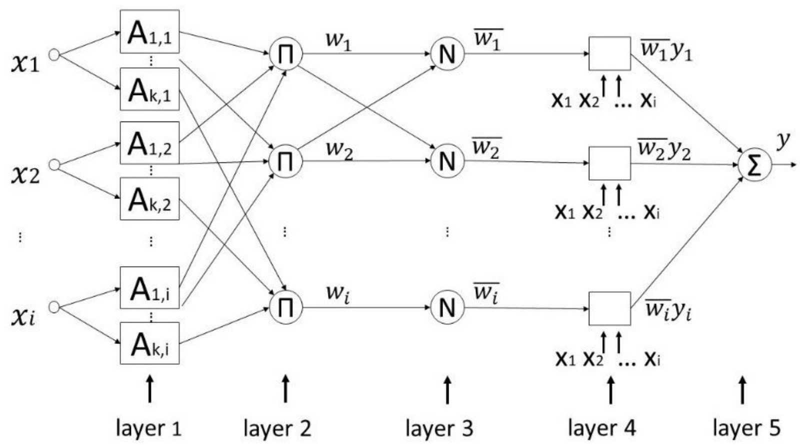


Figure 5.4: The TSK ANFIS architecture [213].

In the first layer, every node i represents a linguistic label and is described by the following membership function, as given in Equation (5.20).

$$A_{i,k}(x_r) = e^{-(\frac{(x_r - v_{i,k})}{\sigma_{\iota,\kappa}})^2}, \qquad for\; r = 1, 2, \dots, i \tag{5.20}$$

where, $A_{i,k}$ is the membership function which is considered to be Gaussian and is described by the center ν and the spread σ.

In the second layer, the firing strength of the rule is computed using multiplicative operator, as presented in Equation (5.21). Firing strength is the weight degree of the IF-THEN rule and determines the shape of the output function for that rule.

$$w_i = \prod_{k=1}^{n} A_{i,k}(x_k) \tag{5.21}$$

In the third layer, the *i*-th node calculates the ratio of the *i*-th rule's firing strength to the sum of the firing strength of all rules. This is the normalization layer which normalizes the strength of all rules and the output of each node is given by Equation (5.22).

$$\overline{w}_i = \frac{w_i}{\sum_{i=1} w_i} \tag{5.22}$$

In the fourth layer, each node is an adaptive node with a function given by Equation (5.23). In this layer, each node calculates a linear function where its coefficients are adapted by using the error function of the multilayer feed-forward neural network.

$$\overline{y}_i = \overline{w}_i y_i \tag{5.23}$$

In the fifth layer, there is only a fixed node indicated as sum of the net outputs of the nodes in Layer 4. It computes the overall output as the sum of all incoming inputs and is expressed by Equation (5.24).

$$y = \sum_i \bar{y}_i \tag{5.24}$$

ANFIS uses a hybrid learning algorithm to train the model. Back-propagation algorithm is used to train the parameters in Layer 1, whereas a variation of least-squares approximation or back-propagation algorithm is used for training the parameters of the fourth layer [214, 215].

5.4.2.2 Proposed ANFIS Architecture Applied in Natural Gas Consumption Forecasting

Regarding an efficient ANFIS model development for NG demand forecasting, a certain process needs to be followed in terms of model's architecture design as well as an exploration process that will properly configure the input and training parameters of the examined model. Priority is given to the definition of the FIS architecture before the training of the network [215]. Among various Fuzzy Inference System (FIS) models, the Sugeno fuzzy model is the mostly used because of its higher interpretability and computational ability, that includes embedded optimal and adaptive techniques [216]. In order to create a fuzzy rule, the input space needs first to be divided. Two methods are used to divide space, comprised by input variables: The *Grid partitioning* method and the *Subtractive clustering* method. The main difference between these two functions refers to the way the partition of the input space is created.

In *Grid partitioning* [215], the input space is divided into a grid-like structure without overlapping parts. *Grid partitioning* performs partitioning of the input space using all possible combinations of membership functions of each variable. This method is used when the number of input variables is small. For example, for 10 input variables and two membership functions for each input variable, then the input space is divided into 2^{10} = 1024 specific areas, representing one rule for each specific area, and the total number of rules is 1024, which is a very complicated structure. Therefore, the *Grid partitioning* method is mainly used when the number of input variables is small.

On the other hand, the *Subtractive clustering* method divides the input space into appropriate clusters, even if the user does not specify their number. If the size of the cluster becomes small, then the number of clusters increases, thus increasing the number of fuzzy rules. A rule is created for each cluster, whereas different values for parameters, like Range of Influence, Squash Factor, Accept Ratio and Reject Ratio, need to be explored for determining an efficient architecture, which will keep the balance between the total number of ANFIS parameters and the total number of rules.

Considering the above specifications, the *Grid partition* option was selected to define the FIS architecture due to its simplicity, less time-consuming performance as well as it can easily explore the number and type of MFs. In this stage, the number and type of membership functions of each input variable, along with the rules and values of parameters that belong to these functions, are determined using the option of *Grid partition*.

When implementing an ANFIS architecture, researchers should have in mind that there is one main restriction: the number of input variables. When these are more than five, then the number of the IF-THEN rules and the computational time increase, hindering ANFIS to model output with respect to inputs [215]. Thus, in this case-study, five variables were chosen as input parameters, i.e month, day, temperature, demand of a day before and demand of current day. As described above, a day-ahead consumption demand was selected as the output variable whose value can be produced by choosing between the option of linear or constant type of MF.

Finding the most efficient ANFIS architecture is a demanding task and entails a rigorous exploration process. Since the main objective is the increment of network's accuracy and decrement of the errors, five necessary configurations should be considered in this direction: (i) the number of membership functions, (ii) types of MFs (triangular, trapezoidal, bell-shaped, Gaussian and sigmoid), (iii) types of output MFs (constant or linear), (iv) optimization methods (hybrid or back propagation) and (v) the number of epochs [217]. For the convenience of readers, these steps are visually represented in the flowchart in Figure 5.5.

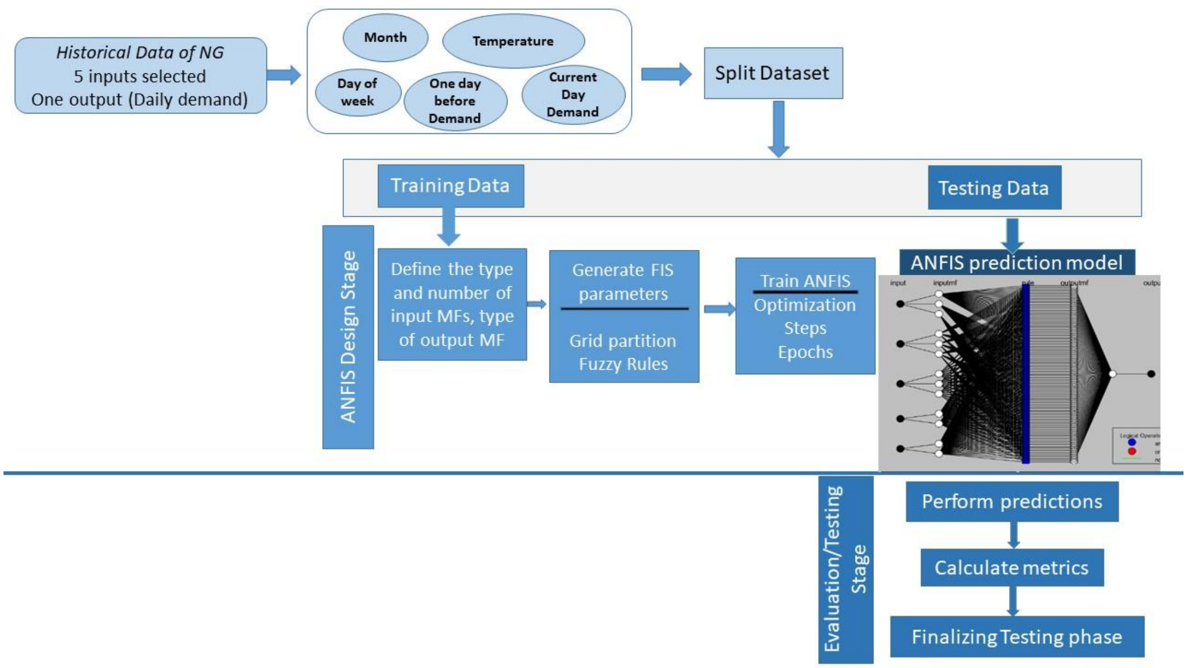
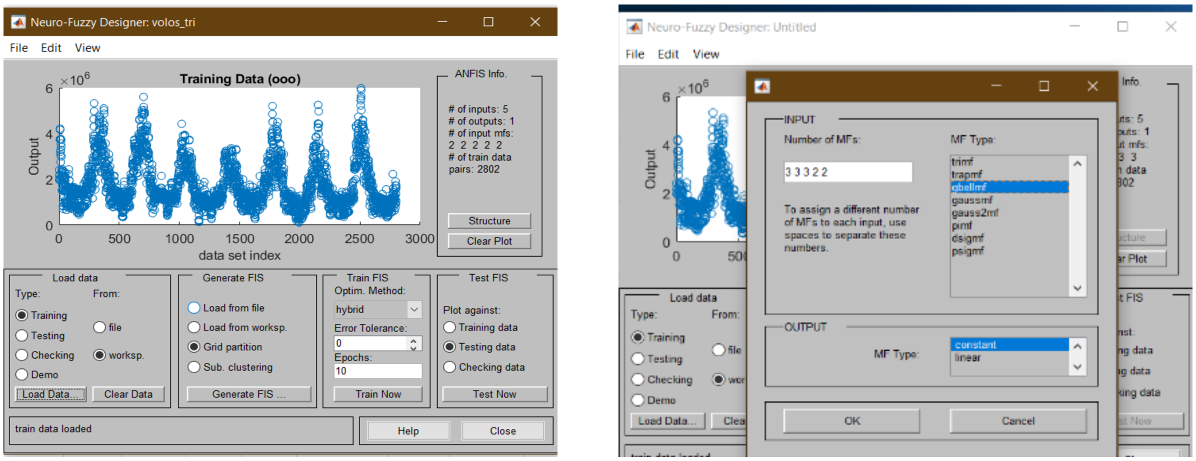


Figure 5.5: Flowchart of the proposed ANFIS methodology

The aforementioned set of configurations needs to be deployed in order to generate FIS and next to train the ANFIS model. Accordingly, the dataset that includes the five input variables (ie. month, day, temperature, demand of a day before, demand of current day) has been selected to determine the only output (day-ahead demand). Initially, the training dataset is loaded in the ANFIS tool, as shown in Figure 5.6(a). The next step is the design of the neuro-fuzzy model using the option "Generate FIS". The *Grid partition* option is selected according to the description above (see Figure 5.6(a)). These two settings, concerning the fuzzy input variables along with their membership functions, are the most important parts to design the ANFIS. An example of selecting the number and type of MFs is illustrated in Figure 5.6(b).



(a) (b)

Figure 5.6: Screenshots regarding (a) the training dataset configuration, (b) the number and type of MF configuration

The number and type of membership functions were assigned to the input parameters following the trial-and-error approach. The different types of MFs that are offered by the MATLAB ANFIS editor include the triangular, trapezoidal, generalized bell (Gbell), Gaussian curve, Gaussian combination, difference between two sigmoid functions and product of two sigmoid functions (see Figure 5.6(b)). Regarding the type of output MFs, in the Sugeno-type fuzzy system, there are two options: a constant-type conclusion or a linear-type conclusion function. In the case of linear function, the output y is defined as:

$$y = k_0 + k_1 * x_1 + k_2 * x_2 + \cdots + k_n * x_n \tag{5.25}$$

where, $x_1, x_2, \ldots, x_n$ are the n inputs. In this case, ANFIS needs to define k_0, k_1, k_2 up to k_n, and it is really time consuming to calculate efficiently the outputs when a large number of parameters is considered. On the other side, when a constant MF is selected, the algorithm needs to define only one parameter to provide a reliable forecasted value. Thus, the computational time is really low.

The selected configuration also includes the hybrid optimization method, while the number of epochs selected to train the model, were between 10 and 50. The hybrid optimization method uses back propagation learning algorithm for parameters associated with input MF and least-square estimation algorithm for parameters associated with output MF, thus, it was selected as the most proper one [218]. Various sets of ANFIS configurations are presented in Table 5.3, regarding different sets of number for MFs.

Table 5.3: Different configurations of the selected ANFIS architectures for constant output MF

ANFIS RUN	TYPE OF INPUT MF	NUMBER OF MFS	TYPE OF OUTPUT MF	NUMBER OF EPOCHS	LEARNING METHOD
1	trimf	2-2-2-2-2	Constant	10	Hybrid
2	trapmf	2-2-2-2-2	Constant	10	Hybrid
3	gbellmf	2-2-2-2-2	Constant	10	Hybrid
4	Gaussmf	2-2-2-2-2	Constant	10	Hybrid
5	Gauss2mf	2-2-2-2-2	Constant	10	Hybrid
6	pimf	2-2-2-2-2	Constant	10	Hybrid
7	dsigmf	2-2-2-2-2	Constant	10	Hybrid
8	psigmf	2-2-2-2-2	Constant	10	Hybrid
9	trimf	2-2-3-3-3	Constant	10	Hybrid
10	trapmf	2-2-3-3-3	Constant	10	Hybrid
11	gbellmf	2-2-3-3-3	Constant	10	Hybrid
12	Gaussmf	2-2-3-3-3	Constant	10	Hybrid
13	Gauss2mf	2-2-3-3-3	Constant	10	Hybrid
14	pimf	2-2-3-3-3	Constant	10	Hybrid
15	dsigmf	2-2-3-3-3	Constant	10	Hybrid
16	psigmf	2-2-3-3-3	Constant	10	Hybrid
17	trimf	3-3-3-2-2	Constant	10	Hybrid
18	trapmf	3-3-3-2-2	Constant	10	Hybrid
19	gbellmf	3-3-3-2-2	Constant	10	Hybrid
20	Gaussmf	3-3-3-2-2	Constant	10	Hybrid
21	Trimf	3-3-3-3-3	Constant	10	hybrid
22	Trimf	3-3-3-3-3	Constant	10	backpropa
23	trapmf	3-3-3-3-3	Constant	10	hybrid
24	trapmf	3-3-3-3-3	Constant	10	backpropa
25	gbellmf	3-3-3-3-3	Constant	10	hybrid
26	gbellmf	3-3-3-3-3	Constant	10	backpropa
27	trimf	3-3-3-3-3	Constant	30	hybrid
28	trimf	3-3-3-3-3	Constant	50	hybrid
29	trapmf	3-3-3-3-3	Constant	30	hybrid
30	trapmf	3-3-3-3-3	Constant	50	hybrid
31	gbellmf	3-3-3-3-3	Constant	30	hybrid
32	gbellmf	3-3-3-3-3	Constant	50	hybrid
33	trimf	3-3-4-4-4	Constant	10	hybrid
34	trimf	3-3-5-5-5	Constant	10	hybrid
35	trapmf	3-3-4-4-4	Constant	10	hybrid
36	trapmf	3-3-5-5-5	Constant	10	hybrid
37	gbellmf	3-3-4-4-4	Constant	10	hybrid
38	gbellmf	3-3-5-5-5	Constant	10	hybrid
39	gaussmf	3-3-3-3-3	Constant	10	hybrid
40	gaussmf	3-3-4-4-4	Constant	10	hybrid
41	gaussmf	3-3-5-5-5	Constant	10	hybrid
42	gauss2mf	3-3-3-3-3	Constant	10	hybrid
43	gauss2mf	3-3-4-4-4	Constant	10	hybrid
44	gauss2mf	3-3-5-5-5	Constant	10	hybrid
45	pimf	3-3-3-3-3	Constant	10	hybrid
46	pimf	3-3-4-4-4	Constant	10	hybrid
47	pimf	3-3-5-5-5	Constant	10	hybrid

Regarding the Output MFs, constant and linear MF were accordingly investigated after certain numbers of experiments conducted. From these experiments and for the linear output, it was observed that the number of rules increases significantly, as well as the computational time, even in the case of problems with small number of inputs (see Table C.3 in Appendix C). Thus, the linear type was not considered as an appropriate parameter of output MF since it is extremely time consuming. In this context, the trial-and-error approach was followed for the selection of the input-output type of MFs. Figure 5.7 illustrates an indicative ANFIS model, which was constructed with the following configuration set: 3-3-3-2-2, gbell MF, constant output MF, 10 epochs, hybrid.

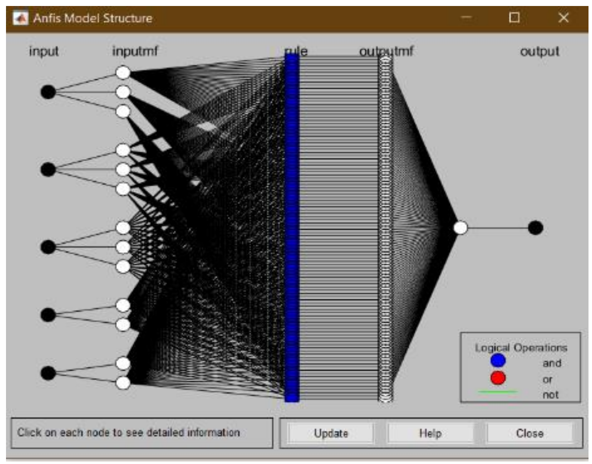


Figure 5.7: Screenshot of the constructed ANFIS model

5.5 Testing and Evaluation

The testing process for both models is accomplished by using the testing data, which are completely unknown to the model. The predictor makes predictions on each day and finally compares the calculated predicted value with the real value.

In order to evaluate the prediction of NG demand, certain statistical indicators are needed. The most popular and widely used performance metrics or evaluation criteria for time series prediction are the following: mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and coefficient of determination (R2). The mathematical equations of the statistical indicators as described in [197], are presented below.

1. Mean Squared Error:

$$\mathrm{MSE} = \frac{1}{T}\sum_{t=1}^{T}(Z(t) - X(t))^2 \tag{5.26}$$

2. Root Mean Squared Error:

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \tag{5.27}$$

3. Mean Absolute Error:

$$\mathrm{MAE} = \frac{1}{T}\sum_{t=1}^{T}|Z(t) - X(t)| \tag{5.28}$$

4. Mean Absolute Percentage Error:

$$\mathrm{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{Z(t) - X(t)}{Z(t)}\right| \tag{5.29}$$

5. Coefficient of Determination:

$$\mathrm{R} = \frac{T\sum_{t=1}^{T} Z(t) \cdot X(t) \ - (\sum_{t=1}^{T} Z(t))(\sum_{t=1}^{T} X(t))}{\sqrt{T\sum_{t=1}^{T}(Z(t))^2 - (\sum_{t=1}^{T} Z(t))^2} \cdot \sqrt{T\sum_{t=1}^{T}(X(t))^2 - (\sum_{t=1}^{T} X(t))^2}} \tag{5.30}$$

where, $X(t)$ is the forecasted value of the NG at the t-th iteration, $Z(t)$ is the actual value of the NG at the t-th iteration, $t = 1, \dots, T$, where T is the number of testing records.

However, the goodness of fit and the performance of the studied models, when they applied to a natural gas prediction process, were evaluated and compared using two of these five commonly used statistical indicators. That is, MSE and MAE [149].

The lower values of MSE and MAE as well as the higher values of R^2, i.e. closer to 1, indicate that the model performance is better with respect to the prediction accuracy, and the regression line fits the data well. A coefficient of determination value of 1.0 points out that the regression curve fits the data perfectly.

5.6 Results

5.6.1 Case study results implementing ensemble forecasting using FCMs

The natural gas consumption datasets that are used in this case study examining the applicability and effectiveness of the proposed forecast methodology, correspond to five years (2013-2017). Following the first step of the proposed methodology, the dataset is split in training, validation and testing. For the convenience of handling properly the dataset, the data of the first three years were defined as the training dataset (1095 days), the data of the fourth year as the validation dataset (365 days) and the remaining data (5th year) as the testing dataset (365 days), which approximately correspond to 60%, 20% and 20%, respectively, as presented in section 5.5.1.3. Thus, it was easier for this analysis to handle the above values as annual datasets and have a clearer perception of the whole process.

Out of the three years of the defined training dataset, the first two were used as the initial training dataset while the third (3rd) year was used as a dataset reservoir for the purposes of the bootstrapping procedure. This year was properly selected to be part of the initial dataset, as for each value of k (the bootstrapping step), a corresponding number of days/weeks/months is additionally needed to be included in the training dataset during the bootstrapping process. Thus, any possible data shortage and/or deterioration that would lead to inaccurate results is avoided.

Moreover, for the purposes of this case study, only three out of ten datasets that correspond to historical consumption data provided by DESFA for specific cities in Greece are involved. More specifically, the Greek cities of Thessaloniki, Athens, and Larissa were selected for the conducted simulation analysis and comparison of the best performing algorithms.

In this chapter, both the AVG and the EB methods were applied in two different cases: case (A) where scores were calculated for individual forecaster of each one of the methods ANN, hybrid, RCGA-FCM, and SOGA-FCM, and case (B), where scores were calculated for each ensemble forecaster (ANN ensemble, hybrid ensemble, RCGA-FCM ensemble, and SOGA-FCM ensemble).

Considering case (A), Table 5.4 shows the calculated errors and scores based on the EB method for individual forecaster of the two forecasting methods: ANN and hybrid for the city of Athens. The rest calculated errors and scores, based on the EB method, for individual forecaster for the other two remaining forecasting methods RCGA-FCM and SOGA-FCM for Athens can be found in Appendix C (see Table C.4). In Appendix C, parts of the corresponding results for the other two examined cities (Larissa and Thessaloniki) are also presented (see Tables C.5 and C.6).

Table 5.4: Case (A)-Calculated errors and weights for each ensemble forecaster based on scores for EB method (Athens).

	VALIDATION		TESTING				TESTING		
	MAE	**MSE**	**MAE**	**MSE**	**Weights**		**MAE**	**MSE**	**Weights**
ANN1	0.0334	0.0035	0.0350	0.0036	0.2552	*Hybrid1*	0.0336	0.0034	0.2520
ANN2	0.0354	0.0041	0.0387	0.0043	0	*Hybrid2*	0.0387	0.0043	0
ANN3	0.0350	0.0037	0.0375	0.0039	0.2442	*Hybrid3*	0.0363	0.0037	0
ANN4	0.0341	0.0038	0.0365	0.0039	0	*Hybrid4*	0.0352	0.0035	0
ANN5	0.0335	0.0036	0.0358	0.0037	0.2505	*Hybrid5*	0.0339	0.0034	0
ANN6	0.0337	0.0039	0.0355	0.0038	0	*Hybrid6*	0.0348	0.0036	0.2468
ANN7	0.0336	0.0037	0.0362	0.0038	0	*Hybrid7*	0.0345	0.0035	0.2506
ANN8	0.0340	0.0039	0.0360	0.0039	0	*Hybrid8*	0.0354	0.0036	0
ANN9	0.0341	0.0039	0.0367	0.0040	0	*Hybrid9*	0.0349	0.0036	0
ANN10	0.0332	0.0036	0.0355	0.0037	0.2501	*Hybrid10*	0.0359	0.0038	0
ANN1	0.0338	0.0038	0.0365	0.0039	0	*Hybrid11*	0.0353	0.0038	0
ANN12	0.0345	0.0038	0.0349	0.0037	0	*Hybrid12*	0.0347	0.0033	0.2506
AVG	0.0336	0.0037	0.0359	0.0038		*AVG*	0.0350	0.0036	
EB	0.0335	0.0036	0.0358	0.0037		*EB*	0.0340	0.0034	

*MSE: Mean Square Error, MAE: Mean Absolute Error.

Considering case (B), Table 5.5 presents the calculated weights based on scores for each ensemble forecaster (ANN ensemble, hybrid ensemble, RCGA ensemble and SOGA ensemble) for all three cities.

The calculated weights based on scores for EB method, are computed using Equation (5.16). According to this equation, the weights of the component forecasts are inversely proportional to their in-sample forecasting errors, concluding that the model with more error is assigned the less weight to it and vice versa [202]. In this case study, as the values of errors are really high for certain ensemble forecasters, the corresponding weights are approximately zero, so they are considered to have a zero value for the purposes of further predictions.

Table 5.5: Case (B)-Calculated weights for each ensemble forecaster based on scores for EB method.

	ATHENS	**THESSALONIKI**	**LARISSA**
	Weights based on scores		
ANN	0.3320	0.34106	0.3369
HYBRID	0.3357	0.35162	0.3546
RCGA-FCM	0.3323	0	0
SOGA-FCM	0	0.30731	0.3083

The obtained forecasting results of the individual and combination methods are depicted in Table 5.6 up to Table 5.11, respectively, for the three cities. In each of these tables, the best results (i.e. those associated with least values of error measures) are presented in bold letters. In Figures 5.8 and 5.9, the forecasting results concerning Thessaloniki and Larissa are visually illustrated for both ensemble methods (AVG, EB). Moreover, Figure 5.10 gathers the forecasting results for all three cities considering the best ensemble method.

Table 5.6: Calculated errors for each individual forecaster based on scores for Athens.

Validation	ANN	Hybrid	RCGA	SOGA	Ensemble AVG	Ensemble EB
MAE	0.0328	0.0333	0.0384	0.0391	0.0336	0.0326
MSE	0.0036	0.0035	0.0036	0.0037	**0.0032**	**0.0032**
Testing						
MAE	0.0321	0.0328	0.0418	0.0424	0.0345	0.0328
MSE	0.0033	0.0032	0.0038	0.0040	0.0032	**0.0031**

Table 5.7: Calculated errors for each ensemble forecaster based on scores for Athens.

Validation	ANN ensemble	Hybrid ensemble	RCGA ensemble	SOGA ensemble	Ensemble AVG	Ensemble EB

MAE	0.0335	0.0330	0.0388	0.0380	0.0337	0.0337
MSE	0.0036	0.0035	0.0036	0.0035	**0.0032**	**0.0032**
Testing						
MAE	0.0358	0.0340	0.0422	0.0422	0.0352	0.0352
MSE	0.0037	0.0034	0.0038	0.0037	**0.0032**	**0.0032**

Table 5.8: Calculated errors for each individual forecaster based on scores for Thessaloniki.

Validation	ANN	Hybrid	RCGA	SOGA	Ensemble AVG	Ensemble EB
MAE	0.0343	0.0341	0.0381	0.0380	0.0347	0.0340
MSE	0.0029	0.0028	0.0032	0.0032	0.0028	**0.0027**
Testing						
MAE	0.0366	0.0381	0.0395	0.0399	0.0371	0.0369
MSE	0.0032	0.0033	0.0035	0.0036	0.0032	**0.0031**

Table 5.9: Calculated errors for each ensemble forecaster based on scores for Thessaloniki.

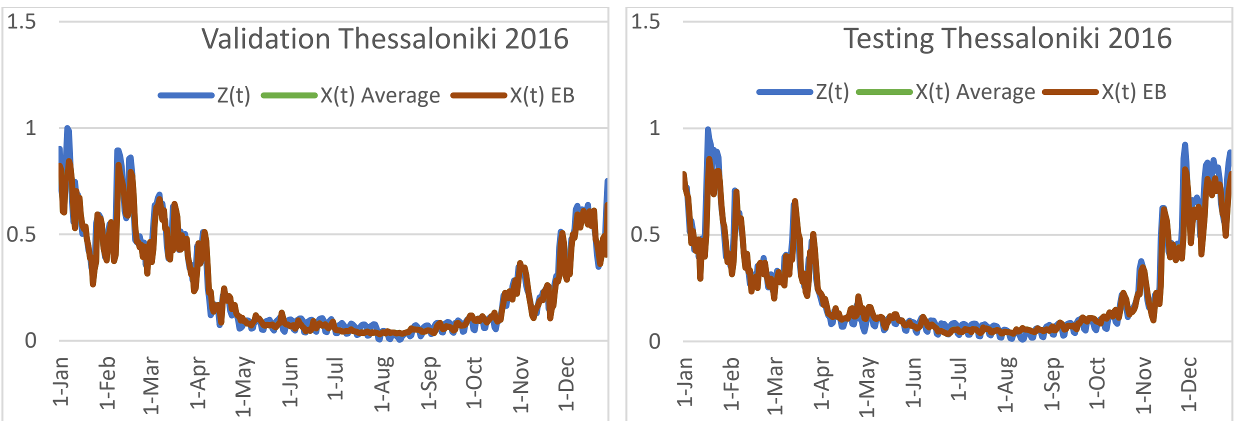
Validation	ANN ensemble	Hybrid ensemble	RCGA ensemble	SOGA ensemble	Ensemble AVG	Ensemble EB
MAE	0.0363	0.0361	0.0378	0.0374	0.0355	0.0355
MSE	0.0031	0.0031	0.0031	0.0030	**0.0028**	**0.0028**
Testing						
MAE	0.0393	0.0394	0.0399	0.0391	0.0381	0.0381
MSE	0.0037	0.0037	0.0036	0.0034	**0.0034**	**0.0034**

Table 5.10: Calculated errors for each individual forecaster based on scores for Larissa.

Validation	ANN	Hybrid	RCGA	SOGA	Ensemble AVG	Ensemble EB
MAE	0.0322	0.0324	0.0372	0.0365	0.0326	0.0319
MSE	0.0030	0.0028	0.0033	0.0032	**0.0027**	**0.0027**
Testing						
MAE	0.0412	0.0417	0.0466	0.0468	0.0427	0.0417
MSE	0.0043	0.0041	0.0047	0.0047	**0.0040**	**0.0040**

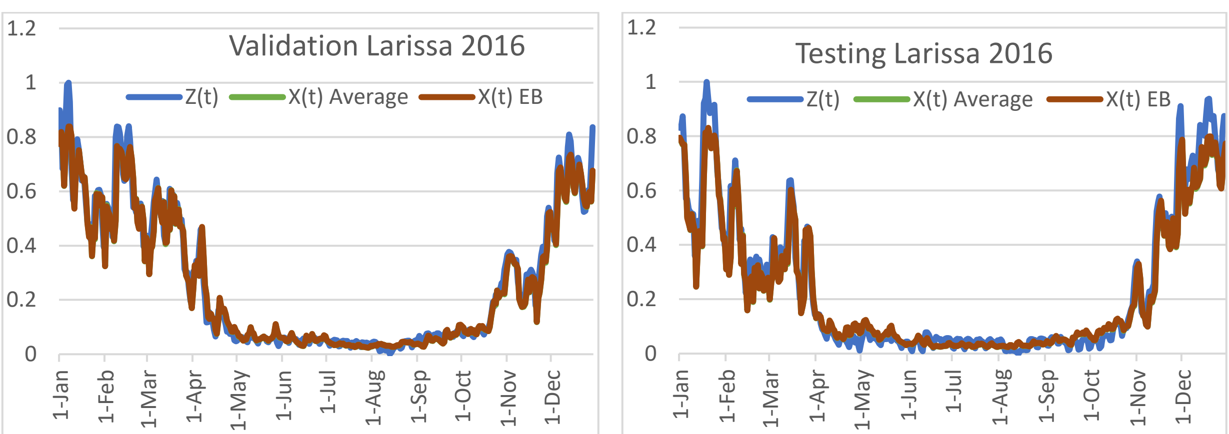
Table 5.11: Calculated errors for each ensemble forecaster based on scores for Larissa.

Validation	ANN ensemble	Hybrid ensemble	RCGA ensemble	SOGA ensemble	Ensemble AVG	Ensemble EB
MAE	0.0337	0.0332	0.0371	0.0362	0.0329	0.0326
MSE	0.0032	0.0030	0.0032	0.0031	0.0027	**0.0026**
Testing						
MAE	0.0428	0.0417	0.0458	0.0460	0.0426	0.0423
MSE	0.0048	0.0044	0.0045	0.0045	0.0041	**0.0040**



(a) (b)

Figure 5.8: Forecasting results for Thessaloniki considering the two ensemble methods (AVG, EB) based on scores. (a) Validation, (b) Testing.



(a) (b)

Figure 5.9: Forecasting results for Larissa considering the two ensemble methods (AVG, EB) based on scores. (a) Validation, (b) Testing.

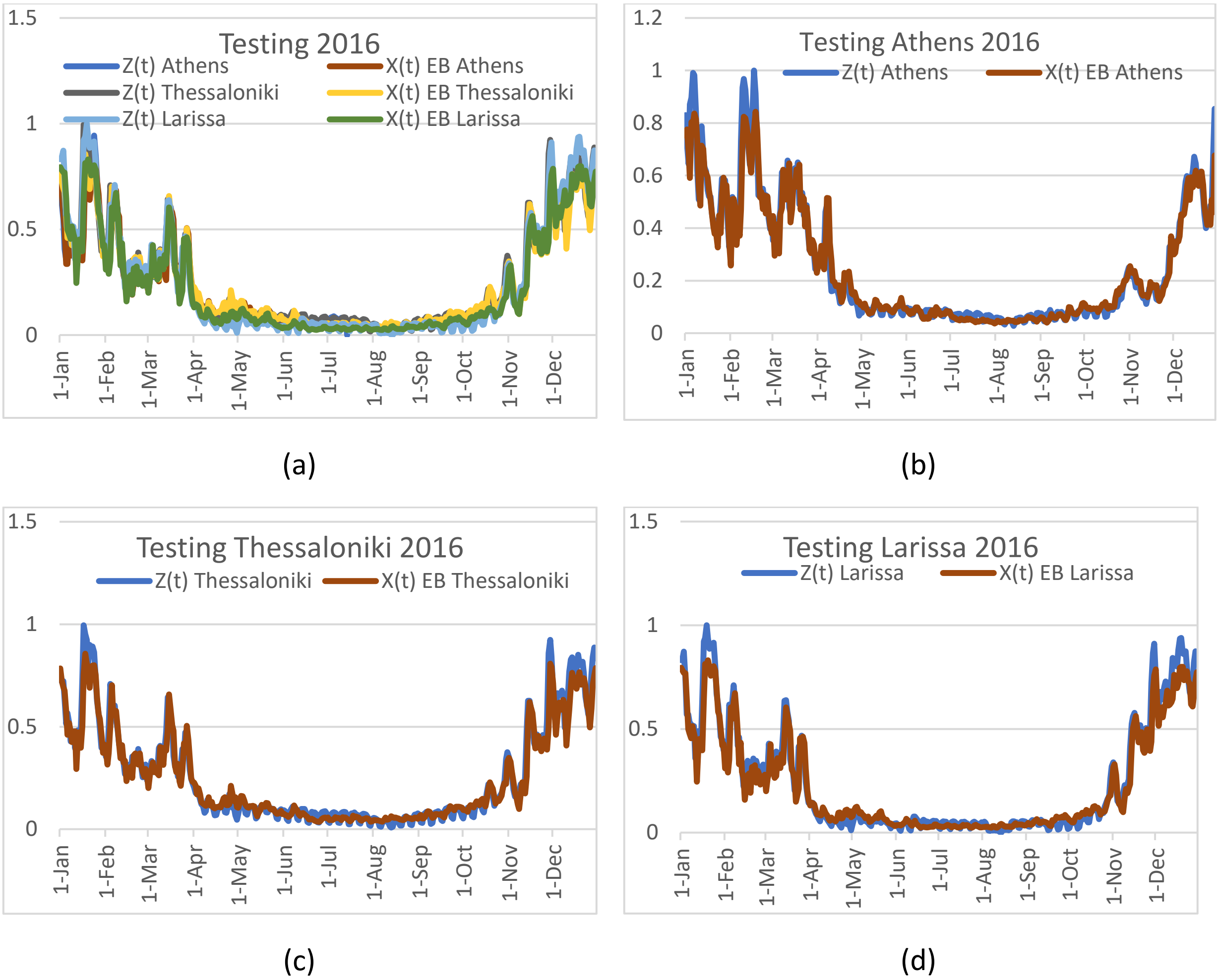


Figure 5. 10: Forecasting results for the three cities considering the best ensemble method. (a) Testing all cities, (b) Testing Athens, (c) Testing Thessaloniki, (d) Testing Larissa.

5.6.2 Case study results implementing forecasting using ANFIS

This section presents the exploration analysis results for various ANFIS architectures as proposed in section 5.4.2.2. Considering the ANFIS architecture described in section 5.4.2.1 and illustrated in Figure 5.5, the initial dataset is split in training and testing. During the training process, the ANFIS model is designed for each one of the suggested configurations. After the training process of ANFIS, NG consumption demands for the next day (one day ahead prediction) are calculated from the generated FIS. The NG consumption results only for the city of Athens (as an indicative example) regarding all configurations tested, are presented in Table 5.12, whereas Table 5.13 gathers the best three results of NG consumption demand obtained from ANFIS for each one of the 10 cities. To evaluate the performance of the models, the statistical indicator mean absolute percent error (MAPE) was used [191]. MAPE is a relative measurement, independent of scale, and it is the most common performance metric in time series forecasting, due to being reliable and valid [168].

Table 5.12: Testing results for the examined ANFIS architectures concerning the city of Athens

Anfis Run	Type of Input MF	Number of MFs	Type of Output MF	Number of Epochs	Optimization	MSE	RMSE	MAE	MAPE	R^2
1	trimf	2-2-2-2-2	Constant	10	Hybrid	0.0010	0.0320	0.0192	12.688	0.9849
2	trapmf	2-2-2-2-2	Constant	10	Hybrid	0.0013	0.0366	0.0245	19.887	0.9806
3	gbellmf	2-2-2-2-2	Constant	10	Hybrid	0.0011	0.0335	0.0209	14.749	0.9834
4	Gaussmf	2-2-2-2-2	Constant	10	Hybrid	0.0011	0.0326	0.0201	13.842	0.9842
5	Gauss2mf	2-2-2-2-2	Constant	10	Hybrid	0.0011	0.0324	0.0197	13.578	0.9845
6	pimf	2-2-2-2-2	Constant	10	Hybrid	0.0015	0.0389	0.0254	19.548	0.9782
7	dsigmf	2-2-2-2-2	Constant	10	Hybrid	0.0014	0.0378	0.0244	18.785	0.9794
8	psigmf	2-2-2-2-2	Constant	10	Hybrid	0.0014	0.0378	0.0244	18.785	0.9794
9	trimf	2-2-3-3-3	Constant	10	Hybrid	0.0015	0.0388	0.0232	15.884	0.9774
10	trapmf	2-2-3-3-3	Constant	10	Hybrid	0.0020	0.0448	0.0269	19.272	0.9698
11	gbellmf	2-2-3-3-3	Constant	10	Hybrid	0.0014	0.0379	0.0227	15.505	0.9785
12	Gaussmf	2-2-3-3-3	Constant	10	Hybrid	0.0014	0.0379	0.0226	15.764	0.9784
13	Gauss2mf	2-2-3-3-3	Constant	10	Hybrid	0.0017	0.0410	0.0241	15.822	0.9747
14	pimf	2-2-3-3-3	Constant	10	Hybrid	0.0130	0.1141	0.0347	21.671	0.8552
15	dsigmf	2-2-3-3-3	Constant	10	Hybrid	0.0020	0.0448	0.0254	16.780	0.9698
16	psigmf	2-2-3-3-3	Constant	10	Hybrid	0.0020	0.0448	0.0254	16.780	0.9698
17	trimf	3-3-3-2-2	Constant	10	Hybrid	0.0012	0.0348	0.0210	14.611	0.9819
18	trapmf	3-3-3-2-2	Constant	10	Hybrid	0.0018	0.0430	0.0297	27.025	0.9723
19	gbellmf	3-3-3-2-2	Constant	10	Hybrid	0.0013	0.0355	0.0212	14.424	0.9810
20	Gaussmf	3-3-3-2-2	Constant	10	Hybrid	0.0011	0.0337	0.0198	12.898	0.9829
21	trimf	3-3-3-3-3	Constant	10	hybrid	0.0021	0.0455	0.0242	15.496	0.9698
22	trimf	3-3-3-3-3	Constant	10	backprop	0.0559	0.2365	0.1610	74.965	0.7447
23	trapmf	3-3-3-3-3	Constant	10	hybrid	0.0031	0.0556	0.0281	21.581	0.9562
24	trapmf	3-3-3-3-3	Constant	10	backprop	0.0501	0.2238	0.1527	72.262	0.7404
25	gbellmf	3-3-3-3-3	Constant	10	hybrid	0.0014	0.0374	0.0217	14.653	0.9791
26	gbellmf	3-3-3-3-3	Constant	10	backprop	0.0015	0.0392	0.0265	25.179	0.9793
27	trimf	3-3-3-3-3	Constant	30	hybrid	0.0016	0.0403	0.0224	13.319	0.9759
28	trimf	3-3-3-3-3	Constant	50	hybrid	0.0017	0.0417	0.0224	13.227	0.9745
29	trapmf	3-3-3-3-3	Constant	30	hybrid	0.0029	0.0539	0.0245	17.223	0.9590
30	trapmf	3-3-3-3-3	Constant	50	hybrid	0.0017	0.0416	0.0233	16.461	0.9745
31	gbellmf	3-3-3-3-3	Constant	30	hybrid	0.0013	0.0366	0.0213	13.207	0.9799
32	gbellmf	3-3-3-3-3	Constant	50	hybrid	0.0019	0.0432	0.0236	13.444	0.9724
33	trimf	3-3-4-4-4	Constant	10	hybrid	0.0023	0.0479	0.0251	15.422	0.9662
34	trimf	3-3-5-5-5	Constant	10	hybrid	0.0078	0.0884	0.0320	17.315	0.9006
35	trapmf	3-3-4-4-4	Constant	10	hybrid	0.0021	0.0454	0.0275	23.176	0.9695
36	trapmf	3-3-5-5-5	Constant	10	hybrid	0.0098	0.1084	0.0450	19.315	0.8806
37	gbellmf	3-3-4-4-4	Constant	10	hybrid	0.0022	0.0472	0.0256	16.163	0.9669
38	gbellmf	3-3-5-5-5	Constant	10	hybrid	0.0044	0.0660	0.0307	18.097	0.9376
39	gaussmf	3-3-3-3-3	Constant	10	hybrid	0.0013	0.0365	0.0212	13.823	0.9800
40	gaussmf	3-3-4-4-4	Constant	10	hybrid	0.0019	0.0431	0.0241	14.771	0.9720
41	gaussmf	3-3-5-5-5	Constant	10	hybrid	0.0056	0.0746	0.0314	17.530	0.9185
42	gauss2mf	3-3-3-3-3	Constant	10	hybrid	0.0017	0.0409	0.0235	16.262	0.9755
43	gauss2mf	3-3-4-4-4	Constant	10	hybrid	0.0040	0.0632	0.0260	17.386	0.9407
44	gauss2mf	3-3-5-5-5	Constant	10	hybrid	0.0072	0.0847	0.0290	17.733	0.9048
45	pimf	3-3-3-3-3	Constant	10	hybrid	0.1224	0.3499	0.0482	26.090	0.3608
46	pimf	3-3-4-4-4	Constant	10	hybrid	0.0026	0.0510	0.0307	24.762	0.9615
47	pimf	3-3-5-5-5	Constant	10	hybrid	0.0022	0.0466	0.0285	22.355	0.9678

Table 5.13: Testing results for the best three ANFIS architectures based on MAPE value

City	*Anfis Run*	*Type of Input MF*	*Number of MFs*	*Number of Rules*	*Time (sec)*	*MSE*	*RMSE*	*MAE*	*MAPE*	*R^2*
Alexandroupoli	17	trimf	3-3-3-2-2	72	5	0.0024	0.0494	0.0351	10.527	0.9638
	39	gaussmf	3-3-3-3-3	243	47	0.0031	0.0557	0.0355	10.155	0.9538
	20	gaussmf	3-3-3-2-2	72	5	0.0023	0.0480	0.0341	10.112	0.9659
Athens	1	trimf	2-2-2-2-2	32	7	0.0021	0.0457	0.0295	20.179	0.9825
	17	trimf	3-3-3-2-2	18	19	0.0026	0.0511	0.0315	19.797	0.9786
	20	gaussmf	3-3-3-2-2	108	19	0.0022	0.0467	0.0306	21.292	0.9818
Drama	17	trimf	3-3-3-2-2	108	19	0.0026	0.0511	0.0363	6.2547	0.8997
	1	trimf	2-2-2-2-2	32	5	0.0026	0.0513	0.0361	6.2235	0.8975
	20	gaussmf	3-3-3-2-2	108	13	0.0026	0.0508	0.0371	6.4071	0.8995
Karditsa	17	trimf	3-3-3-2-2	108	12	0.0019	0.0434	0.0242	13.839	0.9789
	1	trimf	2-2-2-2-2	32	4	0.0018	0.0421	0.0236	11.619	0.9801
	4	gaussmf	2-2-2-2-2	32	4	0.0019	0.0431	0.0248	13.384	0.9792
Larissa	1	trimf	2-2-2-2-2	32	4	0.0012	0.0352	0.0203	10.956	0.9817
	4	gaussmf	2-2-2-2-2	32	4	0.0012	0.0352	0.0204	10.983	0.9817
	20	gaussmf	3-3-3-2-2	108	19	0.0010	0.0314	0.0184	10.523	0.9858
Markopoulo	1	trimf	2-2-2-2-2	32	5	0.0091	0.0956	0.0728	25.088	0.6593
	4	gaussmf	2-2-2-2-2	32	5	0.0096	0.0980	0.0755	26.751	0.6364
	17	trimf	3-3-3-2-2	108	19	0.0259	0.1609	0.1087	36.717	0.5126
Serres	1	trimf	2-2-2-2-2	32	5	0.0007	0.0271	0.0176	10.472	0.9839
	4	gaussmf	2-2-2-2-2	32	5	0.0008	0.0279	0.0185	11.242	0.9831
	39	gaussmf	3-3-3-3-3	243	45	0.0008	0.0285	0.0194	12.116	0.9824
Thessaloniki	17	trimf	3-3-3-2-2	108	13	0.0015	0.0382	0.0229	16.104	0.9773
	20	gaussmf	3-3-3-2-2	108	13	0.0013	0.0363	0.0219	14.194	0.9795
	39	gaussmf	3-3-3-3-3	243	45	0.0021	0.0459	0.0256	15.203	0.9672
Trikala	1	trimf	2-2-2-2-2	32	4	0.0019	0.0433	0.0232	10.581	0.9815
	4	gaussmf	2-2-2-2-2	32	4	0.0020	0.0450	0.0245	11.141	0.9800
	20	gaussmf	3-3-3-2-2	108	13	0.0028	0.0530	0.0271	11.763	0.9708
Volos	1	trimf	2-2-2-2-2	32	4	0.0021	0.0459	0.0317	13.252	0.9564
	4	gaussmf	2-2-2-2-2	32	4	0.0021	0.0460	0.0314	13.162	0.9563
	20	gaussmf	3-3-3-2-2	108	12	0.0020	0.0445	0.0323	13.971	0.9588

The corresponding graphical representation of the results regarding the best three out of 47 total ANFIS architectures for the city of Athens, is illustrated in Figure 5.11. Also, the best ANFIS model for each city can be found in Table 5.14 which provides the most reliable ANFIS architecture results for each city. All the results have been previously ranked, based on the minimum value of MAPE and subsequently the minimum values of MSE, RMSE and MAE. The priority was given to MAPE as one of the most crucial evaluation metrics, according to the literature [191, 193], which was used in this chapter to compare various models obtained from ANFIS and other soft computing and neural networks methods. As a relative and easy to interpret measurement, MAPE is reliable, valid and independent of scale. The smaller the values of MAPE, the closer the forecasted values to the actual values.

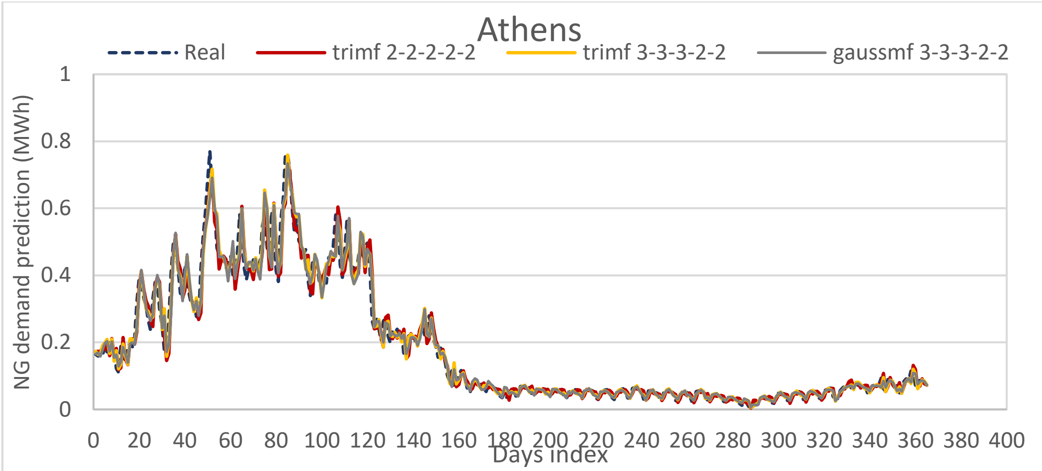
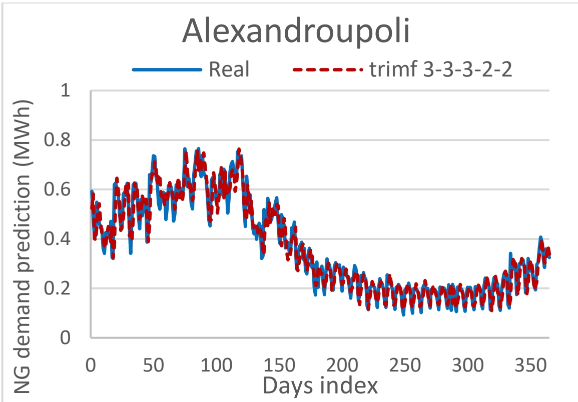


Figure 5.11: Forecasting results for the best three ANFIS architectures for Athens.

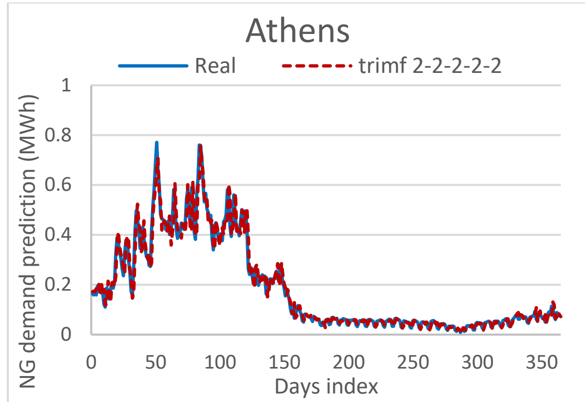
Table 5.14: The best ANFIS models for all the cities under investigation (10 epochs and hybrid optimization).

CITY	ANFIS RUN	TYPE OF INPUT MF	NUMBER OF MFS	TYPE OF OUTPUT MF	OPTIMIZATION	MSE	RMSE	MAE	MAPE	R^2
ALEXANDROUPOLI	20	gaussmf	3-3-3-2-2	Constant	Hybrid	0.0023	0.0480	0.0341	10.112	0.9659
ATHENS	17	trimf	3-3-3-2-2	Constant	Hybrid	0.0026	0.0511	0.0315	19.797	0.9786
DRAMA	1	trimf	2-2-2-2-2	Constant	Hybrid	0.0026	0.0513	0.0361	6.2235	0.8975
KARDITSA	1	trimf	2-2-2-2-2	Constant	Hybrid	0.0018	0.0421	0.0236	11.619	0.9801
LARISSA	20	gaussmf	3-3-3-2-2	Constant	Hybrid	0.0010	0.0314	0.0184	10.523	0.9858
MARKOPOULO	1	trimf	2-2-2-2-2	Constant	Hybrid	0.0091	0.0956	0.0728	25.088	0.6593
SERRES	4	gaussmf	2-2-2-2-2	Constant	Hybrid	0.0008	0.0279	0.0185	11.242	0.9831
THESSALONIKI	20	gaussmf	3-3-3-2-2	Constant	Hybrid	0.0013	0.0363	0.0219	14.194	0.9795
TRIKALA	4	gaussmf	2-2-2-2-2	Constant	Hybrid	0.0020	0.0450	0.0245	11.141	0.9800
VOLOS	4	gaussmf	2-2-2-2-2	Constant	Hybrid	0.0021	0.0460	0.0314	13.162	0.9563

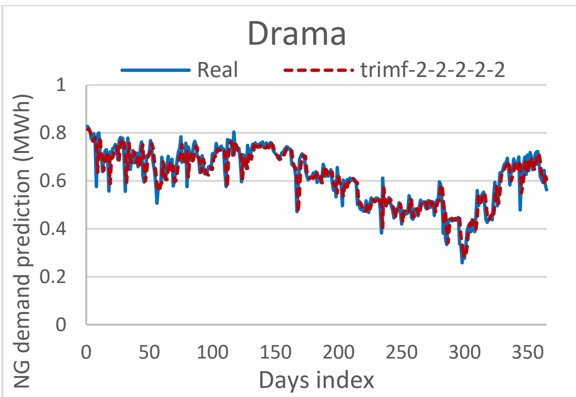
As illustrated in Table 5.14, ANFIS models appear to perform best, mostly when triangular MFs are used for the input variables, three MFs for the first three input variables (month, day of week and mean temperature) and two or three MFs for the rest two input variables (daily demand for current day and one day before). Also, constant MFs are selected for output variable and hybrid optimization method. The graphical representation of the best ANFIS models for each city is illustrated in Figure 5.12.


Alexandroupoli
Real
trimf 3-3-3-2-2
NG demand prediction (MWh)
Days index

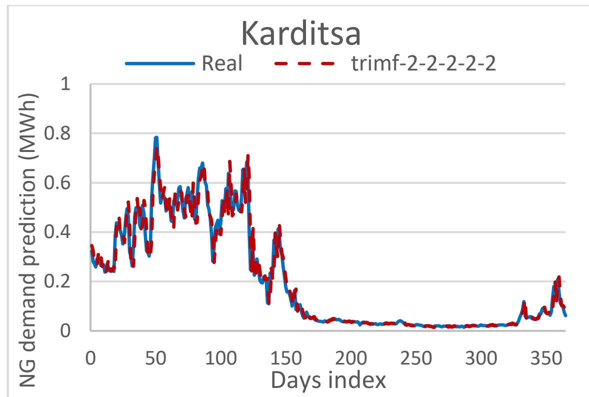
(a)


Athens
Real
trimf 2-2-2-2-2
NG demand prediction (MWh)
Days index

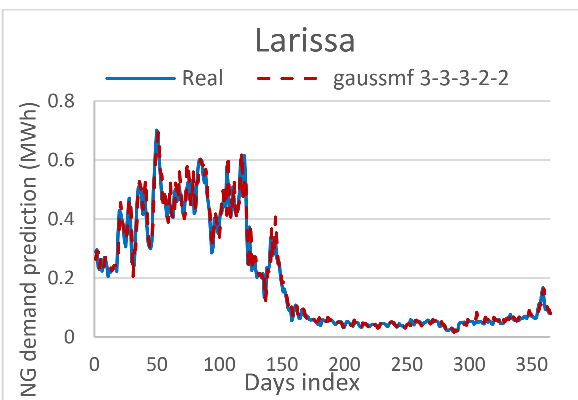
(b)


Drama
Real
trimf-2-2-2-2-2
NG demand prediction (MWh)
Days index

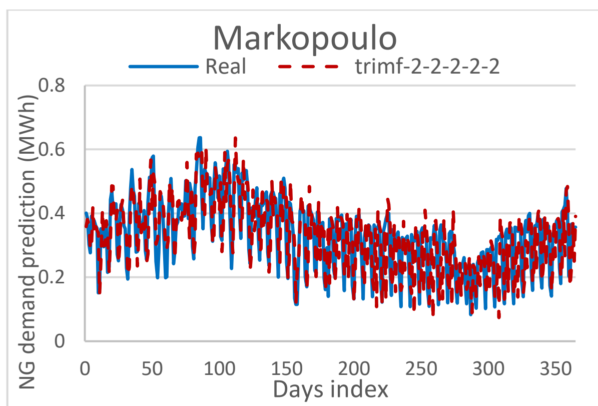
(c)


Karditsa
Real
trimf-2-2-2-2-2
NG demand prediction (MWh)
Days index

(d)


Larissa
Real
gaussmf 3-3-3-2-2
NG demand prediction (MWh)
Days index

(e)


Markopoulo
Real
trimf-2-2-2-2-2
NG demand prediction (MWh)
Days index

(f)

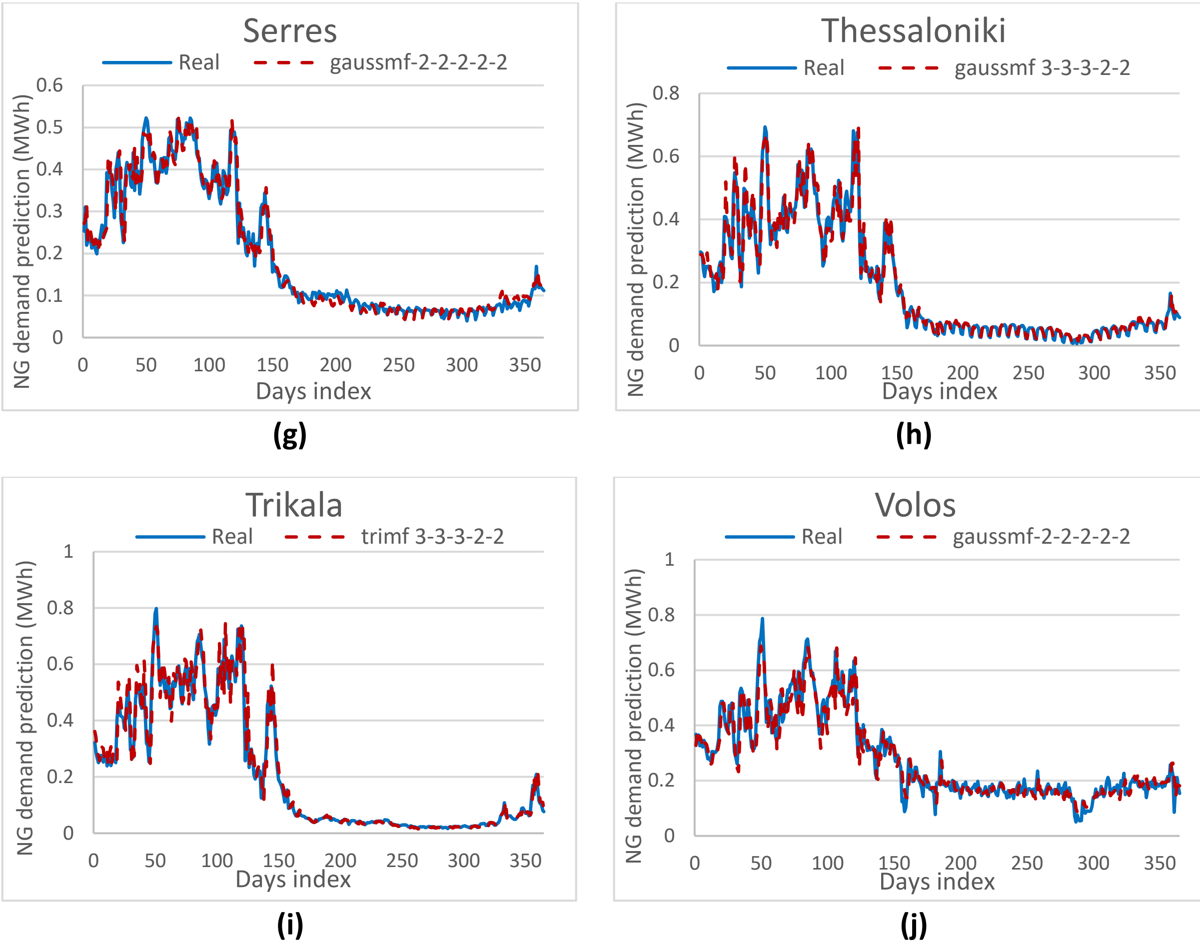


Figure 5.12: Forecasting results for all cities considering the best ANFIS method. (a) Testing Alexandroupoli, (b) Testing Athens, (c) Testing Drama, (d) Testing Karditsa, (e) Testing Larissa, (f) Testing Markopoulo, (g) Testing Serres, (h) Testing Thessaloniki, (i) Testing Trikala, (j) Testing Volos.

It is worth mentioning that all three most efficient ANFIS architectures with respect to MAPE values, have triangular or gaussian MFs and 2-2-2-2-2 or 3-3-3-2-2 number of input MFs, whereas the output MF is constant and the learning algorithm is hybrid. In addition, the application of other MFs combinations does not seem to give results that could be on top of the list. Because of the limitation of the total number of parameters that should not exceed the number of training data pairs, the number of MFs was chosen based on the number of input parameters. Figure 5.13 shows the exponential increase of the number of rules, when the number of MFs increases, whereas Table C.7 in Appendix C gathers the time and number of rules for all the proposed ANFIS configurations.

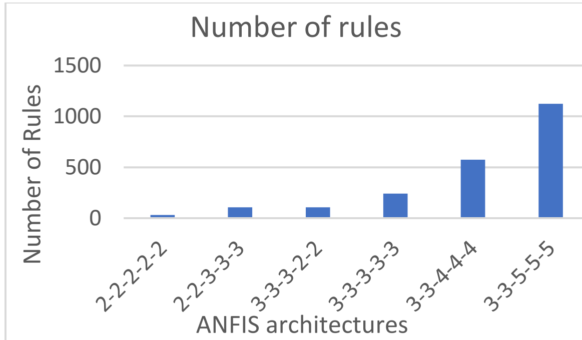


Figure 5.13: Number of Rules for various ANFIS architectures

5.7 Comparative Analysis for the proposed models

To further investigate the performance of the proposed ANFIS architectures, an extensive comparative analysis between the state-of-the-art ANNs, soft computing methods of FCMs and their hybrid combination of FCMs with ANNs was performed. The architecture of the analyzed ANN was multilayer feed forward network with an input layer containing five inputs (month, day, temperature, demand of a day before, current demand), a hidden layer with 10 neurons and an output layer with one output (a day-ahead demand prediction). Sigmoidal activation function was used in all layers and implemented Levenberg-Marquardt algorithm to train the network.

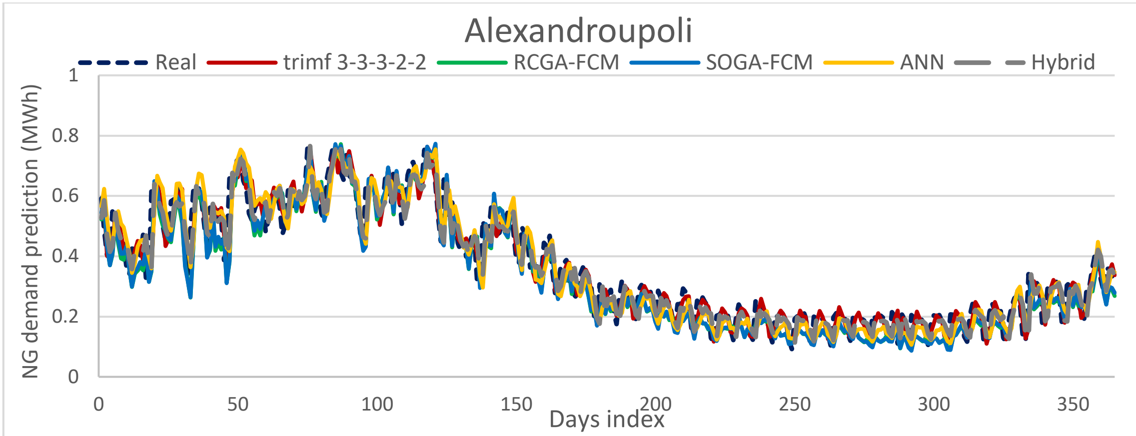
The implementations of FCMs differ from ANFIS, even though they both belong to the soft computing family. In this case study, FCMs which are learned with the use of RCGA and SOGA algorithm, as well as their ensemble architecture, contain 5 concepts (month, day, temperature, demand of a day before, current demand).

The applied hybrid approach for time series prediction is based on FCMs and ANNs and has been previously proposed in [219]. It allows to select the most significant concepts for FCM using SOGA. These concepts are used as the inputs for ANN. The hybrid approach utilized artificial neural networks with an input layer with 5 inputs selected by the SOGA-FCM approach, a hidden layer with 10 neurons and an output layer with one output (one day-ahead demand prediction). Sigmoidal activation function and Levenberg-Marquardt learning algorithm were used. All the simulations for FCMs and hybrid FCM-ANN configurations were performed with the software tool ISEMK [195] which has been developed for time series forecasting purposes. An analytical description of FCM-based models and hybrid FCM-ANN can be found in [53, 86, 197, 198], whereas they are used in this work only for comparison purposes.

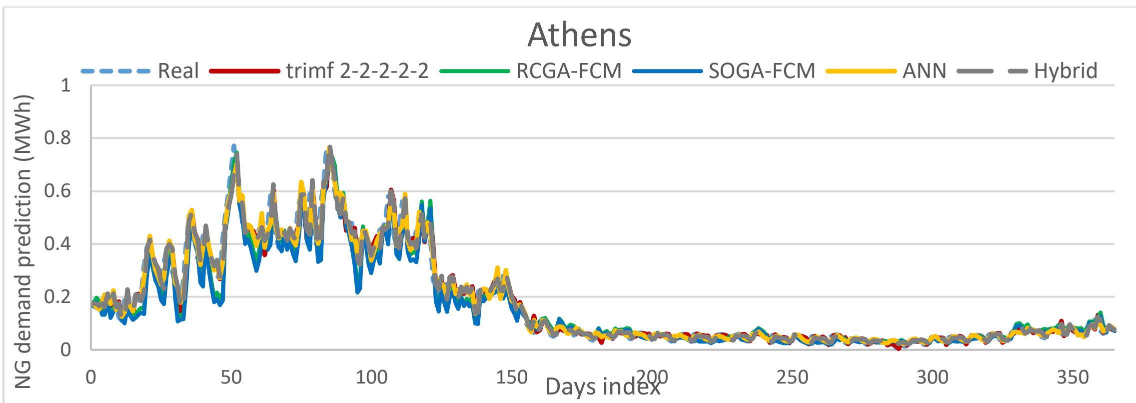
In what follows, Table 5.15 gathers the results of the explored ANN and soft computing models, which are straightforward compared with the best performed ANFIS configuration, for each one out of the 10 cities, suggested in this chapter. In Figure 5.14, three indicative graphs of cities Alexandroupoli, Athens, and Drama, are illustrated regarding the predicted values of NG demand for all the best proposed architectures.

Table 5.15: Comparison results among ANN, FCM, hybrid FCM-ANN and best ANFIS

CITY	METHOD	MSE	RMSE	MAE	MAPE	R^2
ALEXANDROUPOLI	RCGA-FCM	0.0047	0.0684	0.0538	17.6233	0.9450
	SOGA-FCM	0.0045	0.0672	0.0526	17.1707	0.9484
	ANN	0.0042	0.0645	0.0505	16.1131	0.9439
	Hybrid FCM-ANN	0.0034	0.0579	0.0427	14.3034	0.9498
	Best ANFIS	**0.0023**	**0.0480**	**0.0341**	**10.1123**	**0.9659**
ATHENS	RCGA-FCM	0.0022	0.0473	0.0303	23.5985	0.9676
	SOGA-FCM	0.0029	0.0539	0.0337	22.7453	0.9646
	ANN	**0.0010**	**0.0323**	**0.0198**	**14.2464**	**0.9844**
	Hybrid FCM-ANN	0.0014	0.0374	0.0230	17.5418	0.9790
	Best ANFIS	0.0026	0.0511	0.0315	19.7972	0.9786
DRAMA	RCGA-FCM	0.0080	0.0894	0.0749	12.9942	0.8691
	SOGA-FCM	0.0056	0.0748	0.0600	10.1766	0.8796
	ANN	**0.0025**	**0.0501**	**0.0357**	**6.1657**	**0.9025**
	Hybrid FCM-ANN	0.0028	0.0526	0.0363	6.2502	0.8941
	Best ANFIS	**0.0026**	**0.0513**	**0.0361**	**6.2235**	**0.8975**
KARDITSA	RCGA-FCM	0.0039	0.0624	0.0379	27.5914	0.9591
	SOGA-FCM	0.0488	0.2210	0.1397	50.2112	0.9711
	ANN	0.0016	0.0405	0.0245	17.4579	0.9819
	Hybrid FCM-ANN	0.0017	0.0407	0.0245	18.4095	0.9817
	Best ANFIS	**0.0018**	**0.0421**	**0.0236**	**11.6196**	**0.9801**
LARISSA	RCGA-FCM	0.0027	0.0515	0.0331	22.2481	0.9638
	SOGA-FCM	0.0025	0.0505	0.0328	22.9579	0.9649
	ANN	0.0013	0.0355	0.0209	13.2479	0.9812
	Hybrid FCM-ANN	0.0013	0.0356	0.0215	13.1974	0.9811
	Best ANFIS	**0.0010**	**0.0314**	**0.0184**	**10.5236**	**0.9858**
MARKOPOULO	RCGA-FCM	0.0075	0.0868	0.0726	26.0003	0.6975
	SOGA-FCM	0.0078	0.0883	0.0739	26.3345	0.6955
	ANN	0.0172	0.1310	0.1048	34.8594	0.4765
	Hybrid FCM-ANN	**0.0070**	**0.0836**	**0.0667**	**23.7166**	**0.7094**
	Best ANFIS	0.0091	0.0956	0.0728	25.0887	0.6593
SERRES	RCGA-FCM	0.0017	0.0409	0.0274	16.5199	0.9648
	SOGA-FCM	0.0495	0.2225	0.1632	72.9785	0.9772
	ANN	**0.0008**	**0.0275**	**0.0179**	**10.9948**	**0.9842**
	Hybrid FCM-ANN	0.0008	0.0289	0.0190	11.5000	0.9821
	Best ANFIS	0.0008	0.0279	0.0185	11.2421	0.9831
THESSALONIKI	RCGA-FCM	0.0029	0.0541	0.0339	29.9713	0.9565
	SOGA-FCM	0.0029	0.0539	0.0340	30.1471	0.9568
	ANN	0.0017	0.0412	0.0262	23.8748	0.9735
	Hybrid FCM-ANN	0.0019	0.0441	0.0266	23.8835	0.9696
	Best ANFIS	**0.0013**	**0.0363**	**0.0219**	**14.1944**	**0.9795**
TRIKALA	RCGA-FCM	0.0059	0.0770	0.0453	21.9722	0.9528
	SOGA-FCM	0.0433	0.2082	0.1287	42.7427	0.9715
	ANN	0.0020	0.0443	0.0258	14.1183	0.9804
	Hybrid FCM-ANN	0.0019	0.0432	0.0251	13.9034	0.9815
	Best ANFIS	**0.0020**	**0.0450**	**0.0245**	**11.1412**	**0.9800**
VOLOS	RCGA-FCM	0.0028	0.0526	0.0397	17.8195	0.9436
	SOGA-FCM	0.0027	0.0520	0.0395	17.8988	0.9445
	ANN	0.0020	0.0444	0.0319	13.2504	0.9588
	Hybrid FCM-ANN	0.0020	0.0446	0.0307	12.7881	0.9587
	Best ANFIS	**0.0021**	**0.0460**	**0.0314**	**13.1629**	**0.9563**



(a)



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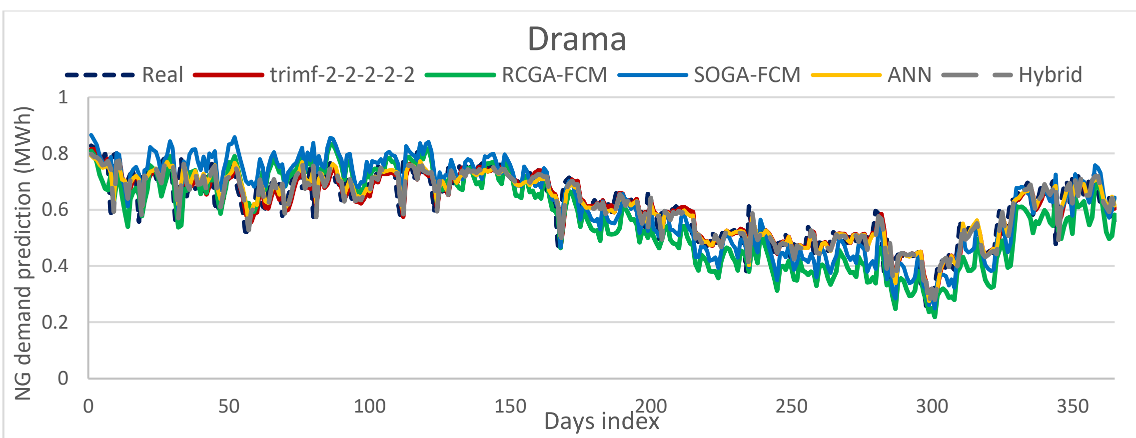

(c)

Figure 5.14: Comparison of forecasting results for each city considering all examined methods. (a) Testing for Alexandroupoli, (b) Testing for Athens, (c) Testing for Drama.

For a deeper analysis of the examined architectures (ANFIS, ANN, FCM, hybrid FCM-ANN), further details are reported regarding the parameters of each model used in this study. The ANN and FCM models have been previously applied for NG demand prediction in several research works, such as those in [53, 86, 197, 198]. The models were sufficiently described and the hyperparameters were properly configured to offer optimum performance of the investigated FCM models.

Table 5.16 depicts the optimum parameters for all cities considering the neural and FCM evolutionary methods (ANN, RCGA-FCM, SOGA-FCM, Hybrid), compared with the proposed best performed ANFIS. Average running time is also presented in Table 5.16, which was calculated for each soft computing architecture for all models. It is worth mentioning that a rigorous exploratory analysis for all the investigated neuro-fuzzy, soft computing techniques and ANNs, with different parameters for training and model optimization has been conducted to reach the highest prediction accuracy with respect to the evaluation metrics.

Table 5.16: Parameters and Average Running Time for each architecture

ARCHITECTURES	PARAMETERS FOR ATHENS CITY	AVERAGE RUNNING TIME
ANN	Multilayer feed forward network, six inputs, 10 neurons, one output, sigmoidal activation function, Levenberg-Marquardt learning, epochs=20	16-20 sec
RCGA-FCM	Uniform crossover with probability 0.4, Mühlenbein's mutation with probability 0.4, ranking selection, elite strategy, population size 200, maximum number of generations 200	808 sec
SOGA-FCM	Uniform crossover with probability 0.4, Mühlenbein's mutation with probability 0.4, ranking selection, elite strategy, population size 200, maximum number of generations 200, learning parameters b_1=b_2=0.01	799 sec
HYBRID FCM-ANN	Multilayer feed forward network, four inputs selected by SOGA-FCM (month, temperature, demand of a day before, current demand), one hidden layer with 10 neurons, one output, sigmoidal activation function, Levenberg-Marquardt learning, epochs=20	811 sec
BEST ANFIS	Triangular mf, 2-2-2-2-2 or 3-3-3-2-2, Constant output, epochs=10, Hybrid optimization	4-19 sec

In the case of the proposed forecasting ensemble approach of multivariate time series, in order to show its effectiveness, an experimental analysis for comparison purposes was conducted with a new and well-known effective machine learning technique for time series forecasting, the LSTM (long short-term memory). LSTM algorithm encloses the characteristics of the advanced recurrent neural network methods and is mainly applied for time series prediction problems in diverse domains.

LSTM was applied in one day-ahead natural gas consumption prediction concerning the same dataset of the three Greek cities (Athens, Thessaloniki, and Larissa) in [220]. For the LSTM implementation, one feature of the dataset as a time series was selected. As explained in [220], LSTM was fed previous values, and, in that case, the time-step was set to be 364 values to predict the next 364. For validation, 20% of random data from the training dataset was used, and for testing, the same dataset that was used for the ANN, RCGA-FCM, SOGA-FCM, and hybrid FCM-ANN, as well as with their ensemble structures implementation. In [220], various experiments with different numbers of units, number of layers, and dropout rates were accomplished. Through the provided experimental analysis, the best results of LSTM emerged for one layer, 200 units, and dropout rate = 0.2. These results are gathered in Table 5.17 for the three cities.

Table 5.17: Comparison Results with LSTM (with best configuration parameters).

	Best ensemble		**LSTM (dropout=0.2)**
	Case (A) (individual)	**Case (B) (ensemble)**	**1 layer**
Validation		**ATHENS**	
MAE	0.0326	0.0337	0.0406
MSE	0.0032	0.0032	0.0039
Testing			
MAE	0.0328	0.0352	0.0426
MSE	0.0031	0.0032	0.0041
Validation		**THESSALONIKI**	
MAE	0.034	0.0355	0.0462
MSE	0.007	0.0028	0.0043
Testing			
MAE	0.0369	0.0381	0.0489
MSE	0.0031	0.0034	0.0045
Validation		**LARISSA**	
MAE	0.0319	0.0326	0.0373
MSE	0.0027	0.0026	0.0029
Testing			
MAE	0.0417	0.0423	0.0462
MSE	0.0040	0.0040	0.0042

it emerges that both ensemble forecasting methods can achieve high accuracy in the predictions of the energy consumption patterns in a day-ahead timescale.

5.8 Discussion of Results

In this chapter, two soft computing methodologies, an ensemble approach using FCMs and an ANFIS architecture were investigated, with respect to all the variables carefully determined in the developed models, and after a careful analysis of the Tables and Figures presented in the relevant sections above.

In the case of the proposed ensemble-based forecast combination methodology, which combines SOGA-based FCMs, RCGA-based FCMs, efficient and adaptive ANNs architectures, and a hybrid structure of FCM-ANN, whose performance was discussed through the Average and the Error-based ensemble methods, the following important observations are noticed. More specifically and according to the produced results, none of the two forecast combination methods has attained consistently better accuracies comparing to each other, as far as the cities of Athens and Thessaloniki are concerned. In that instance, the MAE and MSE values across the two combination methods are similar for the two cities, as can be observed in Tables 5.6 to 5.11. However, their errors are lower than those produced by each separate ensemble forecaster. Additionally, as regards the amount of improvement presented when a forecasting method is applied, a slightly better performance of both ensemble forecasting methods can be noticed. This constitutes a strong evidence about the efficiency of the examined method in the domain of natural gas demand forecasting.

In the case of ANFIS approach, different sets of model configurations were tested. However, only one ANFIS architecture reached the optimum performance, in terms of forecasting accuracy, considering the minimum value of MAPE and subsequently the minimum values of MSE, RMSE and MAE values produced. In particular, it emerged that the optimum ANFIS configuration is 2-2-2-2-2 with triangular MFs for input variables, which produces the simplest (concerning the number of rules), fastest (see Table C.7 in Appendix C) and most accurate model for this energy forecasting problem. In general, it is observed that best results are produced from the combination of triangular or gaussian MFs regarding the input variables, and the constant MFs regarding the output layers.

The comparative analysis (see Table 5.15 in Section 5.8) regarding the demand forecasting performance of the two proposed techniques and other ANN and soft computing methods reported in the literature and already applied in the specific domain, revealed that the ANFIS best model produced the best results in terms of MAPE values. The smaller the values of MAPE are, the closer to the actual values the forecasted values are. For example, MAPE values of RCGA-FCM, SOGA-FCM, ANN, hybrid and ANFIS models for the city of Alexandroupoli, are calculated as 17.62%, 17.17%, 16.11%, 14.30% and 10.11%, respectively.

In order to examine the efficiency of the proposed ensemble algorithm, a statistical test was additionally conducted to reveal no statistical significance. Concerning the individual methods, a t-test paired two samples of mean was previously conducted in [198] for the cities of Thessaly (Larissa, Volos, Trikala and Karditsa), for the year 2016, showing that there is no statistical significance among these techniques. In current work, a t-test paired two samples of mean was also performed, regarding the ensemble methods (Average and Error-based) for the examined cities (Athens, Thessaloniki and Larissa), regarding the dataset of the same year. The results of the hypothesis tests reveal no statistical significance between these techniques. In all cases, the calculated p-value exceeds 0.05, so no statistical significance was noticed from the obtained statistical analysis. Therefore, there is no particular need to conduct a post-hoc statistical test, since a post-hoc test should only be run when you have an overall statistically significant difference in group means, according to the relevant literature [221, 222].

Considering the same dataset linked to only three cities (Athens, Thessaloniki, and Larissa) out of ten participated in the case study, a day-ahead NG consumption prediction was investigated in [220], applying ANN and LSTM approaches and in [198], implementing the SOGA-FCM method and a hybrid combination of it. These methods and their results in terms of MSE and MAE values for three benchmark cities, are all gathered in the following table and certain results can be concluded. The main reason for selecting the statistical indicators MSE and MAE in the following figure is to accomplish a straightforward comparison with the results published in previous works.

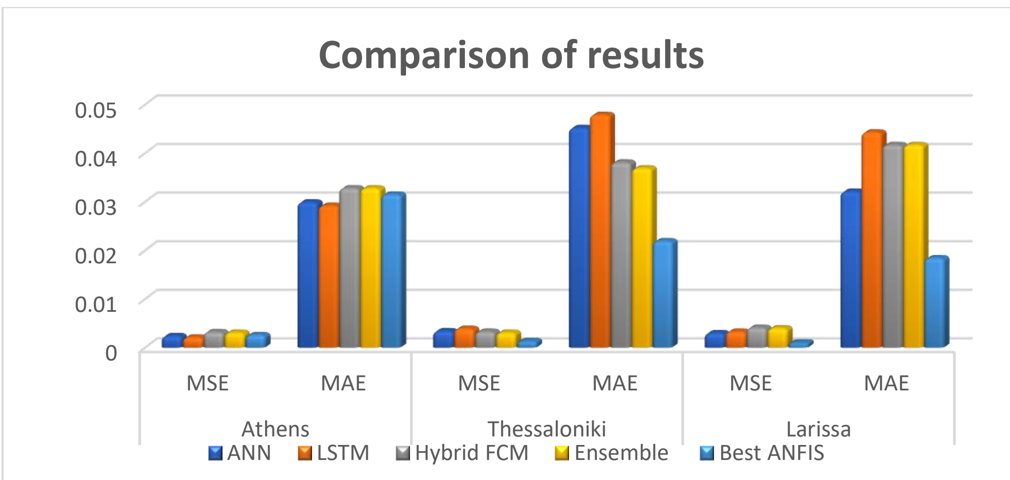

Figure 5.15: Comparison of results between machine learning and soft computing methods for three benchmark cities.

In Figure 5.15, it can be noted that all methods achieve high accuracy in NG consumption predictions, using the same dataset. The best ANFIS approach seems to excel over the ensemble and hybrid methods. Consequently, the proposed ANFIS architecture, which handles more efficiently the fuzziness of data, outperforms all the other examined methods in most cases, with a rather remarkable difference. ANFIS is less time consuming and more flexible than ANN, and as it employs fuzzy rules and membership functions incorporating with real-world systems, it can be used as alternate method to ANN forecasting.

It is observed that the proposed method exhibits better or similar performance to other well-known ANN, FCM or hybrid FCM-ANN architectures for the ten cities under investigation. The produced results highlight the significance and superiority of neuro-fuzzy methods over the other examined methods in terms of prediction accuracy, when they deal with time series forecasting problems in energy. This is in accordance with the main advantageous features of ANFIS models. Those are, their ability to capture the nonlinear structure of a process, their adaptation capability, and fast training characteristics. As reported in the literature, ANFIS models are able to cope with uncertainty and fuzziness that characterize energy domain when other intelligent methods cannot tackle.

The main findings in this chapter can be summarized as follows:

i) Both soft computing approaches (ensemble based on FCMs and ANFIS) are powerful and efficient forecasting methods in the Natural Gas domain.

ii) The Error-Based (EB) ensemble method presents lower errors concerning the individual forecasters (ANN, Hybrid, RCGA-FCM and SOGA-FCM) for all three cities (Athens, Thessaloniki and Larisa), as can be seen in Tables 5.6 to 5.11. EB seems to outperform the AVG method in terms of achieving overall better forecasting results when being applied to individual forecasters (see Figure 5.10).

iii) The proposed ANFIS method exhibits best performance when certain configuration settings are selected for the examined datasets. The "best" ANFIS model configuration is a distinct architecture featuring a 2-2-2-2-2 triangular or gaussian MFs which was determined after several experiments and a trial-and-error approach have been properly conducted.

iv) The proposed ANFIS architecture is superior to the four benchmark and well-known ANN and FCM methods (ANN, SOGA-FCM, RCGA-FCM, Hybrid FCM-ANN) previously used in NG consumption forecast. The best ANFIS model holds the best prediction accuracy among all these methods, with respect to various error indicators and the R^2 values (see Table 5.15).

v) The proposed ANFIS model shows significant capacity when applied to forecast NG demand, since it exhibits better performance (see Table 5.15) with less running time (see Table 5.16) and more flexibility to handle fuzziness than other well-known ANN and FCM architectures.

5.9 Concluding Remarks

This chapter tried to address the task of Natural Gas demand forecasting by introducing two promising soft computing methods that are proved to be highly efficient in this context, achieving exceptional prediction accuracies using historical data.

The performance of the ANFIS model whose best configuration was determined after a proper exploration process regarding its input and training parameters, was assessed through its comparison with other well-known ANN and soft computing models that are commonly used for energy demand prediction purposes. The ANFIS method demonstrates significant performance in the field of energy demand prediction, outweighing the traditional ANN and FCM architectures. In addition, the running time of the proposed architecture is much less than those of other examined models, making it the right decision for day-ahead demand forecasting of NG. The investigated approach is an accurate estimation method as it makes efficient short-term predictions in natural gas demand, showing minor deviations between the real and the predicting values. The ANFIS approach can be applied in various other domains such as medicine, environmental modelling, various energy systems, like solar and wind, as well as other engineering applications due to the generalization capabilities of the proposed architecture. As regards the energy sector, the results show that the proposed ANFIS method finds great applicability due to its high prediction accuracy, robustness, and easiness to use. These characteristics make it a powerful tool for regulatory authorities and decision makers to perform rigorous forecasting of natural gas demand. It can be also useful especially for distribution operators, providing them with the ability to make long-term planning decisions and apply the correct strategic policies in this direction. An overall positive impact in environmental and economic sustainability can be noticed.

In the case of the proposed ensemble forecasting approach, this combines individual ANN, RCGA-FCM, SOGA-FCM, and hybrid FCM-ANN methods incorporating the two most popular ensemble methods for error calculation in forecasting problems. The effectiveness of the ensemble learning approach in time series prediction was examined through an experimental analysis, using the MAE and MSE error statistics. The results of this chapter show that the examined ensemble approach through designing an ensemble structure of various ANN, SOGA-FCM models by different learning parameters and their hybrid structures can significantly improve forecasting. Moreover, the obtained results clearly demonstrate that a relatively higher forecasting accuracy is noticed when the applied ensemble approach is compared against independent forecasting approaches, such as ANN or FCM, as well as with LSTM. The whole framework seems to be a promising approach for ensemble time series forecasting which can be easily applied in a plethora of scientific domains as it offers generalization capabilities.

Chapter 6

Conclusions and Future work

This chapter provides an overview of the key results and the major research contributions as emerged throughout this dissertation, along with future directions in the research field.

6.1 Research contributions and Conclusions

During the last decades, world has drawn attention into sustainability across various forms and domains including social, economic, environmental and energy. Decision making on these crucial for humanity complex systems requires a thorough study and exploration which can be attained through their proper modeling and simulation. Fuzzy Cognitive Maps have become a suitable knowledge-based methodology for modeling and simulating complex systems [4], providing a more flexible and natural ability for knowledge representation and reasoning. The motive behind this research is to propose suitable FCM-based modelling and simulation approaches for complex dynamic systems, efficient FCM aggregation methods and FCM-based demand prediction models that will allow governments, regulatory authorities and policy makers to formulate the right strategies and develop certain policies in this direction. Below, the resulting conclusions of this research are listed chapter-wise.

i) The first chapter presents the scope of this thesis along with a literature review in the context of FCM-based participatory modeling and scenario analysis, sustainability planning and decision-making, as well as forecasting with the use of FCMs. These subjects constitute the backbone of this research effort and provide the foundations to the proposed methods and architectures, that are discussed in the later chapters.

ii) Chapter 2 provides an overview of the FCM framework which constitutes the basis of this study's proposed approach to tackle the challenging task of modelling and analyzing real-world complex systems from the sustainable development point of view. The contribution of this chapter is two-fold: to present two newly developed FCM-based tools, namely FCMWizard and OWA FCM, elaborated for modeling and scenario analysis purposes and to introduce an OWA-based aggregation algorithm, developed to fill the gap in the relevant literature regarding the weights learning process using OWA operators. The OWA aggregation methodology was developed to overcome certain limitations over the implementation of other existing methods in the aggregation process and tackle the challenging task of efficiently aggregating the individual knowledge acquisition from numerous and multiple experts and/or stakeholders from the application domains. Considering the results produced, the novel aggregation approach improves the reliability of the overall model making it less susceptible to potentially inaccurate knowledge of a single expert as well as eliminates potential knowledge inconsistency among the participants. Thus, it becomes widely applicable and highly efficient in terms of performance when a large number of participants/stakeholders are present. In this context, a novel user-friendly Java-based tool was also developed to provide the research community with an automated method for aggregating a large number of individual FCMs. Among its advanced functionalities, the OWA tool also applies the credibility weight methodology in ranking experts for most efficient FCM models for scenario analysis and policy making, offering an added value to this dissertation. Among the contributions of this chapter is the development and proposal of a new web-based software tool, namely FCMWizard, entailing advanced functionalities for automatic FCM construction and scenario analysis. It proves to be quite useful and supportive for policy makers and governments in their effort to analyze real-life problems, model similar complex systems and predict their behavior as well as elicit accurate outcomes of proposed policies that deal with social resilience and sustainable socio-economic development strategies. The new OWA-based aggregation method, when combined with FCM-based simulations, along with the new, simple and time-saving aggregation tool, have the potential to contribute further to the automated preparation of more appropriate, equitable, and effective policy scenarios and responses towards more sustainable socio-economic approaches, and the development of better governance capacities at multiple scales.

iii) In chapter 3, the contribution of the proposed OWA-based FCM aggregation methodology is based on some encouraging and promising findings with respect to socio-economic sustainability and livelihood diversification of poor women in rural areas. The OWA-based aggregation methodology, through the application of learning OWA operators in weights considering the confidentiality of the participants, showed a remarkable efficiency overcoming the limitations of the average aggregation of FCM weights. Additionally, the supremacy of the OWA-FCM approach with respect to performance was revealed in most cases, through a straightforward comparative analysis with the Average and the expert-based FCM model. Furthermore, the proposed aggregation method proved its generic applicability and convenience when a significantly large number of participants are involved in designing FCMs. The second contribution of this chapter lies in the fact that through the conducted scenarios along with the use of powerful software tools, complex interactions were identified within social, economic and environmental systems. In addition, certain conclusions were emerged towards the improvement of livelihood and the promotion of social resilience and economic empowerment of the poor rural women, driving towards the formulation of appropriate policies in a variety of domains.

iv) The main contribution of chapter 4 focuses on the use of FCMWizard as a tool for energy domain stakeholders to design FCMs and conduct scenarios under different configurations in the renewable energy sector. Additionally, policy makers and governmental institutions are able to determine certain strategies for better Energy Supply Chain Management which is directly connected to a country's socio-economic growth thus, assuring environmental sustainability. The findings that emerged through the deployment of the FCMWizard tool demonstrated that the development of the PSE sector in Brazil is mainly affected by economic and political factors. In particular, government incentives constitute the most crucial factor that could offer a relative stability to Brazil's Renewable Energy system, whereas the involvement of private sector in the PSE could have a positive impact on the dynamics of the system and the everyday life of Brazilian citizens.

v) Chapter 5 contributes to the research by introducing two novel soft computing methodologies as an alternative to the existing forecasting methods for time series prediction. First, the proposed easy to use and robust ANFIS model proved its remarkable prediction performance and generalization capabilities through a deep exploration process regarding its architecture fine-tuning. This model was applied to a case study regarding natural gas consumption in Greece and the produced results revealed its ability to make more accurate load predictions compared to several other ANN-based and hybrid forecasting methods reported in the literature. Its superior performance is based on the ability to tackle fuzziness in data handling, flexibility in large datasets, easiness of use and low execution time requirements.

vi) The second contribution of this chapter (chapter 5) is the introduction of an innovative and accurate non-linear time series architecture for the prediction of natural gas demand. This ensemble-based forecast combination methodology combines FCMs, ANNs, and hybrid FCM-ANN models, exploiting the advantageous characteristics of its component AI-based methods. A rigorous comparative analysis was carried out to assess the prediction capability of the ensemble forecasting approach against other state-of-the-art methods. The results demonstrated that the proposed architecture attained better accuracies and an improved overall performance against other individual AI and soft computing forecasting models (evolutionary FCMs, ANFIS), making it a useful tool for future works in the energy sector.

6.2 Future research directions

Although this thesis offers an enormous value to research, there are still some limitations that need to be considered and further examined.

While FCMs have proved to possess enhanced modeling and decision-making capabilities, there is not enough research yet to incorporate fuzziness in FCM modeling. That would offer FCMs the capability to efficiently tackle uncertainty and transparency in FCM decision making and cope with interpretability issues, too. Therefore, further steps need to be taken in the direction of exploring effective ways to make the best performing FCM methods more transparent, re-traceable, and understandable, explaining why certain decisions have been made [223]. Also, investigating a stronger mathematical formulation of FCMs, including advanced dynamic state space approach [111], making them more powerful to perform reasoning and inference tasks in more complex real-life problems, is still an open research topic.

Fuzzy Cognitive Maps (FCMs) have been widely used for efficient modeling complexity, yet they are still not fully ready to provide comprehensible explanations of decisions made. The introduction of explainability in FCM reasoning is a challenging task for future work and thus, fuzzy models could be a promising solution in explaining FCM systems. Fuzzy models have recently brought out their notable ability to generate Natural Language explanations, while they also feature accurate interpretability and feasibility under a careful model design [224]. In this direction, fuzzy models are upgraded from interpretable to explainable [225]. Consequently, to address the limitation of explainability and transparency in FCM-based modeling, and to further integrate the notion of interpretability in policy making, future work is oriented to introduce a model-driven explainable FCM for decision-making tasks. This FCM will utilize the main aspects of explainable AI and the “Cause and Effect Reasoning” fuzzy model of human cognitive skills.

Future directions could be also given towards further validation of the proposed FCM framework applying it in diverse complex policy making problems in Renewable Energy domain. More variables will be considered, while the producing results will be further analyzed and compared to those of the current thesis. Also, future work is devoted to the development of the data-based construction of FCMs where no qualitative or expert/stakeholder knowledge is available to design an FCM model for scenario analysis. Beyond that, a further validation of the generic applicability of the proposed framework is needed in the case that a significantly large number of experts and/or stakeholders and other data-oriented sources of knowledge are involved in designing FCMs. This could facilitate the preparation of more appropriate, equitable, and effective policy scenarios and responses, including shifting investment, production, distribution, and consumption. These will show the way towards more sustainable approaches, and the development of better governance capacities at multiple scales.

Considering Demand Forecasting, future work will be devoted to the application of the advantageous forecast combination approach to a larger number of distribution points nationwide, as well as to investigate new forecasting structures incorporating explainable AI features. Towards this direction, new powerful ensemble algorithms combining FCMs and other efficient deep learning and regularized recurrent neural networks attaining explainability, need to be explored for time series modelling and prediction in the energy sector.

In conclusion, the proposed FCMWizard tool is under continuous development to further include more and advanced functionalities, such as the straightforward use of fuzzy sets for FCM design, interval fuzzy values for weights, other efficient (i.e. intuitionistic, type 2-fuzzy) and state-of-the-art fuzzy models as well as neuro-fuzzy systems so as to enhance FCM interpretability. Furthermore, the development of other novel, open source and user-friendly tools and platforms for automatic construction of FCM-based models for policy making that can incorporate both human knowledge and data, is a challenge and still remains an open research direction.

Appendix A

Results of the Experiment

The list of questions related to the examined case-study are the following:

a. Is it possible to differentiate that your tank is programmed, and autonomous control has no human intervention? Explain.
b. During the game is it possible to perceive the hierarchy of robots in what way?
c. Was it possible to see that, in addition to the x, y coordinates in the plane, an exemplified angle during the battle would be necessary to perceive the different states and their attacks and defenses?
d. Is it possible to define a combat strategy to defeat the enemy?
e. Develop a state machine that models the player's actions to defeat the opponent.

Among several answers presented by the students, the most complete and comprehensible ones are those answered by students 1 and 2 for each one of the questions.

<u>Question (a)</u>

Student 1: "Yes, because the tank that is controlled by the user responds to the commands that we indicate, and the other one is autonomous, because it responds according to the events that took place during the game according to its logical construction".

Student 2: "It is possible that the opponent's tank has its strategy without using any command, that is, without any human intervention. While the player's tank is controlled by the keyboard at each cycle".

<u>Question (b)</u>

Student 1: "The hierarchy that is noticed is that the tank checks first, the priority, for its own defense, and then it acts with the intention of winning, destroying the opponent. Our tank, as it is controlled by the user, has no hierarchy, since it acts according to our actions".

Student 2: "It is possible to perceive hierarchy when shooting opponents, dodging obstacles in the scenario and deflecting the opponent's attack to maintain the integrity of the tank (objective of the game)".

<u>Question (c)</u>

Student 1: "The angle serves to have a more precise control of where the tank is, for example. If it is in position x = 0, y = 0. And I tell him to move forward x=1, the tank will not necessarily move forward as it may be rotated and thus move to another position".

Student 2: This question was not answered.

Question (d)

Student 1: "The strategy to defeat the enemy would be to dodge the shots and shoot in a predictive manner, predicting that the enemy tank will be in place at the time of the shot".

Student 2: "It is necessary to use a strategy to avoid the enemy attack and attack it. Hierarchy is to first maintain the integrity of the tank then chase the opponent for attack".

Question (e)

Student 1: One of the interpretations of the finite-state machine was considered satisfactory for the movement of the tank in the proposed game, as presented by Student 1 (Figure A.3).

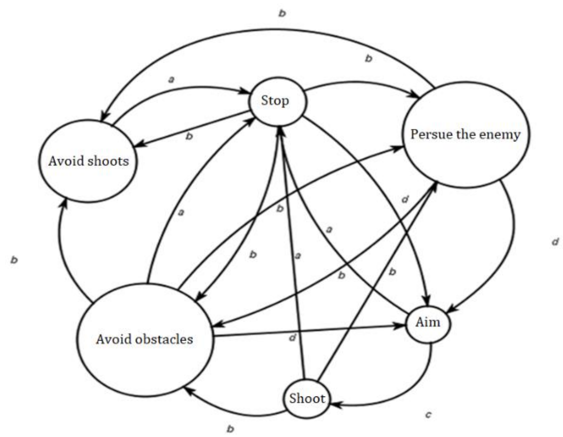

Figure A.3 Finite-state machine presented by Student 1.

The vocabulary presented by Student 1 contains the following:

i. Do nothing.
ii. Press arrows.
iii. Left click on the mouse.
iv. Rotate mouse.

Student 2: It is noteworthy that the interpretation of Student 2 was more complete, and obviously more faithful to the operation of the tanks in the game, as shown in Figure A.4.

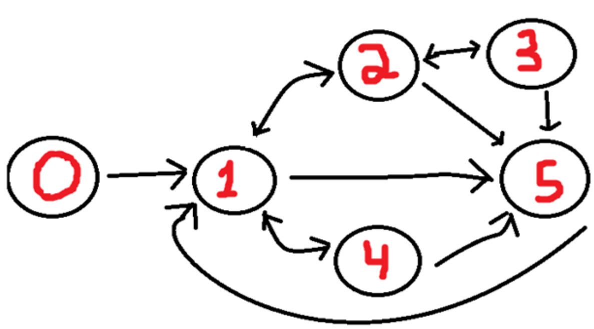

Figure A.4 Finite-state machine presented by Student 2.

The states and the interactions of this student's finite-state machine are described as follows.

- State 0: State machine stopped. The game has not yet started;
- State 1: Game started: tank is currently idle;
- State 2: The tank is moving;
- State 3: The tank while moving, it aims and fires;
- State 4: The tank while stopped, it aims and shoots;
- State 5: The tank is in the dead state awaiting respawn;
- State 0→1: The button to start the game must be pressed;
- State 1→2: Press the directional buttons to move the tank;
- State 2→1: Tank in motion, stop pressing the movement buttons;
- State 2→3: The tank while in motion, aim at the target and press the shoot button;
- State 3→2: The tank in motion, release the shoot button;
- State 1→4: The tank stopped, aim at the target and press the button to shoot;
- States 1,2,3,4→5: The tank was shot;
- State 5→1: x time has passed; the tank has respawned.

Student 3, on the other hand, made the finite-state machine and did not created any vocabulary. That is, it is possible to observe that different interpretations emerged. However, the students managed to understand some relevant concepts of robotics. Especially autonomous robotics.

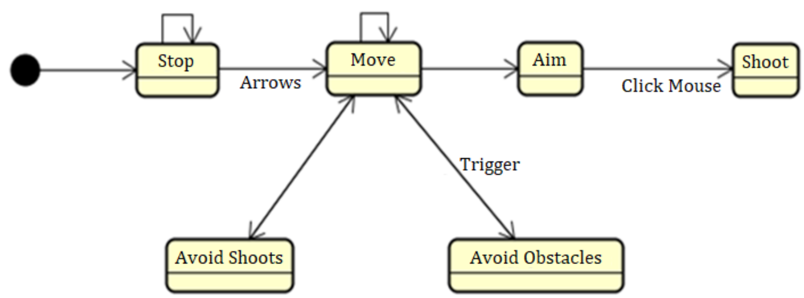

Figure A.5 Finite-state machine presented by Student 3.

The result of Student 4 had a slightly different abstraction. He left the vocabulary in the finite-state machine itself with a good interpretation of the concept of the activity, as presented in Figure A.5.

Appendix B

Table B.1: The table with the degree of significance for all sub-concepts for Kashmir region.

Key Concept	Sub-Concept	SHG	VO	CLF	CRP	Average
C1: Building Strong CBOs						**8.79**
	Building SHGs	8.3	8.5	9.1	9.6	8.72
	Building VOs	8.0	8.4	8.6	9.8	8.58
	Building CLFs	7.9	9.1	9.3	9.8	9.07
C2: Governance of CBOs						**8.92**
	Practicing panch sutra	8.2	9.3	9.4	9.8	9.21
	Developing repayment culture	8.0	8.6	8.6	9.6	8.63
C3: Capacity building						**8.69**
	Training on SHG concept and management	8.6	8.5	8.9	9.8	8.75
	Training on VO concept and management	8.1	8.5	8.5	9.8	8.60
	Training to SHG and VO on bookkeeping	8.6	8.5	8.9	9.8	8.73
C4: Financial literacy						**7.73**
	Analytical literacy	7.7	7.1	8.1	8.6	7.91
	Functional literacy	8.2	7.8	8.0	8.1	8.15
	Technical literacy	8.0	7.1	8.6	8.3	7.91
	Institutional literacy	8.4	7.6	6.3	7.9	7.81
	Adoption of better financial technology	7.1	6.3	6.3	7.6	6.89
C5: Access to formal credit						**8.18**
	Inter-loaning	8.6	8.4	9.4	9.4	8.98
	High-cost loan into low-cost loan	5.6	7.8	8.1	8.0	7.70
	Banking awareness	7.8	7.8	7.1	8.9	7.81
	SHG-Bank linkage	8.0	7.9	8.6	9.3	8.24
C6: Savings, investments, and insurance						**5.97**
	SHG savings	8.8	9.1	10.0	9.9	9.36
	Regular savings accounts (individual or joint)	8.8	9.1	8.9	9.6	9.09
	Life insurance	4.9	4.6	5.8	8.0	5.56
	Health insurance	3.4	3.1	3.0	5.1	4.17
	Vehicle insurance	4.4	3.9	2.8	1.5	4.02
	Livestock insurance	3.6	3.4	4.1	2.4	3.65
C7: Income						**6.62**
	Income from agriculture/ horticulture	6.6	6.6	5.5	6.6	6.48
	Income from animal husbandry	7.4	7.1	7.9	8.1	7.53
	Income from self-employment	7.4	7.3	5.4	8.4	7.17
	Income from wage labour	5.0	5.4	3.9	5.9	5.30

C8: Consumption expenditures						**5.47**
	Usage of freeze, mixer, etc.	5.0	4.6	4.2	4.4	4.64
	More expenditure on clothes	4.9	4.6	3.3	4.3	4.77
	Usage of bed, sofa, etc.	4.2	3.3	3.0	4.0	3.67
	Usage of TV, radio, tape recorder, etc.	4.8	5.0	3.4	5.8	4.97
	Expenditure on more nutritious food	6.4	6.4	5.2	6.5	6.16
	More expenditure on health	6.8	6.8	4.9	6.6	6.36
	More expenditure on education	8.1	7.9	7.6	6.5	7.70
C9: Enterprise development						**5.76**
	Enterprise development	6.3	6.8	8.2	3.0	6.75
	Enterprise management	5.9	6.1	7.1	2.9	6.19
	Decision-making with regard to enterprise	6.1	6.1	6.6	2.3	6.02
	Fostering entrepreneurship	5.4	6.1	5.8	6.4	6.17
	New livelihood activities/interventions	6.9	7.6	7.5	7.0	7.43
	Skill development training	5.3	5.9	6.2	4.0	5.77
	Guidance from experts and professionals	5.8	5.6	5.4	5.8	5.60
	Value addition	5.2	5.3	8.9	6.5	6.26
	Market identification	4.2	4.0	2.2	3.8	3.63
	Market linkages	3.6	4.7	1.8	3.3	3.75
C10: Livelihood diversification						**7.03**
	Agriculture	7.4	7.9	7.4	6.3	7.52
	Horticulture	7.6	7.1	7.8	5.9	7.40
	Livestock rearing	7.9	7.8	7.7	9.0	7.96
	Self-employment	7.6	7.8	5.9	8.1	7.42
	Wage labour	3.8	5.4	4.3	4.1	4.88
C11: Education						**7.17**
	Better implementation of Aanganwadi scheme	8.1	6.0	6.3	7.0	6.46
	Increased access to education for children	8.2	7.8	8.9	8.3	8.12
	Improved quality of education	8.0	7.7	7.5	6.9	7.60
	Increased literacy among children	7.7	7.8	7.6	7.9	7.72
	Better avenues for higher education for children	7.4	6.7	6.5	6.1	6.67
	Easy access to mid-day meals	7.3	7.0	6.3	6.4	6.84
	Easy access to information about schooling	7.2	7.9	5.7	7.9	7.34
	Reduced school drop-out rate	7.0	6.5	6.1	7.0	6.65
C12: Health, hygiene, and sanitation						**7.32**
	Reduced open defecation	8.1	6.6	6.7	8.3	7.03
	Better sanitation and hygiene	6.8	7.9	5.4	7.9	7.21
	Increased access to hospitals	7.1	7.7	4.9	8.6	7.13
	Vaccination	8.1	7.9	8.9	9.4	8.31

	Reduced epidemic	7.3	6.8	4.9	7.6	6.67
	Reduced malnutrition among children	7.8	7.8	6.6	6.4	7.37
	Increased nutritional security	7.1	7.7	8.2	5.9	7.52
C13: Natural assets						**6.05**
	Purchase of land	4.9	4.3	2.6	4.1	4.08
	Purchase of livestock	7.9	7.8	8.7	8.1	8.03
C14: Physical assets						**5.11**
	Productive assets	6.2	6.6	7.4	6.8	6.73
	Consumptive assets	5.8	5.1	5.8	6.6	5.52
	Asset in the name of women	5.1	3.6	2.2	4.6	3.72
	Community owned assets	6.0	4.8	1.8	5.0	4.48
C15: Political empowerment						**6.27**
	Political inclusion	5.2	6.0	1.8	4.9	5.02
	Political justice	6.4	5.8	5.8	4.3	5.79
	Awareness of rights	6.9	7.4	8.0	7.0	7.42
	Exercising rights	6.0	7.7	5.8	6.3	7.00
	Initiatives focusing on women development	7.3	8.0	4.6	7.1	7.32
	Participation in political groups/ parties	5.7	5.9	3.5	5.8	5.54
	Participation in Village Development Committee	7.8	6.6	4.1	7.4	6.31
	Participation in Village Education Committee (VEC) / School Management Committee (SMC)	8.1	7.6	5.9	8.1	7.36
	Participation in Village Health Committee	7.2	7.3	5.9	8.3	7.24
	Participation in Mahila Mandal	6.8	6.6	5.4	6.0	6.81
	Participation in Mother's Committee	5.4	7.3	5.4	4.1	7.28
	Participation in Watershed Committee	4.7	5.1	2.4	4.0	4.93
	Approaching to higher officials in block and district for exercising rights	4.3	8.9	8.0	3.8	7.94
	Participation in Social Audit	4.3	4.3	1.9	2.9	3.98
	Participation in Vigilance Committee (for MGNREGS and other schemes)	5.0	5.0	2.5	3.6	4.65
	Participation in Gram Sabha	7.1	7.8	4.3	8.1	7.01
	Role in policy making	5.1	6.1	2.2	4.3	5.06
C16: Social empowerment						**8.25**
	Universal social mobilization	7.3	8.4	7.1	9.3	8.12
	Universal social inclusion	7.1	7.9	7.7	9.3	8.05
	Improved social behavior	7.7	8.8	8.1	9.4	8.57
	Increased social values	7.4	104	7.6	9.3	9.44
	Increased social development	7.3	7.9	8.0	8.8	8.09
	Increased social awareness	7.7	7.8	7.8	8.9	7.93
	Increased social welfare	7.4	7.0	7.7	8.6	7.53
C17: Economic empowerment						**8.37**
	Financial self-sufficiency	7.4	8.1	8.6	7.5	8.03

	Economic decision-making	7.6	6.9	9.4	7.1	8.05
	Increased savings	8.7	8.1	9.4	9.6	9.03
C18: Personal well-being and Personality development						**7.60**
	Adoption of agricultural machines/ equipment	4.4	6.8	3.4	5.5	5.67
	Adoption of better cooking methods/ equipment	5.6	6.6	7.2	6.5	6.58
	Better health and hygiene awareness	7.1	7.2	8.7	7.9	7.57
	Access to basic infrastructure	13.7	6.6	7.7	5.8	7.91
	Increased women literacy	8.1	7.4	8.6	6.5	7.64
	Increased women safety	8.4	7.1	9.0	7.8	8.02
	Increased self-confidence	7.9	7.7	9.0	7.4	8.22
	Engagement with household level issues	7.7	8.0	8.1	7.4	7.88
	Engagement with community level issues	6.9	7.9	7.9	6.9	7.66
	Sense of authority in public space	6.7	7.5	8.6	5.8	7.40
	Recognition in family and society	7.8	8.1	8.9	8.0	8.35
	Power in household decision making	7.4	7.6	9.1	7.1	7.82
	Increased gender equality	7.9	8.2	7.1	6.8	7.86
	Voicing against ill treatments	7.1	7.4	7.6	8.4	7.52
	Individual values/ integrity	7.1	7.7	6.4	6.6	7.21
	Women's identity	8.7	8.3	7.2	7.6	8.03
	Women's independence	8.0	8.0	5.8	7.6	7.48
	Women's mobility	8.0	7.5	6.5	7.8	7.52
	Own perceptions towards changes	7.9	7.8	8.2	8.6	8.09
C19: Intra-household bargaining power						**7.20**
	Mediation in household/ family disputes	7.6	7.4	7.4	6.9	7.39
	Seeking benefit under government schemes	6.0	7.0	7.9	7.6	7.12
	Obtaining ration card	8.0	7.7	8.2	8.1	7.90
	Lodging police complaint	6.2	6.5	2.6	3.1	5.35
	Access to credit	7.3	7.2	6.9	6.5	7.20
	Admissions of children to schools/ colleges	8.0	8.0	9.1	7.9	8.24
	Admissions to hospitals	7.7	7.0	7.9	6.6	7.21
C20: Social harmony						**8.26**
	Community cohesion	7.4	8.2	8.6	8.1	8.16
	Community support	7.7	8.1	8.4	8.3	8.15
	Reduced social tension	7.9	8.0	9.4	7.0	8.16
	Conflict avoidance	8.3	8.2	9.2	6.6	8.22
	Increased tolerance	8.3	8.1	9.0	7.6	8.25
	Solidarity	8.9	8.1	10.0	8.0	8.60

Table B.2: The table with the degree of significance for all sub-concepts for Jammu region.

Key Concept	Sub-Concept	SHG	VO	CLF	CRP	Average
C1: Building Strong CBOs						**9.43**
	Building SHGs	9.3	9.6	9.7	9.0	9.43
	Building Vos	9.3	9.5	9.6	9.0	9.39
	Building CLFs	9.5	9.5	9.6	9.1	9.45
C2: Governance of CBOs						**9.41**
	Practicing panch sutra	9.6	9.8	9.6	9.6	9.62
	Developing repayment culture	9.1	9.2	9.6	8.6	9.19
C3: Capacity building						**8.95**
	Training on SHG concept and management	8.6	9.1	9.1	8.5	8.96
	Training on VO concept and management	8.7	9.2	9.0	8.7	8.90
	Training to SHG and VO on bookkeeping	8.4	9.0	9.0	8.8	9.00
C4: Financial literacy						**6.98**
	Analytical literacy	7.3	6.3	6.6	5.3	6.88
	Functional literacy	7.8	6.3	6.4	6.4	7.20
	Technical literacy	7.6	5.8	6.1	5.6	6.66
	Institutional literacy	8.0	6.5	6.4	5.5	7.05
	Adoption of better financial technology	7.9	6.1	6.3	6.0	7.09
C5: Access to formal credit						**8.74**
	Inter-loaning	9.3	8.9	8.8	9.0	8.96
	High-cost loan into low-cost loan	7.9	7.4	7.4	8.0	7.69
	Banking awareness	9.1	8.9	9.2	9.0	9.07
	SHG-Bank linkage	9.1	9.4	9.2	9.4	9.24
C6: Savings, investments, and insurance						**8.03**
	SHG savings	9.6	9.8	9.5	9.5	9.57
	Regular savings accounts (individual or joint)	9.0	9.5	9.5	9.0	9.26
	Life insurance	8.6	8.7	8.5	8.0	8.45
	Health insurance	7.5	7.4	7.1	6.2	7.28
	Vehicle insurance	6.7	6.9	6.1	4.9	6.43
	Livestock insurance	6.9	7.1	7.4	6.7	7.21
C7: Income						**7.07**
	Income from agriculture/ horticulture	7.5	7.3	6.7	7.3	7.15
	Income from animal husbandry	7.8	7.6	7.2	7.5	7.54
	Income from self-employment	7.8	6.5	7.1	6.6	7.07
	Income from wage labour	6.3	7.2	6.3	6.2	6.51
C8: Consumption expenditures						**6.79**
	Usage of freeze, mixer, etc.	6.9	6.4	6.4	4.7	6.47

	More expenditure on clothes	6.6	6.0	6.5	4.5	6.11
	Usage of bed, sofa, etc.	6.3	5.8	6.2	4.7	6.10
	Usage of TV, radio, tape recorder, etc.	6.2	6.4	6.0	4.9	6.19
	Expenditure on more nutritious food	6.4	6.8	6.9	5.8	6.83
	More expenditure on health	7.3	7.7	8.0	6.2	7.42
	More expenditure on education	8.3	8.6	8.8	7.5	8.39
C9: Enterprise development						**6.61**
	Enterprise development	6.6	6.8	6.7	5.7	6.50
	Enterprise management	6.0	6.7	6.4	5.0	6.19
	Decision-making with regard to enterprise	6.3	6.0	6.0	5.1	6.24
	Fostering entrepreneurship	5.9	6.6	6.0	4.0	6.05
	New livelihood activities/interventions	7.0	6.7	7.2	6.4	6.92
	Skill development training	6.9	6.1	7.1	7.1	7.03
	Guidance from experts and professionals	7.3	6.0	7.5	6.4	7.20
	Value addition	6.0	5.4	5.7	4.4	6.09
	Market identification	7.6	7.6	6.7	6.0	7.14
	Market linkages	7.1	6.9	6.3	5.6	6.76
C10: Livelihood diversification						**7.72**
	Agriculture	7.9	7.7	9.2	8.2	8.51
	Horticulture	6.5	6.3	6.5	6.3	6.76
	Livestock rearing	8.3	8.0	8.6	8.1	8.39
	Self-employment	6.9	7.5	8.1	7.0	7.75
	Wage labour	6.8	6.9	6.9	7.1	7.17
C11: Education						**8.05**
	Better implementation of Aanganwadi scheme	8.2	7.5	8.1	7.0	7.80
	Increased access to education for children	8.4	8.2	8.8	7.5	8.33
	Improved quality of education	8.1	8.5	8.7	7.4	8.26
	Increased literacy among children	8.2	8.6	8.6	7.9	8.34
	Better avenues for higher education for children	8.0	8.6	8.5	7.0	8.20
	Easy access to mid-day meals	7.4	7.4	8.1	6.6	7.79
	Easy access to information about schooling	8.0	8.1	8.7	7.2	8.19
	Reduced school drop-out rate	7.3	7.3	8.2	5.5	7.48
C12: Health, hygiene, and sanitation			0.0			**8.10**
	Reduced open defecation	8.2	9.3	8.7	7.8	8.53
	Better sanitation and hygiene	8.5	8.9	8.6	7.9	8.46
	Increased access to hospitals	7.4	7.4	8.1	7.0	7.61
	Vaccination	8.7	9.5	8.7	8.1	8.75
	Reduced epidemic	7.3	8.5	8.0	6.4	7.59
	Reduced malnutrition among children	7.7	8.0	7.7	7.0	7.60
	Increased nutritional security	7.8	8.9	8.3	7.8	8.18

C13: Natural assets						**6.75**
	Purchase of land	5.1	6.4	5.7	4.7	5.78
	Purchase of livestock	8.1	8.5	6.9	7.6	7.72
C14: Physical assets			0.0			**6.20**
	Productive assets	6.3	6.7	6.9	5.1	6.57
	Consumptive assets	5.7	5.1	6.2	4.8	6.05
	Asset in the name of women	5.3	7.1	6.1	5.5	6.35
	Community owned assets	5.1	5.8	5.0	4.8	5.84
C15: Political empowerment						**7.21**
	Political inclusion	6.4	6.4	7.5	5.2	7.12
	Political justice	6.8	6.3	7.2	5.6	6.91
	Awareness of rights	7.5	8.1	8.2	7.0	7.75
	Exercising rights	7.2	6.9	8.0	6.8	7.58
	Initiatives focusing on women development	7.6	8.3	8.1	7.6	7.99
	Participation in political groups/ parties	7.3	7.1	7.4	6.5	7.50
	Participation in Village Development Committee	7.7	6.9	8.0	7.0	7.72
	Participation in Village Education Committee (VEC) / School Management Committee (SMC)	6.9	6.9	7.4	6.4	7.36
	Participation in Village Health Committee	7.2	7.3	7.5	6.6	7.47
	Participation in Mahila Mandal	7.4	7.0	8.0	5.7	7.57
	Participation in Mother's Committee	6.3	6.2	7.4	4.9	6.91
	Participation in Watershed Committee	5.4	4.9	5.6	3.9	5.83
	Approaching to higher officials in block and district for exercising rights	5.7	8.1	10.6	3.6	8.02
	Participation in Social Audit	5.4	4.8	6.3	4.4	6.01
	Participation in Vigilance Committee (for MGNREGS and other schemes)	5.7	5.3	5.9	5.6	6.68
	Participation in Gram Sabha	7.8	7.4	8.1	6.6	7.65
	Role in policy making	6.3	6.6	7.0	4.7	6.54
C16: Social empowerment						**7.76**
	Universal social mobilization	7.4	7.3	7.7	6.4	7.49
	Universal social inclusion	7.0	7.1	7.9	6.4	7.42
	Improved social behavior	7.6	7.8	8.1	7.4	7.77
	Increased social values	7.8	7.7	7.6	7.2	7.69
	Increased social development	7.6	7.6	8.1	7.5	7.85
	Increased social awareness	8.3	8.6	8.0	7.8	8.26
	Increased social welfare	7.9	8.0	7.3	7.6	7.81
C17: Economic empowerment						**8.06**
	Financial self-sufficiency	7.7	7.9	8.0	6.8	7.72
	Economic decision-making	8.4	8.5	7.7	7.6	8.03
	Increased savings	8.4	8.5	8.1	8.7	8.43

C18: Personal well-being and Personality development						**8.00**
	Adoption of agricultural machines/ equipment	7.4	6.3	7.1	6.8	7.12
	Adoption of better cooking methods/ equipment	7.7	7.1	7.6	6.8	7.45
	Better health and hygiene awareness	8.2	8.0	8.7	7.8	8.25
	Access to basic infrastructure	6.8	7.0	7.8	6.6	7.37
	Increased women literacy	7.7	8.2	8.7	7.6	8.13
	Increased women safety	7.9	8.1	8.4	7.3	8.06
	Increased self-confidence	8.2	8.0	8.6	8.4	8.64
	Engagement with household level issues	7.7	7.8	8.6	6.9	7.97
	Engagement with community level issues	7.4	6.4	7.9	6.7	7.44
	Sense of authority in public space	7.3	5.8	8.1	6.3	7.41
	Recognition in family and society	7.9	8.0	8.4	7.6	8.04
	Power in household decision making	8.0	7.8	8.6	7.9	8.18
	Increased gender equality	7.3	8.0	7.8	6.6	7.45
	Voicing against ill treatments	8.3	9.0	8.8	8.0	8.59
	Individual values/ integrity	5.7	7.2	8.1	5.5	7.64
	Women's identity	8.6	9.1	9.1	8.2	8.77
	Women's independence	8.3	8.9	9.2	7.9	8.66
	Women's mobility	8.2	8.7	9.0	8.0	8.62
	Own perceptions towards changes	8.1	8.2	8.7	7.8	8.28
C19: Intra-household bargaining power						**7.73**
	Mediation in household/ family disputes	7.1	7.2	6.9	6.1	6.96
	Seeking benefit under government schemes	7.7	8.2	8.3	6.9	7.87
	Obtaining ration card	8.4	8.8	9.0	7.7	8.57
	Lodging police complaint	6.3	6.3	7.8	5.5	6.96
	Access to credit	6.7	6.6	7.2	6.0	7.12
	Admissions of children to schools/ colleges	8.7	8.4	9.0	8.4	8.68
	Admissions to hospitals	7.6	7.9	8.2	7.5	7.92
C20: Social harmony						**8.64**
	Community cohesion	8.5	8.6	8.9	8.6	8.69
	Community support	8.2	8.4	8.8	8.6	8.55
	Reduced social tension	8.1	8.7	8.8	8.3	8.52
	Conflict avoidance	8.4	7.9	8.7	8.6	8.48
	Increased tolerance	8.6	8.5	9.2	8.4	8.79
	Solidarity	8.5	8.5	9.2	8.7	8.83

Table B.3: Adjacency weights matrix for OWA-FCM (C) model.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	0.00	0.00	0.00	0.00	0.00	0.3375	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C2	0.3425	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.3250	0.00	0.00	0.2050
C3	0.4150	0.3925	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C4	0.00	0.00	0.00	0.00	0.29	0.00	0.00	0.00	0.00	0.00	0.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.3075	0.2650	0.00	0.00	0.00	0.00	0.00	0.00	0.2950	0.00	0.00	0.00
C6	0.00	0.00	0.00	0.00	0.00	0.00	0.2575	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C7	0.00	0.00	0.00	0.00	0.00	0.3375	0.00	0.2375	0.2450	0.00	0.3325	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.2025
C8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C9	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.2175	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C10	0.00	0.00	0.00	0.00	0.00	0.00	0.3025	0.2575	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C11	0.00	0.00	0.00	0.00	0.00	0.00	0.2550	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.2850	0.30	0.00
C12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23
C13	0.00	0.00	0.00	0.00	0.00	0.00	0.2525	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C14	0.00	0.00	0.00	0.00	0.00	0.00	0.2525	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.2775	0.00	0.2650	0.00	0.2350
C16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	0.00	0.00	0.00	0.00	0.18
C17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23
C18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.3650	0.00	0.00	0.2275	0.00	0.00	0.00	0.3025	0.00
C19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.3575	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.2225	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table B.4: Adjacency weights matrix for Average-FCM (C) model.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	0.00	0.00	0.00	0.00	0.00	0.7450	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C2	0.7675	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.68	0.00	0.00	0.6450
C3	0.8050	0.7575	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C4	0.00	0.00	0.00	0.00	0.6650	0.00	0.00	0.00	0.00	0.00	0.6750	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.6175	0.6850	0.00	0.00	0.00	0.00	0.00	0.00	0.6675	0.00	0.00	0.00
C6	0.00	0.00	0.00	0.00	0.00	0.00	0.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C7	0.00	0.00	0.00	0.00	0.00	0.70	0.00	0.60	0.5925	0.00	0.6750	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.5925
C8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C9	0.00	0.00	0.00	0.00	0.00	0.00	0.62	0.00	0.00	0.5850	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C10	0.00	0.00	0.00	0.00	0.00	0.00	0.6350	0.6150	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C11	0.00	0.00	0.00	0.00	0.00	0.00	0.6275	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.6650	0.65	0.00
C12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.5950
C13	0.00	0.00	0.00	0.00	0.00	0.00	0.6175	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C14	0.00	0.00	0.00	0.00	0.00	0.00	0.6075	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.61	0.00	0.6350	0.00	0.6075
C16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.64	0.00	0.00	0.00	0.00	0.5950
C17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.5975
C18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.6775	0.00	0.00	0.61	0.00	0.00	0.00	0.6450	0.00
C19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.6650	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.6450	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Appendix C

Table C.1: Descriptive statistics values for Real Dataset Z(t), forecasting values of AVG and EB methods for the 3 cities (Testing).

Descriptive Statistics	Athens			Thessaloniki			Larissa		
	Z(t)	*X(t)AVG*	*X(t) EB*	*Z(t)*	*X(t)AVG*	*X(t) EB*	*Z(t)*	*X(t)AVG*	*X(t) EB*
Mean	0.2479	0.2433	0.2433	0.2588	0.2478	0.2478	0.2456	0.2279	0.2291
Median	0.1225	0.1488	0.1488	0.1179	0.1304	0.1304	0.0695	0.0961	0.0972
St. Deviation	0.2159	0.2020	0.2021	0.2483	0.2236	0.2237	0.2742	0.2399	0.2404
Kurtosis	0.6658	0.2785	0.2792	0.1755	-0.1254	-0.1219	-0.0113	-0.1588	-0.1502
Skewness	1.2242	1.1138	1.1140	1.1348	1.0469	1.0479	1.1205	1.0900	1.0921
Minimum	0.0000	0.0359	0.0359	0.0079	0.0358	0.0357	0.0000	0.0233	0.0237
Maximum	0.9438	0.8144	0.8144	0.9950	0.8556	0.8562	1.0000	0.8291	0.8310

Table C.2: t-Test: Paired Two Sample for Means between the ensemble methods (AVG and EB) (Athens).

	X(t) AVG Athens	X(t) EB Athens
Mean	0.243342155	0.243346733
Variance	0.040822427	0.040826581
Observations	196	196
Pearson Correlation	0.99999997	
Hypothesized Mean Difference	0	
df	195	
t Stat	-1.278099814	
P(T<=t) one-tail	0.101366761	
t Critical one-tail	1.65270531	
P(T<=t) two-tail	0.202733521	
t Critical two-tail	1.972204051	

Table C.3: Different configurations of the selected ANFIS architectures regarding linear output MF.

Type of Input MF	**Number of MFs**	**Type of Output MF**	**Number of Rules**	**MSE**	**RMSE**	**MAE**	**MAPE**	**R^2**	**Time (sec)**
trimf	2-2-2-2-2	Linear	32	0.00119	0.03457	0.01942	11.7218	0.98212	148
trapmf	2-2-2-2-2	Linear	32	0.00135	0.03685	0.02086	12.1237	0.97955	148
gbellmf	2-2-2-2-2	Linear	32	0.00126	0.03560	0.01992	11.4644	0.98096	148
Gaussmf	2-2-2-2-2	Linear	32	0.00129	0.03603	0.02025	11.9779	0.98046	148
Gauss2mf	2-2-2-2-2	Linear	32	0.00140	0.03749	0.02087	11.2638	0.97886	148

pimf	2-2-2-2-2	Linear	32	0.00163 5	0.04044 2	0.02217 6	12.0829 8	0.97540 5	148
dsigmf	2-2-2-2-2	Linear	32	0.00142	0.03773	0.02106	11.2672	0.97859	148
psigmf	2-2-2-2-2	Linear	32	0.00142	0.03773	0.02106	11.2672	0.97859	148
trimf	2-2-3-3-3	Linear	108	0.00147	0.03843	0.02094	11.1786	0.97777	328
Gaussmf	2-2-3-3-3	Linear	108	0.00203	0.04514	0.02328	12.7172	0.96924	328

Table C.4: Case (A)-Calculated errors and weights for each ensemble forecaster based on scores for EB method (Larissa).

	Validation		Testing				Testing		
	MAE	MSE	MAE	MSE	Weights		MAE	MSE	Weights
ANN1	0,0339	0,0032	0,0425	0,0047	0.2511	*Hybrid1*	0,0411	0,0043	0.2531
ANN2	0,0353	0,0036	0,0438	0,0052	0	*Hybrid2*	0,0435	0,0051	0
ANN3	0,0343	0,0033	0,0433	0,0050	0	*Hybrid3*	0,0418	0,0045	0.2472
ANN4	0,0347	0,0033	0,0429	0,0049	0	*Hybrid4*	0,0424	0,0048	0
ANN5	0,0353	0,0035	0,0436	0,0051	0	*Hybrid5*	0,0436	0,0051	0
ANN6	0,0352	0,0035	0,0432	0,0049	0	*Hybrid6*	0,0436	0,0051	0
ANN7	0,0354	0,0035	0,0441	0,0053	0	*Hybrid7*	0,0434	0,0050	0
ANN8	0,0348	0,0033	0,0427	0,0049	0	*Hybrid8*	0,0425	0,0047	0.2398
ANN9	0,0351	0,0035	0,0439	0,0052	0	*Hybrid9*	0,0423	0,0047	0
ANN10	0,0343	0,0033	0,0431	0,0049	0.2406	*Hybrid10*	0,0432	0,0050	0
ANN11	0,0342	0,0032	0,0436	0,0049	0.2472	*Hybrid11*	0,0444	0,0053	0
ANN12	0,0331	0,0031	0,0428	0,0047	0.2610	*Hybrid12*	0,0426	0,0043	0.2597
AVG	0,0345	0,0033	0,0431	0,0049		*AVG*	0,0427	0,0048	
EB	0,0337	0,0032	0,0428	0,0048		*EB*	0,0417	0,0044	

Table C.5: Descriptive statistics values for Real Dataset Z(t), forecasting values of AVG and EB methods for the 3 cities (Validation).

Descriptive	Athens			Thessaloniki			Larissa		
Statistics	*Z(t)*	*X(t)AVG*	*X(t) EB*	*Z(t)*	*X(t)AVG*	*X(t) EB*	*Z(t)*	*X(t)AVG*	*X(t) EB*
Mean	0.2540	0.2464	0.2464	0.2611	0.2510	0.2510	0.2689	0.2565	0.2575
Median	0.1154	0.1366	0.1366	0.1335	0.1393	0.1394	0.1037	0.1194	0.1211
St. Deviation	0.2391	0.2203	0.2203	0.2373	0.2228	0.2228	0.2604	0.2429	0.2429
Kurtosis	0.3610	-0.2748	-0.2741	-0.1839	-0.5807	-0.5774	-0.6564	-0.8881	-0.8847
Skewness	1.1605	0.9801	0.9803	0.9328	0.8288	0.8298	0.8112	0.7520	0.7516
Minimum	0.0277	0.0367	0.0367	0.0043	0.0305	0.0304	0.0000	0.0235	0.0239
Maximum	1.0000	0.8429	0.8431	1.0000	0.8442	0.8448	1.0000	0.8361	0.8383

Table C.6: Descriptive statistics values for Real Dataset Z(t), forecasting values of AVG and EB methods for the 3 cities (Testing).

Descriptive Statistics	Athens			Thessaloniki			Larissa		
	Z(t)	*X(t)AVG*	*X(t) EB*	*Z(t)*	*X(t)AVG*	*X(t) EB*	*Z(t)*	*X(t)AVG*	*X(t) EB*
Mean	0.2479	0.2433	0.2433	0.2588	0.2478	0.2478	0.2456	0.2279	0.2291
Median	0.1225	0.1488	0.1488	0.1179	0.1304	0.1304	0.0695	0.0961	0.0972
St. Deviation	0.2159	0.2020	0.2021	0.2483	0.2236	0.2237	0.2742	0.2399	0.2404
Kurtosis	0.6658	0.2785	0.2792	0.1755	-0.1254	-0.1219	-0.0113	-0.1588	-0.1502
Skewness	1.2242	1.1138	1.1140	1.1348	1.0469	1.0479	1.1205	1.0900	1.0921
Minimum	0.0000	0.0359	0.0359	0.0079	0.0358	0.0357	0.0000	0.0233	0.0237
Maximum	0.9438	0.8144	0.8144	0.9950	0.8556	0.8562	1.0000	0.8291	0.8310

Table C.7: Running time and number of rules for all the proposed ANFIS configurations.

Type of Input MF	**Number of MFs**	**Type of Output MF**	**Number of Epochs**	**Optimiz ation**	**Number of Rules**	**Time run**
trimf, trapmf, gbell, gauss, pim, sigm	2-2-2-2-2	Constant	10	Hybrid	32	7sec
trimf, trapmf, gbell, gauss, pim, sigm	2-2-3-3-3	Constant	10	Hybrid	108	11sec
trimf, trapmf, gbell, gauss, pim, sigm	3-3-3-2-2	Constant	10	Hybrid	108	19sec
trimf, trapmf, gbell	3-3-3-3-3	Constant	10	Hybrid	243	68sec
trimf	3-3-4-4-4	Constant	10	Hybrid	576	10 min 10sec
trimf	3-3-5-5-5	Constant	10	Hybrid	1125	40 min
trapmf	3-3-4-4-4	Constant	10	Hybrid	576	12min
trapmf	3-3-5-5-5	Constant	10	Hybrid	1125	70 min
gbellmf	3-3-4-4-4	Constant	10	Hybrid	576	12min 35sec
gbellmf	3-3-5-5-5	Constant	10	Hybrid	1125	50min
gaussmf	3-3-3-3-3	Constant	10	Hybrid	243	4 min
gaussmf	3-3-4-4-4	Constant	10	Hybrid	576	25 min
gaussmf	3-3-5-5-5	Constant	10	Hybrid	1125	47 min
gauss2mf	3-3-3-3-3	Constant	10	Hybrid	243	4 min
gauss2mf	3-3-4-4-4	Constant	10	Hybrid	576	25 min
gauss2mf	3-3-5-5-5	Constant	10	Hybrid	1125	47 min
pimf	3-3-3-3-3	Constant	10	Hybrid	243	3,5 min
pimf	3-3-4-4-4	Constant	10	hybrid	576	20min
pimf	3-3-5-5-5	Constant	10	hybrid	1125	42min

Appendix D

Publications

1. **Papageorgiou, K.,** Singh, P.K., Papageorgiou, E.I., Chudasama, H., Bochtis, D., and Stamoulis, G. Fuzzy Cognitive Map-Based Sustainable Socio-Economic Development Planning for Rural Communities. Sustainability, 2020;12(1):305. doi: 10.3390/su12010305. **(IF: 2,592)**

2. **Papageorgiou K**, Singh PK, Papageorgiou EI, Chudasama H, Bochtis D, and Stamoulis, G. (2020) Participatory modelling for poverty alleviation using fuzzy cognitive maps and OWA learning aggregation. PLOS ONE 15(6): e0233984. doi: 10.1371/journal.pone.0233984 **(IF: 2,870)**

3. **Papageorgiou, K.;** Carvalho, G.; Papageorgiou, E.I.; Bochtis, D.; Stamoulis, G. Decision-Making Process for Photovoltaic Solar Energy Sector Development using Fuzzy Cognitive Map Technique. Energies 2020, 13(6), 1427. doi: 10.3390/en13061427 **(IF: 2,707)**

4. **Papageorgiou, K**.; Poczeta, K.; Papageorgiou, E.; Gerogiannis, V.C.; Stamoulis, G. Exploring an Ensemble of Methods that Combines Fuzzy Cognitive Maps and Neural Networks in Solving the Time Series Prediction Problem of Gas Consumption in Greece. Algorithms 2019, 12, 235. doi: 10.3390/a12110235 **(IF: 1,46)**

5. **Papageorgiou, K.;** I. Papageorgiou, E.; Poczeta, K.; Bochtis, D.; Stamoulis, G. Forecasting of Day-Ahead Natural Gas Consumption Demand in Greece Using Adaptive Neuro-Fuzzy Inference System. Energies 2020, 13, 2317. doi: 10.3390/en13092317 **(IF: 2,707)**

6. Singh, P.K., **Papageorgiou, K.**, Chudasama, H., Papageorgiou, E.I. Evaluating the Effectiveness of Climate Change Adaptations in the World's Largest Mangrove Ecosystem. Sustainability. 2019 Nov;11(23):6655. doi: 10.3390/su11236655 **(IF: 2,592)**

7. N. Papandrianos, A. Anagnostis, K. Papageorgiou, A. Feleki, and E.I. Papageorgiou. Bone metastasis classification using whole body images from prostate cancer patients based on convolutional neural networks application, PLOSone, open access, August 2020. (IF=2.72). https://doi.org/10.1371/journal.pone.0237213

8. N. Papandrianos, E.I. Papageorgiou, A. Anagnostis and K. Papageorgiou. Efficient Bone Metastasis Diagnosis in Bone Scintigraphy Using a Fast Convolutional Neural Network Architecture. Diagnostics, MDPI, 532, 10 (2020). (IF=3.11) https://doi.org/10.3390/diagnostics10080532.

Conferences

9. **Papageorgiou, K.,** Carvalho, G., Papageorgiou, E.I., Masiero, G., Stamoulis, G. Exploring Brazilian Photovoltaic Solar Energy development scenarios using the Fuzzy Cognitive Map Wizard Tool. WCCI2020, Fuzz-IEEE 2020, (https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9177573)

10. **Papageorgiou, K.,** Papageorgiou, E.I., Singh, P.K., Stamoulis, G. A software tool for FCM aggregation employing credibility weights and learning OWA operators. In: 2019 10th International Conference on Information, Intelligence, Systems and Applications (IISA). 2019. p. 1–8. doi: 10.1109/IISA.2019.8900676

11. **Papageorgiou, K.,** Papageorgiou, E., Mourhir, A., Stamoulis, G. Exploring OWA Operators For Aggregating Fuzzy Cognitive Maps Constructed By Experts/Stakeholders In Agriculture. 12th EFITA International Conference. Rhodes Island, Greece. June 27-29, 2019. (https://efita-org.eu/wp-content/uploads/2020/02/8.-efita20.pdf)

12. Singh, P., **Papageorgiou, K.,** Chudasama, H., Papageorgiou, E.I. Exploring Climate Change Adaptations using Fuzzy Cognitive Maps: The Case of Sundarbans, India. 12th EFITA International Conference. Rhodes Island, Greece. June 27-29, 2019.

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