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Analysis of the correlations between the success/failure factors of a project using Fuzzy Cognitive Maps.

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ΠΑΡΑΡΤΗΜΑ 2 – Δήλωση

ΔΗΛΩΣΗ

«Η εργασία αυτή είναι πρωτότυπη και εκπονήθηκε αποκλειστικά και μόνο για την απόκτηση του συγκεκριμένου μεταπτυχιακού τίτλου».

«Τα πνευματικά δικαιώματα χρήσης του μη πρωτότυπου υλικού ΜΔΕ ανήκουν στον μεταπτυχιακό φοιτητή και στο επιβλέπον μέλος ΔΕΠ εις ολόκληρο, δηλαδή εκάτερος μπορεί να κάνει χρήση αυτών χωρίς τη συναίνεση άλλου. Τα πνευματικά δικαιώματα χρησιμοποίησης του πρωτότυπου μέρους ΜΔΕ ανήκουν στον μεταπτυχιακό φοιτητή και στον επιβλέποντα από κοινού, δηλαδή δεν μπορεί ο ένας από τους δύο να κάνει χρήση αυτού χωρίς τη συναίνεση του άλλου. Κατ' εξαίρεση, επιτρέπεται η δημοσίευση του πρωτότυπου μέρους της διπλωματικής εργασίας σε επιστημονικό περιοδικό ή πρακτικά συνεδρίου από τον ένα εκ των δύο, με την προϋπόθεση ότι αναφέρονται τα ονόματα και των δύο (ή των τριών σε περίπτωση συνεπιβλέποντα ως συν-συγγραφέων. Στην περίπτωση αυτή προηγείται γραπτή ενημέρωση του μη συμμετέχοντα στη συγγραφή του επιστημονικού άρθρου. Δεν επιτρέπεται η κατά οποιοδήποτε τρόπο δημοσιοποίηση υλικού το οποίο έχει δηλωθεί εγγράφως ως απόρρητο».

Ο Φοιτητής	*Ο Επιβλέπων*
Επαμεινώνδας Γουμενάκης	*Δημήτριος Εμίρης*

Abstract

Fuzzy cognitive maps (FCM) are a way of modeling that uses human experience and knowledge. It mixes ideas from fuzzy logic and neural networks. FCMs can handle complex systems by thinking, much like a person would. One noticeable thing about FCMs is that they're flexible. You can design, model, and control a system in lots of different ways with them. They're great at showing how things are connected, including feedback loops and hidden connections. FCMs are a bit uncertain because they're often used to describe and understand situations.

Just like in other project analysis fields, FCM can provide lessons and historical data that help improve future project execution and avoid similar issues. Thus, the analysis can be seen as a tool for developing knowledge capital within a business. This knowledge capital is particularly valuable, as it usually involves experts from various cognitive fields, contributing to the overall performance and growth of the enterprise.

This thesis project attempts to connect two distinct areas: one area is the traditional field of Project Management area and the other field is area of Artificial Intelligence. In the second field we opt to work with Fuzzy Cognitive Maps which is a technique that has been used for several years. A fishbone diagram is designed to analyze more the main causes of the project failure and then we attempt to examine the suitable of FCMs to model project failures by using the software FCM Expert.

Key-words

Fuzzy Cognitive Maps, FCM Expert, Project failure

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CHAPTER 1. Introduction

Projects fail because of several reasons. These reasons present a high degree of variety and are sensitive to the project nature. Those failure causes defer from project to project. Based on the literature it has been observed through the years that key causes fall in the areas of scope, cost and time. Several approaches have been proposed to model these causes and their effect to project outcome.

This thesis project attempts to couple two distinct areas: one area is the traditional field of Project Management area and the other field is area of Artificial Intelligence. In the second chapter we opt to work with Fuzzy Cognitive Maps which is a technique that has been used for several years. We attempt to examine the suitable of FCMs to model project failures by using the software FCM Expert.

The structure of the thesis is as follows:

In Chapter 1: The introduction of this Thesis is presented.

In Chapter 2: Fuzzy Cognitive Maps concepts are presented and a literature review is performed.

In Chapter 3: The key causes of project failures are discussed.

In chapter 4: a modeling technique is proposed in FCM Expert

In chapter 5: Conclusions.

The expected outcomes of this work are:

- To systematically model the project failure causes into one single model.
- To illustrate that it is possible to model PM concepts with computational methodology.
- To highlight a gradual development technique. In which the expert can modify as he chooses.

CHAPTER 2. Fuzzy Cognitive Maps

2.1 General info for FCM

Cognitive maps where initially introduced in graph theory by Euler in 1736. Directed graphs were used to connect different concepts together. R. Axelrod was the first to use them as a new way to model decision making in political and social systems and to represent social scientific knowledge. He called these graphs cognitive maps. Subsequently, Kosko made modifications to Axelrod's maps and introduced the concept of fuzzy values into the theory, naming them FCMs (Fuzzy Cognitive Maps). He suggested that the fuzzy values should range between [-1,1]. The purpose of using FCMs is to model causality between concepts rather than a semantic relationship. FCMs have found applications in various scientific fields, including operations research, decision analysis, administrative science, management science, analysis of electrical circuits, economic demographics, and more. Furthermore, the theory has been applied in modelling and supporting plant control systems, analyzing failures, and modeling the head of a control system. [1][2].

2.2 Fuzzy Cognitive Maps

Fuzzy cognitive maps (FCM) represent a methodology for modeling using experience and knowledge based on human experience [1]. It combines theories of fuzzy logic and neural networks. It can deal with complex systems using a reasoning process, exactly as a human would do. One notable benefit of using FCMs is the great degree of flexibility when designing a system, modeling and controlling it. They can represent structure knowledge, permit feedback relationships and/or hidden interrelationships [3]. Fuzzy sets represents have a degree of uncertainty because their often used to describe and analyze a situation [11].

In order to successfully describe the behavior of the model, FCMs use “concepts”. Each one of the concepts represents a characteristic or state of the system. The system can be illustrated by connecting the concepts together creating a graph which describes the cause and effect between the concepts [2]. These concepts have the capacity to interact, influence each other and exchange information [1]. Since FCMs allow feedback in their modeling, the dynamic of the system can be explored by describing the effect of specific changes over the network system [4].

Each concept within the model symbolizes a crucial factor in the system. Each concept is associated with a specific numerical value denoted as "A_i," signifying its level of activation, which denotes to what extent this variable, influences the others [4]. In every FCM, there are a total of 'n' concepts and the system is described by two matrices: **'W' with dimensions 'n x n',** representing the causality of relationships and **'A'** with dimensions **1 x n** describes the values of the **n**-concepts. Each weight ($w_{ij)}$ of the matrix “W” desctibes the weight or correlation between concept C_i and C_j.

There are three different casual relationships between two specific concepts.

- If $W_{ij}>0$ then a positive causality shows that a possible increase in C_i will also increase C_j. and a decrease in C_i will decrease C_j.
- If $W_{ij}<0$ then a negative causality shows that a possible increase in value of C_i will decrease C_j and a decrease in Ci will increase C_j.
- If $W_{ij}=0$ then it indicates there is no connection between two concepts [4].

To model a system using FCM it needs three different characteristic:

- Direction of the correlation between the concepts. It can either C_i influence C_j or vice versa or there will be no connection at all [1].
- The connection of the concepts. It can either be positive $W_{ij} > 0$ or negative $W_{ij} < 0$ or has no connection $W_{ij} = 0$ [2].
- The value of the weight (W_{ij}) is assigned with a fuzzy number or linguistic value and shows how much concept C_i affects the concept C_j. The direction of the arrow shows whether concept C_i affects concept C_j or vice versa [2][3].

The previous matrixes can be concluded in a mathematical form: $\mathbf{A^{(k)} = f(A^{(k-1)} + A^{(k-1)} * W).}$

After performing a number of simulations, an FCM might arrive in three possible states:

- a fixed - point,
- a cyclic state
- totally chaotic behavior.

In the first situation it suggests that a pattern was discovered, while the last two suggest that the FCM struggles to find a normal pattern [4].

2.3 The Learning Methods

Learning within artificial networks involves the pursuit of optimal parameters to satisfy a predefined criterion function, typically denoted as 'J'. These algorithms, which can be either unsupervised or supervised, aim to minimize error, cost, or meet a specific objective. They employ local search techniques to iteratively adjust weight vectors, ultimately converging to solutions that optimize the criterion function. Every algorithm has a mathematical method that searches the weights and describes the convergence for an Artificial Neural Network to reach a stable state.

The general weight learning rule has the following form:

$$\Delta wi = \rho\, r(wi, x)\ x$$

- The ρ is called the learning constant and is a positive number. It is named as rate of learning.
- r is name as the learning signal – its a function of calculating w_i
- x is named as the input signal

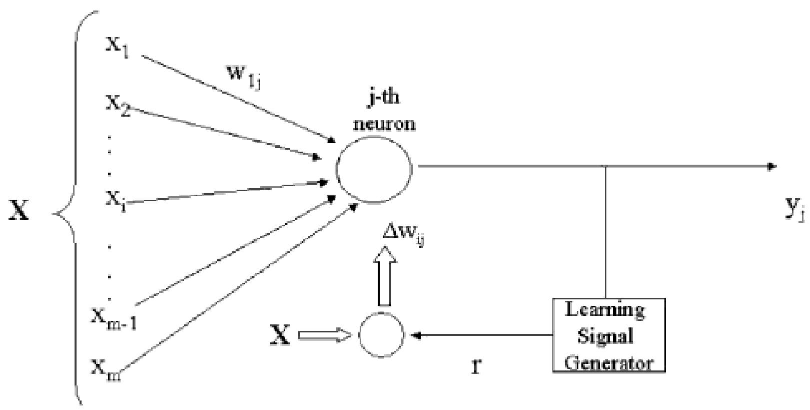


Figure 2.1 The general weight-learning method.

This formula indicates that the increase of the vector w_i is proportional to the product of the learning signal r (function) and the input x. One widely employed algorithm in FCM is the Hebbian learning algorithm. In its simplest form, networks comprise input vectors x and outputs y interconnected by a weight matrix W, where W_{ij} links x_i to y_j. The Hebbian learning law typically employs the following formula [3]:

$$w_{ij}(k+1) = w_{ij}(k) + \rho\, y_i\, x_i$$

Learning in FCM means, updating the strengths of casual links. A learning strategy can improve the FCM by changing its initial casual link by applying a learning algorithm [3].

2.3.1 The active Hebbian learning algorithm

An unsupervised learning algorithm called Active Hebbian Learning (AHL) is introduced and formulated for training Fuzzy Cognitive Maps (FCMs). AHL builds upon the principles of unsupervised Hebbian learning, offering an advanced approach. It introduces the order of the sequence of activation concepts. When the FCM is developed by the experts the sequence of activation is chosen also, the steps of activation and the cycle of simulation. At every simulation step, 1 or more concepts become Activation concept. If all the concepts are described as Activation concepts, according to the sequence that the expert has given of activation the simulation cycle has closed and a new one starts.

The simulation cycle consists of several steps, each of which step includes one or more concepts acting as the activation concepts that can influence the connected concepts and so on till the full search of the sequence of activation that close this cycle. This specific concept, at the next iteration step is named as Activated concept.

For example the j_{th} concept C_j is called as triggering concept and influences the concept C_i. The concept C_j is name as the Activation concept and has the value $A^{act}{}_j$ and it activates the connected corresponding concept with the name of C_i, which is named as Activated concept. For the next iteration step, the concept C_i influence the other connected concepts C_l and so on. It is given as a fact that there is asynchronous stimulation mode due to which the concept C_i is becoming the Activation concept that triggers C_l and the other interconnected concepts and there is a sequence of activation steps. During every simulation step the weight w_{ji} of the interconnections of the related concepts are updated and the changed weight $w^{(k)}{}_{ji}$ is calculated for every iteration step k.

Besides the determination of activation concepts, experts choose a select few concepts as decision concepts or outputs for each specific occasion, known as Activation Decision Concepts (ADCs). Those ADCs are crucial as they represent the main factors and characteristics of the system. We aim to calculate their values, which shows the system's final state [3].

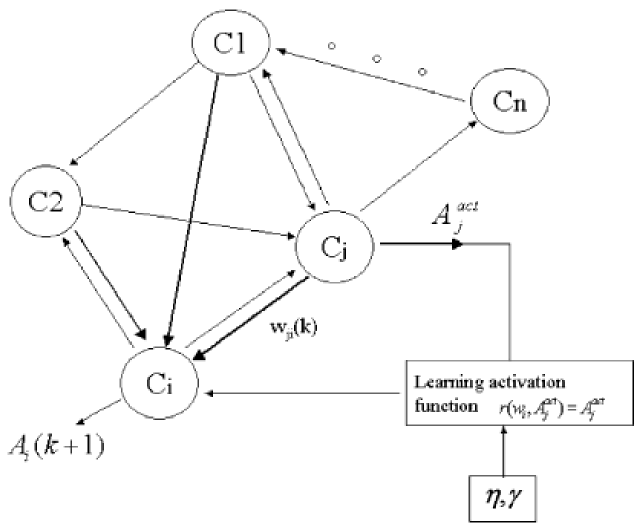


Figure 2.2 The proposed activation weight learning process for FCMs.

The Figure above describes a simple FCM model, its is created with n nodes, the parameter or node C_i is called as the ith concept with gets the value Ai(k), *$1 \leq i \leq n$,* w_{ji} is called as the weight shownig the influence from concept C_j to C_i and its value using the algorithm is $A^{act}{}_j(k)$ (activation value of C_j). C_j affects the connected concepts behaving as Activation concepts, γ is called as the weight decay parameter and n is the learning rate parameter, depending on simulation cycle c and $A_i(k)$ is value of the Activated concept C_i.

The value of the concept $A_i(k+1)$ of the Activated concept C_i, at iteration step k + 1, is calculated, finding the correlation of other Activation concepts with values $A^{act}{}_j$ to the specific concept C_i due to modified weights $w_{ji}(k)$ at iteration step k, through the following mathematical equation:

$$A_i(k+1) = f\,(A_i(k) + \sum_l Al^{act}(k)\, wli(k))$$

Here, A_l epresents the values of the Activation concepts C_l that affect the concept C_i, and $w_{li}(k)$ are the corresponding weights that describe the influence from C_l to C_i. For example, in the Figure above l takes the values 1, 2 and j, and A_1, A_2 and A_j are the values of Activation concepts C_1, C_2 and C_j, respectively, which influence C_i in this simulation step. Therefore, the value of the Activated concept C_i is calculated using the following equation:

$$A_i(k+1) = f(A_i(k) + A_1^{\text{act}}(k) \cdot w_{1i}(k) + A_2^{\text{act}}(k) \cdot w_{2i}(k) + A_j^{\text{act}}(k) \cdot w_{ji}(k))$$

The general mathematical form of AHL is as follows:

$$\Delta w_{ji} = \eta \cdot r(w_{ji}, A_j^{\text{act}}) \cdot A_i - \gamma \cdot w_{ji}$$

- n, γ are positive learning factors called learning parameters.
- $r(w_{ji}, A^{act}_j)$ is the signal function as the general rule $r(w_i, x)$.

In this algorithm it is proposed the learning function r to be equal to the Activation value A^{act}_j of concept C_j that is considered as the Activation concept influencing the other concepts of FCM :

$$r = r(w_{ji}, A^{act}_j) = A^{act}_j$$

By combining the 2 previous equations we get:

$$\Delta w_{ji} = \eta \cdot A_j^{\text{act}}(k-1) \cdot A_i(k-1) - \gamma \cdot w_{ji}(k-1)$$

The difference between input or output concepts relies on system being modeled and the experience of the experts. All concepts can be inputs that receive their values from external sources or intermediates that are affected by other concepts and in turn influence the output concepts. In the training phase a limited number of outputs are selected.

First criterion: objective function

In this algorithm, certain concepts are designated as Activation and Activated concepts during each iteration with Activated concepts being influenced by other interconnected Activation concepts. Additionally, outputs or Activation Decision Concepts are defined to represent the final values of corresponding concepts following a specific method and stimulations. J is a function proposed for the AHL, which searches the values of outputs concepts that have the values of Activation Concepts we are searching for.

$$J = ||ADC_i - A^{min}_i||^2 + ||ADC_i – A^{max}_i||^2$$

A^{min}_i is the minimum target value of the concept ADC_i and A^{max}_i is the maximum target value of ADC_i. After the last simulation is finished, the value of J function is calculated and searches for the Euclidean distance of ADC_i value from the minimum and maximum target values of the desired ADC_i, respectively. The minimization of the criterion function J is the ultimate goal, according to which we update the weights and determine the learning process.

Second criterion: function

The second criterion is used to terminate the algorithm after a limited number of cycles, when the desired values for ADCs are reached.

$$|ADC^{(c+1)}_i – ADC^{(c)}_i|<e$$

The e is proposed to be equal to 0.001.

The first criterion guarantees the convergence of the desired values for ADCs with the minimization of J and the 2nd criterion ensures the minimization of the variation of the ADCs.

Determination of learning parameters

The learning factor $n^{(c)}$ takes the following formula:

$$n^{(c)} = 0,02*e^{(-0,2*c)}$$

The learning factor $\gamma^{(c)}$ takes the following formula:

$$\gamma^{(c)} = b_2*e(-\lambda_2*c)$$

b2 and λ2 are positive constants which are determined using trial and error.

The suggested bounds of the parameters is suggested to be [0, 0,1].

Implementation of AHL

Professionals utilize their expertise and experience to identify the concepts within the FCM, which mirror the behavior and functioning of the system. Drawing upon their understanding of relevant factors and key system characteristics, they ascertain the quantity and nature of concepts comprising the FCM. Subsequently, they establish the structure and interconnections of the FCM through the application of fuzzy conditional statements and the specification of the sequence of activation concepts and DC(s).

The following example is consisted of seven steps, n is the number of concepts and p is the number of synchronously Activated concepts. An FCM with 6 nodes and the 3 of them are triggered at the same iteration step (p=3).

Step 1: The first values of concepts of vector A^0 and the weight matrix of $w^{initial}$ are signed, the sequence of activation concepts and the Activation Decision Concepts (ADCs).

Step 2: Sequence of learning parameters $n^{(c)}$ and $\gamma^{(c)}$, the 1st simulation cycle starts (c=1).

Step 3: The 1st Activation concept is C_j and triggers C_i (Activated concept). The new value of C_i is calculated and the new weight matrix.

The Activation concept is C_i and triggers the next concept C_l (Activated concept). The new value of C_l is calculated and the new weight matrix and so on.

At the last iteration the concept A^{act}_{final} is calculated. The values of the last ADC at c-cycle are used below.

Step 4: If c<M=100, J is calculated of the c-cycle else go to step 2.

Step 5: If J(c-2)>J(c-1)>J(c) is true go to next step else return to step 3 and a new cycle starts.

Step 6: check for $|ADC^{(c+1)}_I - ADC^{(c)}_i| < e$. If it is false go to step 3.

Step 7: If the two criteria from above are satisfied at the same time and the system converges in equilibrium state within accepted bounds, the process STOPs operating and the results are showed.

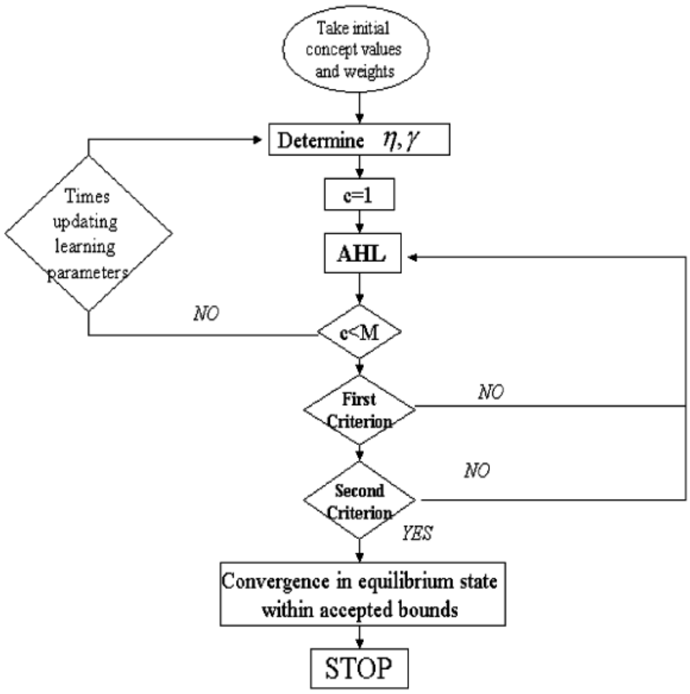


Figure 2.3: Flowchart of AHL procedure.

2.3.2 The Nonlinear Hebbian learning algorithm

The NHL is one of the most well known unsupervised algorithm used in FCM [10]. The algorithm is based on the assumption that all the concepts in the FCM model are synchronously affect at each iteration step of the simulation and change their values synchronously. Within this triggering process, the weights (w_{ij}) of the causal interconnections of the concepts are updated and the modified weight is derived for iteration step k.

The value A_i of concept C_i, at iteration step k+ 1 is calculated, finding the influence of interconnected concepts with values A_j to the specific concept C_j due to modified weights w_{ji} at iteration step k, through the equation. The NHL algorithm does not introduce new interconnections, and zero weights retain their original values. Determining upper and lower bounds for the learning parameter n typically involves employing trial and error experimental values [3].

The steps to calculate NHL are as follows:

Step 1: Initialize concepts $A_i^{(k)}$, weights w_{ji} using the knowledge of the experts, learning rate parameter usually nk = 0,001, weight decay parameter usually is γ=0,98 and $T_{imin} \leq T_i \leq T_{imax}$, where i is the number of decision concept.

Step 2: Repeat steps 3 - 6 for each k value until the stopping criteria are satisfied.

Step 3: At every simulation step k, the value A_i of a concept is calculated.

Step 4: The value of $w_{ji}^{(k)}$ is calculated.

Step 5: The Δwji is calculated for each k.

Step 6: After condition 1 or 2 are satisfied the process stops [10].

2.3.3 DHL and Balanced Differential Algorithm

Kosko initially introduced Differential Hebbian Learning (DHL) as a type of unsupervised learning, but he did not provide any mathematical formulation or practical implementation for real-world problems. The Balanced Differential Learning algorithm, which is based precisely on DHL, has also been explored for training FCMs. This modified version of DHL appears to be more effective in learning patterns and modeling a specific domain compared to traditional methods. However, to date, there is no established procedure for applying DHL and the Balanced Differential Learning algorithm to Fuzzy Cognitive Maps (FCMs).

Differential Hebbian Learning (DHL) is used as an unsupervised learning method for Fuzzy Cognitive Maps (FCMs). According to the DHL law, it correlates the changes between two concepts. If concept A and concept B both move in the same direction (for example, B increases when A increases), the causal link between them is strengthened. Conversely, if they move in opposite directions, the strength of their connection is weakened. Training involves processing a sequence of state vectors, adjusting the FCM matrix based on the DHL law for each state vector. [7].

The most challenging aspect of FCM is the construction of the map. An expert constructs the map based on their knowledge and experience, assigning varying degrees of causation, both positive and negative, between different concepts using fuzzy logic. The process of map creation may involve the collaboration of multiple experts, by sharing their experience and knowledge they can determine the factors that should be present in the map [2], afterwards they deicide relationship between the concepts.

2.4 FCM Expert general info

FCM Expert is a software tool application developed to create FCM-based systems. This software is coded in the Java programming language. The program explores three teams of functions that are organized in five different menus: **File, Edit, Build, Run and Reset.**

The first set of functions is focused on designing FCM-based models, allowing experts and users in specific domains to model complex systems. Importantly, it doesn't demand an extensive background in mathematics or computer science.

The second set incorporates machine learning algorithms designed to fine-tune model parameters and optimize its performance.

The third set includes procedures for exploiting the FCM-based system, as a tool for supporting decision-making processes [4].

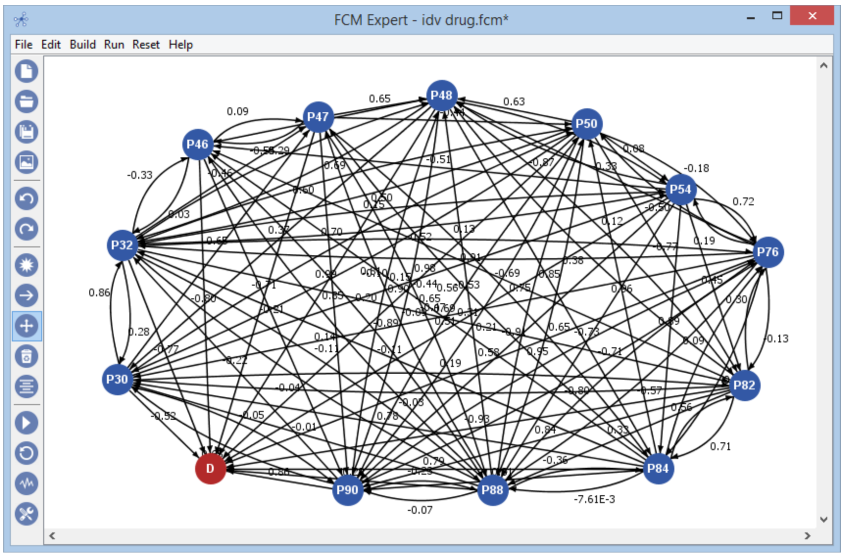


Figure 3

Figure 2.4. FCM expert example [4].

FCM Expert enables to design an FCM system from the beginning. This involves either drawing the network structure by hand or inserting the weight matrix from a CSV file. It enables conducting **IF-WHAT** simulations by directly adjusting the activation values of each concept and next running the inference process. This procedure results in the creation of a chart and a matrix with the values of each concept at each simulation step.

Selecting the appropriate learning methods to compute the weight set is a critical aspect of designing an FCM-based system. The major algorithms for FCM learning may be gathered into two main groups: **unsupervised and supervised** models.

The unsupervised learning algorithms are designed in a way to modify them and make adjustments to the weight set with a small deviation from the initial configuration. Nonetheless, due to their limited ability to generalize, hence they are not advised when solving pattern classification problems in such situations, it is preferable to use (supervised) learning algorithms.

Choosing an algorithm

The main strengths of FCM Expert lie in its Machine Learning algorithms. It incorporates both unsupervised and supervised algorithms to calculate the weight set that defines the FCM model, optimize the network structure, and enhance system convergence while retaining all relevant information.

This feature enables the automatic learning of the weight matrix associated with the FCM network. These algorithms are crucial because they determine the system's behavior. You can access these methods via the menu: Run | Learning algorithms | Compute weight matrix.

FCM Expert incorporates several Hebbian-based algorithms, including Differential Hebbian Learning, the Balanced Differential Algorithm, and Nonlinear Hebbian Learning. For these algorithms, the expert needs to define two parameters: one for weight decay and one for the learning rate, along with the example data used to train the model.

2.5 Creating a FCM in FCM Expert

2.5.1 Basic steps

In the process of creating a new Fuzzy Cognitive Map (FCM), it is important to clearly define the function of each concept within the modeled topology. These concepts are categorized into two distinct roles: **input concepts and decision concepts**. These classifications are formalized as follows:

Definition 1: An independent input neuron is defined as a neural processing entity (Ci), whose activation value remains unaffected by the activation of other input neurons.

Definition 2: A dependent input neuron is characterized as a neural processing entity Ci, if its activation value is influenced by the activation of other connected neurons.

Definition 3: An output neuron is described as a neural processing entity Ci, and its activation value is only determined by the connected input neurons, with no external factors involved.

FCM Expert offers the flexibility to work with various **architectures** suitable for both scenario analysis and pattern classification. In the first scenario, the FCM does not comprise a decision concept. In the second scenario, we have two different architectures that vary in the number of decision concepts.

The first architecture is referred to as the **single-output architecture**. It features a solitary decision concept, where decision classes are characterized as closed partitions within the decision space. On the other hand, the **class-per-output architecture** assigns an output neuron to define each class. It's important to note that each neuron within this architecture has the option to use its own transfer function [5].

In the *single-output architecture*, configuring the decision concept involves establishing a partition of the decision space based on decision classes. Each decision entry is characterized by its decision label and by its lower and upper bounds.

2.5.2 Creating complex networks - Augmented topology

This feature allows the integration of multiple FCMs into a single knowledge-based model. Using input from multiple experts or knowledge sources can lead to more robust and consistent models. You can access this function through the menu: Build | Augmented topology. The software merges multiple FCMs into one averaged FCM. If the FCMs share the same concepts, the combined FCM can be easily computed as the average, median, or weighted average of their causal matrices. If the FCMs have different concepts, each causal matrix must be augmented by adding new columns and rows filled with zeros for each additional concept.

2.5.3 Reasoning and parameter settings

When conducting experiments or simulations, the expert must set the parameters for the FCM reasoning rule. These options are available in the menu: Run | Customize settings.

More explicitly, the domain expert can determine the reasoning rule used to update the activation values of neural concepts and the transfer function used by all concepts in the network. If the sigmoid transfer function is selected, the user can also specify the slope and offset parameters.

More explicitly, FCM Expert includes the following inference rules:

- Kosko’s activation rule: The rule is applied repeatedly until a stopping condition is found. At each step t, a new activation vector is computed. After a set number of iterations, the FCM will reach one of the following states: (i) equilibrium point, (ii) limit cycle, or (iii) chaotic behavior.
- Kosko’s activation rule with self-memory in this rule, neurons also consider their own previous values. This approach is favored for updating the activation of neurons that operate independently, meaning they are not influenced by other neural processing entities.
- Rescaled activation rule with self-memory is used to avoid conflicts in the case of non active neurons. It deals with scenarios where there is not information about an initial neuron-state and helps preventing the saturation problem.

FCM Expert offers two criteria to stop the reasoning process: either the network reaches a stable point of convergence, or it completes a maximum number of iterations. If the convergence option is chosen but the network fails to stabilize, the inference process automatically halts after 20 iterations.

CHAPTER 3. Project failures

3.1 Reasons for a project failure

Projects often do not follow the predetermined plan and may be changes due to disruptive outcomes that may lead to delays in schedule, quality, and cost. In such cases, project managers must ensure their project schedules and take appropriate corrective measures when the schedule needs to be revised.

The failure of a project is determined by many factors, it can mean a delay in project delivery, deviation from financial goals, negative impact on reputation, and so on. A failed project may have achieved significant results even if it did not precisely meet its objectives. The important thing after the failure of a project is learning from the mistakes that led to its failure, which will contribute to better planning and monitoring in future projects.

The reasons for the failure of the project can be divided into two groups: design (poor planning and unclear objectives) and human factors. Indicators of project failure may be included from other corresponding projects in the same sector, predictions by experts, and indicators specific for the existing project [7].

The uncertainty in a project signifies a lack of knowledge. This, along with complexity in the project, leads to ambiguity and risk and should be addressed appropriately [7].

Setting strict constraints on the schedule, budget, and clearly defining requirements help the project team better understand their goals. The reasons for the failure of a project are many, either because companies/managers are not aware of them, or they ignore them, or they do not know how to manage them [7].

Unrealistic Expectations – Incorrect Estimates

Most of the time, the budget and also the scheduling, are communicated to the project team at the beginning of the project. When the schedule is announced there may be very little understanding of the difficulty of the project and even less understanding of the project management. Decision makers may insist on setting final dates that may be unrealistic and do not accept hearing from the project manager that the schedule is unrealistic.

Unclear definition of the project scope

One of the most significant reasons for the failure of a project is the unclear definition of the project scope in the project management plan. The plan must be well defined, clear and can be completed with the tools and resources already assigned to the project. When the project scope is defined beforehand it's easier to deliver the deliverables on time and within the budget.

Scheduling Delays

Design is one of the essential elements of a project. With poor design, unexpected or negative incidents are more likely to occur, increasing the likelihood of project failure. Poor interaction among participants, funding issues, etc., can lead to delays or stop the progress of a project. Another critical aspect is assessing the delay, more specifically some delays are due to the contractor, employer and some other belong to both of them.

Poor cost estimation

As work progresses, costs may increase or decrease [7]. It's more common to see an increase in cost as the work progresses than a decrease. It's not uncommon also to see an underestimation of the cost. Cost increases may be due to either incorrect planning or external factors beyond the control of project managers such as bad weather conditions, inexperience in similar projects, lack of historical data, lack of guidelines for how to estimate.

Lack of support from management

The lack of management involvement can lead to project failure. Successful projects require the support of management to achieve their goals. Research has shown the results of project improvement increase proportionally to the level of involvement of top management [7].

Lack of communication

Effective communication among stakeholders is an equally important factor for the success or failure of a project. Meetings, reports (daily, weekly, etc.) can significantly improve team communication. A project manager must spend most of his time communicating about goals, expectations, progress and any problems that may arise during the project. Inadequate communication can have negative impacts on areas such as progress, guidance, and project outcomes. A clear communication plan is a determining factor in how important project information will be communicated. With a solid communication plan, the project team can save time to complete other processes or to better address project goals. In case there are many participants in a project, the relationship between them becomes an important factor for the success or failure of the project, they are responsible for the continuous smooth operation of the project, roles, tasks, responsibilities. When there is poor communication and cooperation, poor interpersonal relationships between participants, the more misunderstandings and unexpected incidents may happen and it could lead to much higher chances of a project to fail.

Human Resources (HR)

Incorrect team composition

One of the fundamental elements in project management is the proper composition of a team. It is important to define the correct project team and the number of ‘’main project managers’’ who can understand the difficulty and the duration of the project before the project starts. Many times, assigning certain tasks to the wrong individual or team can create problems in the progress of the project [7].

Insufficient Resources

A project may fail because the initially estimated resources are insufficient. Initial estimates are based on the assumption that certain individuals will collaborate on different tasks and activities. The project management plan must clearly identify the resources, secure those resources, and allocate budget to those key elements.

Insufficient training

Insufficient training can lead to project failure. It contributes to the development of awareness, knowledge, and "soft" skills related to tools and practices. Only in a few cases they encourage their employees to learn from their mistakes or the experience of other experts.

Lack of rewards and recognition

The motivation of the employees can greatly affect projects. To maintain employee's interest in the project, they should be rewarded for efforts in improvement tasks they undertake. The lack of rewards can negatively impact team performance and the progress of the project.

Inconsistent monitoring and control

Monitoring and controlling the project ensure its proper improvement and performance. It helps prevent failures and ensures accurate assessment. During ongoing projects, evaluation helps monitor and control projects, guide decision making and change, and even terminate projects if necessary.

Wrong choice of process improvement methodology and techniques.

The results of the improvement of a project can be achieved by selecting the correct tools and techniques. It's necessary also to collect data and have enough resources that will be used as inputs for the tools.

3.2 Project Failure Indicators

Indicators related to the success or failure of a project is found in few studies [7]. Perhaps due to the different projects/fields, it is almost impossible to determine failure indicators that apply on a broad scale.

3.2.1 Existence of many similar projects

The existence of many similar projects in the same sector serves as a warning for possible project failure. Numerous corresponding projects already active in the same sector can be an indicator of risk for the project, due to the saturation that is created [7].

3.2.2 Incorrect estimation

Incorrect upfront estimation by an expert can be considered an indicator of failure in future projects. When specialists advise a change or termination of a particular project, their advice should be regarded as a timely warning sign for potential failure [7].

3.2.3 Continuous readjustment of the schedule

The continuous adjustment of schedules is an indication of possible project failure. Successful projects have strict schedules, unlike projects that fail [7].

3.3 Ishikawa diagram (Fishbone)

The Ishikawa diagram or fishbone is a tool to for finding the root causes of quality problems. It offers in a systematically a way to find the effects and the causes that create the problem. They are used for a better visualization of the root causes of a problem. The design of the diagram looks like a fish skeleton.

In order to create the diagram a problem must be first identified and then the main root causes can be found with their secondary effects. After that a prioritization list can be created and the diagram can be created [8].

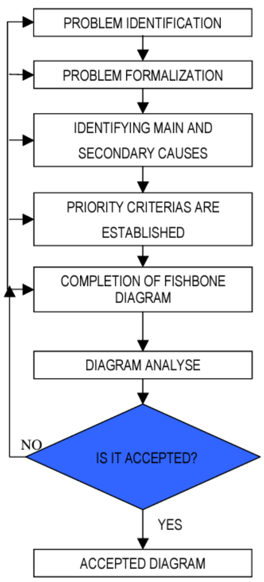


Figure3.1. Creation of a fishbone diagram [8]

3.2.1 Fishbone diagram for project failure

In order to create a diagram based on the project failure the main causes are discussed with their secondary causes:

Project Failure

Main Cause	Sub cause
Cost	Cost overestimation
	Cost underestimation
Scope	Unrealistic expectations
	Unclear definition of the project scope
	Bad WBS
Time	Delay in deliverables
	Bad planning
	Delay in scheduling
Quality	Too strict quality measurements
	Too loose quality measurements
	Damaged products
Management	Insufficient training
	Wrong team composition
	Bad monitoring and control
Stakeholders	Lack of communication
	Unrealistic expectations
	No updating

Based on the above, the fishbone diagram is created.

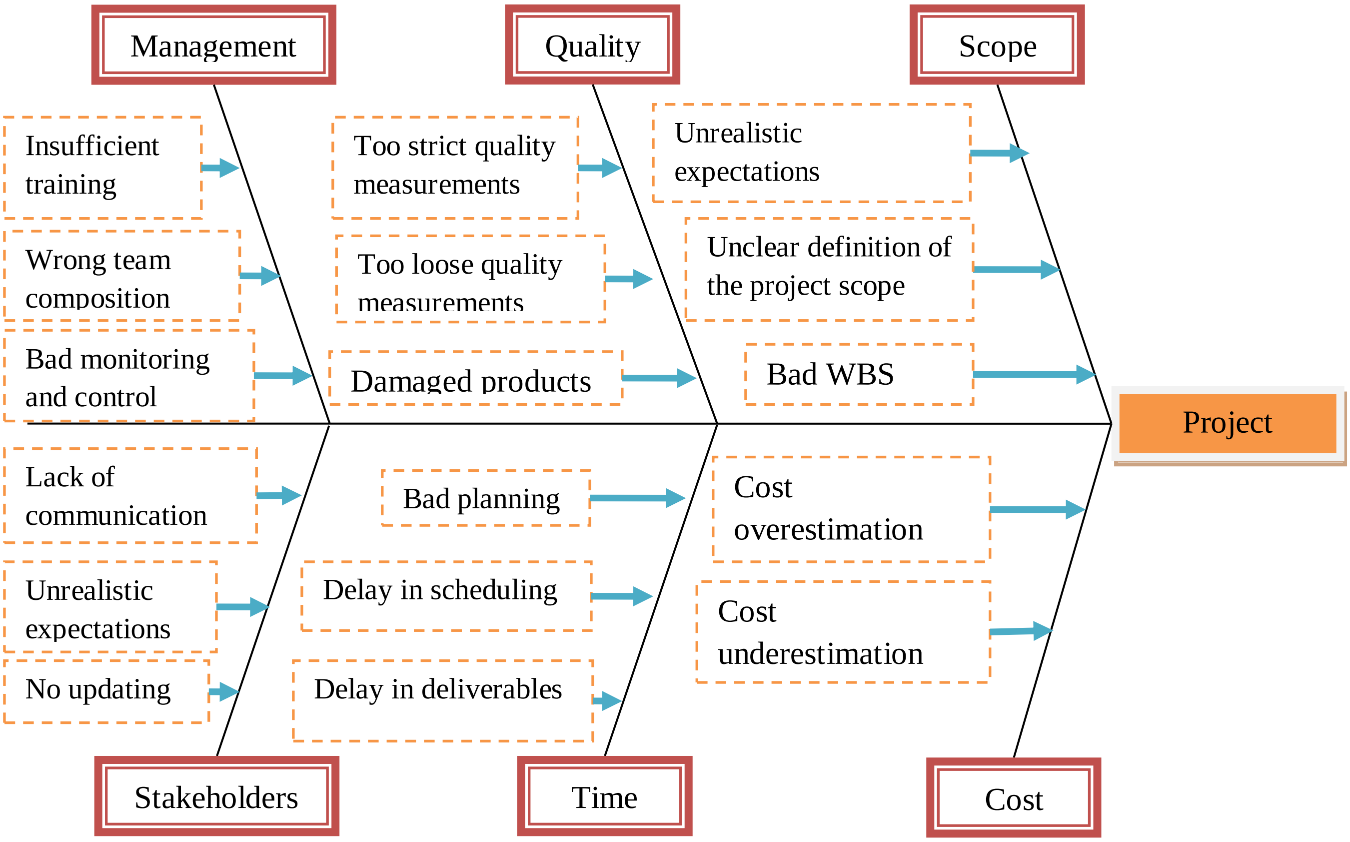


Figure 3.2. Fishbone diagram

The above diagram is characterized by six main cause (Scope, Cost, Quality, Time, Management, Stakeholders) and 17 secondary causes. The causes of the diagram are designed from the most important to least important causes (Cost→Stakeholders)

CHAPTER 4. Modeling in FCM expert

4.1 Model design

In this chapter, a model is being designed in FCM Expert. Every root cause in the fishbone diagram is designed with its secondary causes. The concepts S, T, C, St, Q, M and F represents the main root causes: S = Scope, T = Time, C = Cost, St = Stakeholders, Q = Quality, M = Management and F represents the Failure. In every main cause used from the fishbone diagram, its secondary causes are also used.

In order to describe the connection of the causes, a five point scale is being designed from to 0 to 1. Zero (0) corresponds to no connection between the concepts, 0,2 corresponds to a very small causality between the concepts, 0,4 corresponds to a small causality, 0,6 corresponds to strong causality, 0,8 corresponds to very strong causality and 1 corresponds to an absolute causality between the concepts. Every number represents the percentage of the correlation (e.g. C_1 with $w_{1,2}$=0,4 can affect with 40% the value of the concept C_2).

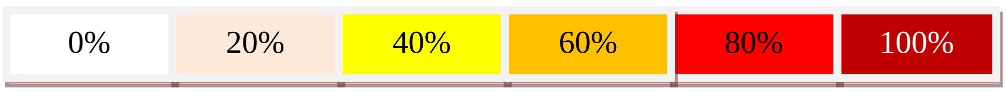


Figure 4.1. Scale of the causes from 0% to 100%

Approach of the test runs:

In order to describe the importance of every main failure cause, a what – if analysis is performed for the “F” concept. If the result is x≥0,70 its important for the failure of the project, else x<0,70 its less important for the failure of the project.

Three different approaches are used to calculate the values of the concepts:

- The weights are stable
- The weights are not stable and are changed according to Non Hebbian Learning
- A bigger model is designed.

The first approach calculates the value of the "F" concepts based only on the experience of the experts. The second approach calculates the new weight matrix by giving a less fuzzy result. The third approach tries to find the significance of the main causes by changing their activation value.

4.1.1 Scope

In this diagram the main factor of the scope was designed with three secondary effects were used: S1=unrealistic expectations, S2=bad WBS, S3=unclear definition of the project scope.

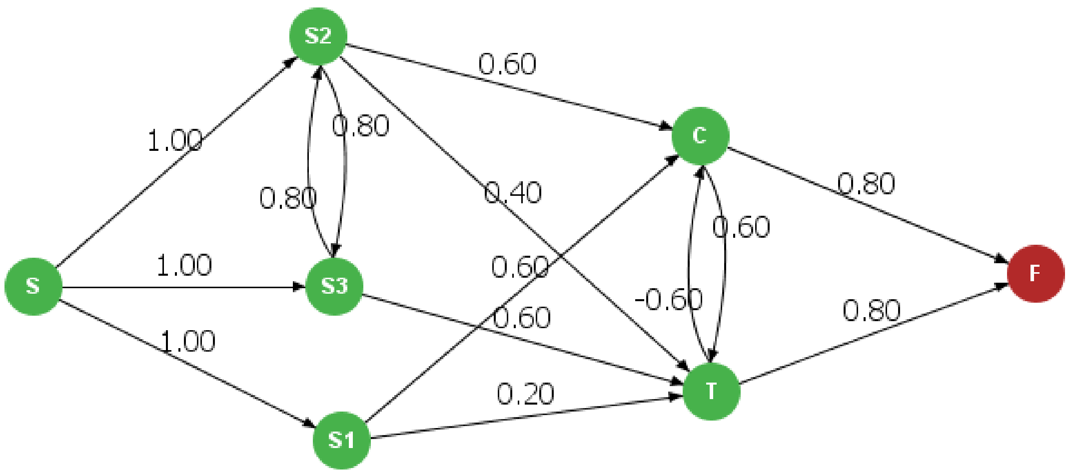


Figure 4.2. Simple scope diagram in FCM Expert

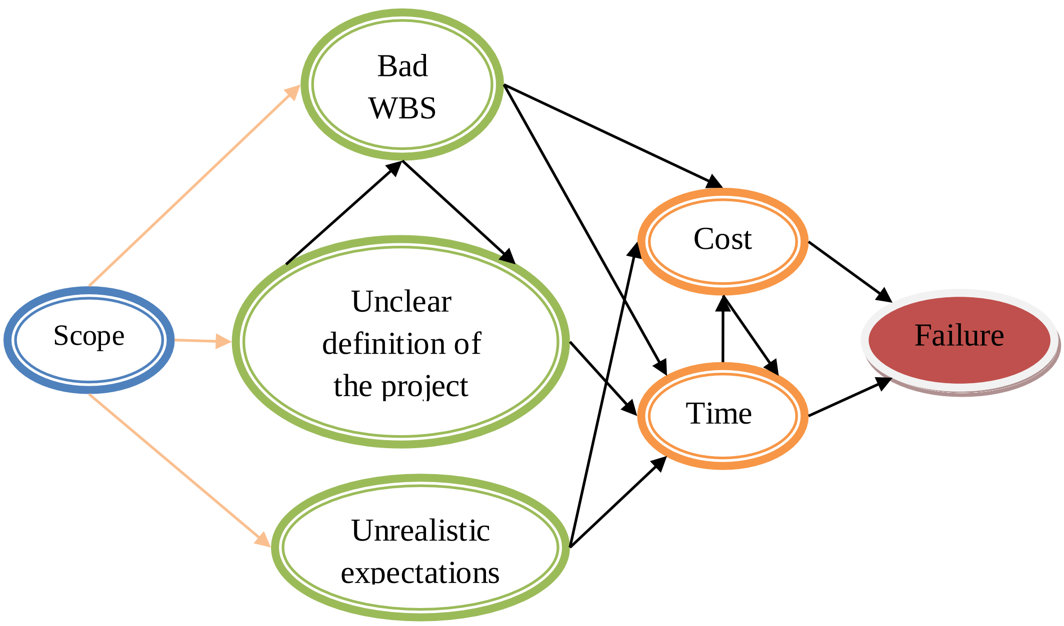


Figure 4.3 Simple scope diagram

The above diagram describes the connection between Scope – Time – Cost – Failure of the project.

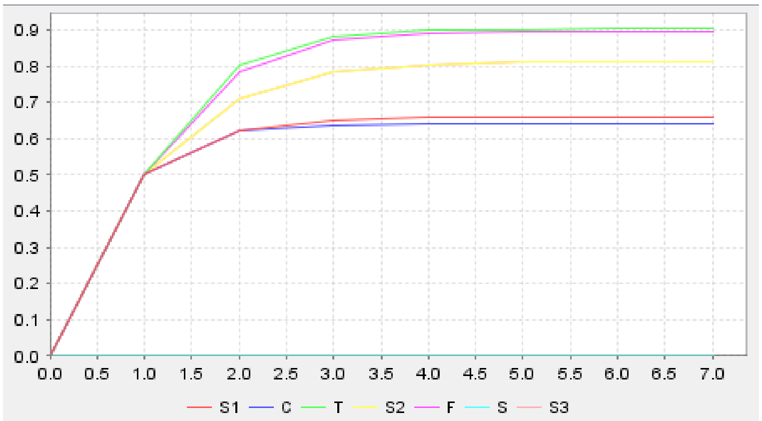
<u>Describing the above diagram:</u>

Unrealistic expectations have a positive causality with time and cost.

Likewise, when the definition of the project scope is unclear, it has positive causality with bad WBS and time. In other words, the more unclear the definition of the project scope is the worst is WBS and vice versa and more time can be needed to finish the project.

Test runs:

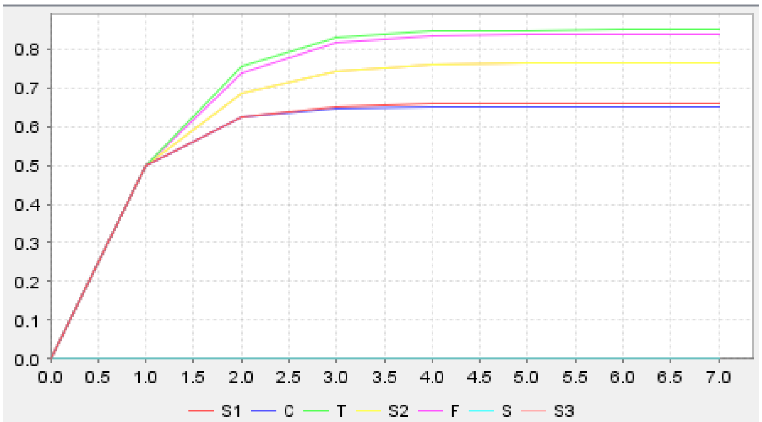
First approach: After doing the first test run without changing the weight matrix, the results are as follows. Based on the assumption that the weights are stable, the activation value of the Failure is 0.8937. It can be assumed that Scope plays an important role for the failure or success of the project.



Step	S1	C	T	S2	F	S	S3
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.0	0.5
2	0.6225	0.6201	0.8022	0.7109	0.7858	0.0	0.7109
3	0.6508	0.6351	0.8818	0.7824	0.8725	0.0	0.7824
4	0.6572	0.6392	0.898	0.8035	0.8895	0.0	0.8035
5	0.6586	0.6411	0.9017	0.8094	0.8928	0.0	0.8094
6	0.659	0.6418	0.9027	0.8111	0.8935	0.0	0.8111
7	0.659	0.642	0.903	0.8115	0.8937	0.0	0.8115

Figure 4.4. Scope – test runs A

Second approach: The weight matrix is computed and the results are:



Step	S1	C	T	S2	F	S	S3
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.0	0.5
2	0.6225	0.6237	0.7535	0.6835	0.7387	0.0	0.6835
3	0.6508	0.6464	0.8269	0.7412	0.8149	0.0	0.7412
4	0.6572	0.6508	0.8443	0.7579	0.8334	0.0	0.7579
5	0.6586	0.652	0.8484	0.7626	0.8376	0.0	0.7626
6	0.659	0.6524	0.8494	0.7639	0.8385	0.0	0.7639
7	0.659	0.6525	0.8497	0.7643	0.8388	0.0	0.7643

Figure 4.5. Scope – test runs B

With this approach Scope plays a less important role for the failure of the project. The value of the failure = 0,8388 and can be seen as important.

4.1.2 Stakeholders

In this diagram the main factor of stakeholders was designed with three secondary effects were used: ST1=Strict quality measurements, ST2=Lack of communication, ST3=unrealistic expectations.

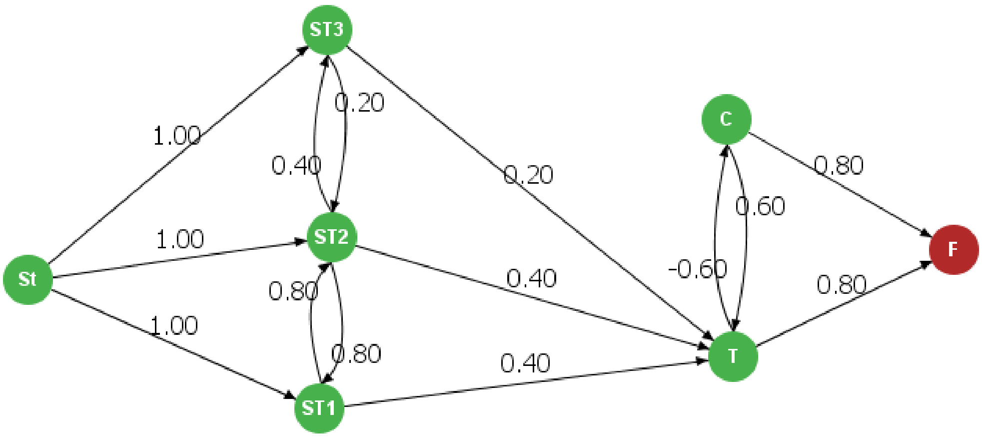


Figure 4.6. Simple Stakeholders diagram in FCM Expert

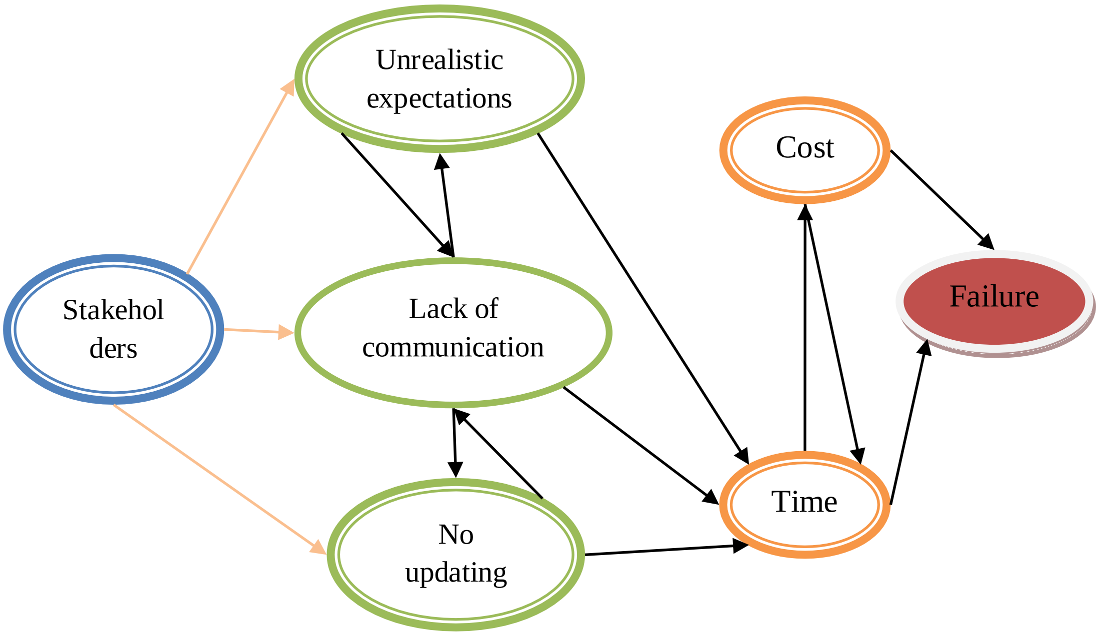


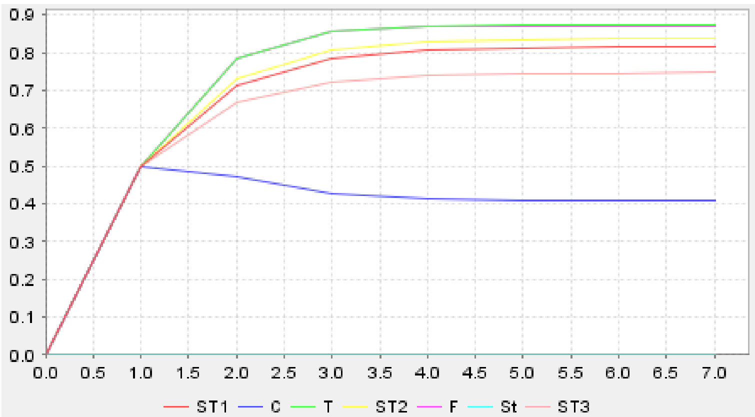
Figure 4.7. Simple Stakeholders diagram

The above diagram describes the connection between Stakeholders – Time – Cost – Failure of the project.

Lack of communication has positive causalities between no updating, unrealistic expectations and time. That means the more lack of communication exist during the project the more unrealistic expectations will be (and vice versa) and no updating will be (and vice versa), thereby contributing to delays.

Test runs:

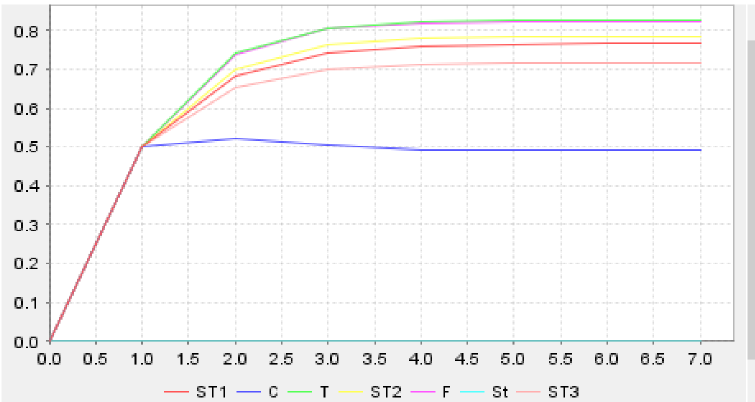
First approach: After doing the first test run without changing the weight matrix, the results are as follows. Based on the assumption that the weights are stable, the activation value of the Failure is 0.8693. It can be assumed that Stakeholders plays an important role for the failure or success of the project.



Step	ST1	C	T	ST2	F	St	ST3
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.0	0.5
2	0.7109	0.4725	0.7858	0.7311	0.7858	0.0	0.6682
3	0.7851	0.4275	0.8557	0.8074	0.8572	0.0	0.7232
4	0.8071	0.4131	0.8692	0.8292	0.868	0.0	0.74
5	0.8131	0.4098	0.8721	0.8352	0.8692	0.0	0.7449
6	0.8148	0.4091	0.8728	0.8368	0.8693	0.0	0.7463
7	0.8152	0.4089	0.873	0.8372	0.8693	0.0	0.7467

Figure 4.8. Stakeholders – test runs A

Second approach: The weight matrix is computed and the results are:



Step	ST1	C	T	ST2	F	St	ST3
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.0	0.5
2	0.6835	0.5241	0.7408	0.6987	0.7385	0.0	0.6543
3	0.7428	0.5039	0.8067	0.7615	0.8053	0.0	0.6999
4	0.7602	0.4945	0.8215	0.7794	0.8192	0.0	0.7129
5	0.7651	0.4916	0.8248	0.7844	0.8217	0.0	0.7166
6	0.7665	0.4909	0.8256	0.7858	0.8221	0.0	0.7176
7	0.7669	0.4907	0.8258	0.7862	0.8222	0.0	0.7179

Figure 4.9. Stakeholders – test runs A

With this approach Quality plays a less important role for the failure of the project. The value of the failure = 0,8222 and can be seen as important.

4.1.3 Quality

In this diagram the main factor of quality was designed with three secondary effects were used: Q1=Strict quality measurements, Q2=Loose quality measurements, Q3=damaged product.

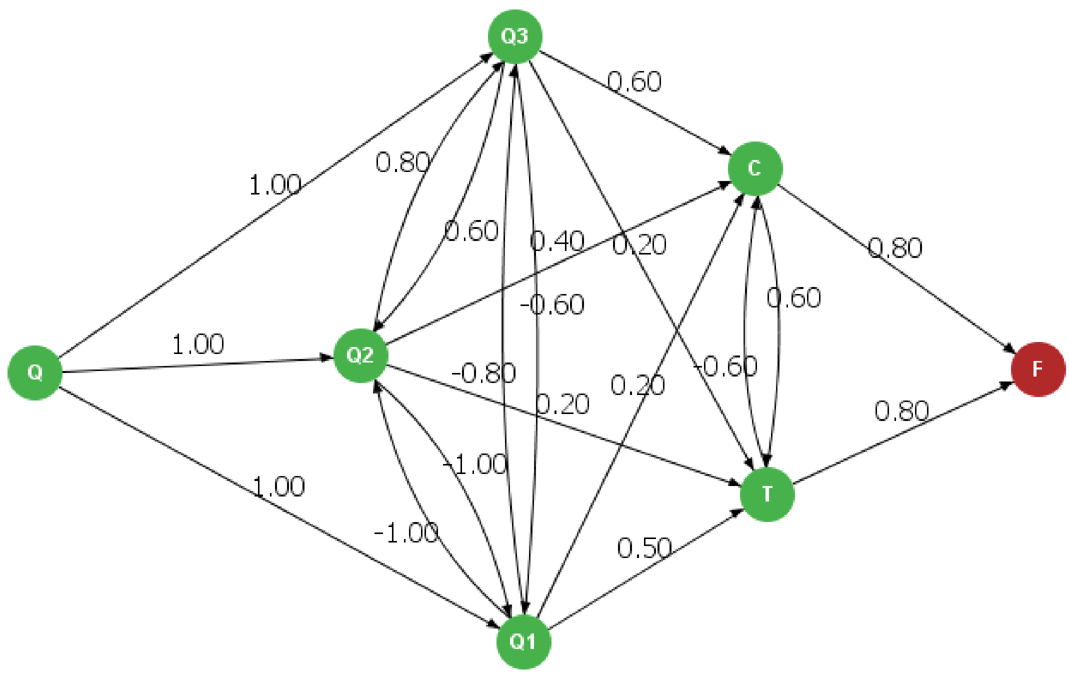


Figure 4.10. Simple Quality diagram in FCM Expert

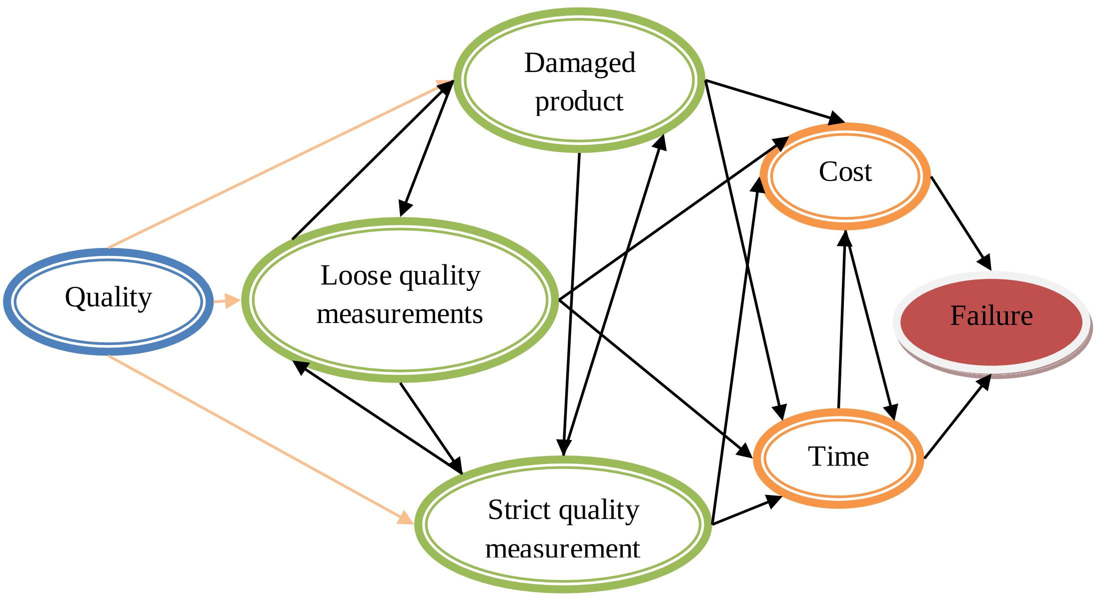


Figure 4.11. Simple Quality diagram

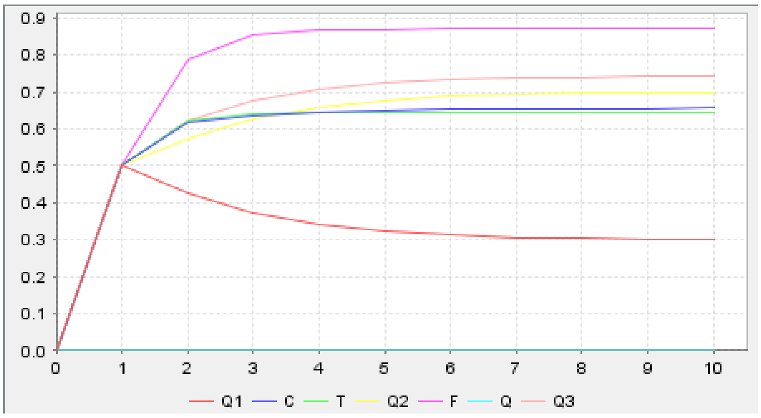
The above diagram describes the connection between Quality – Time – Cost – Failure of the project.

Loose quality management has a positive causality between damaged products. The looser the quality measurements are the more damaged products will be and vice versa. On the other hand it has a negative causality with strict quality measurements and cost.

A negative causality can also be found between damaged products and strict quality measurements.

Test runs:

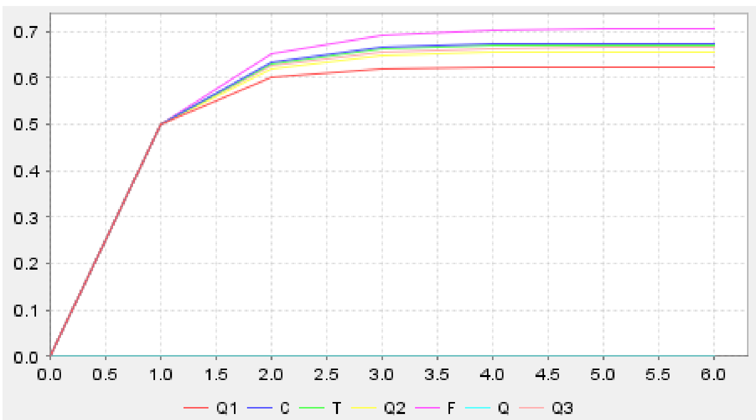
First approach: After doing the first test run without changing the weight matrix, the results are as follows. Based on the assumption that the weights are stable, the activation value of the Failure is 0.8858. It can be assumed that Quality plays an important role for the failure or success of the project.



Step	Q1	C	T	Q2	F	Q	Q3
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.0	0.5
2	0.4256	0.6201	0.6225	0.5744	0.7858	0.0	0.6225
3	0.3723	0.6342	0.6399	0.6277	0.8557	0.0	0.6773
4	0.3403	0.6431	0.6445	0.6597	0.867	0.0	0.7072
5	0.3222	0.6488	0.6457	0.6778	0.8696	0.0	0.7236
6	0.3122	0.6522	0.6459	0.6878	0.8705	0.0	0.7327
7	0.3068	0.6541	0.6459	0.6932	0.8709	0.0	0.7375
8	0.3039	0.6552	0.6459	0.6961	0.8711	0.0	0.7401
9	0.3023	0.6558	0.6458	0.6977	0.8712	0.0	0.7415
10	0.3015	0.6561	0.6458	0.6985	0.8713	0.0	0.7423

Figure 4.12. Quality – test runs A

Second approach: The weight matrix is computed and the results are:



Step	Q1	C	T	Q2	F	Q	Q3
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.0	0.5
2	0.6009	0.6326	0.6309	0.6199	0.6514	0.0	0.6262
3	0.6196	0.6649	0.6625	0.6478	0.692	0.0	0.6565
4	0.6228	0.6724	0.6699	0.6543	0.7023	0.0	0.6637
5	0.6232	0.6741	0.6716	0.6558	0.7048	0.0	0.6654
6	0.6233	0.6745	0.672	0.6562	0.7054	0.0	0.6658

Figure 4.13. Quality – test runs B

With this approach Quality plays a less important role for the failure of the project. The value of the failure = 0,7054 and can be seen as important.

4.1.4 Management

In this figure the main factor of management was designed and three secondary effects were used: M1 = Insufficient training, M2 = Wrong team composition, M3 = Bad Monitoring and Control.

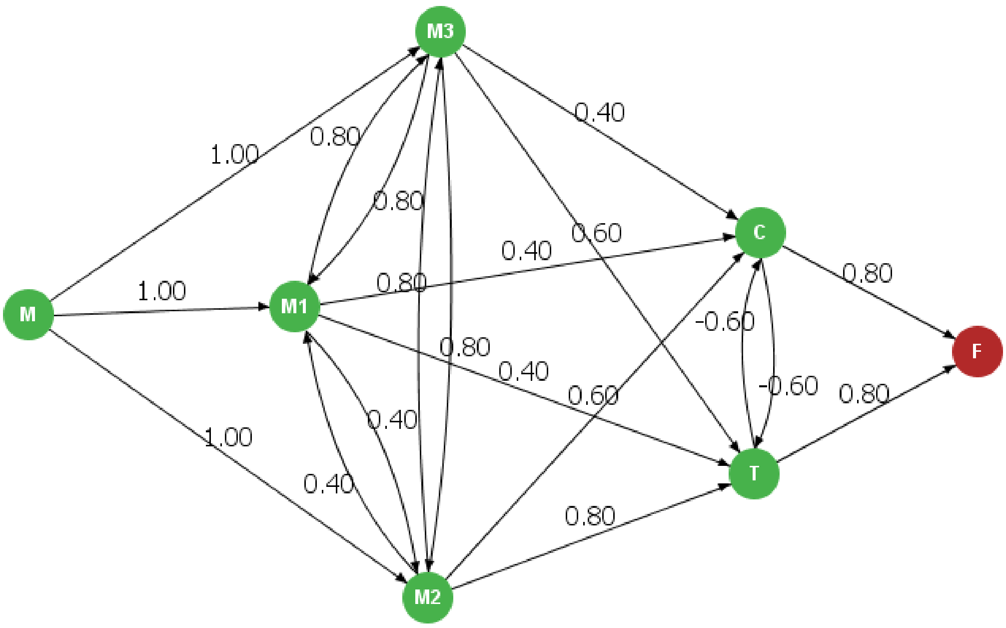


Figure 4.14. Simple Management diagram in FCM Expert

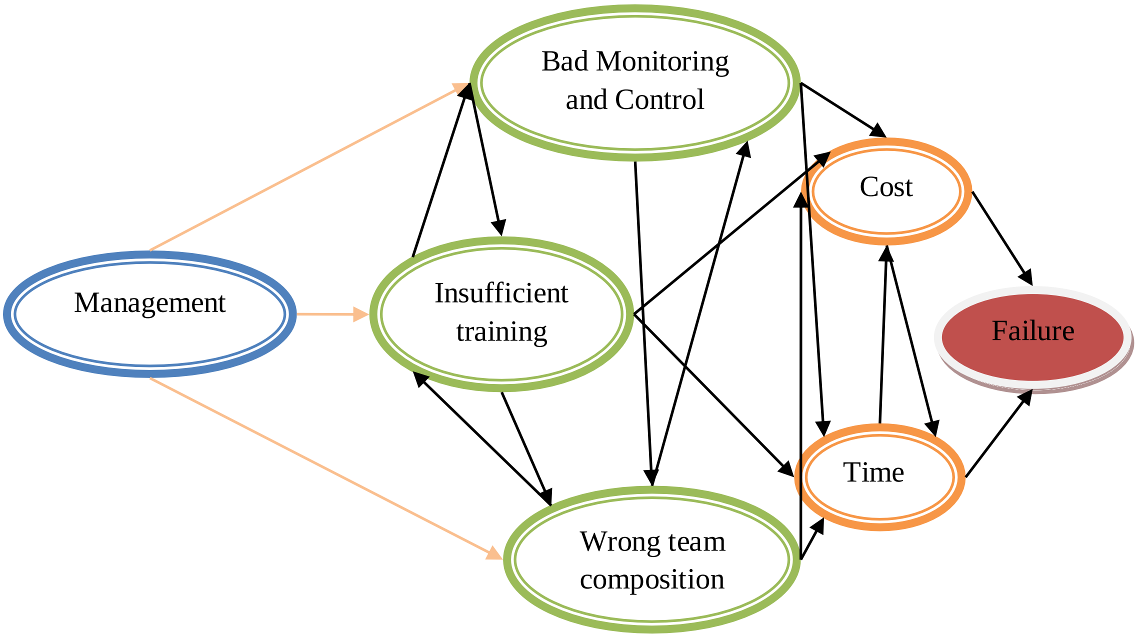


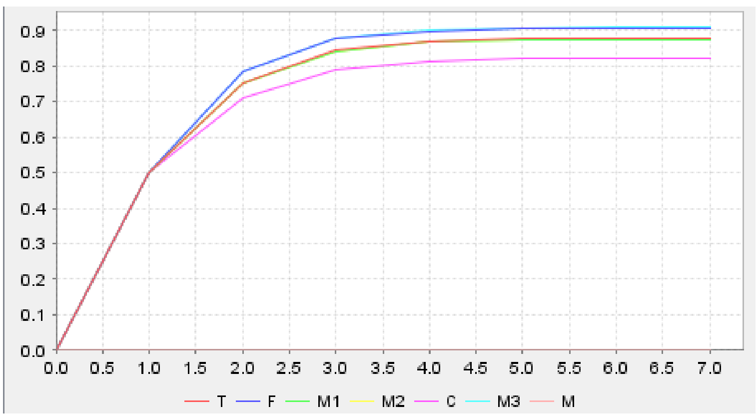
Figure 4.15. Simple Management diagram in FCM Expert

The above diagram describes the connection between Management – Time – Cost – Failure of the project.

Wrong team composition, insufficient training and bad monitoring and control have a positive causality between them.

Test runs:

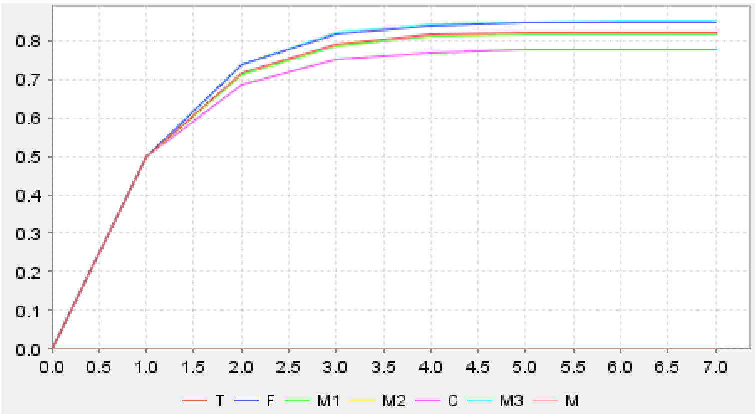
First approach: After doing the first test run without changing the weight matrix, the results are as follows. Based on the assumption that the weights are stable, the activation value of the Management is 0.9061. It can be assumed that Management plays an important role for the failure or success of the project.



Step	T	F	M1	M2	C	M3	M
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.5	0.0
2	0.7503	0.7858	0.7503	0.7503	0.7109	0.7858	0.0
3	0.8449	0.876	0.8428	0.8428	0.7901	0.8793	0.0
4	0.871	0.8988	0.868	0.868	0.8142	0.9027	0.0
5	0.8771	0.9044	0.8741	0.8741	0.8206	0.9082	0.0
6	0.8785	0.9057	0.8755	0.8755	0.8223	0.9094	0.0
7	0.8788	0.9061	0.8758	0.8758	0.8226	0.9097	0.0

Figure 4.16. Management – test runs A

Second approach: The weight matrix is computed and the results are:



Step	T	F	M1	M2	C	M3	M
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.5	0.0
2	0.7145	0.7389	0.7128	0.7128	0.6868	0.739	0.0
3	0.7909	0.817	0.7875	0.7875	0.7503	0.819	0.0
4	0.814	0.8388	0.8098	0.8098	0.7697	0.8416	0.0
5	0.8204	0.8448	0.816	0.816	0.7754	0.8478	0.0
6	0.8221	0.8464	0.8177	0.8177	0.7769	0.8494	0.0
7	0.8225	0.8469	0.8181	0.8181	0.7774	0.8499	0.0

Figure 4.17. Management – test runs B

With this approach Management plays an important role for the failure of the project. The value of the failure = 0,8469 and can be seen as important.

4.1.5 Time

In this figure the main factor of time was designed and three secondary effects were used: T1=Bad planning, T2 = Delay in scheduling, T3 = Delay in deliverables.

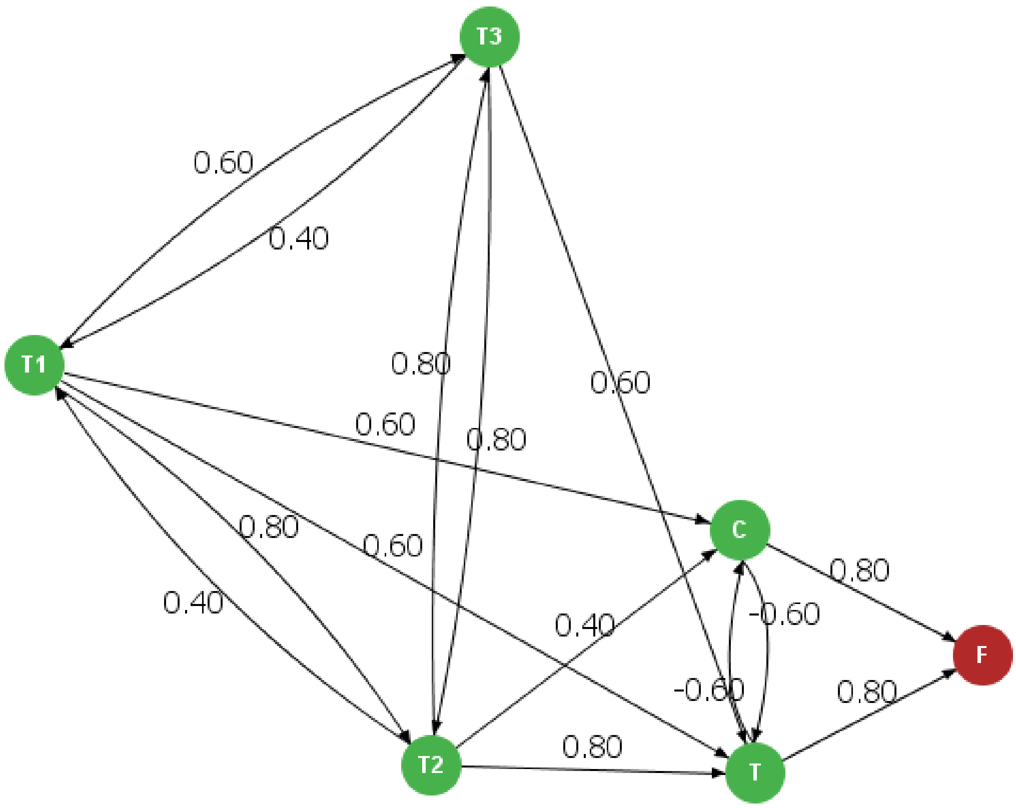


Figure 4.18. Simple Time diagram in FCM Expert

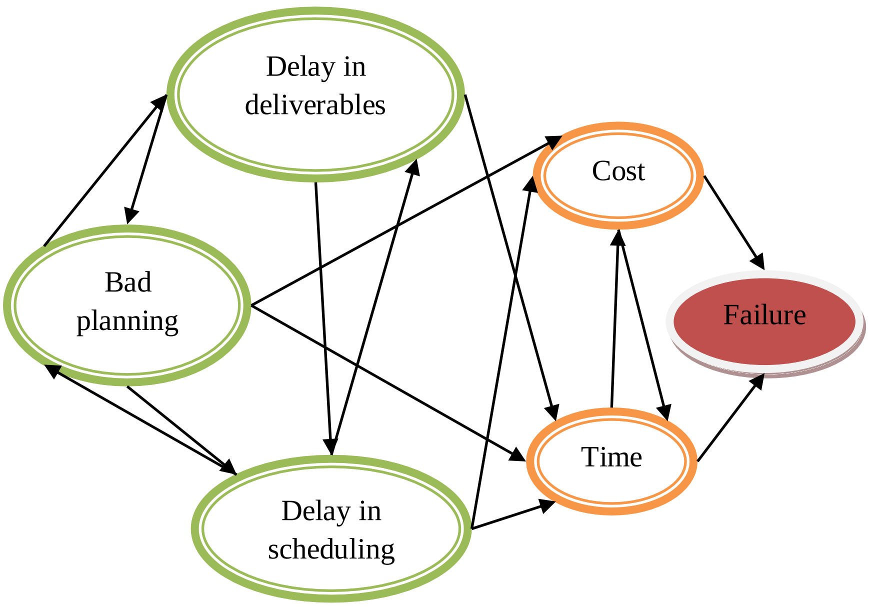


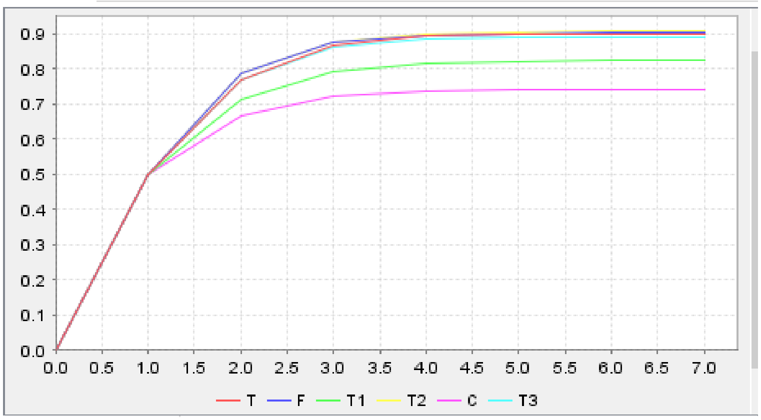
Figure 4.19. Simple Time diagram

The above diagram describes the connection between Time – Cost – Failure of the project.

Bad planning, delay in scheduling and delay in deliverables all have positive causality between them.

Test runs:

First approach: After doing the first test run without changing the weight matrix, the results are as follows. The activation value of the Failure is 0.9016. It can be assumed that Time plays an important role for the failure or success of the project.

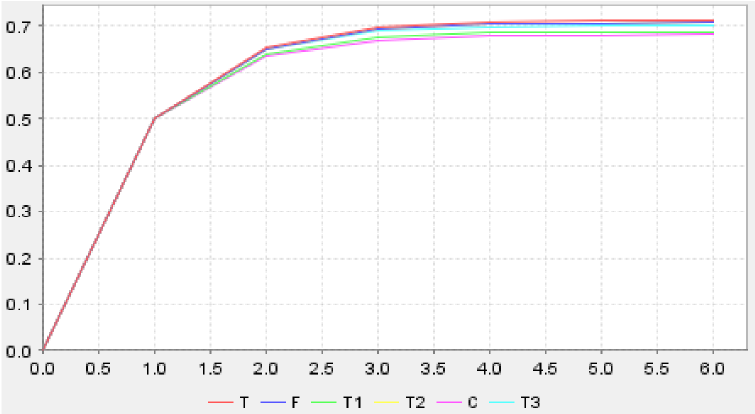


Step	T	F	T1	T2	C	T3
0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.5
2	0.7685	0.7858	0.7109	0.7858	0.6682	0.7685
3	0.8681	0.8738	0.7913	0.8775	0.7207	0.861
4	0.8937	0.8952	0.8156	0.9002	0.7361	0.8847
5	0.8996	0.9002	0.8219	0.9055	0.7406	0.8903
6	0.9009	0.9014	0.8235	0.9068	0.742	0.8917
7	0.9012	0.9016	0.8239	0.9071	0.7424	0.892

Figure 4.20. Time – test runs A

Second approach:

The weight matrix is computed and the results are: The value of the Failure = 0,7077. It can be assumed that time plays an important role for the failure of the project.



Step	T	F	T1	T2	C	T3
0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.5
2	0.6541	0.6519	0.6401	0.6519	0.6362	0.649
3	0.6969	0.6934	0.6767	0.6935	0.6707	0.6894
4	0.7081	0.7042	0.686	0.7043	0.6792	0.6999
5	0.7111	0.707	0.6884	0.707	0.6813	0.7026
6	0.7118	0.7077	0.689	0.7077	0.6819	0.7033

Figure 4.21. Time – test runs B

4.1.6 Cost

In this figure the main factor of the cost was designed and 2 secondary effects were used: C1 = Cost overestimation, C2 = Cost underestimation.

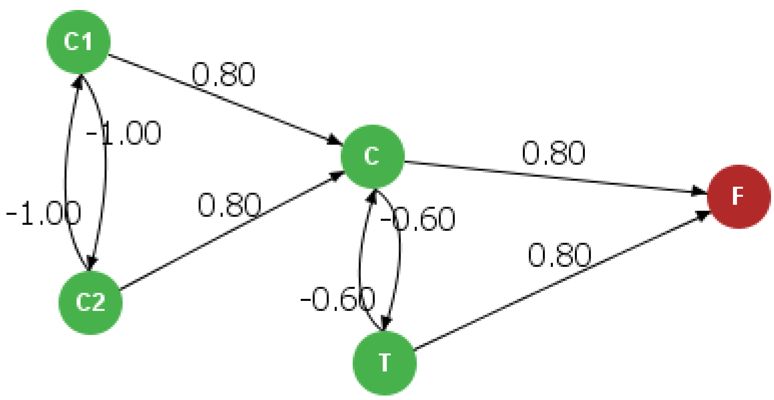


Figure 4.22. Simple Quality diagram in FCM Expert

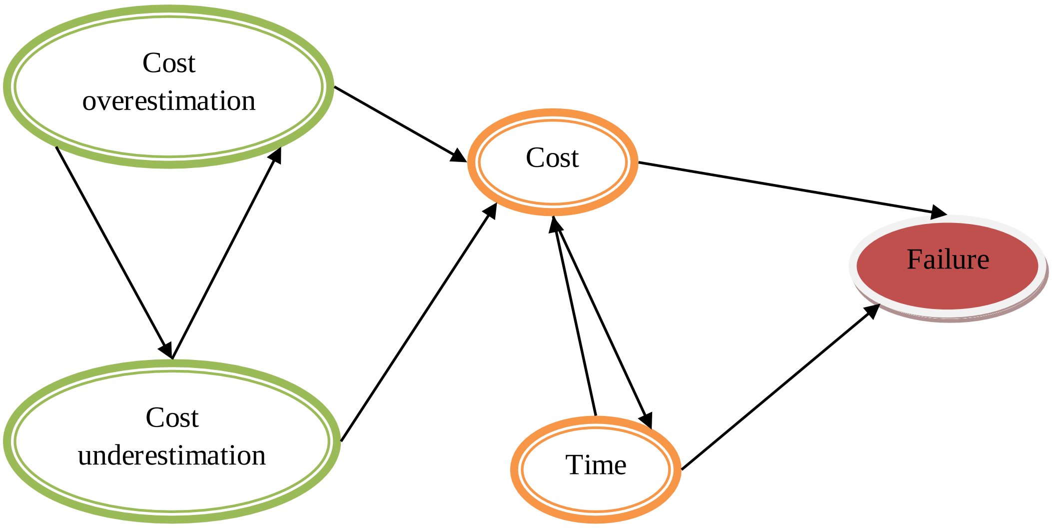


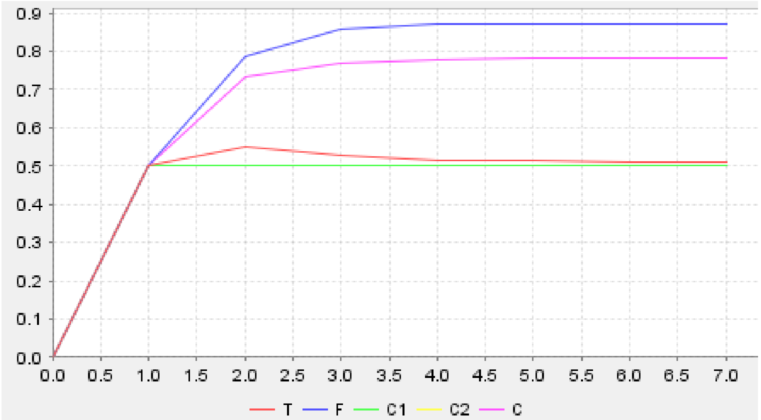
Figure 4.23. Simple Cost diagram

The above diagram describes the connection between Cost – Time – Failure of the project.

There is an inverse relationship between cost overestimation and cost underestimation. Overestimating costs may result in unnecessary resource purchases, leading to higher expenditures. Conversely, underestimating costs overlooks certain expenses, potentially leading to larger unforeseen costs later in the project lifecycle.

Test runs:

First approach: After doing the first test run without changing the weight matrix, the results are as follows. The activation value of the Failure is 0.8704. It can be assumed that Cost plays an important role for the failure or success of the project.

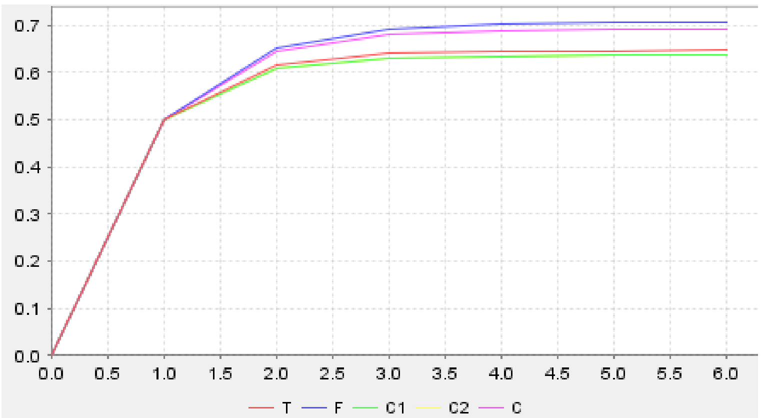


Step	T	F	C1	C2	C
0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5
2	0.5498	0.7858	0.5	0.5	0.7311
3	0.5278	0.8594	0.5	0.5	0.7687
4	0.5166	0.8695	0.5	0.5	0.7777
5	0.5125	0.8704	0.5	0.5	0.7803
6	0.5111	0.8704	0.5	0.5	0.7812
7	0.5106	0.8704	0.5	0.5	0.7815

Figure 4.24. Cost – test runs A

Second approach:

The weight matrix is computed and the results are:



Step	T	F	C1	C2	C
0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5
2	0.6153	0.6514	0.6084	0.6084	0.6438
3	0.6401	0.6919	0.631	0.631	0.6803
4	0.6453	0.7021	0.6356	0.6356	0.6891
5	0.6464	0.7046	0.6365	0.6365	0.6911
6	0.6466	0.7052	0.6367	0.6367	0.6916

Figure 4.25. Cost – test runs B

With this approach Cost plays a less important role for the failure of the project. The value of the failure = 0,7052 and can be seen as important.

4.1.7 Comparison of the first test runs

Comparing all the values of Failure:

Table 4.1. Comparing all the values of failure.

Management	0.8469
Scope	0.8388
Stakeholders	0.8222
Time	0.7077
Quality	0.7054
Cost	0.7052

By comparing all the values of Failures it can be seen that Management plays the most important role for the failure of the project. Every cause was calculated individually and not all of them together. In the next section a whole design is being designed that includes every main cause linked with the other main causes.

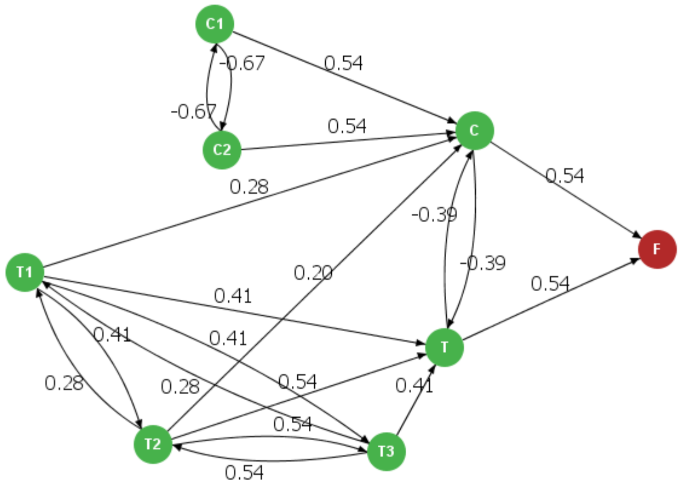
4.2 Design of bigger models

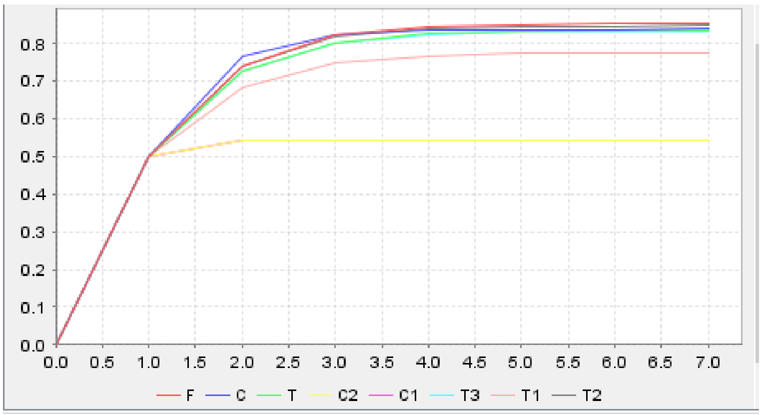
A more complex FCM was designed. The main causes were put into one bigger model. This approach tries to search if the main causes of the project failure can be put under one single model. At first 3 main causes were out together for calculations. Only the last model is consisted of 2 main causes together: time and cost.

4.2.1 Modeling Cost – Time

The first model that was designed was Cost and Time. For this design all the secondary causes were used from Cost and Time.

By calculating the new weights the FCM becomes as follows:





Step	F	C	T	C2	C1	T3	T1	T2
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
2	0.739	0.7656	0.7279	0.5416	0.5416	0.7261	0.685	0.7389
3	0.8244	0.8244	0.803	0.5451	0.5451	0.8031	0.7485	0.8178
4	0.8461	0.8359	0.826	0.5454	0.5454	0.8251	0.7681	0.8397
5	0.8513	0.8381	0.8327	0.5454	0.5454	0.8311	0.7737	0.8456
6	0.8526	0.8386	0.8346	0.5454	0.5454	0.8327	0.7752	0.8472
7	0.8529	0.8387	0.8351	0.5454	0.5454	0.8331	0.7756	0.8476

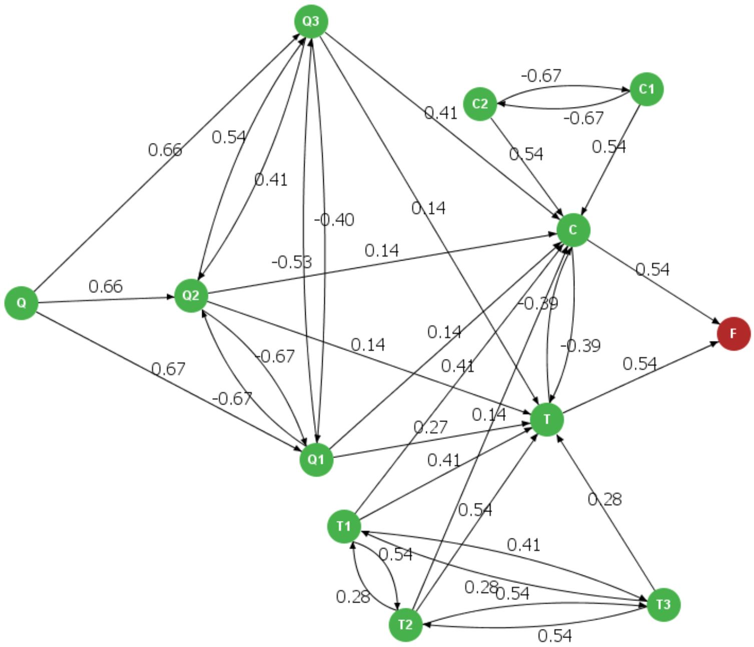
Figure 4.26. Cost – Time – test runs C

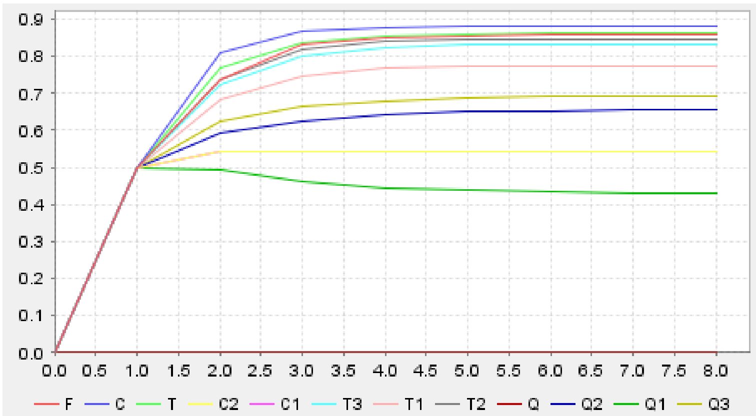
By combining the above concepts, the final value of the Failure is 0.8529 which is considered high.

4.2.2 Modeling Cost – Time – Quality

The second model that was designed was Cost – Time – Quality. For this design all the secondary causes were used from Cost, Time and Quality.

By calculating the new weights the FCM becomes as follows:





Step	F	C	T	C2	C1	T3	T1	T2	Q	Q2	Q1	Q3
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
1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.0	0.5	0.5	0.5
2	0.7391	0.8118	0.7796	0.5416	0.5416	0.7261	0.685	0.7389	0.0	0.5912	0.4923	0.6231
3	0.8321	0.8677	0.8516	0.5451	0.5451	0.8031	0.7485	0.8178	0.0	0.6261	0.463	0.6635
4	0.8536	0.8773	0.8699	0.5454	0.5454	0.8251	0.7681	0.8397	0.0	0.6425	0.4461	0.68
5	0.8581	0.8795	0.8748	0.5454	0.5454	0.8311	0.7737	0.8456	0.0	0.6504	0.4376	0.6874
6	0.8591	0.8801	0.8761	0.5454	0.5454	0.8327	0.7752	0.8472	0.0	0.6542	0.4335	0.6909
7	0.8593	0.8804	0.8764	0.5454	0.5454	0.8331	0.7756	0.8476	0.0	0.6559	0.4315	0.6925
8	0.8594	0.8805	0.8765	0.5454	0.5454	0.8332	0.7758	0.8477	0.0	0.6568	0.4306	0.6933

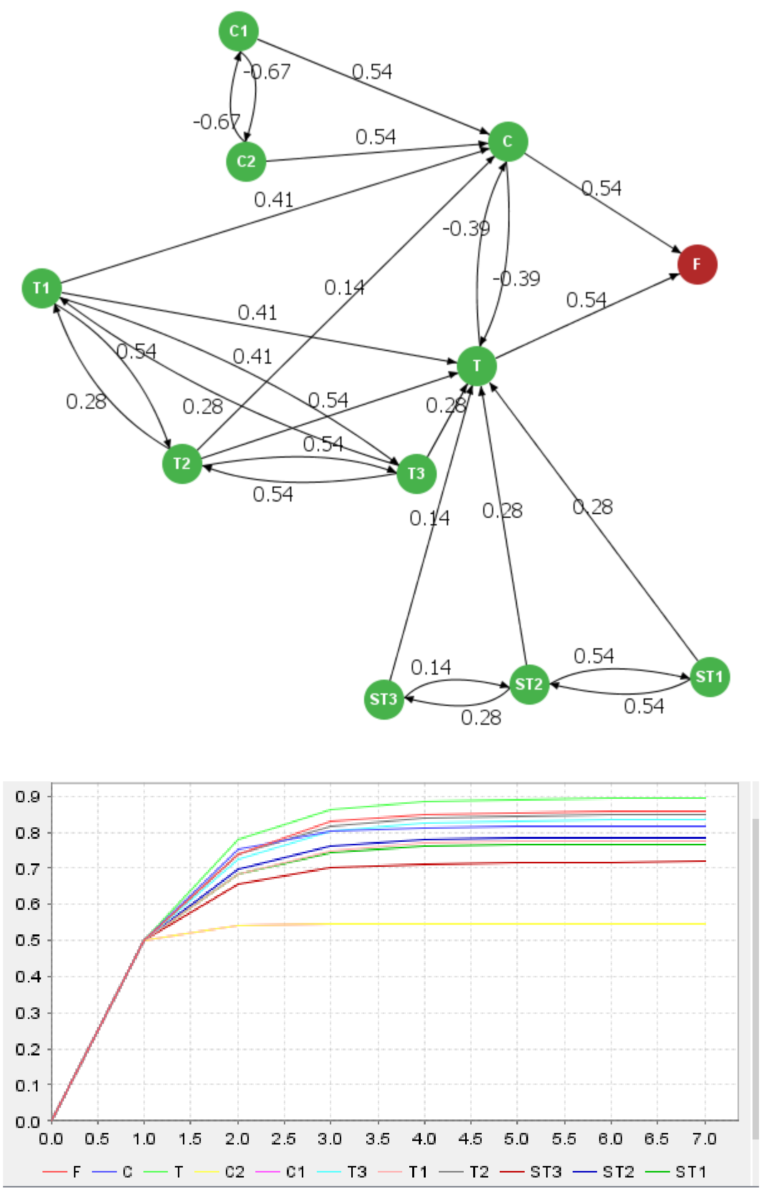
Figure 4.27. Cost – Time – Quality – test runs C

By combining the above concepts, the final value of the Failure in the last simulation is 0.8594 which is considered high.

4.2.3 Modeling Cost – Time – Stakeholders

The third model that was designed was Cost – Time – Stakeholders. For this design all the secondary causes were used from Cost, Time and Stakeholders.

By calculating the new weights the FCM becomes as follows:



Step	F	C	T	C2	C1	T3	T1	T2	ST3	ST2	ST1
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
2	0.739	0.7533	0.7808	0.5416	0.5416	0.7261	0.685	0.7389	0.6543	0.6987	0.6835
3	0.8277	0.8044	0.8641	0.5451	0.5451	0.8031	0.7485	0.8178	0.6999	0.7615	0.7428
4	0.8495	0.8136	0.8853	0.5454	0.5454	0.8251	0.7681	0.8397	0.7129	0.7794	0.7602
5	0.8543	0.8154	0.8908	0.5454	0.5454	0.8311	0.7737	0.8456	0.7166	0.7844	0.7651
6	0.8554	0.8159	0.8923	0.5454	0.5454	0.8327	0.7752	0.8472	0.7176	0.7858	0.7665
7	0.8556	0.816	0.8927	0.5454	0.5454	0.8331	0.7756	0.8476	0.7179	0.7862	0.7669

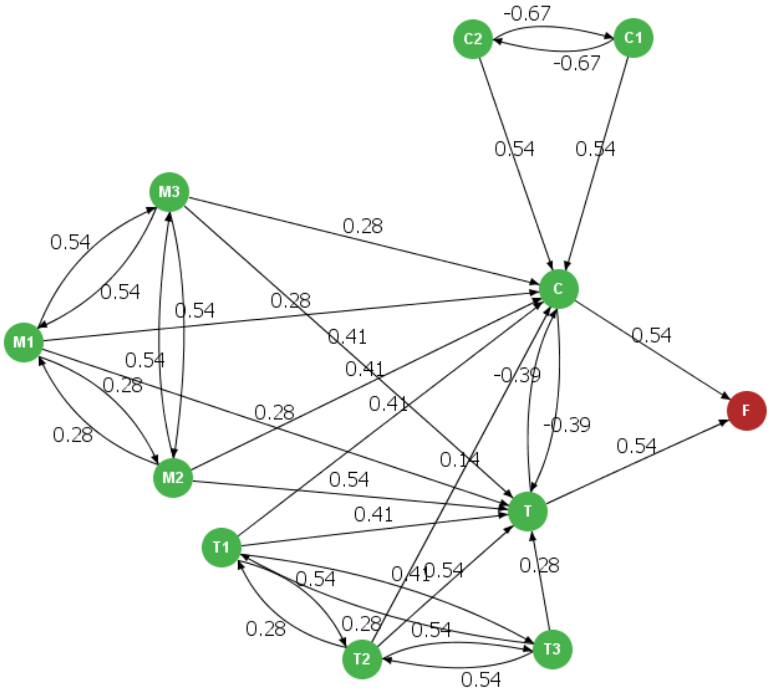
Figure 4.28. Cost – Time – Stakeholders – test runs C

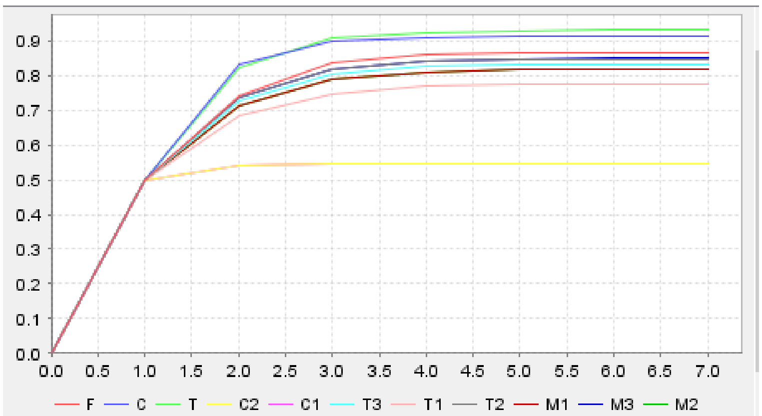
By combining the above concepts, the final value of the Failure in the last simulation is 0.8556 which is considered high.

4.2.4 Modeling Cost – Time – Management

The fourth model that was designed was Cost, Time and Management. For this design all the secondary causes were used from Cost, Time and Management.

By calculating the new weights the FCM becomes as follows:





Step	F	C	T	C2	C1	T3	T1	T2	M1	M3	M2
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
2	0.7392	0.8321	0.8231	0.5416	0.5416	0.7261	0.685	0.7389	0.7128	0.739	0.7128
3	0.837	0.8979	0.9066	0.5451	0.5451	0.8031	0.7485	0.8178	0.7875	0.819	0.7875
4	0.86	0.9107	0.9252	0.5454	0.5454	0.8251	0.7681	0.8397	0.8098	0.8416	0.8098
5	0.8647	0.9138	0.9297	0.5454	0.5454	0.8311	0.7737	0.8456	0.816	0.8478	0.816
6	0.8658	0.9146	0.9309	0.5454	0.5454	0.8327	0.7752	0.8472	0.8177	0.8494	0.8177
7	0.866	0.9149	0.9312	0.5454	0.5454	0.8331	0.7756	0.8476	0.8181	0.8499	0.8181

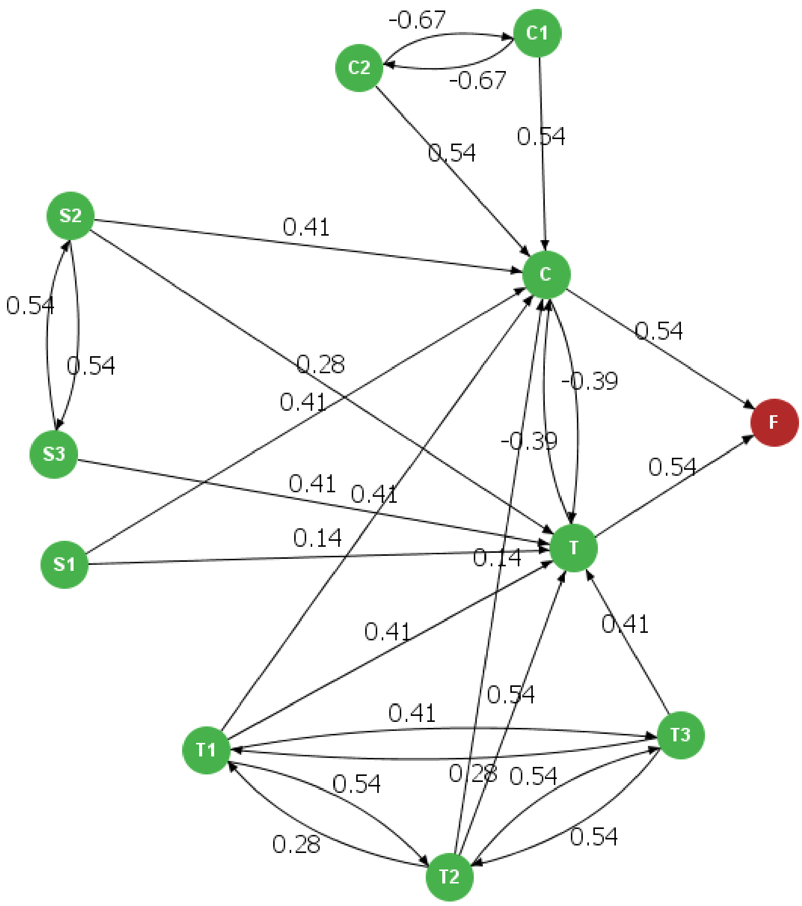
Figure 4.29. Cost – Time – Management – test runs C

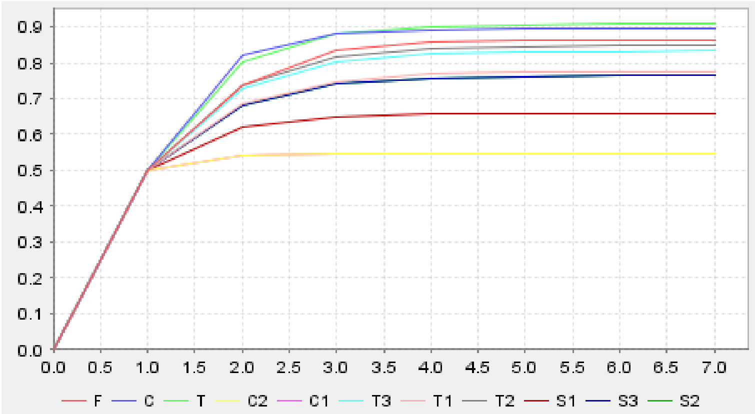
By combining the above concepts, the final value of the Failure in the last simulation is 0.866 which is considered high.

4.2.5 Modeling Cost – Time – Scope

The fifth model that was designed was Cost, Time and Scope. For this design all the secondary causes were used from Cost, Time and Scope.

By calculating the new weights the FCM becomes as follows:





Step	F	C	T	C2	C1	T3	T1	T2	S1	S3	S2
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
2	0.7392	0.8213	0.8021	0.5416	0.5416	0.7261	0.685	0.7389	0.6225	0.6835	0.6835
3	0.8346	0.8816	0.8826	0.5451	0.5451	0.8031	0.7485	0.8178	0.6508	0.7412	0.7412
4	0.857	0.8922	0.9019	0.5454	0.5454	0.8251	0.7681	0.8397	0.6572	0.7579	0.7579
5	0.8616	0.8944	0.9067	0.5454	0.5454	0.8311	0.7737	0.8456	0.6586	0.7626	0.7626
6	0.8626	0.895	0.908	0.5454	0.5454	0.8327	0.7752	0.8472	0.659	0.7639	0.7639
7	0.8629	0.8952	0.9084	0.5454	0.5454	0.8331	0.7756	0.8476	0.659	0.7643	0.7643

Figure 4.30. Cost – Time – Scope – test runs C

By combining the above concepts, the final value of the Failure in the last simulation is 0.8629 which is considered high.

4.2.6 Comparison of the second test runs

Comparing all the values of Failure:

Table 4.2 Comparing all the values of failure.

Causes	Result
A) Cost, Time	0.8529
B) Cost, Time, Quality	0.8594
C) Cost, Time, Stakeholders	0.8556
D) Cost, Time, Management	0.866
E) Cost, Time, Scope	0.8629

By comparing all the values of Failures it can be seen that D) Cost, Time, Managements plays the most important role for the failure of the project. The second factor that affects more the project failure is E) Cost, Time, Scope and the third is B) Cost, Time and Quality.

CHAPTER 5. Conclusions and future work.

In this Master Thesis an attempt was made to connect two distinct areas: the traditional field of Project Management and the area of Artificial Intelligence. The Fuzzy Cognitive Maps were used and modeled in the software of FCM expert.

The research tries to find how to systematically model the project failures into one single model. If it is possible to model it and gradually create a modelling technique in which the expert can modify as he chooses.

Firstly a fishbone was designed in which the FCM was leaned on. For the first FCMs: six main failure causes were used and then they combined together to create a bigger model: Management, Scope, Stakeholders, Time, Quality and Cost. The first results of the test runs were as follows:

Management	0.8469
Scope	0.8388
Stakeholders	0.8222
Time	0.7077
Quality	0.7054
Cost	0.7052

The results showed that Management plays the most important role for the failure of a project.

For the second test runs three main causes were put together (Cost – Time and one of the other main causes for every rest run). The results were as follow:

Causes	Result
A) Cost, Time	0.8529
B) Cost, Time, Quality	0.8594

C) Cost, Time, Stakeholders	0.8556
D) Cost, Time, Management	0.866
E) Cost, Time, Scope	0.8629

Management, Time and Cost play the most important role for the failure of the project. More emphasis should be given on those three main causes in order to increase the possibility of the project success. In every test run the results showed that Management is the most important factor for the failure.

The results obtained from the Fuzzy Cognitive Map (FCM) method carry a degree of uncertainty. This uncertainty comes from the fact that constructing FCMs often requires input from one or more experts in the field of their expertise. However, the opinions and perspectives of these experts may vary, leading to potential discrepancies in the constructed maps and their associated outcomes. Additionally, the context of different projects may introduce variability in the results, as each project may have unique characteristics and requirements. Therefore, it is essential to acknowledge and address this inherent uncertainty when utilizing FCMs for decision-making or analysis.

This tool can be used as a secondary tool for project management. Its primary objective revolves around identifying the factors that could lead to project failure, thereby enabling project managers to take proactive measures to mitigate these risks. By integrating this tool into their account, project managers can cultivate a foresight and proactive decision-making, ultimately leading to more successful project outcomes.

Fuzzy Cognitive Maps (FCMs) offer several contributions to Project Management (PM) practitioners. Below are listed some ideas for the contribution of the FCMs:

1. **Risk Anticipation**: FCMs help PM practitioners anticipate potential risks and uncertainties in projects by modeling complex causal relationships among various project factors. By identifying interconnected variables and their potential impacts, practitioners can proactively develop risk management strategies to mitigate adverse outcomes.

2. **Decision Support**: FCMs serve as decision support tools for PM practitioners by providing a visual representation of project dynamics and dependencies. By analyzing the causal links within the map, practitioners can make informed decisions regarding project planning, resource allocation, and problem-solving.

3. **Scenario Analysis**: FCMs enable PM practitioners to conduct scenario analysis to evaluate the potential consequences of different project scenarios. By simulating various conditions and inputs, practitioners can assess the robustness of their project plans and develop contingency measures to address unforeseen challenges.

4. **Stakeholder Engagement**: FCMs facilitate stakeholder engagement and collaboration by providing a common framework for discussing project complexities and uncertainties. PM practitioners can involve stakeholders in the development of the FCM model, fostering a shared understanding of project risks and objectives.

5**. Continuous Improvement**: FCMs support continuous improvement in project management practices by enabling PM practitioners to iteratively refine and update the model based on new insights and feedback. By capturing lessons learned and adjusting the FCM accordingly, practitioners can enhance their ability to anticipate and address project challenges effectively over time [9].

Future uses for FCM include policy making, healthcare decision support, environmental management, business strategy, education, and supply chain optimization.

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