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# Analysis of Complex System Development Based on Fuzzy Cognitive Mapping

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## LIST OF ABBREVIATIONS

| | |
|---|---|
| FCM | Fuzzy Cognitive Maps |
| SISP | Strategic Information System Planning |
| IT | Information Technology |
| CSF | Critical Success Factors |
| MPS | Mobile Payment Systems |
| FLC | Fuzzy Logic Controllers |
| P&L | Profit and Loss |
| JFCM | Java Fuzzy Cognitive Mapping |

## ABSTRACT

**This paper aims of analysing the possible way to implement the fuzzy cognitive map in development of the complex systems. In the science community Abstract Fuzzy Cortical Maps (FCMs) tend to rise in prominence. Basically FCM are used to model the behaviour of a complex system. Some Basic algorithm and mathematical theories are also discussed alongside the characteristics of fuzzy logic and neural networks. For the case study, using the available FCM modelling tools and their algorithm, Fuzzy cognitive map for a pipeline plant has been discussed.**

**In its operating mode, the proposed FCM Modeler Tool is presented in detail with real examples so as to understand the purpose of the tool. Next the reader can get a more complete picture of the FCM design project from Fuzzy Cognitive Maps creating and processing tools.**

**The FCM simulation methodology is used to simulate actual systems in a case study and then to execute tests and findings demonstrating the effect of structural improvements on the condition of process efficiency in an enterprise.**

***Keywords:-*** *Fuzzy Cognitive Maps, FCMs, Complex System, Tools, Neural Networks, Big Data, Mathematical Theories.*

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# CHAPTER ONE
# INTRODUCTION

➢ *Introduction*

Growth of modern technologies always had positive impact towards the human society, organisation and the systems. While the modern technology helps in revolutionising the industries, currently we are in the Industry 4.0 phase, where most of the industrial work are fully automated, thanks to the rapid growth of the modern technology and next generation systems. While talking about the technical systems and structures, todays technical systems and structures itself are complex and typically consist of a larger number of communicating and linking entities. They are also known as subsystems or components. Technology itself is complex and now has made the organisational system complex. In today's time, we can consider most of the system as a complex system. The system's today has very high dimensions and very large amount of variables and factors which makes them complex. The nonlinear behaviour is what makes the system complex and these system simply cannot be derived from analysing and summarising the single component behaviour. Right now, the contribution of traditional or usual way of controlling and modelling the systems have very limited contribution towards the case of complex systems and it has been widely recognised also. Because of this, nowadays the complex system requires new methods and way of controlling and modelling these systems which can be utilised by the existing knowledge and with help of the new technology and human experience.

Manufacturing processes have used computer and automation technological capabilities in recent decades and made much gains and has advanced rapidly. The criteria for more complex production systems, distinguished by high self-sufficiency and knowledge, have driven developers and engineers to discover and develop new innovations that incorporate and merge complex methodologies, at the heart of complex production systems. New techniques for modelling and control frameworks instead of conventional hypotheses must be built up for these complex systems. Thus, The paper suggests the analysis and application of new techniques and approaches, incorporating with prior knowledge and information , cognitive skills, fault detection and recognition capabilities and adapting with the given inaccuracy and ambiguity.

New methodologies for complex frameworks that utilises human insight, knowledges have been created with skills capable of adapting to any computing technologies which are versatile and are registered to its advancements and usefulness, for example, Error or fault forecast and recognition characteristics. This paper suggests the simulation of complex systems in the Fuzzy Cognitive Maps (FCM). The use of the FCM will add to the push to build and fabricate better control methodologies and self-governing complex systems. Fuzzy Cognitive Maps helps in generating or drawing a generic picture that helps representing the system's pattern and behaviour. The FCM idea cooperates as per uncertain guidelines and complex framework activities are re-enacted or simulated. As per the non-linear enactment Fuzzy Cognitive Maps can model complex dynamic frameworks that changes over the time. So as to characterise and demonstrate the structure of complex systems, FCMs utilises a symbolic portrayal. A Fuzzy Cognitive Maps is made out of terms that clarify various aspects of framework conduct, every one of which mirrors the element of the framework, and these terms speak with one another to model and show the dynamics of the system elements.

A range of scientific areas were covered by the fuzzy cognitive map (FCM). In the simulation of distributed system, FCMs are used to create a model and describe the behaviour of a system and its application. For decision making and organisational studies and research , these methods have been used. As a generalised judgment evaluation framework and organiser of distributed co-operative agents, FCMs was proposed. FCM was used to illustrate and monitor a particular plant to address models of dissatisfaction and impacts with a system model and to show the management process administrator. It is clear that the use of FCMs in a wide range of various scientific disciplines is of high interest, but the extensive use of FCMs on process and production problems that require such methods remains to be seen.

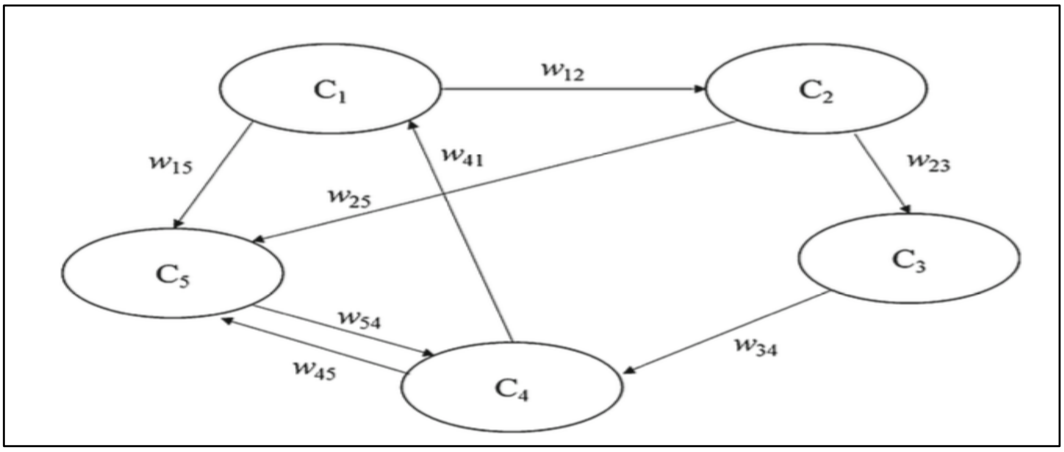


Fig 1 Simple Fuzzy Cognitive Mapping

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In the Figure 1 , we can see a clear definition of an FCM score of five node concepts. The quality of causality between two concepts is represented in weight *Wij*. In the interval [−1, 1] a weight takes its value. The weight image shows positive causality if *Wij* > 0 , This implies an expansion in concept nodes *Ci* would bring about an improvement in concept node *Cj* . Similarly, if the value of weight *Wij* is negative, it implies the negative causality. Suppose if there is no existing relationship between the two concepts then the value of weight becomes 0 i.e. *Wij* = 0 . The concepts are typically fuzzified by mapping their linguistic estimations such as very low, low ,high, middle etc. to the estimation of fuzzified interval value [0,1] . Each fuzzified concept has a fuzzy meaning, based on the size of the fuzzification scheme. The fuzzification of vocabulary measurements makes qualitative indicators transformable into quantitative concepts by decision-makers. (Choi, Lee and Irani, 2018)

- *Research Aims and Objectives*

The goal of this chapter is to concentrate on the design and implementation of FCM in complex system modelling. The use of FCMs in the service of a complex systems is illustrated in order to leverage the knowledge and interactions that people have acquired for years. These methodologies are simply the analogues to methods that occur and arise in behavioural processes pertaining to such entities in both human and animal environments. A FCM thus symbolically introduces information and analogously connects states, variables, events and inputs. The aim of engineers to create smart systems can be reinforced by this approach because the more sophisticated a system becomes, more symbolically and fluently it is portrayed(Groumpos P. P., 2010),(Kosko, 1992) . The aim of this research is to establish FCMs on the basis of the furthest logic principle, to study the advantages and possible use of FCM in the simulation of complex structures, and to demonstrate how FCMs use relevant expert expertise and experience in the description and simulation of complex plant operations.

The FCM is formed by using terms for environment definition. FCM represents and relates knowledge in a manner similar to that of humans to states, variable values, events, inputs and output. This technique can help people create advanced systems because the more symbolic and seamlessly represented a system, the more sophisticated the system becomes, in general, the system will be acknowledged. The aim of this paper is to fully clarify the core notions of Fuzzy Cognitive Maps (FCMs). It also provides an aid in the simulation of strategic model with unclear relationships while quantifying the effects of structural decisions on the overall development of complex system. This theory attempts to incorporate the integration of hierarchy of the Fuzzy Cognitive Maps into systems creation operation by evaluating the development of complex processes to construct process-based maps.

- *Literature Review*

The two last words (Cognitive Maps) are used to describe the origin of Fuzzy Cognitive Maps that identify a new field. Edward Tolman made the first reference to the cognitive maps in 1948, but they were fully developed as from 1976. Specifically the theory introduced on cognitive maps by R. Axelrod and the theory of fuzzy sets introduced by L.A Zadeh states that “A fuzzy random sample A of a discourse universe U is marked by a basis functions with each element y of U number μ(χ) in the interval [0,1], representing the grade of membership of y in A” (Zadeh , 1965).

$$\mu_a : U \rightarrow [0,1]$$

Axelrod in his cognitive theory suggests that “Cognitive maps are digital signatures that capture a person's causal statements on a certain area and use it to evaluate the impacts of alternatives e.g. policies, decisions, etc.” (Axelrod, 1976) . Cognitive maps are a great way to represent ideas and the relationships between them in a certain domain and to achieve the certain results people can easily be able to produce and modify them. Additionally, cognitive or intellectual maps are more closer to how one individual can survey the complex situations.

Bart Kosko, who developed the notion of fuzziness into cognitive maps, added the third word "Fuzzy" in 1986 (Kosko, 1986). As Bart Kosko interpreted, he is the first researcher who has developed Fuzzy Cognitive Maps (FCM) theory. He also introduced the idea of fuzzy weight which means that in interval values can be taken in the relationship between two concepts called nodes (-1,1). Basically with his theories and algorithm and above reasons Bart Kosko is considers as the father of Fuzzy Cognitive Maps(Glykas, 2010) .

It is also worth mentioning that the idea of a FCM perfectly demonstrates important components and features of a modelling complex system that stands for: inputs , outputs, statements, events, objectives, variables and trends of each complex system, which is constantly modelled and demonstrated. The mutual relationship among concepts and its degree are clearly represented by the graphic display. It should be noted, however, that in two examples of dynamic and complex systems, the main objective of this section is the mathematical study, design and application of these cognitive maps (Groumpos P. P., 2010) .

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➢ *Research Methodology*

The first step in the analysis approach is to collect valid data from large data sources in order to obtain fluid values and weight estimates for the FCM. When an FCM has been developed with determined volumes and weights, an evaluation of decisions can be carried out by comparing the simulation outcome with different fundamental values of key decision parameters. Figure 2 demonstrates the working principle of FCM for big data usage systems. (Choi, Lee and Irani, 2018)

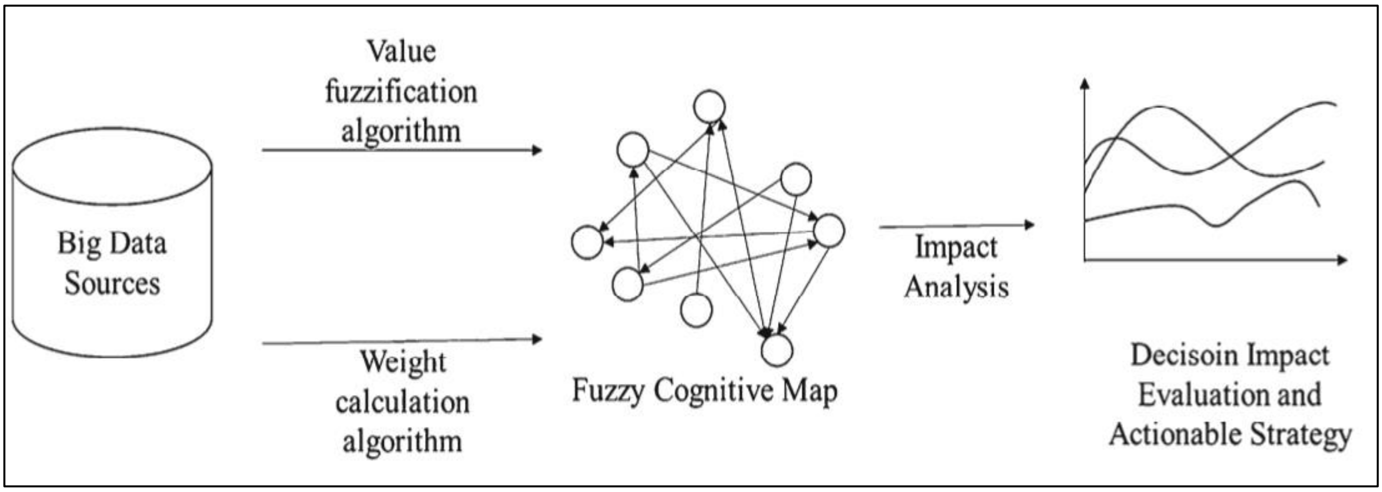


Fig 2 Framework Research: Use of Data for Impact Assessment by FCM
(Choi, Lee and Irani, 2018)

➢ *Structure of the Paper*

Chapter 2 introduces the underlying ideas of Fuzzy Cognitive Maps. This chapter also introduces and analyses basic mathematical equations of Fuzzy Cognitive Maps to improve the completeness of Fuzzy Cognitive Maps. An algorithm will be shown to demonstrate the effectiveness of Modelling of complex systems, the FCM approach. This chapter also discusses the types of FCM and their differences. Furthermore, the methods for building FCMs are presented and also described the step by step process of producing different FCMs. Additionally, for the effective assessment, FCMs was proposed for the modelling and management of complex systems, like the modelling method of Complex Systems Supervisors and the implementation of the Fuzzy Cognitive Map.

Several cases of application of FCMs in various scientific fields will be studied in Chapter 3. The application of FCMs in the field of Information technology (IT), engineering, computer vision, production system, and other scientific fields will be thoroughly studied, beginning with the engineering industry featuring the pipeline company and their operation management. Development of FCM on complex plant will also be discussed alongside the two level architecture of FCM, however the case study will specially focus on the lower level of FCM only.

Chapter 4 provides a comprehensive reference to the FCM modelling tool for the development and processing of FCM. Additional information is provided on the tool's user interface and its different functions, such as the node link process. Features like simulation, final program export reports after simulation and information on tool software will also be presented.

Chapter 5 discusses the case study of the where development of complex system or pipeline plant has been discussed using fuzzy cognitive mapping.

# CHAPTERTWO
# BASIC THEORIES

➢ *Introduction*

The soft computing methodology of Fuzzy Cortical Maps (FCM) employs a method that is perceived as something like both human logic and the underlying method of making human decisions. (Groumpos & Karagiannis, 2013). Recently, studies of Fuzzy Cognitive Maps have shown that they deliver a practical and valuable method to solve many social problems. An algorithm to prove that the FCM approach is made effective in the analysis of complex structures. (Groumpos P. P., 2010). The process of assigning quantitative weights and linguistic variables to the fuzzy cognitive map for all applicable methods of constructing Fuzzy Cognitive Maps are densely detailed. Moreover, the presentation of the study is one of the main concerns on Fuzzy Cognitive Maps are a foundational tool as a form of modelling, and often explain how various Fuzzy cognitive maps are synthesised.(Kosko , 1992).

In addition to the FCM forms, the Fuzzy Cognitive Maps Neural Network Structure is also discussed extensively in this first chapter. This chapter ends with Fuzzy 's proposal to design and control complex systems such as the Modelling Process of Complex Systems Supervisors.

➢ *Traditional Fuzzy Cognitive Maps*

Within a landmark 1986 paper, Kosko (Kosko, 1986) has presented "Fuzzy Cognitive Maps" and discusses contextual SD behaviour by cause-related inference using expert views or expectations. FCM is also characterised by Kosko [10] as fuzzy signed diagrams and feedback graphs and he also suggested that. they are "analogous to how neural network learns" (Kosko, 1993). Moreover Kosko (Kosko, 1986) and his later studies [10-12] seek to merge fuzzy logical and neural networks in such a way that causal inference is replicated in terms of words.

Moreover Kosko (Kosko, 1986) and his later studies (Kosko,1992) (Kosko,1993) seek to merge fuzzy logical and neural networks in such a way that causal inference is replicated in terms of words. FCMs, basically as we know them are nodes articulated in definitions or language terms. The relationship between concepts is clarified by guided arrows with weights. The weights define the casual relationship with ({−1, 0} and {0, 1}) to reflect the casual decrease and increase. Nodes and guided arrows with their weights describe the structure of the (given) system are the principles and their interactions (Nair, Reckien and Maarseveen, 2019).This comes in the form of an adjacent matrix which permits standard algebraic operations to find connections between nodes and to learn weights automatically (Carvalho, 2013).

Equation 1 expresses the simulated mathematical formula of FCMs introduced by Kosko (Kosko, 1986).

$$C_j(t+1) = f\left(\sum_{\substack{i=1 \\ i\neq j}}^{n} w_{ij} \bullet C_i(t)\right) \quad \text{......Equation 1}$$

Where,

n = number of concepts

$C_j(t+1)$ = Concept meaning in the next iteration

$C_j(t)$ = The concept value of the iteration definition at t

$W_{ij}(t)$ = The presence between cause and effect weight association.

The equation is then transformed with the transformation functions into a predefined domain of debate, most often with fractal dimension and hyperbolic distortion factors (Glykas, 2010).

➢ *FCM Mathematical Representation*

A simple FCM composed of five concepts and eight weighed arches is show on figure 1. Therefore we can say that FCMs are also directed graphs that can model complex relationships or causalities that exist between concepts. The basic aspects of an FCM are principle factors and causal relations. Nodes such as C1 , C2, C3 , C4 and C5 are described in Figure 1 by concept variables (Groumpos P. P., 2010).

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The theory or principle variables occur on the root of arrows, mostly casual variables, while on the other side, the concept variables are described at the finishing points of arrows. For instance, when we look at figure 1 we can conclude that C1 has impact on C2 at C1 → C2. This is because C1 is considered casual variable whereas C2 is considered the effect variable. Each concepts can be defined using the number Ai that represents the principle meaning, and this results from the interval translation of the true value of the function variable that is part of this concept[0,1] (Groumpos P. P., 2010). For sole reason of that the weights of the interrelated weights can vary within the interval [-1,1], the conceptual causality allows causality degrees rather than allowing usual binary logic. The system is represented by Fuzzy cognitive maps in such a way that they reflect a single-layer network where nodes may be allocated term meanings and interconnection weights provide causal relations between concepts.

The Fuzzy Cognitive Map can be represented as a graph displaying the casual relationship between degrees among the definitions of map information expression where the casual relationship is described by fuzzy weights.

The FCM structure and configuration nodes tend to rely directly on the expertise of the device. Each nodes represent nothing more than a separate single main factor for the system. There are three forms of interaction between concepts (Groumpos P. P., 2010):

- Displaying a positive causal relationships between two principles ($W_{ij} > 0$ )
- Displaying a negative causal relationships between two principles ($W_{ij} < 0$)
- Displaying no causal relationships between two principles ($W_{ij} = 0$)

The meaning representing the degree of control between the concepts Ci and Cj is expressed by the variable Wij. Similarly the direction affecting the concepts Ci and Cj are affected by the same variable Wij. It shows the situations where the Ci affects the Cj concepts and vice versa.

Equation 2 displays a proposed new formulation of the Fuzzy Cognitive Map to calculate the values of concepts at each step:

$$A_i^t = f(k_1 \sum_{\substack{j=1 \\ j \neq i}}^{n} A_j^{t-1} W_{ji} + k_2 A_i^{t-1})$$

…………………………………………………………………Equation 2

Where

$k_1$ → Represents the power of integrated concepts when constructing $A_i$ value.

$k_2$ → Calculates the portion of the output of the previous value of the term in the estimation of the actual value.

This current formulation suggests that the term is connected to itself by weight, which gives us $W_{ij} = k_2$

Assuming $k_1$ = = 1 we can conclude that the effect of the previous values of each concept is high. This indicates that the prior value of each definition has a significant impact on the judgment of the current meaning. After every recalculation, the application of the preceding value of each term in the estimation law results in a finer change in the values of the concept. This becomes evident in the FCM modelling of the supervisor. The value Ai is calculated according to the following rule for each concept (Groumpos P. P., 2010):

$$A_i^t = f(\sum_{\substack{j=1 \\ j \neq i}}^{n} A_j^{t-1} W_{ji} + A_i^{t-1})$$

……………………………………………………………...Equation 3

The above equation 3 is the result by setting the values k1 and k2 equal to 1. Let's see what each value represents:

$A_i^t$ → Represents the value of concept Ci at time t

$A_i^{t-1}$ → Represents the value of concept Ci at time t-1

$A_j^{t-1}$ → Represents the value of concept Cj at time t-1

$W_{ij}$ → Represents the weight of interconnected form of Ci and Cj

$f$ → Represents the threshold function consists of the outcome values that can be located at interval [0,1].

In accordance to equation 3, in each step, the values of all residing concepts are re-computed and changed, which gives the Fuzzy cognitive map a discrete nature. This process is called as the FCM model running cycle and is very important for FCM theory.

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

In fuzzy cognitive map theory there are two kinds of threshold function used, the unipolar sigmoid function $\lambda \succ 0$ that determines the curvature of the continuous function $f$ (Groumpos P. P., 2010):

The following function is used if the concept 's nature is adverse and its values are within the interval [-1,1]:

$$f(x)=\tanh(x)$$

By their mathematical representation and operation, the simplicity of the FCM model becomes evident. Let us suppose that we have a cognitive map of n concepts at this point. The (1 x n) state vector which is described mathematically, collects the n concept values and (n x n) collects the weight of matrix W. The values of the weight of $W_{ij}$ between concepts Ci and Cj are given for any $W_{ij}$ element of matrix W. The matrix diagonal is empty since no definition is expected to exist. And thus it becomes $W_{ij} = 0$

The following equation describing the FCM operation with a compact mathematical model can be transformed from Equation 3:

$$\mathbf{A}^{t}=f(\mathbf{A}^{t-1}\mathbf{W}+\mathbf{A}^{t-1}) \quad \text{Equation 4}$$

The new vector is dependent upon the preceding condition $A^{t}$ and upon the multiplication by the weight matrix W of the previous t-1 vector, $A^{t-1}$.

The equation 4 can also be expressed as:

$$\mathbf{A}^{t}=f(\mathbf{A}^{t-1}\mathbf{W}^{new}) \quad \text{Equation 5}$$

Where $\mathrm{W}^{\mathrm{new}}$ → represents the new weight of the matrix W of the fuzzy cognitive map with all unit-equal to its diagonal elements, this means that every concept has a weight $\mathrm{W}_{\mathrm{ij}} = 1$. This is a distinct method than other representations from the Fuzzy Cognitive Maps in literature, where there is believed to be no definition or concept to itself and the W matrix diagonal value is zero (Groumpos P. P., 2010).

- *Methods of Construction of FCM*

For its use in the simulation of complex structures, the creation and design of Fuzzy Cognitive Map (FCM) is quite important. The advancement of a Fuzzy Cognitive Map has certainly been based on human knowledge and experience because let's not forget that Fuzzy cognitive maps are just the representation of human expertise and ideas on the systems operation. As it is based on the human expertise, the result of such maps are based on the expert's experience on a very complicated system(Groumpos P. P., 2010). So basically, FCMs are built by specialists using their expertise and understanding with the complex system. Creating methodologies depend on professional expertise in the concept and behaviour of the program. Depending on the experience it is determined on the correct number of concepts and the form of concept to be included in each situation.

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The number and type of concepts consisting of the FCM and the interaction among its concepts are determined by experts. Experts are conscious of the key influences that are influencing the actions of the complex system, each of which has a meaning and are represented by that concept. Experts, based on their knowledge, they defines FCM principles that stand for activities, behaviour, goals, beliefs and patterns in the complex systems. Experts are also aware of the systems that might have influence over other elements; for such reason the corresponding concepts have either negative or positive effect on another concept and they are done with fuzzy degree of causation(Groumpos P. P., 2010). There are specific guidelines suggested via experts to determine whether two events should be adversely affected or affected positively. The following paragraph analyses such processes.

- *Assigning Numerical Weight*

As the Awareness of a complex system 's actions is very empirical, the expertise of a group of specialists is recommended to use to create a more detailed representation of the complicated structure. Furthermore, experts assembles together to discuss and examine the factors that are critical in an FCM that stands out as a node. They then agree on the amount of concept which includes the FCM and the character of the system described through each concepts. The experts are then asked separately to clarify the origin of these concepts. The outcome would be a set of various FCMs that have the same nodes, but with specific relations between concepts and/or weights of different interconnections (Groumpos P. P., 2010). After that all the individual FCMs need to be combined in one group of FCM. The following equation shows the sum of various weighted matrices:

$$\mathbf{W} = f\left(\sum_{1}^{N} \mathbf{W}_k\right) \quad \text{……Equation 6}$$

Where,

$W$ → Represents the number of overall matrices

$W_k$ → Represents the individual weight matrix, created by N experts

$f$ → Represents the threshold function, also known as the sigmoid function where it transforms the sum of weights in interval [-1,1].

Knowledge of a complex system are very subjective and every expert that works on FCM has that knowledge and each experts also have different expertise. Therefore the result of their efforts to build Fuzzy Cognitive Maps could be increased by the weight $b_k$ which is credible and non-negative (Groumpos P. P., 2010). Thus the equation can be written as:

$$\mathbf{W} = f\left(\sum_{1}^{N} b_k \mathbf{W}_k\right) \quad \text{……Equation 7}$$

Where,

$b_k$ → Represents the non-negative and credible weight for $k_{th}$ expert.

$W_k$ → Represents matrix of the FCM of $k_{th}$ expert.

N → Represents the number of the present experts.

Nonetheless there is a situation in which an expert should take a position at his own authority, i.e. in the event that his/her preference is different from some other expert, it will carry a very small to nearly zero credibility of the weight. We might as well assume that a process needs to be established which represents what kinds of weights are likely to be allocated to what expert and in which way.

Because of this reason, new algorithm was created to set the weight of each interconnected links and to set the credibility to the weight that was specifically chosen by the experts. The following algorithm gathers and compares all the associated weights those were collected by expert gathering when creating the map. But mainly the algorithm makes use of the average of the interconnected weights. The tests of weight which put experts in a complex system is basically the main operation of this algorithm. If the weight value of the same symbol is less than $\pi * N$, therefore is not obvious to the experts whether the causality between two definitions is positive or negative. Because of that weights are reassigned by the experts. and in other cases the process keeps on running and the selected weights are proposed based on the default weights. Additionally, if it is not too above the average weight for the weight chosen by experts to come into the method, only some part of the weight value is taken into consideration (Groumpos P. P., 2010). The algorithm steps can be found below :

Table 1 Steps of Algorithm (Groumpos P. P., 2010)

| Steps | Algorithm Process |
|---|---|
| 1 | The credibility weight of $b_k$ should be set for all N experts |
| 2 | For i,j = 1 to n |
| 3 | For every concept ($C_i$ to $C_j$) test N weights $W_{ij}^k$ that each $k_{th}$ experts has assigned |
| 4 | IF , $W_{ij}^k$ weights are present with different signs and the number of weights of that sign are less than that of $\pi * N$<br>THEN , Ask experts to allocate weight for this particular link and go back to Step 3<br>ELSE, Consider the weight of larger group having the same sign and also penalize the expert considering there are no weights and create a whole new credibility where weight $b_k = \mu 1 * b_k$ |
| 5 | For the weight of larger group of same sign assign the average value $W_{ij}^{avg} = \frac{(\sum_{k=1}^{N} b_k W_k)}{N}$ |
| 6 | IF $\lvert W_{ij}^{avg} - W_{ij}^k \rvert \geq \omega_1$ THEN consider $W_{ij}^k$ is not present and penalize the $k_{th}$ expert using $b_k = \mu 2 * b_k$ and go back to step 5 |
| 7 | IF (n x n) interconnection are not tested than go back to step 2<br>ELSE Proceed on the construction of new weight W which has the elements of $W_{ij}^{avg}$<br>END |

- *Association of Lingustic Variable on FCM*

The linguistic variable is associated with the weight of FCMs as another method to build a Fuzzy Cognitive Map that is closer to the fuzzy logic. The causality of the concepts must be represented by the so-called experts using the linguistic terminology. Negative or Positive influence of one concept on another concept must be agreed upon by every experts and the impact of influence such as "strong" , "weak" and etc.(Lin & Lee, 1996) must be decided by expert using the notions of linguistic variables (Kosko, 1986).

The term T(influence) could be set, where the impact of the influence of concept to another is interpreted as linguistic variable where it takes values from the universe U where U = [-1,1] Therefore T(influence) impact can be interpreted as:

T(influence) = { (-ve) very strong , (-ve) strong , (-ve) medium, (-ve) weak, (+ve) weak, (+ve) medium, (+ve) strong, (+ve) very strong }

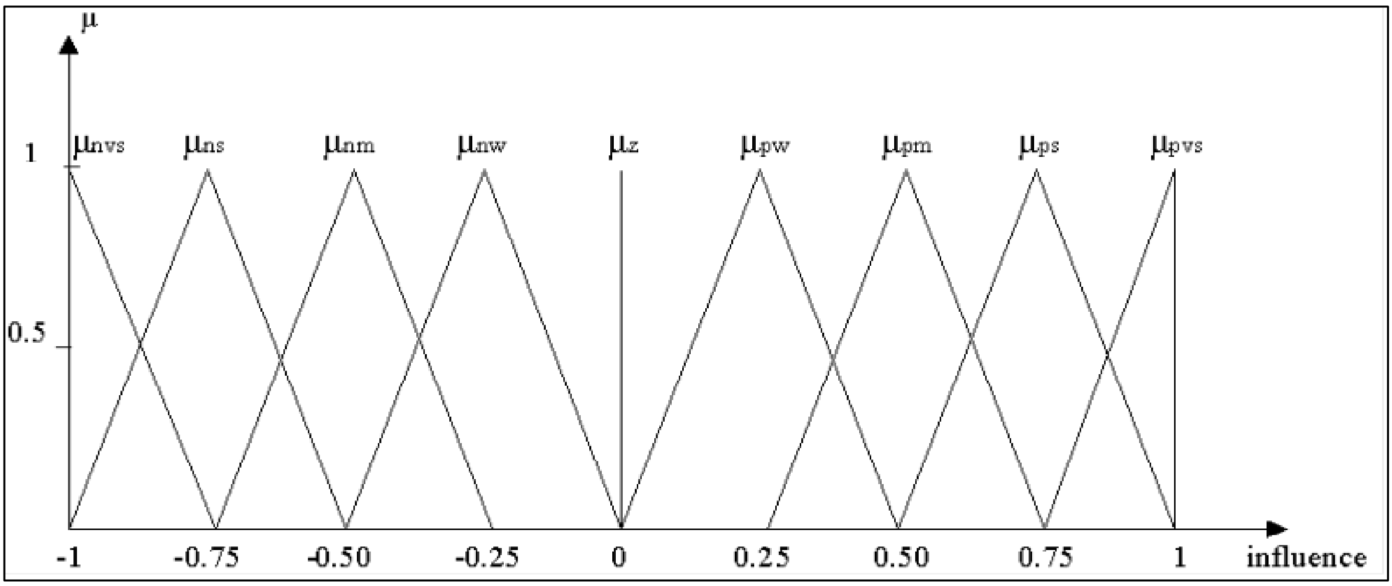


Fig 3 Linguistic Variable Influence Terms (Groumpos P. P., 2010)

The semantic rules M denoted by µ followed by the above picture is characterised below:

$\mu_{nvs}$ : negatively very strong , represented by semantic rule M and influence level below -75%

$\mu_{ns}$ : negatively strong, represented by semantic rule M and influence level close to -75%

$\mu_{nm}$ : negatively medium, represent by semantic rule M and influence level close to -50%

$\mu_{nw}$ : negatively weak, represented by semantic rule M and influence level close to -25%

$\mu_{z}$ : Influence level close to 0 and also represented by semantic rule M

$\mu_{pw}$ : positively weak, represented by semantic rule M and influence level close to 25%

$\mu_{pm}$ : positively medium, represented by semantic rule M and fuzzy set impact level close to 50%

$\mu_{ps}$ : positively strong, influence level close to 75% and represented by semantic rule M

$\mu_{pvs}$ : positively very strong , fuzzy set influence level above 75% and represented by semantic rule M

For attribute meanings for concepts a common approach may be used. The experts are often asked to explain every concept with the aid of once language terms. Measuring a concept is often known to be a textual vector with interval values[-1,1]. Terms are set as T(measurement) and T(influence) which are equal. Additionally, new semantic rule is also added which is represented by $M_2$ and is analogous to M and it characterises the membership function $\mu_2$ which is also analogous to **µ** with the help of fuzzy sets (Groumpos P. P., 2010).

The overall linguistic variable will followed after the combination of linguistic variables that describe each connectivity. The product of the defuzzifier, which utilizes the Centre of Gravity (CoG) to generate such a firm weight, is a numerical weight for increasing of the connectivity (Nie & Linkens, 1995).

Practically speaking, based on past records and statistical evaluation, tendencies, pleasant practices, and so forth. stakeholders can provide expert assessments . This evaluation method has nothing to do with the perfect description system of professional linguistic variables. The idea of fuzzy membership features offers an in depth description of such variables (Xirogiannis, Glykas, & Staikouras, 2010).

➢ *Fuzzy Cognitive Maps And Their Nature Of Neural Network*

Fuzzy maps are heavily based on both the neural and fuzzy logic networks. Many manufacturing processes are not easily and cost-effectively managed by modern technologies and this has been reported that fuzzy logic can manage good, typically multi-variable, not linear and temporal processes. Additionally, Fuzzy logic may also approach unspecified structures with uncertain dynamics as a prior mathematical model with plant construction is not needed (Stylios and Groumpos, 1999). The development along linguistic lines is one of the major benefits of using fuzzy logic control. Set of conditional linguistic assumptions or rules that can be easily elaborated from rational thinking , are present on the fuzzy controller (Dickerson and Kosko, 1994).

Neural networks provides the simpler solutions to the complicated under power problems because it has the ability to learn from input-output features. In fact, nonlinear structures can be considered as neurons, therefore we can say that neural networks are basically nonlinear processes which gives the ability to understand, learn and solve the nonlinear control problems that do not often have ideal solutions to both theoretical and modern control methods(Lin & Lee, 1996).

The development of soft computing methods is driven by the synergetic and parallel usage of fuzzy logic and neuro-computing or neural networks. In order to define and model the of complex systems, soft computing methodologies should be investigated and proposed. Fuzzy cognitive mapping also falls under the category of soft computing methodologies. In the context of sophisticated methods for understanding and solving real life situations, neuro - fuzzy structures are usually imprecise and need human involvement (Jang, Sun and Mizutani, 1997).

It should be remembered that the basic distinction between FCM and neural networks is that all FCM definitions are clearly semantically described by the concept's modelling. In comparison, the neural network input/ output nodes are poorly semantic and only can be represented by the mathematical formulations. Of course, it can be anticipated that there are sufficient learning rules granting FCMs valuable features such as fault tolerance, the potential to render adaptive conditions more accommodating and even to arbitrary nonlinear mappings (Groumpos P. P., 2010).

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➢ *Modelling Complex Systems With Fcm*

Complex systems often contain large dimensions and are most frequently unpredictable in their complexities. The reality that the majority of companies around the world are lacking a core based control system is one trend which has been noticed very frequently. In other terms, it does not occur without a core system or individual entity. And Because of this reason this form of systems cannot however be managed effectively by traditional or conventional techniques. Therefore we can say that Fuzzy Cognitive Maps (FCM) is a prospective methodology to model the supervisor of complex systems. And for this sole reason Fuzzy Cognitive Maps has been created with another approach for modelling the complex system supervisor (Groumpos P. P., 2010).

Figure 4 displays the proposed model of hierarchic structure for large scale and complex systems. The machine, which is operated by conventional controllers, is on the lower level of the framework. These specific controllers carry out basic tasks reflecting the framework of the plant, using traditional control methods, among the typical operating conditions. The supervisor model was designed as a FCM, so it should be said. An initial attempt was made early in 2000 to model a supervisor of a complex system based on the FCM concept (Groumpos P. P., 2010), (Stylios and Groumpos, 1999), (Stylios and Groumpos, 1998).

Thanks to the flow of huge chunks of data and information, and in order to process, communicate and transform that information it is necessary to have an interface which will transfer that information from lower level structures to the higher level structures i.e. to the supervisor -FCM. The equation 3 is used to interact with the cognitive map where the FCM has new values that are subsequently transmitted to the conventional system controllers. Because of this interface procedures follows the opposite direction, where changes on more than one element of the FCM could mean the altercation in the value of more than one concepts of the system.

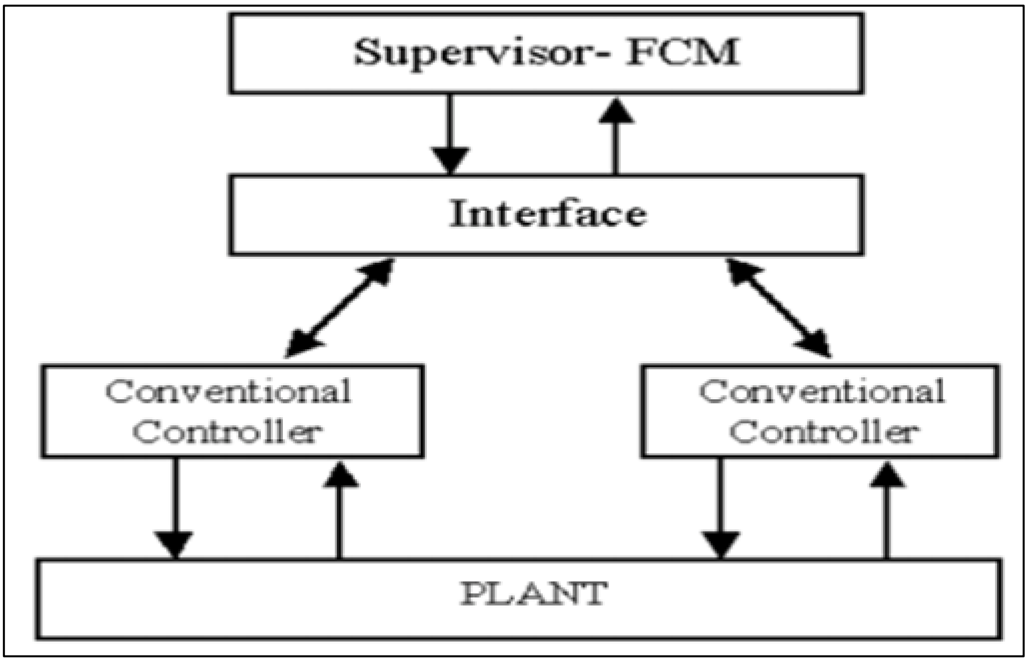


Fig 4 FCM – Supervisor Model of a Complex System (Groumpos P. P., 2010)

FCM 's capacity to await and re-define a method that helps the consumer to calculate and forecast the outcome in case of changing parameters is another very useful function. This will allow the experts to determine and forecast the result if any device configurations were modified. Another helpful part of the FCM is its predictive performance , and specifically its estimation of what will occur from an entire situation or what might occur from unexpected moves in a state. In the operation of FCM, human expertise is the fundamental need. It is also critical that an individual has a detailed understanding of key facets of the program as a whole. The specialist will then use the correct principles to correctly represent what he needs through FCMs (Groumpos P. P., 2010).

The FCM-Supervisor contains definitions which can display the variables in the failure state, configuration variables and erratic workings of certain device elements, along with variables of failure impact or even the magnitude of the result. Furthermore, this model also incorporates the concepts that determines how a specific operation is handled by the system and the model will also be used to make decision and strategic plans. This model is a core component of the plant and represents the operating situation of the facility. To create this model, many expert opinions are needed for constructing an FCM that has analytical and predictive capabilities(Athanasios, 2017), (Groumpos P. P., 2010).

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# CHAPTER THREE
# FUZZY COGNITIVE MAPS APPLICATION

➢ *Introduction*

The FCMs' dynamics and methods of learning make them essential to modelling , analysis, prediction and decision-making, as many different systems appear to improve their performance(Papageorgiou E. I., 2011). A specifically realistic, easy and effective instrument used in many application fields are constituted by Fuzzy Cognitive Maps. In this chapter we will discuss some application of FCM on different sectors specially focusing on IT, Engineering , Banking and production companies sector.

➢ *FCM in Information Technology (It)*

Information Technology (IT) is definitely a significant factor for businesses spending trillions of dollars in IT programs (Salmeron J. L., 2010). In 80s there were lots of article and journal that concentrated on SISP i.e. Strategic Information System Planning where they extensively addressed the critical role of IT in current and future organisations. Since then, numerous modes have been displayed and demonstrated as a means of creatively evaluating information technology and implementing new IT ventures (Kardaras & Karakostas, 1999).

A FCM-based approach leads to performance forecasting in the area of Information Technology (IT) project management. There are a range of limitations in existing systems and methods used to define, characterize and measure common performance measures of IT ventures. Modelling observations and relationship between the Critical Success Factors (CSF) might be overwhelmed by the use of FCM tool to map success (Rodriguez-Repiso, Setchi, & Salmeron, 2007). In the light of a recent technology concept, the Mobile Payment System (MPS), which is a technology found in the rapidly emerging mobile telecommunications environment, experts have demonstrated the applicability of the FCM approach by qualitative study (Rodriguez-Repiso, Setchi, & Salmeron, 2007).

The use of fuzzy-cognitive maps was proposed in 2010 by Salmeron for better IT risk management (Salmeron J. L., 2010). Because this strategy suggests, the attempts to determine the right IT solution will be combined with programs to handle the multiple risks involved. To reduce the possibility of a perceived mistake of execution we seek for the basic argument. The dangers of implementation of information technology risks are disclosed by this very methodology and in addition relationship among FCMs are tied between them. It indicates the key evidence that the highest chance of all the policies would have the biggest effect on the IT programs (Salmeron J. L., 2010).

In 2009, experts evaluated and simplified the functionality of standard applications with the aim of detecting a technical failure in accessibility and enhancing specific issues. To describe the relationship between software quality and provide the fully trained arithmetic and also to represent the quality of those arithmetic technique the made the use of Fuzzy cognitive Maps (Lai, Zhou, & Zhang, 2009).

Despite various software reliability approaches being available, there are still challenges that require more research with a singular objective of successful decision-making and software quality improvement. The usage of Fuzzy Cognitive Maps (FCMs) may also be viewed as a software reliability modelling method. FCMs capture information in relationship among concepts. The captured information are dynamic and are concealed. They later combine those data and make it tuneable. Initial testing indicated that the proposed program offers a solid foundation for the software reliability modelling process (Chytas, Glykas, & Valiris, 2010).

In 2010 another novel method was proposed by Furfaro. This also developed the FCM hypothesis to analyse remotely captured data in planet exploration, and to recognize and explain locations that provide the strong potential for Titan's volcanic activity (Furfaro, Kargel, Lunine, Fink, & Bishop, 2010).

➢ *FCM in Engineering*

Fuzzy Cognitive Maps have found a true number of uses in this area, especially in terms of management and forecasting. In the field of engineering FCM is used for different simulation and enhancement of plant control system. The model are also utilise in order to establish malfunction and to the impact analysis also they are capable of adjusting the fuzzy logic controllers and also helps in modelling the FCM supervisors for complex system. While the FCM was studied by Stylios and Groumpos for the analysis of the complex system of supervision and regulation (Stylios & Groumpos, 2004). Papageorgiou used learning techniques to train FCM model which regulates problems in industrial processes in the light of non-linear Hebbian laws (Papageorgiou, Stylios, & Groumpos, 2006).

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As a cognitive model, a hybrid of a cognitive map and a fuzzy enterprise system has been suggested, which is targeted at the creation and self-fine tuning of the Online FLC (Gonzalez, Aguilar, & Castillo, 2009). This new model which is not the same as the previously existing Fuzzy Cognitive Maps (FCMs) aims to display the hierarchy architecture. The process of the Fuzzy Cognitive Map, which is officially accessible in a facility, controls objective information for representing knowledge in order to create a total architecture of the FLC and parameters. Model can help in software usability, suggesting that the software is modular, offering good potential for almost optimised controller generation.

- *Fcm in Banking Sectors*

Mainly quantitative appraisals of certain major financial indicators are a standard business plan. Obviously, strategic strategy of financial sector organizations (and vice versa) can be a methodological supplement to traditional financial strategies. Fuzzy Cognitive Maps was introduced by Xirogiannis in 2010 as a modern addition to strategic banking funding (Xirogiannis, Glykas, & Staikouras, 2010). This includes a management framework and business targets structure of stages in the formulation of routine financial policy initiatives through promoting theoretical simulation of profit and loss (P&L) performance as well as a "wise" logical evaluation of the potential impact of structural transition operations on a typical financial sector company's financial situation.

This method utilizes the FCM's flimsy functional features as a modern modelling method to create a functional understanding of complex financial values, taking into account the overarching goal of establishing centralized number of interconnected measures of financial performance. The method that was proposed basically simulates the effectiveness of highly complex financial nodes with smooth but inaccurate relations whilst still measuring the influence on overall P&L status of strategic changes (Xirogiannis, Glykas, & Staikouras, 2010). Fuzzy thinking capacities greatly improve the utility of the FCM system and minimise efforts throughout the development of techniques to define precise profit and loss quantities.

In terms of the strategy creation and the exchange - rate impact assessments, this strategy offers an effective framework for strategic level financial management. The framework also proposed the main beneficiaries and Structural development project partners (banking operation, planning and finance operations, group managers serving customers, interval accountants, etc) enabling them to argue effectively the state of the financial maturity indicators, if structural adjustments (actual or hypothetical) are introduced (Xirogiannis, Glykas, & Staikouras, 2010).

- *FCM in Production Companies*

Fuzzy Cognitive Maps may be an incredibly useful approach to the issue of determining variables that have an effect on user efficiency, and can also be explored in manufacturing processes for human efficiency (Bertolini & Bevilacqua, 2010).

They studied the human efficiency of manufacturing processes as an excellent way to look at a manufacturing cycle and to gain precious interpretations of the effects decided by selection of at minimum one component throughout the method being tested.

There was a model proposed in 2010 by Lo Sorto, the model suggested a systematic framework to analyse the reasoning mechanisms carried out in the software development department by persons to handle problematic situations at the user criteria description level (Lo Storto, 2010). Throughout the sense of this methodology, Fuzzy cognitive maps were used to invoke cognitive processes and to create up an human measure of resistance to instability. Fuzzy Cognitive Maps have become more far-flung, as it has outstanding idea interpretation and logical abilities to develop game-based learning processes (Luo, Wei, & Zhang, 2009). A modern game centred learning paradigm has been built consisting of a sub-model for instructors, a student sub-model and a collection of blended learning.

# CHAPTER FOUR
# FCM MODELLING TOOLS

➢ *Introduction*

The key objective of the FCM modelling tool creation is to build a market output and productivity model, which directly complements established system architecture. Such specific designs have been customised and illustrated in the financial industry and show their validity in the service industries more broadly.

The company policy, human factors and technologies are expressed in this and are demonstrated in Fuzzy Cognitive Maps (FCMs) modelling tools. Based on the Fuzzy cognitive Maps (FCMs), this computerised market performance measurement method is built.

➢ *Basic Algorithm of FCM Modelling Tools.*

The table below suggests the basic algorithm of Fuzzy cognitive map modelling tools, however they use the same mathematical principle discussed in chapter 1.

Table 2 Basic Algorithm Process of FCM Modelling Tools

| Steps | Algorithm Process |
|---|---|
| 1 | Get the values of nodes |
| 2 | Get the value of weights |
| 3 | Weight Matrix construction |
| 4 | Multiplying weight matrix with value of nodes |
| 5 | Normalizing the result |
| 6 | Acquire new point of state values |
| 7 | If there are some nodes that are not affected by other nodes, initial value should be kept unchanged |
| 8 | Repetition of steps 4 to 7 until systems are in equilibrium |

➢ *Available FCM Tools*

- *Fcm Expert Tool*

FCM Expert is an FCM-based system software tool. It is comprised of more than 25,000 code lines, spread in 120 references. This program is written in Java. The files in FCM expert tools are organised into five global packages which are algorithms, software, learning, network and resources. They are also organised in various other small sub packages. The package structure in FCM Expert, including main and some sub packages are demonstrated in Figure 7.

The FCM Expert consists of three groups of functions in a rough picture that are spread over five menus: File, Edit, Construct, Run, and Reset. The first group is focused on designing the FCM-based model, in which the user can model a complex system in a given domain (visual options don't require extensive experience in mathematics or computer science).The second category involves machine learning algorithms to modify and refine the model parameters.

Finally , the third section involves methods to use the FCM framework as a method to facilitate decision-making (Nápoles, Espinosa, Grau and Vanhoof, 2018).

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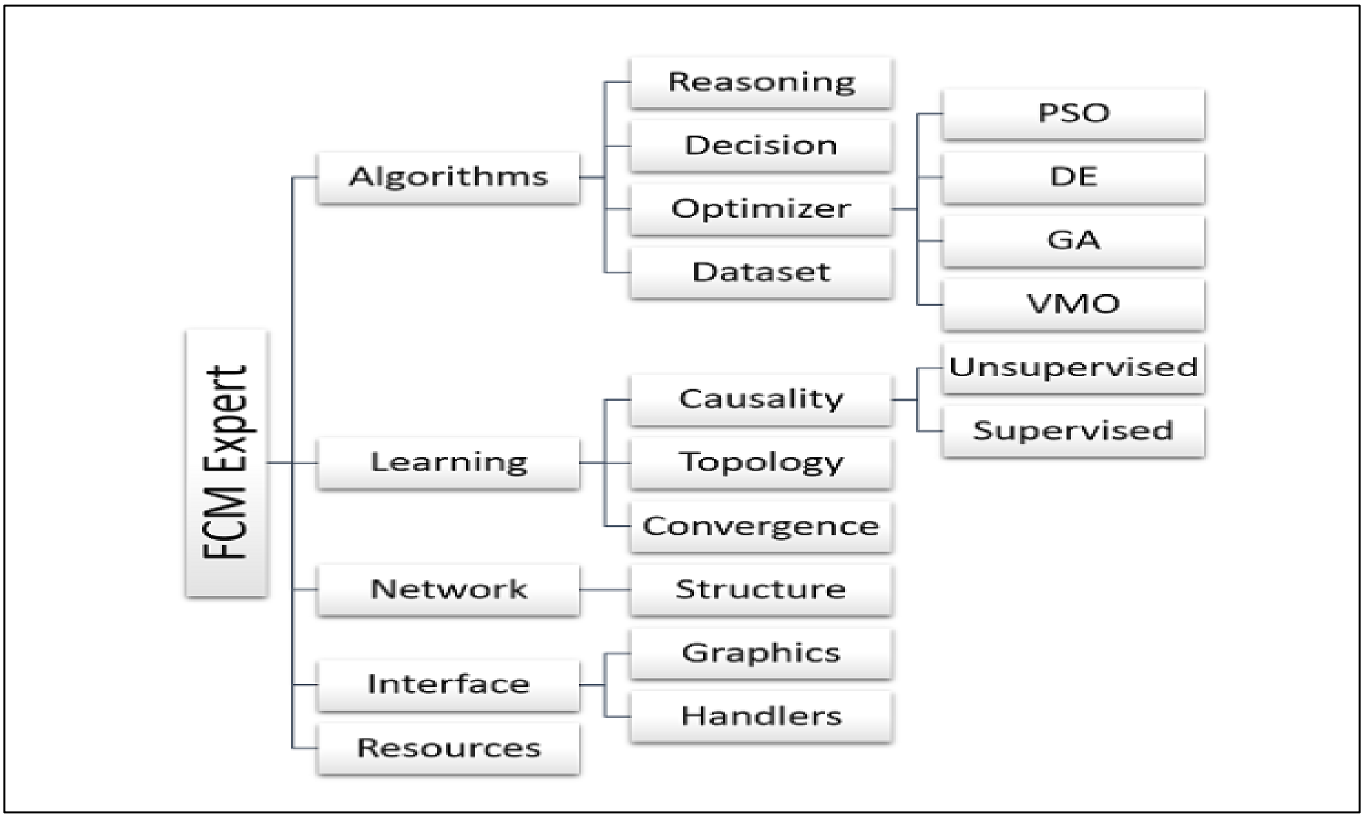


Fig 5 Working Principle of FCM Expert Tool (Nápoles, Espinosa, Grau and Vanhoof, 2018)

FCM Expert also offers scratch design of an FCM system. This may be achieved by drawing the set of weights from a CSV file , by hand or importing the network architecture. This latter option includes a recursive design process to draw the network architecture effectively, which minimises the separation among concepts and the cuts among graph borders and conceptual concepts.

The program proposed applied the deduction rules proposed in this chapter 's basic theories and transmitting mechanism and thus implies that definitions may be set to [−1, 1] or [0, 1] values and have consistency during modelling.

FCM Expert tools enables WHAT-IF simulation to take place by direct modification of each concept's activation values and corresponding inference. This creates a plot and a table for the stimulation indicated with the vital signs at each successive iteration. FCM Expert also allows simultaneous performance in a visual format, which match the characteristics of each concept by its activation value. The combination of several FCM systems into one knowledge-based framework is another important feature (Nápoles, Espinosa, Grau and Vanhoof, 2018).

- *FCM Mental Modeler*

Mental modeler takes the form of Dr. Steven Gray's modeling tool that can explicitly explain stakeholder mental models. In this regard, it offers the alternative of combining diverse features of expertise in ecological decision taking, identifying testing theories and running simulations for the determination of the expected outcomes of policy ideas. The software has been developed in particular to allow stakeholders to develop a quality computational model, create simulations, evaluate system improvements and review their project in the light of process performance across imaginable circumstances. Mental Modeler is composed of three major UIs: the idea mapping interface which provides space to build models as well as the parameterization ofs model configuration in the format needed for FCM-Analysis; the algorithms applied which allows for cognitive map layout, Enabling participants to test and evaluate improvements within the structure across various possible scenarios by looking at pair way relationships and the scenario framework and referring to and revising their templates at the design modelling framework presented this new knowledge (Athanasios, 2017).

- *FCModeler*

This is modelling tool the publicly accessible software program for displaying and modelling physiological and molecular network maps on plants the biologist may use (Dickerson J. A., 2005). It was developed together with team members from different academic institutions by Dr. Julie A. Dickerson and Dr. Eve Wurtele (FCModeler site, 2017). Java is the interactive interface software. The program is currently implemented with an XML interface between packages in Matlab (FCModeler site, 2017).

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FCModeler intends to support hypothesis growth and assessment as well as provide a modeling basis for the assessment of numerous data gathered by experimentation on highly performed gene regulation. This program enables Biologists to monitor and design relationships at multiple stages, to combine data on expression of genes details. The selected three-dimensional virtual environment offers exciting new ways of viewing complex network topologies. The ability to connect complicated physiological structures to behavioural and biochemical flux representations should opens up new biology teaching strategies (Dickerson J. A., 2005).

- *FCM Designer Tool*

This is a method for designing the map structure (definition of concepts and their relationships). As defined by the Kosko's approaches, the casual relationships between concepts can be defined by this tool. Different high correlations may be formed through either static or dynamic modelling question (Kosko, 1986). These depend on, among other things, logic rules, mathematical computations and fuzzy logic, because of dynamic relationship between variables. The inferences from the given data are also made and can be tracked to a map. By utilising this method, it is also possible to interrupt the map progression during its runtime, to inject new details into the database, to continue a past implementation etc. A versatile method for planning and then operating the FCM is the FCM Layout Method (Jose & Contreras, 2010). The proposed method involves an professional knowledge of the topic to be learned to assess the form of dynamic link between definitions, and information about the Java instrument and the language in order to prepare the precise connection of the question (Jose & Contreras, The FCM Designer Tool, 2010).

- *JFCM or Java FCM Modelling Tools*

This resource consists of an open source library compiled with the JavaTM programming language by Dimitri De Franciscis. The suggested JFCM consumers are students who are able to learn FCMs and scientists who play with different learning algorithms and FCM variants.

Program developers need an easy, validated and configurable repository. The JFCM library allows networks to be built from XML files with enhanced accessibility of the collection. The key concept behind the library is to create modular components that can be used if an FCM approach is needed for a certain issue (De Franciscis, 2014).

➢ *Comparison Table of FCM Modelling Tools*

Table 3 Comparison of FCM Tools (Nápoles, Espinosa, Grau and Vanhoof, 2018)

| | | Main Features | | | |
|---|---|---|---|---|---|
| | Year | Experimentation Facilities | Learning Algorithms | Graphical Support | Application Domain |
| **FCM Modeler** | 1997 | Not at all | Only one | Poor | Ecosystem |
| **FCM Designer** | 2005 | Some, but not enough | Not at all | Adequate | Supervision, Control |
| **Mental Modeler** | 2013 | Some, but not enough | Not at all | Adequate | Social Sciences, Ecological Systems |
| **JFCM** | 2013 | Few, only for developers | Not at all | Not at all | Traffic Analysis |
| **FCM Tool** | 2011 | Many, but oriented to the domain | Only one | Adequate | Transportation Management |

If we differentiate with the technical instruments we test for certain characteristics, the assumption can be drawn that the FCM Designer / Mental Modeler / FCM Analyst / FCM Resources provide the experts with the graphically correct help to evaluate and investigate scenarios and new circumstances.

# CHAPTER FIVE
# CASE STUDY

➢ *Developing Fuzzy Cognitive Maps For Plant*

The plant has a growing strategic process management information framework composed of the computerized and operational control systems used between manufacturing and service providers (Mayer, Morel, Lung and Leger, 1996). The data may be compiled and used for creating a fuzzy cognitive mapping , describing a logical, administrative and operating structure model (Craiger, Goodman, Weiss and Butler, 1996). The awareness of plants involves the field structure, the planned actions of certain areas of the plant, a mixture of essential qualities or efficiency factors. This data is collected using the above-defined fuzzy cognitive map structure. The specialist refers to a method for one method or a sequence of procedures or a method for one specific output cycle (Stylios and Groumpos, 1999).

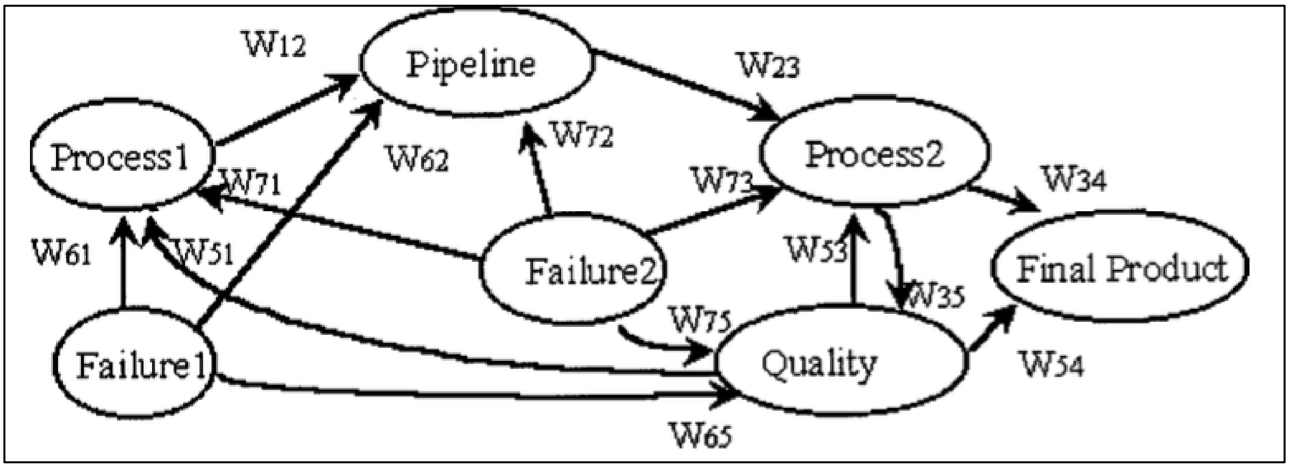


Fig 6 Simple FCM for Plant (Stylios and Groumpos, 1999)

As the figure show, the standard plant consists of two processes i.e. Process 1 and Process 2, which are used in two sub plants. Process 1 product is then put into the process 2 via a pipeline which connects to the sub plants. These two processes are managed by traditional controls and the entire operation is supervised by experts interaction. A fuzzy cognitive map of the plant to model the human control system is shown in the figure above (Stylios and Groumpos, 1999).

It contains seven principles reflecting general plant characteristics and is established by a community of specialists who track and understand how the device works. The Seven concepts are:

- Concept 1 : Current state of Process 1
- Concept 2 : Pipeline that connect 2 processors
- Concept 3 : Current state of Process 2
- Concept 4 : Final Product that comes out of two processes.
- Concept 5 : Represents the final products quality
- Concept 6 : Represents the failure 1 of process 1
- Concept 7 : Represents the failure 2 of process 2

The approach suggested in basic theories in this paper and strength of all causal interrelationships between concepts are used according to the preliminary representation of the fuzzy cognitive map and the interpretation of mutual interactions between the concepts. After the construction of fuzzy cognitive maps, the consistency of the finished or final product and the impact of failures of that final products are simulated to the mode of activity by the constructed maps. The definitions shift according to equation 2 ,at any point of the experiment the fuzzy cognitive map mimics the actions of the true real system or structure. Concept values represent some variables and machine states and thus their underlying definition values reflect the values of parameters in the actual world, with certain definitions including the variables of the system designed as inputs (Stylios and Groumpos, 1999).

The newly established dynamic cognitive map does not do any supervisory features but monitors several components and information concurrently in diverse real-life manufacturing networks, managers and machine specialists, taking difficult judgments based on expertise and scientific understanding. If all such activities are repeated, the supervisor must have specialized skills, such as control, evaluation of loss, preparation, and decision taking. The supervisor must be knowledgeable of all this process. A two-tier system for supervisor, composed of two fuzzy cognitive maps has been suggested as shown in figure below for this reason.

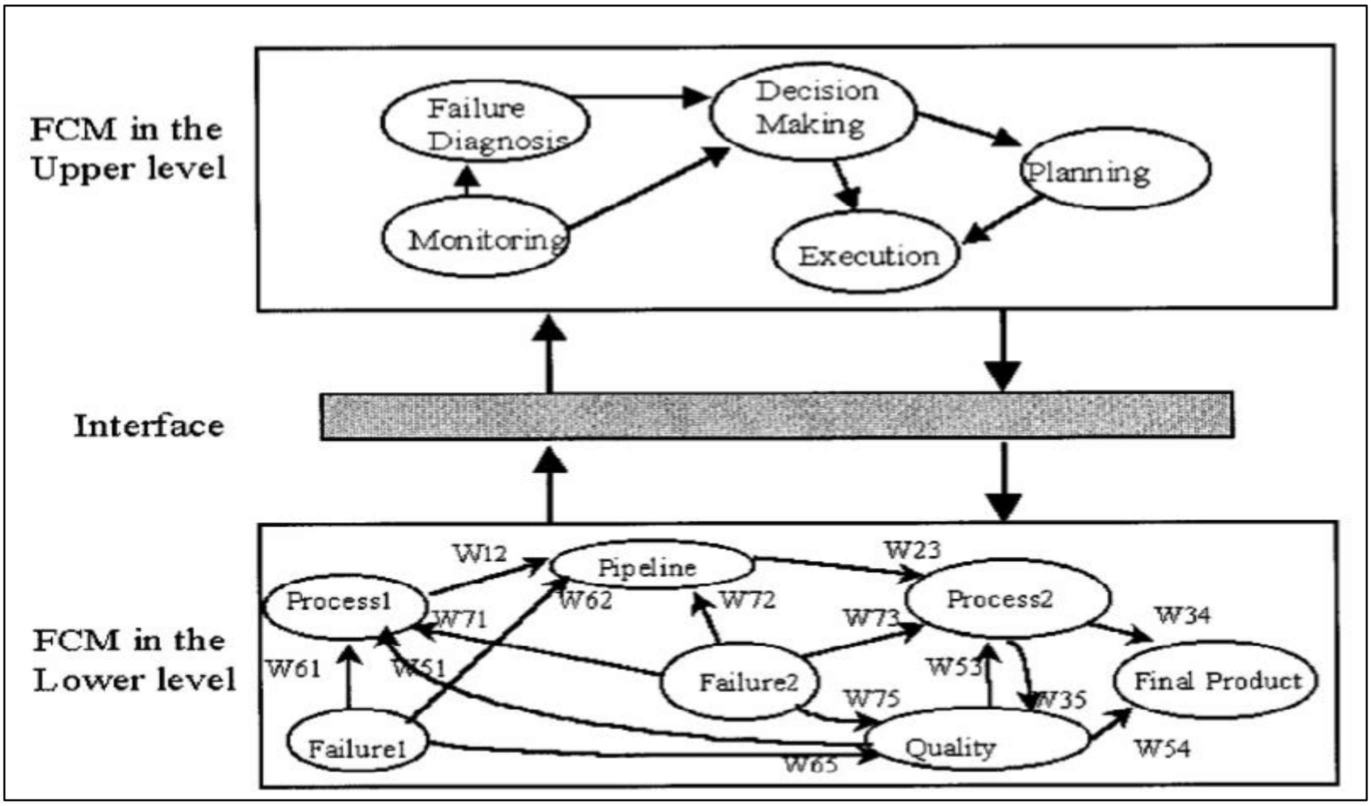


Fig 7 Two Tier System for Supervisor of Plant (Stylios and Groumpos, 1999)

The formerly designed FCM as show in figure 5 lies at the lower level stage, while a more improved fuzzy cognitive program lies at the top end, each of the principles is essentially an FCM itself, and we also have this same option of decision making FCM alongside monitoring and execution FCM implementation. The FCM decision maker analyses warning signals, process signal errors and other feedback from the lower tier, and sends FCM control signals that affect the mechanism to the lower level (Stylios and Groumpos, 1999). There is an overlap between two levels in the two-stage system and there is a ton of knowledge which needs to be transferred from one level to another levels. Basically, the user interface consists of two parts: the one component transmits data from the lower-level controller to the fugitive upper-level cognitive processing, whereas the other section converts data in the reverse direction.

Because many organisational factors are interlinked, for most decision-making activities , expert must take into account as much as possible different data on these variables. As we have mentioned before, a number of methods for weight determination are proposed, but most come from the Hebbian approach, with a critical disadvantage as far as the scalability of the methods is concerned. In terms of dealing with complicated models of mere data volumes, the FCM is separated into a single sheet back - propagation question and structured rather than the learning and test process. We will achieve scalability (Choi, Lee and Irani, 2016).

Basic FCM concept using the datasets provided to me is shown in the figure below. This concept will be later use to create the fuzzy scale value from absolute scale value in the datasets.

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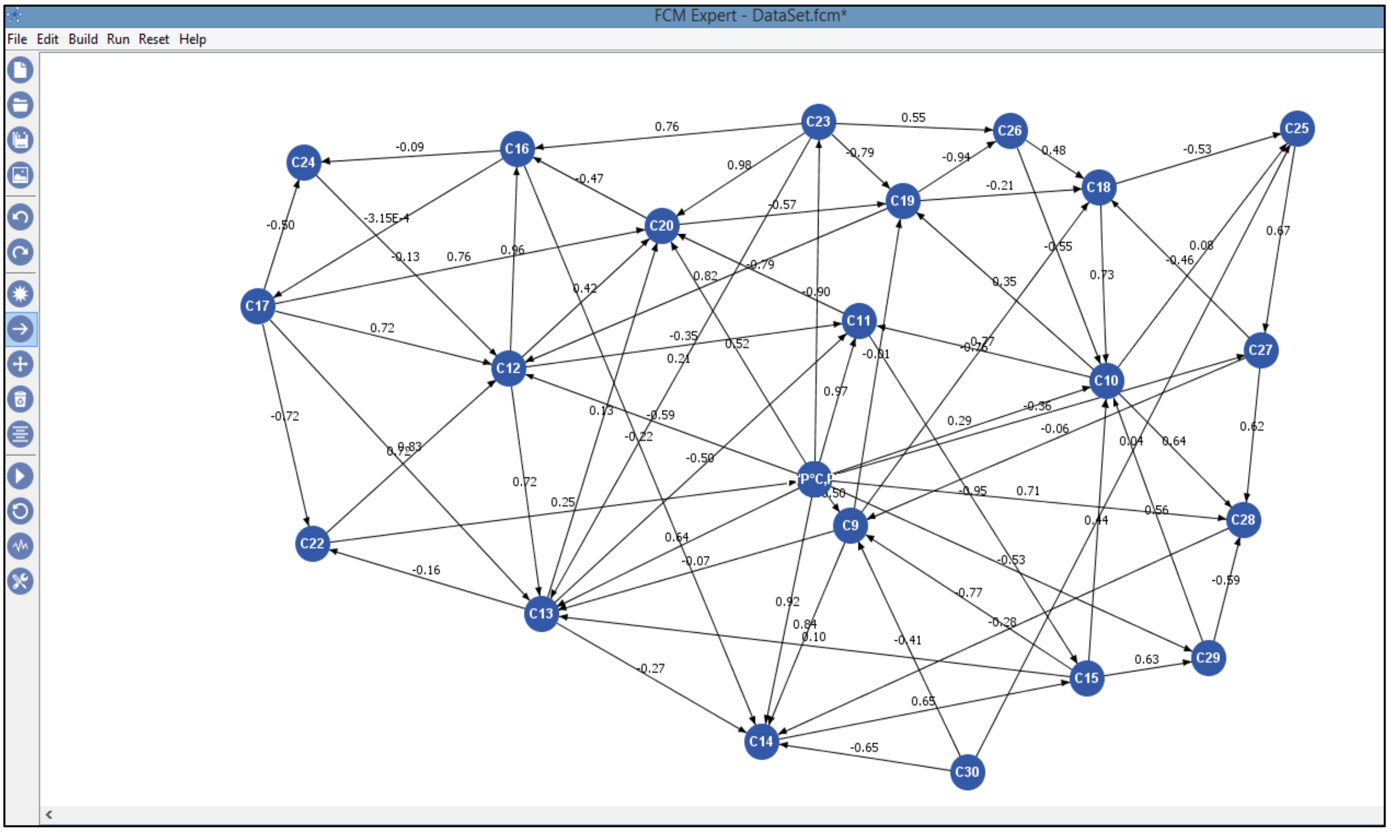


Fig 8 FCM of Dataset of Pipeline Company

The first task to be carried out for an FCM simulation is to assign fuzzy values to concepts in FCM. The development of a fuzzification method which matches digital values from open data into linguistic measurement, that is, fuzzy values, is a pre-requisite for data-driven decision modelling and simulation via FCMs. With no sophisticated fuzzing scheme, the basic function with an equal fuzzing scheme has been used. Each sub-interval can be conveniently translated into a fluctuating value by splitting the maximum and minimum values into the numbers of the scale. The figure below shows the table of change of absolute values to fuzzy value including the concepts and weights.

Inference results

Plotter | Table

| Step | PrP°C,P° | PrP°C,P° | PrP°C,P° | PrP°C,P° | PrP°C,P° | C9 | C10 | C11 | C12 | C13 | C14 | C15 | C16 | C17 | C18 | C19 | C20 | C22 | C23 | C24 | C25 | C26 | C27 | C28 | C29 | C30 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 |
| 1 | 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 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| 2 | 0.6518 | 0.6225 | 0.6225 | 0.6225 | 0.6225 | 0.4092 | 0.7741 | 0.7211 | 0.7901 | 0.8406 | 0.5598 | 0.5857 | 0.7557 | 0.6224 | 0.5064 | 0.4969 | 0.8188 | 0.5151 | 0.5122 | 0.5507 | 0.5728 | 0.5762 | 0.5717 | 0.7663 | 0.6334 | 0.6225 |
| 3 | 0.6863 | 0.6508 | 0.6508 | 0.6508 | 0.6508 | 0.3421 | 0.8355 | 0.779 | 0.8345 | 0.9181 | 0.5027 | 0.5646 | 0.8214 | 0.6507 | 0.5263 | 0.4725 | 0.8811 | 0.4831 | 0.481 | 0.5422 | 0.5961 | 0.597 | 0.575 | 0.8458 | 0.6577 | 0.6508 |
| 4 | 0.6919 | 0.6572 | 0.6572 | 0.6572 | 0.6572 | 0.3244 | 0.846 | 0.7933 | 0.8343 | 0.9285 | 0.4757 | 0.5366 | 0.8294 | 0.6571 | 0.5472 | 0.4693 | 0.8866 | 0.4669 | 0.4654 | 0.5351 | 0.6006 | 0.6033 | 0.5761 | 0.8621 | 0.6561 | 0.6572 |
| 5 | 0.6922 | 0.6586 | 0.6586 | 0.6586 | 0.6586 | 0.324 | 0.8474 | 0.797 | 0.8324 | 0.9294 | 0.4691 | 0.5218 | 0.8285 | 0.6586 | 0.5566 | 0.4718 | 0.8853 | 0.4613 | 0.4603 | 0.5324 | 0.5992 | 0.6035 | 0.5764 | 0.8655 | 0.6511 | 0.6586 |
| 6 | 0.692 | 0.659 | 0.659 | 0.659 | 0.659 | 0.3262 | 0.8473 | 0.7979 | 0.8319 | 0.9293 | 0.4684 | 0.5162 | 0.8276 | 0.6589 | 0.5588 | 0.4737 | 0.8845 | 0.4596 | 0.459 | 0.5315 | 0.5978 | 0.6023 | 0.5762 | 0.8664 | 0.6478 | 0.659 |
| 7 | 0.6919 | 0.659 | 0.659 | 0.659 | 0.659 | 0.3276 | 0.847 | 0.798 | 0.832 | 0.9292 | 0.4687 | 0.5145 | 0.8273 | 0.6589 | 0.5587 | 0.4745 | 0.8842 | 0.4592 | 0.4587 | 0.5313 | 0.5971 | 0.6014 | 0.5759 | 0.8666 | 0.6463 | 0.659 |
| 8 | 0.6918 | 0.659 | 0.659 | 0.659 | 0.659 | 0.3283 | 0.8468 | 0.7979 | 0.832 | 0.9292 | 0.469 | 0.5141 | 0.8273 | 0.659 | 0.5583 | 0.4748 | 0.8841 | 0.459 | 0.4586 | 0.5312 | 0.597 | 0.601 | 0.5758 | 0.8667 | 0.6457 | 0.659 |

Fig 9 Absolute Scale Value Changed into Fuzzy Values

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This table includes the concept and weights and follows all the mathematical theories and algorithm discussed in above chapters. An initial weight matrix has to be modified by the iterative minimization method. The suggested learning algorithm. The original weight matrix was acquired by the correlation coefficients between ideas using historical data. Recent values is to be used for the estimation of input values and to compute the errors , the output of the values will be the most recent historical information i.e. the most recent values. Dataset provided me was used to show revised FCM weights and its Simulation parameter (i.e. weights and fluctuating values for concept). For concept value flushing we used 5 scale values from 0.2 (very low) through 1.0 (very high) and 8 scale values from −1.0 (very negative) to 1.0 (strong positive) with weight matrix values. The calculated fuzzy values for the definitions are generally consistent with the expert's opinion, except for the value for "broadband penetration rate," since they are often small (Choi, Lee and Irani, 2016). Below figure 8 shows the FCM simulation generated from the above FCM maps and tables.

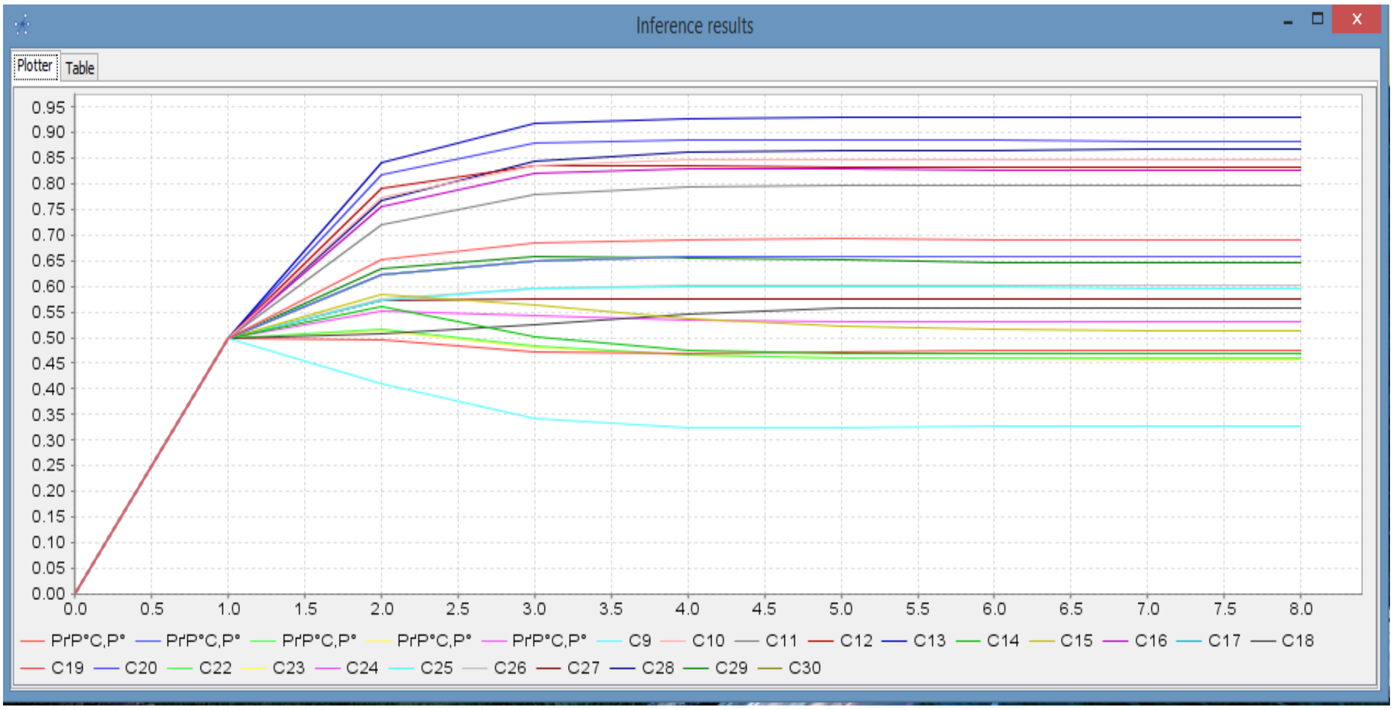

Fig 10 FCM simulation

➢ *Drawbacks Faced*

In spite of numerous theoretical developments and their successes in simulation, there are still a number of disadvantages and shortcomings. One major problem is in mistake on understanding statistical relations as a causal relation. The main disadvantage of the automatic approaches proposed is that they are weak with many variables. Furthermore, FCM does not cope with several triggers co-occurrences, i.e. cases in which the cumulative impact of trigger factors that FCM is not able to model it (Pandey and Litoriya, 2020).

In several simulations we have observed that because of the weights calculated by increasing the number of iterations of the Algorithm, the cause overturns and all or some of Wij became more positive in order to achieve a consistent condition. It's a huge drawback because it alters the causality among concepts and we'll have a bigger result on many instances, not only in terms of interpreting the result but also in terms of stability issues for several systems. This is a major problem (Groumpos, 2018).

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# CHAPTER SIX
# CONCLUSION

The main aim of this paper was to analyse the Fuzzy cognitive mapping methodologies and how it can help in developing the complex system. And with the analysis of different FCM methodologies with their basic mathematical theorem alongside the FCM algorithm, FCM was created for the complex system as discussed in the case study. As per my analysis I found many FCM methodologies, however I decided to work with Fuzzy cognitive mapping soft computing methodology because for my case study it was the most suitable methodology.

- *Limitations*

While this topic was totally new for me the major restrictions for me was time. I only had 4 months of time to research all the theories about FCM and neural networks, and I was also not familiar with using FCM modelling tools.

Another limitations was, that there were not lots of FCM modelling tools available. And some of the tools that are available are not easy to use. Some of the tools were only available as the web version but not as a desktop version, so analysing the data was rather difficult.

The tool I got familiar with was developed by Mr. Gonzalo Nápoles. However I was at learning phase and found it hard to integrate the accessible modern software on the user interface of the tool. As a result the price of the maps' concepts and weights was not easily assigned. That being said, the tool usually works and gives all of its users the desired results.

- *Future Works*

Future analysis that should be carried out involves the application of the method and measurement system in an established enterprise. It makes the method even more common for company output modelling and calculating.

For future Development the FCM expert tool, for particular user experience and compatibility with modern computer applications, should be enhanced. While major chapter of this paper discuses on the theories and algorithms of FCM and little on practical. In future, I would probably more focus on the practical side of implementation of FCM to develop the complex systems.

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## APPENDICES

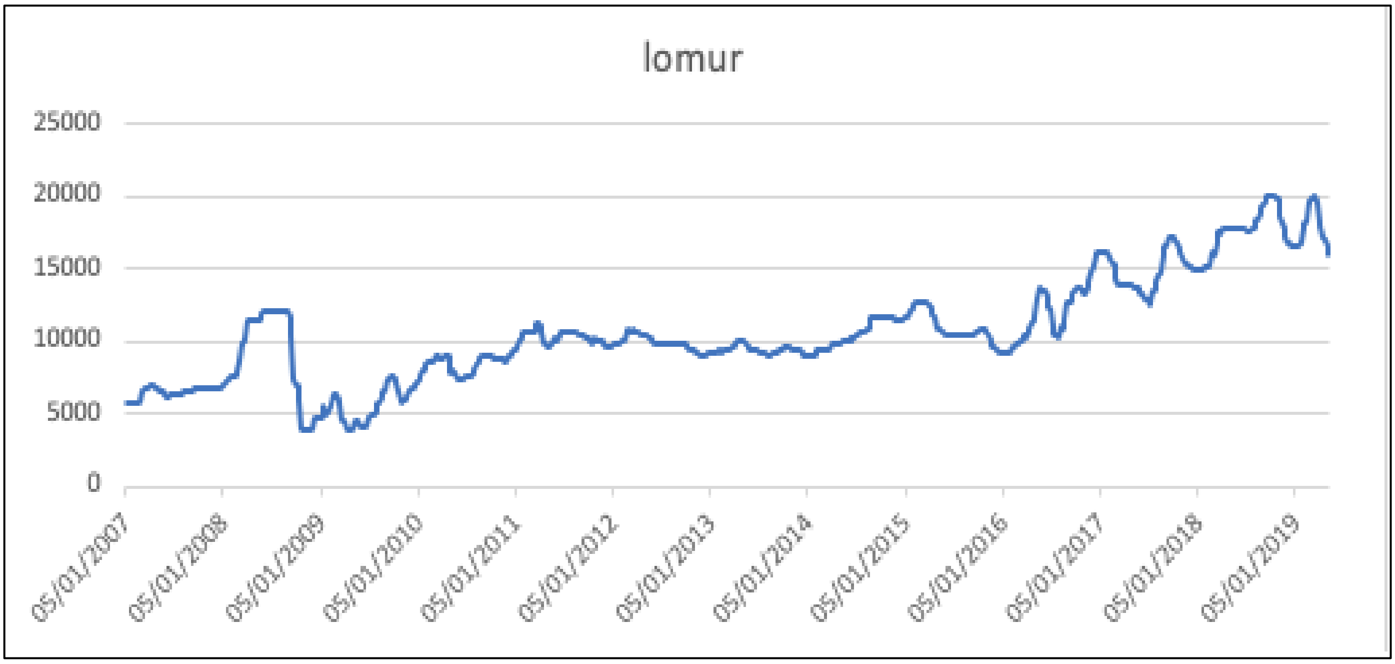


Fig 11 Price Fluctuations

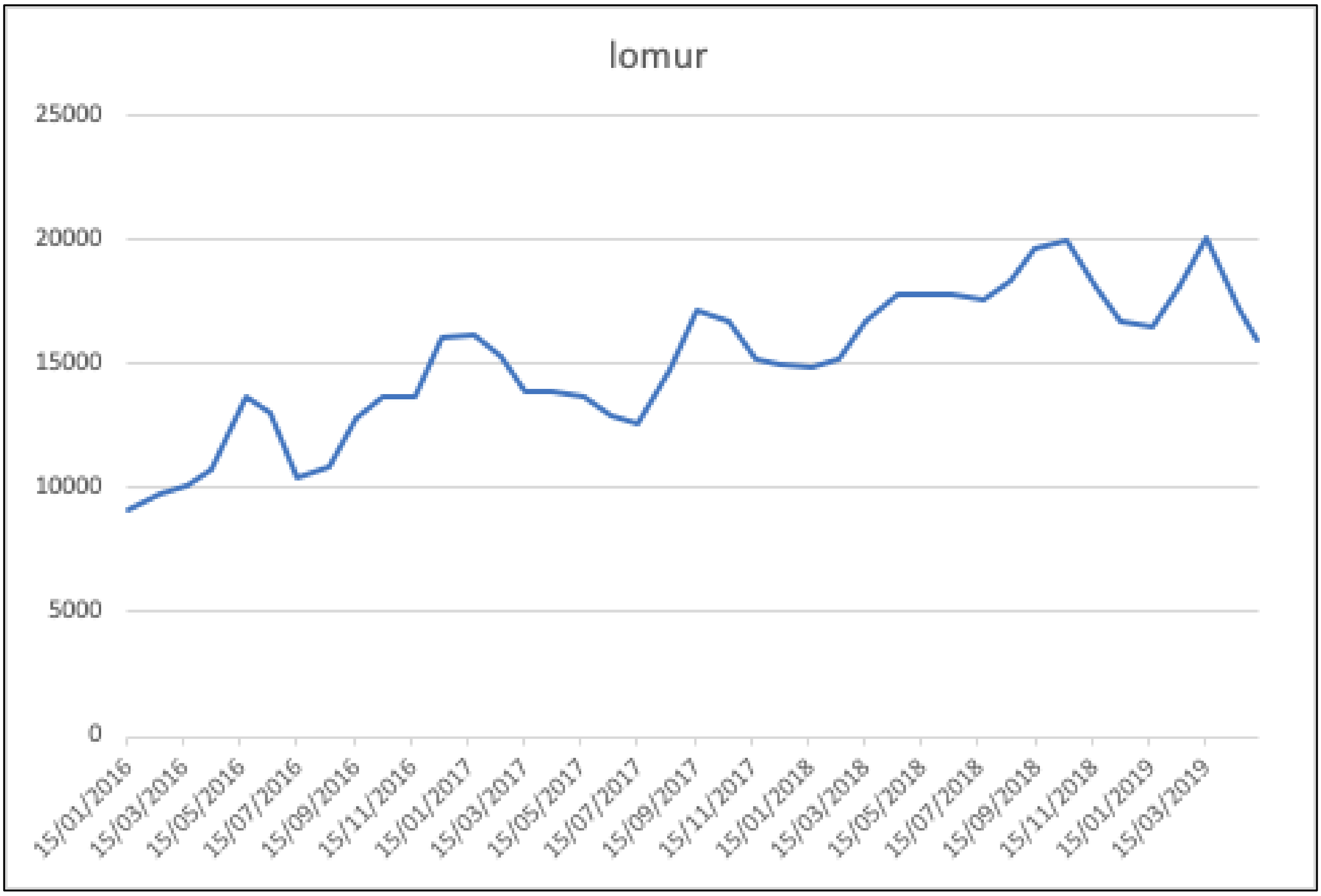


Fig 12 Price Fluctuation by Month

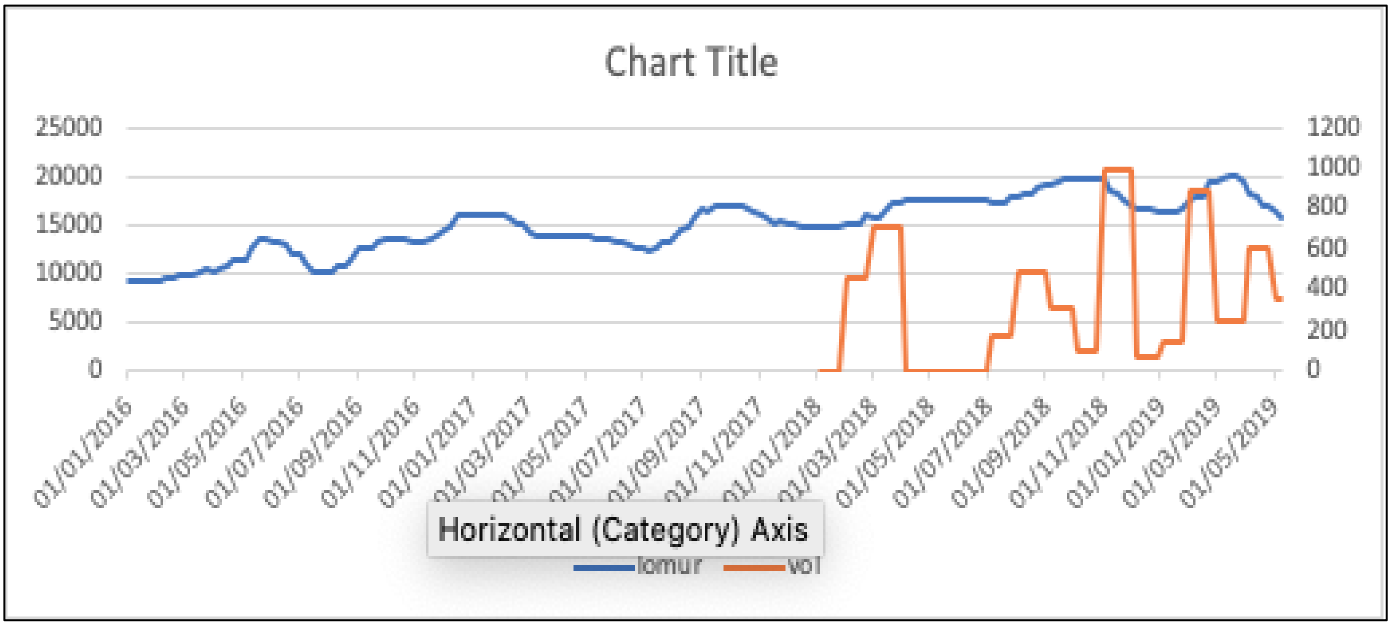


Fig 13 Price Fluctuation by Year

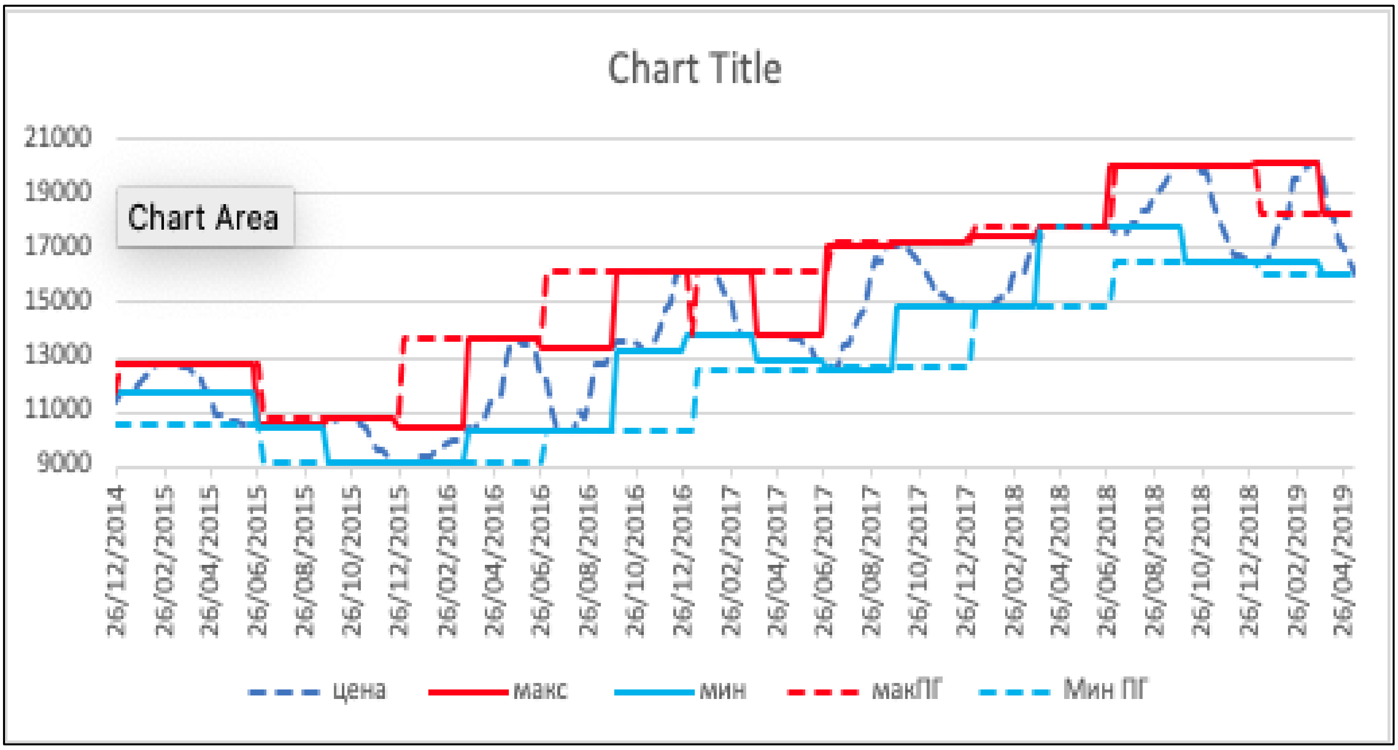


Fig 14 Final Analysis of Price