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ISTANBUL SABAHATTIN ZAIM UNIVERSITY

COMPUTER ENGINEERING DEPARTMENT

COMPUTER SCIENCE AND ENGINEERING

MAKING AND PRIORITIZING MANAGERIAL DECISIONS USING FUZZY LOGIC AND ARTIFICIAL NEURAL NETWORKS

MASTER THESIS

AHMAD ALI

Istanbul

January 2022

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Thesis advisor

Asst. Prof. Dr. Mohammed VADİ

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THESIS APPROVAL

This study has been approved in partial fulfillment of the requirements for MA Degree in English Language and Literature

Chairperson of jury

Asst. Prof. Mohammed VADİ

Member of jury

Asst. Prof. Ali HAMİTOĞLU

Member of jury

Asst. Prof. Wisam ELMASRY

Approval by

Institute of Science and Technology

Signature

Prof. Dr. Metin TOPRAK

Director, Graduate Education Institute

SCIENTIFIC ETHICS STATEMENT

I have strictly adhered to scientific ethics and academic norms in the process from the proposal stage to the completion stage of the study entitled “MAKING AND PRIORITIZING MANAGERIAL DECISIONS USING FUZZY LOGIC AND ARTIFICIAL NEURAL NETWORKS," which I prepared as my master's thesis, I have obtained all the information in the thesis in the framework of scientific ethics and traditions, which I declare that I have prepared in accordance with this article, and that I refer to every citation I have directly or indirectly provided in this study, and that the works I have benefited from are those described in the bibliography.

Ahmad ALI

PREFACE

I would like to express my sincere gratitude and respect to those who helped me complete this work. First of all, I would like to thank the esteemed thesis supervisor, Asst. Prof. Dr. Mohammed Vadi. In addition, all the teaching staff during my master's study as well as the university administration. I would also like to thank Dr. Mohamed Melhem for his assistance and administrative data. Finally, I would like to thank my family and friends for their support.

Ahmad ALI
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ABSTRACT

MAKING AND PRIORITIZING MANAGERIAL DECISIONS USING FUZZY LOGIC AND ARTIFICIAL NEURAL NETWORKS

Ahmad ALI
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Management is one of the most critical factors for success in life in general. Management is important at the personal level in terms of managing money, time, effort, and other things, as well as at the level of companies and institutions and even at the level of countries.

From this point of view, there was interest in the decision-making processes, and the machine had a role in this process, an example of that was its role in assisting bank owners in determining who deserves loans from others, as well as in the stock market in buying and selling operations and other matters. However, these decisions were limited to aspects and not others, which are the financial aspects, because of the ease of calculation for the machine and the availability of data that help in completing the work.

However, in this thesis, we have worked to pay attention to administrative decisions in their broader concept and in their general areas, which are not limited to money only. We created a machine model that simulates human thinking using fuzzy logic systems and artificial neural networks, and then we compared the two models. The results we obtained were satisfactory, despite the scarcity of data available in this field, and we have indicated the reasons in the appropriate sections.

Keywords: Managerial decisions, fuzzy logic, deep learning, artificial neural network, machine learning, priorities in decisions.

ÖZET

BULANIK MANTIK VE YAPAY SİNİR AĞLARI KULLANARAK YÖNETSEL KARARLARIN VERİLMESİ VE ÖNCELİKLENDİRİLMESİ

Ahmad ALI
Yüksek Lisans, Bilgisayar Bilimi ve Mühendisliği
Tez Danışmanı: Dr. Öğr. Üyesi Muhammed VADİ
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Yönetim, genel olarak hayatta başarı için en önemli faktörlerden biridir. Yönetim, para, zaman, emek ve diğer şeylerin yönetimi açısından kişisel düzeyde olduğu kadar şirketler ve kurumlar düzeyinde ve hatta ülkeler düzeyinde de önemlidir.

Bu açıdan bakıldığında, karar alma süreçlerine ilgi vardı ve makinenin bu süreçte rolü vardı, bunun bir örneği banka sahiplerine kimin diğerlerinden krediyi hak ettiğini belirlemede ve bunun yanı sıra kredi verme sürecindeki rolüydü. Borsa alım satım işlemleri ve diğer konularda. Ancak, bu kararlar, makine için hesaplama kolaylığı ve işin tamamlanmasına yardımcı olan verilerin mevcudiyeti nedeniyle, finansal yönler olan diğer yönlerle değil, yönlerle sınırlıydı.

Ancak bu tezde, idari kararların sadece para ile sınırlı olmayan, daha geniş kavramı ve genel alanları ile dikkate alınmasına çalıştık. Bulanık mantık sistemleri ve yapay sinir ağları kullanarak insan düşüncesini simüle eden bir makine modeli oluşturduk ve ardından iki modeli karşılaştırdık. Elde ettiğimiz sonuçlar bu alandaki verilerin azlığına rağmen tatmin ediciydi ve nedenlerini uygun bölümlerde belirttik.

Anahtar Kelimeler: Yönetsel kararlar, bulanık mantık, derin öğrenme, yapay sinir ağı, makine öğrenmesi, kararlarda öncelikler.

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ABBREVIATIONS

FL	:	Fuzzy Logic
ML	:	Machine Learning
MF	:	Membership Function
ANN	:	Artificial Neural Network
FNN	:	Fuzzy Neural Network
DM	:	Decision-Making
SOI	:	Strength of Interest
IOI	:	Inclusion of Interest
EOI	:	Expectation of Interest
FOI	:	Fields of Interest
DOP	:	Degree of Priority
MSE	:	Mean Squared Errors

CHAPTER I

INTRODUCTION

The decision is the choice made between a set of alternatives when feeling doubt and uncertainty, and the decision is defined as the opinion of a person who has sufficient ability and influence to make decisions. We can also define the decision as to the action that contributes to deciding a particular issue or something to reach the best and most correct results.

The taken decisions vary according to the areas to which they are related and the degree of their importance. For example, decisions related to personal matters such as the decision to determine the student's university branch or to buy a house or a car are not of the same degree of importance as decisions that relate to more individuals, for example, a large institution or company, nor is it equally important when these decisions pertain to entire societies and nations.

Furthermore, let's talk about different fields. Financial decisions are not of the same degree of importance as administrative decisions or political decisions. Moreover, there may be a high degree of overlap between these levels and others. Thus, the degree of importance varies from one field to another, not only for the sake of the sector but for the time of the decision. For instance, some decisions are urgent, while others can be postponed.

1.1. Purpose of the Study

The purpose of study is using the scientific principles of deep learning and enabling the machine to simulate humans in administrative decisions using fuzzy logic systems and artificial neural networks.

1.2. Statement of the Problem

The decisions are not just words released, and the matter ends. Instead, it is related to future success, failure, wealth, poverty, strength, weakness, and other matters. Therefore, this decision is about determining what current matters will lead to, or at least giving a vision of what will lead to it.

Therefore, from the foregoing, we see the importance of the Decision-Making (DM) process and the extent of its impact on various levels and even various areas of life, so this topic was of great importance to take a space of research, thinking and development.

Knowing that decisions in general are not taken randomly without thinking and studying the reality and understanding current data with studying models, facts, similar and previous experiences, with keeping pace with contemporary events and anticipating what is future.

So, from all the above it is clear that DM is not so simple, but is of an enormous amount of complexity, and that by the time it becomes more complex due to the increase in the factors affecting DM.

Therefore, from this point of view, the thought of introducing modern science into the DM process is not a substitute for the human being, but at least an assistant and a guide. It helps him to save a lot of time, effort, material resources, and others, as it is based on different principles, the most important of which is machine learning (ML), as we can access models that help in DM, especially in the huge amount of information we live in our time.

We found that many of these studies were directed to the economic field, such as the stock market and e-marketing.

Some of these studies help shop owners to know the right decisions in buying and selling the goods and other decisions that benefit the owners increase their money.

1.3. Research Questions

This study aims to focus upon finding the answers to the following questions:

1. Can a machine simulate a human thinking in managerial decisions based on liguestic variables?
2. How can a simulation of managerial decision-making be done using the fuzzy logic system?
3. How to simulate managerial decision making using artificial neural networks?
4. Which of the two previous systems show efficiency in simulating human thinking in making managerial decisions?

1.4. Significance of the Study

Despite all the above, we tried in this thesis to build a model that shows the importance and capabilities of the machine in DM and focus on the different areas that affect DM. The advantage of these areas is that they include large fields that help the decision-maker and direct him to the best options available for a particular problem.

This does not mean that we neglect the financial aspect, but rather it is considered one of the important areas that affect DM. The administrative decision may affect the decision-maker's financial, health, political, or other circumstances and those who represent them in DM.

So, despite the lack of administrative data for the reasons mentioned earlier, we built two models, one using Fuzzy Logic (FL) and the other using Artificial Neural Networks (ANNs) to work on reaching models that simulate human thinking in the DM process, comparing decisions and choosing priority from them.

Therfore, when the used data is more quantity, higher accuracy, and higher realism, the results will be higher quality, accuracy, and effectiveness. Thus, we can turn them into ML models that help decision makers reach accurate decisions in the perfect time.

1.5. Limitations of the Study

As for the interest in administrative decisions, the using of ML principle it was weaker than other areas which the machine was used for DM. We can mention the reasons as following:

1. That the impact of administrative decisions is not as clear and direct as other decisions. It may be beneficial after many years.
2. Secondly, many decisions in administrative sectors based on data may be non-numerical data, as is the case in the economic field, which its data contains numerical data that can be used and measured as intended.
3. Thirdly, it is difficult to get administrative data, as it often considers the private and confidential aspect of any institution
4. Fourthly, few organizations archive data and make decisions based on it to build an ML model.

1.6. Organization of Chapters

This study is divided into five different chapters:

Chapter I: In this section, the introduction and purpose and significance of the thesis with the limitations are discussed.

Chapter II: This section provides information about the literature review.

Chapter III: This chapter talks about research methodology of the used systems.

Chapter IV: This section explains and discuss the implementation of FL & ANNs in our study with comparison between them.

Chapter V: This section shows conclusions and future work.

CHAPTER II

LITERATURE REVIEW

This section will review some previous works similar to what we will do in making administrative decisions, the areas in which they have been applied, and how the application mechanism has been implemented.

In the beginning, we find that most businesses interested in decision-making are directed to financial and commercial matters more than to administrative decisions for different factors. One is that financial and commercial activities depend clearly and practically on numbers and their changes. Hence, it is easy to measure and obtain results. In addition, these effects appear, and their changes are instantaneous and often fast, in contrast to the purely administrative decisions. Therefore, we needed to review all areas of DM and how the mechanisms are used in them.

Verónica Gurrea et al. (2014) mention the literature review of the application of FL in performance management. Shuhadah Othman et al. (2010) explain that the rules of the fuzzy conditional of the decision support system were used in stock trading, and three linguistic variables were adopted to be the inputs to the rule and these variables were: view from the expert, the earnings per share, and the price-earnings ratio. The objective of this system was to assist investors in making the appropriate decision regarding their shares. This paper was based on helping the investor determine his decision according to five proposed outputs: sell and strongly, sell, hold, buy, buy strongly.

Himadri Shekhar et al. show that the current world depends on technical evaluation. A fuzzy-based model has been proposed, which is helpful for DM criteria. Through this model, the customer's surprise level is measured, which will be helpful to the business strategy maker for help in understanding the process of marketing the product and increasing the demand for it. Mamdani model is applied as the inference engine. The triangular membership function (MF) is used as a membership function. In the defuzzification process, the Max-membership method is applied.

N.H. Mateou et al. (2005) propose a strategic management methodology using fuzzy Influence Diagrams to represent and model decision problems while describing influence diagrams, propose their extension via FL, and demonstrate their use in crisis management and DM. Using a different kind of fuzzy reasoning, such as scalable monotonic chaining, improved the flexibility of that method.

A common technique for evaluating and solving an ID is based on the Bayesian Theorem. They had presented the empirical results of simulating the 1996 crisis at Imia between Greece and Turkey using a dedicated FID as proof for their suggested model.

Heinrich J. Rommelfanger (1998) represents a new method for solving multicriteria decision problems. The lowest level goals were evaluated using linguistic variables based on cardinal or ordinal scales that experts proposed. The evaluations of the subgoals were aggregated by using expert rules and fuzzy inference.

Victor I. Sigov et al. (2017) explain the necessity to teach social aspects to future business people or top managers; the following criteria have been studied as one of the primary criteria for innovative growth: social institutions and social risks; socially intertwined or delusional goods; and new business modeling that incorporates human creativity, to implement the human ability to solve complex problems and apply them to a machine, ANNs need the ability to handle uncertainty in a human-like manner, so FL was added to ANNs, and the concept of the fuzzy neural method was introduced.

Corporate management considers the interests of different stakeholders and needs to predict their behaviors in political, social, or economic fields to weigh the priorities that belong to the diverse worlds. The fuzzy neural networks (FNNs) also provide the possibility to "manually" adjust the parameters and to correct the belonging of each unit of data.

Marat Rakhmatullaev (2019), based on the principle of "Situation-Reason-Action" this system or model was proposed which was called Fuzzy Correspondence Models (FCM), the operation of fuzzy inclusion of sets was used, as well as the method of priority coefficients were used to determine the priority of the chosen cause or action. Fuzzy correspondence models (FCM) are implemented in situational control systems; the main areas of application of the model are medicine. Diagnosis and treatment, technological or production tasks.

Samaneh Berenjian et al. (2016), show that Automatic Intrusion Response Systems (AIRS) chosen to select responses impose a lower cost on the system they want to protect so that they use different methods to trigger effective responses. Since most risk assessment methods produce ambiguous results, they use ambiguous logic in risk assessment and appropriate DM.

The proposed AIRS had contained components like Web traffic analyzer, a fuzzy system, and a response execution module. The rules in this system were created with the knowledge of experts, which numbered thirteen rules. This system protects web applications from common web attacks and makes the right decision depending on less cost.

Yuan Yao et al. (2010) propose an FNN system used for management DM and composed of three separate networks. This research is of great importance and relevance to its close relationship in our research, as it shows that people who make decisions use many factors influencing the decision and experience to take the appropriate decision. However, the diversity and complexity of the world always make the decision go in the wrong direction.

The causes of uncertainty generally arise due to three aspects. The first is that the information used in DM is not integrated. The second is that DM is a function of decision variables and contains subjective factors. Third, the identification process is often unclear.

Therefore, simply using quantitative management science methods to solve complex management DM problems in a complex environment is challenging.

The standard NN model ignores the ambiguity of the input vector and does not consider that one input vector can produce a variety of DM methods. In this paper, the FNN provides a method to express MF using fuzzy input vectors to resolve the problem. This approach would reduce the ambiguity of information and improve the quality of DM and network robustness.

The method proposed in resolving management DM problems is exploratory research. The combination of fuzzy and ANNs has great significance in management science.

Marcel-Ioan Boloș et al., (2019) An ambiguous logical management decision tool was proposed to reach the assets that provide an ideal ratio between the acquisition cost and economic performance for the benefit of the organization. Mysterious; The global membership score vector for bids to the selection criteria and the maximum global membership score as an inference operator to establish the bids validated by the algorithm. Two asset acquisition scenarios were tested.

After simulations, it was determined that the proposed fuzzy rationale management decision tool combines, with outstanding results, the cost of asset acquisition with its economic performance. The multicriteria FL algorithm is essentially based on determining the MFs for each asset acquisition criterion selected.

Katarína Valášková et al., (2015) show the importance of the fuzzy planner, its basic operations, and the impact of applying the fuzzy model on automotive safety, given the type of vehicle, manufacturer, and Intelligent Transportation Systems (ITS) created, and how the fuzzy package helps make informed purchasing decisions are explained. The construction and application of expert systems have been applied.

Jože BENČINA et al. (2009) shows a solution to some problems related to the evaluation and appraisal of investment projects by proposing the work of FL for DM. The fuzzy decision tree was proposed, which combines the theory of fuzzy sets and FL and the decision tree.

A. Fevzi Baba et al. developed Fuzzy Group for Decision Support Systems (FGDSS). The software can be used for multi-purpose DM processes. It helps users define the main and sub-evaluation criteria and their weights and evaluate performance according to the number of decision-makers and the evaluation weights for the criteria. Using the Delphi programming language, it was applied to evaluate the performance of research assistants at Marmara University, Faculty of Art Education.

Mirza B. Murtaza et al. (1994) presents an innovative approach to DM using self-organizing multi-layered ANNs. The model helps in making a decision regarding the construction of an industrial processing plant which is a significant problem in construction management due to its economic impact. Both the expert system approach and the ANN have been shown and can be helpful in DM problems, although the ANN approach is superior to the expert system approach in some cases.

Shorouq Fathi Eletter et al. (2010) developed a proposed model that identifies an ANN as an enabling tool for assessing credit applications to support loan decisions in Jordanian commercial banks. A proposed model uses a multilayer ANN with a backpropagation learning algorithm.

Noppakorn Klintong et al., (2012) An ANN was used to develop a decision support system to benefit from it in selecting which projects are most appropriate for the process of product development and innovation maintain the company's strength and competition. The ANN model has been shown to provide a fast, flexible and powerful predictive capability.

Bohdan S. Butkiewicz (2002) explains the method of selecting employees for the company using FL based on the institution's board of directors in selecting the nomination criteria for the employee before. In order to avoid the subjective and unfair selection of people by other employees, this is a solution in medium or large organizations where the board of directors cannot choose employees personally.

Elin Wihlborg et al., (2016) explain the implications of automated DM for professional administrators in a Swedish public organization. Amir Karami et al., (2012) propose an integrated framework for multicriteria decision-making (MCDM) to effectively deal with uncertainty and subjectivity in the selection process of IT service providers. An FL approach integrates qualitative survey data into traditional multicriteria decision models such as Data Envelope Analysis (DEA), Analytical Hierarchy Process (AHP) methods, and TOPSIS.

The decisions were divided into three sections in terms of organization, which are as follows: structured, unstructured ,and semi-structured. This matter depends on the degree of certainty in representing the problem and its solution.

A structured decision can be defined as inevitable with a known solution, while an unstructured decision can be defined as a decision dependent on a specific decision-maker, and that decision-maker has little or no knowledge of the solution.

While structured decisions do not require any judgment for any part of the decision-maker, we find that unstructured decisions depend mainly on the experiences or suggestions of the decision-maker. Between these two divisions of decisions, there is a wide range of problems called semi-structured decisions. It can be argued that semi-structured decisions depend on analytical models or data, and that is why these decisions receive the most attention from technical assistance.

It is described how to include artificial intelligence tools in any of the above types of decisions to perform complex calculations. A set of AI tools have been reviewed and included in Intelligent Decision Support Systems IDSS decision-making processes. Some of them have been applied to healthcare and clinical DM. The AI tools reviewed are ANNs, FL, evolutionary computing, and intelligent agents. (Gloria Phillips Wren, 2012).

An improved method has been proposed using an AI tool to monitor the network and uses a hybrid system of FL and ANNs. The system was formed based on the dual database. One of the databases contains the values of the MF to perform the process of inference and comparison, while the other database is based on rules formulated by the network administrator, who is characterized by experience and efficiency.

It was shown that with the proposed system using the hybrid system of FL and ANNs, there are many advantages, including the ability of the system to learn and control under various conditions. It encounters the possibility of dealing with possibilities and uncertainty, its efficiency in dealing with unexpected situations and new data, and the possibility of its sufficiency in the event of network development. (Azruddin Ahmad et al., 2013).

A proposal was presented for a technique to be used to select land for commercial buildings in Rio de Janeiro city, and this technique was based on the principle of FL and analytic hierarchy (AHP). These methods were chosen because of their flexibility, applicability, and appropriate solutions to the desired DM processes. The programs used were: Super Decisions and MATLAB. The factors affecting the choice of land were presented in order of priority, then alternatives were proposed and arranged based on pre-defined scenarios. (Nilson Brandalise et al., 2019).

A multi-group classification algorithm has been proposed. This algorithm is based on a hybrid system of ANNs and FL. The primary role of this method is that the membership association can adapt to any new data. Therefore, the modification was allowed with dynamic modification of functions during training. The algorithm has been implemented and verified using real economic data and proven successful. (Ralf Ostermark, 1999).

An analysis was done on the German stock index DAX-30, and it was confirmed that the path of these indicators could be predicted using a hybrid system of FL and ANNs.

Different models were applied, and HyFIS models were trained and applied to sub-random samples approximately 10,000 times. The database includes 4,345 trading days from 8th December 1999 to 30th January 2017. Information about opening, low, high, and closing prices is available for each trading day.

The database was divided into two groups: (1) the training sample, which lasts from December 1999 to November 2014 and contains 87% of the data, and (2) the testing sample, including the remaining trading days, which were used as out-of-sample data . (Fernando Garcia et al., 2018).

In other work, ML methods and data analysis methods were reviewed with their application in implementing decision support system methods. As the work is based on efficient data analysis, complicated relationships are found that help in the DM processes in a balanced and flexible manner. (Savenkov & Ivutin, 2019).

In another work, the focus was on supporting DM at the strategic level. This work was done in the field of DM assistance in higher academic institutions. Three supervised ranking algorithms were used to predict graduation rates from real data for South American undergraduate engineering students. Receiver operating characteristic (ROC) curve analysis and its accuracy were carried out as measures of effectiveness to compare and evaluate decision trees, logistic regression, and random forest and study their results. (Yuri Nieto et al., 2019).

In another work, a hybrid FNN system for function approximation is presented. This system can process both ambiguous and numeric inputs simultaneously. Gaussian fuzzy clusters represented all connections. The method of activation propagation in the network was adopted on a non-obvious exchanger scale. Base (hidden) node activations are also counted as a fuzzy internal product.

The digital outputs are computed using size-based noise cancellation for specific digital blur inputs. A supervised learning procedure based on gradient descent is used to train the network. The model was tested on two different approximation problems: Approximate the sine and cosine function and the Narazaki-Ralescu function and show their natural ability to infer, approximate the function, and classify. (Amit Mishra & Zaheeruddin, 2010).

In another job, work was done on supply chain management so that an appropriate assessment of suppliers is made, which directly affects the success or failure of the supply chain. Therefore, a model based on continuous evaluation of suppliers was proposed based on FL to deal with the various factors associated with supplier evaluation problems.

Therefore, four Mamdani multi-input fuzzy inference systems (MISO) for supplier evaluation were proposed. A particular model for the supplier evaluation process has been developed by collecting data using a questionnaire for 66 Indian textile organizations. (Darshan Kumar et al., 2013).

In the field of contracting, institutions and individuals face a problem in evaluating bids submitted by competing construction institutions, as the evaluation is based on essential variables, and these variables may be difficult to compare between them.

Therefore, a fuzzy-logic methodology was proposed to compare the offers submitted by different construction companies. The basis on which the research is based is choosing an appropriate group of parametric MFs to be based on selection and DM so that DM is not dependent on the bid price only without considering other factors. (Caballero & Mitrani, 2000).

In another research that focused on the issue of car safety, a model was proposed that adopts FL to take into account car safety, studying car safety depending on the type of car, intelligent transportation systems (ITS) used, and the manufacturer. This model illustrates how the fuzzy set helps in making the right purchasing decision. (Katarína Valášková et al., 2014).

In another work, a model based on reinforcement learning and object response theory was applied to evaluate the performance of artificial intelligence and compare its DM process with human decision. This idea has been applied in manufacturing. This idea uses the minimum applicable setup for AI systems to later identify opportunities in manufacturing. Operational production management decisions have been approved. (Peter Burggräf et al., 2020).

Paliuka & Savaneviciene, (2018) A study concerned with the issue of quality management was conducted, as it revealed the main obstacles facing creative and rational decisions and affecting quality management. Artificial intelligence techniques have been used in the Quality Management System (QMS). One of the main obstacles that have been reached in the face of creative and rational management decisions in the quality management process is qualitative, redundant data that the artificial intelligence system cannot do. Second, a clear division of responsibility and assignment between data entry and expert translators.

Another study looks at the receptivity of people and administrators to machine interference in the DM process. Five pilot studies were performed (total N = 1025 directors). The results indicated that managers do not want to exclude machines completely and do not want them to be independent in DM simultaneously, but they want to use the machine as a partner in DM. The proposed weight for both human and machine participation in managerial decisions was as follows: humans weighed about 70% and machines 30%. (Tessa Haesevoets et al., 2021).

In another paper, FL has been utilized in making policy decisions about restoring resilience while taking into account national economic growth. A fuzzy controller has been proposed that performs an automated estimation process in which the period required to restore the elasticity level is calculated. The study was applied to Barcelona, Spain. This decision support system is beneficial in disaster mitigation by giving decision-makers, rulers, or institutions the possibility of achieving reliable recovery time estimates. (J. Rubén G. Cárdenas et al., 2016).

In another work, to help the DM process in the medical field, it was proposed to use a fuzzy expert system to help doctors in the DM process regarding the condition of the footballer because the Football Association (FIFA) required before the competitions that there be a medical evaluation for each player (PCMA). Since cardiology is an essential part of this examination, an FL system has been proposed to help deal with the uncertainty in the measurements, and accordingly, the appropriate decision is taken. (Najar Yosra & Ketata Raouf, 2013)

CHAPTER III

RESEARCH METHODOLOGY

Our research methodology is based on presenting the scientific bases that we will use in the artificial neural network system and the fuzzy logic system, and then creating a prototype for each system. We will later apply the data we have to these models. After that, the calculations will be done, and the results will be obtained and discussed.

3.1. Artificial Neural Networks

3.1.1 Fundamentals of ANN

ANNs are one of the methods used in deep ML, and it was proposed based on the idea of a biological system in humans, which, as it is known, consists of a large number of interconnected neurons that work in perfect harmony and synchronization to solve specific problems.

ANNs learn in a way that simulates human learning in real life, meaning that every piece of information and situation they gain experience helps them make the right decisions later.

3.1.2. The Biological Neuron

The human brain comprises billions of neurons that transmit and process data. Each of these neurons can be called a simple processor. The continuous and simultaneous interaction of all cells and their rapid data processing gives the brain enormous capabilities. Figure 3.1 represents a human neurobiological unit. The parts that a biological neural network consists of have been demonstrated.

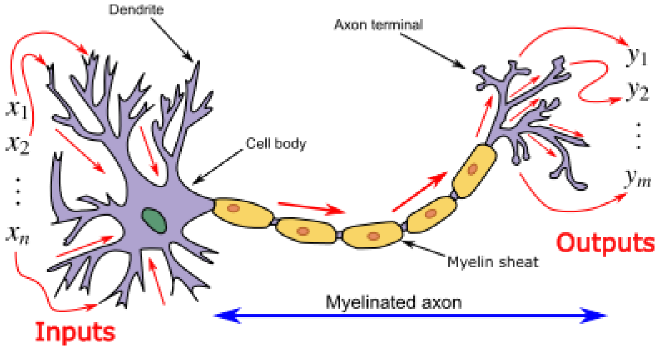


Figure 3. 1. Biological Neural Network (Wikipedia, 2019)

The neuron consists of the body (soma), dendrites, synapses, and axons.

The cell body contains the cell nucleus and its dendrites which are branched fibers attached to it, their role in receiving or transmitting electrical signals. The neuron's body receives electrical (neuron) signals from other neurons via the dendrites of another cell neuron or from another neuron's axon via synapses. A synapse is a space where a neuron branch or axon meets a neuron in another cell to transmit electrical signals utilizing chemicals called neurotransmitters. The neurotransmitters are numerous tiny switches at the end of an axon that releases chemicals, including acetylcholine, adrenaline, and noradrenaline.

The axon of a neuron is an extension that exits the cell body and transmits electrical signals from the neuron. Neuron terminal buttons are the little switches at the end of an axon that release chemicals called neurotransmitters.

3.1.3. Artificial Neuron Model

Artificial neurons are a mathematical function that has been proposed as a simple model for real life.

3.1.3.1. Basic Elements of ANN

An ANN comprises three essential components - weights, thresholds, and an activation function. The ANN model was formed based on the human nervous system and is shown in Figure 3.2.

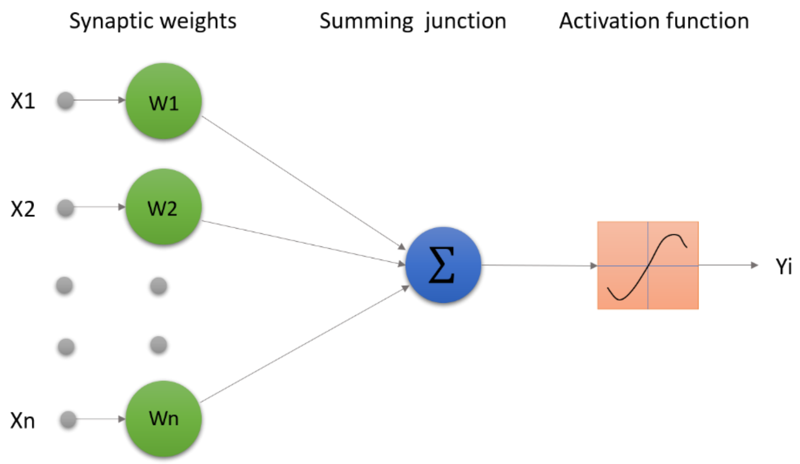


Figure 3. 2. Basic Elements of ANN

The structure of artificial neurons is similar to that of biological neurons. Artificial neurons form an ANN by connecting them. An artificial neuron consists of five main parts:

• **Input:** information received from the ANN by the user or from another cell.

• **Weights:** the parameters that determine the value of the information received into the cell and the level of activity on the cell. Weights values can be zero, positive, or negative. The high weight value of the relevant input means that it is strongly associated with the artificial neuron. A smaller weight value of the related inputs means a weaker correlation. When the weight value is zero, the cell has no activity.

• **Summation function:** multiplies the entry in the cell by the relevant weights and adds up. This calculates the net income of the cell. Several different assembly functions are available. Therefore, different grouping activations are used depending on the problem. However, the ideal function is generally determined by trial and error.

• **Activation function:** It provides the determination of the cell's output by subjecting the net input to a mathematical treatment. These functions are usually nonlinear. When selecting related functions, researchers ensure that their derivatives are simply computable.

• **Output:** These are the output values obtained after processing by activation functions. Depending on the problem, the output can be sent to users, cells of different layers, or as input for itself.

3.1.3.2. Different Learning Rules

Before explaining Deep Learning, we need to explain what ML and ANNs are.

ML is a branch of ANN that allows computers to predict and model future events by acting on experiences obtained from past information. According to the data structure, ML algorithms are divided into two groups: Supervised Learning and Unsupervised Learning.

Supervised learning algorithms are the most widely used algorithms. Supervised algorithms use labeled data to predict future events based on what they have learned. The data to be used during the training and the data classes are known in advance. In line with this information, the system learns and evaluates the new data according to what it has learned. Good system training means that its predictions will be more consistent in the future. Supervised learning algorithms are suitable for solving many machine-learning problems, including classification and regression. Most of the problems solved in ML today are trained with supervised learning.

Unsupervised learning algorithms: at which only input data is available. Therefore, there is no output variable to correspond to the input data. Existing algorithms aim to learn more about the data by modeling the underlying structure in the data. The learning algorithm is not given labels and is expected to learn by itself to find the structure in the data. In some pattern recognition problems, the training data consists of input vectors x with no corresponding objective values. In such unsupervised learning problems, the aim is to find similar sample groups in the data, called clustering, or determine how the data is distributed in space, known as density estimation. Especially in clustering, many unsupervised learning algorithms are successful.

3.1.4. Artificial Neural Networks Structure

ANN, one of the techniques of artificial intelligence, and these techniques, as we mentioned above, analyze the data entered into the system in a way similar to the work of biological neural networks. The human brain and these techniques try through the entered data to set rules to understand them and then make a conclusion or prediction of the results of data that were not entered from before using different algorithms. The primary function of the ANN is to take the input data and then perform some complex calculations on it and then send the obtained results to the output part of the network. It is possible to use these systems in various fields such as business administration, industry, science, etc.

3.1.4.1. The Architecture of Artificial Neural Networks

The development of the ANN (Rosenblatt, 1958) began with introducing the concept of a single layer of sensory perception. A single-layer sensor is one of the simplest types of networks. Figure 3.3 shows the simple structure of a monolayer perceptron. It takes multiple inputs to get the output result as 0 or 1, and it works by calculating the sum of the weights of these input values.

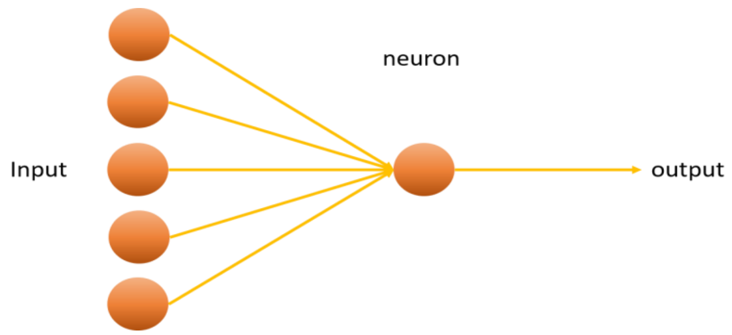


Figure 3. 3. Structure of the 1st Perceptron

This simple monolayer perceptron structure was the starting point for later structures. It can be seen that single-layer sensors, which are the first and basic models of ANN, are quite capable of solving linear problems. However, it is insufficient for nonlinear problems. Multilayer sensors have been developed to solve this problem. Multilayer sensors consist of three basic parts: input, intermediate, and output.

The first part is known as the input layer. It is the layer where the input comes from the outside world. The input is sent to the next layer without any processing in the input layer.

The middle part is called the hidden layer or layers. Information from the input layer is sent to this layer. Each layer consists of several neurons, each neuron in a layer is connected to all neurons in the previous layer.

The last part, called the output layer, is the layer in which the information from the middleware is processed, the output is produced in response to the data from the input layer.

Depending on the process, the number of cells in the output layer can be more than one. Each cell in this layer is connected to all cells of the previous layer. Figure 3.4 shows the basic architecture of a multilayer ANN. Weights connect the cells in the grid. Weights express the numerical value of cell connections and show the effect on the cell.

In some cases, an additional branch called the bias is connected to the neuron. The bias value is +1 or -1 and does not depend on the cells of the previous layer. The primary purpose of bias is to improve the problem-solving performance of ANNs.

According to their ANN structures, they are divided into feedforward and feedback categories. The following section will describe these structures: recurrent neural networks, convolutional neural networks, etc. Various DL architectures are also created by increasing the number of layers in an ANN.

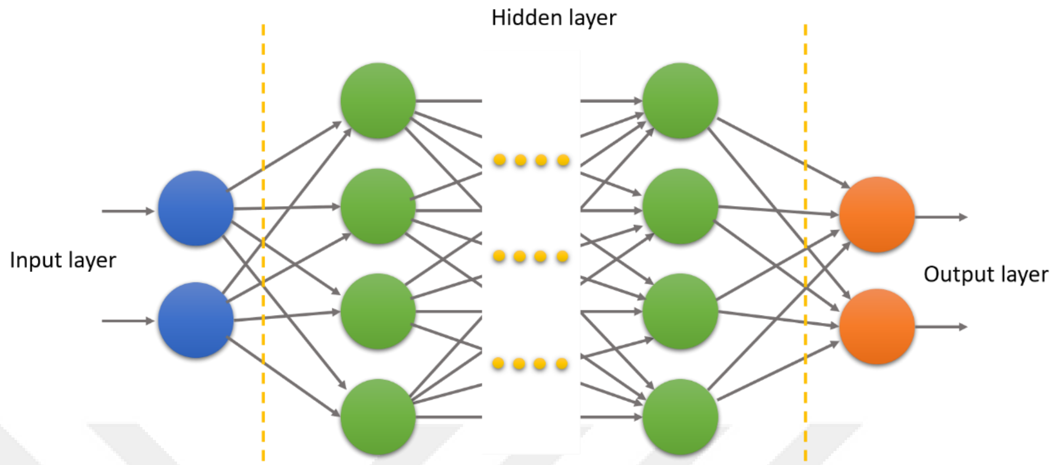


Figure 3. 4. The basic structure of a multilayer ANN

3.1.4.2. Working Principle of Artificial Neural Networks

The way ANNs work is as follows: First, inputs, also known as input vectors, are received in the input layer, then each neuron in the hidden layer takes all the values in the input layer using weights, and besides, the bias (threshold or bias) depends on the function chosen as the neuron which performs the calculation and produces output results.

The next layer takes the output results of the previous layer as the input value, performs the calculation according to the activation function, and produces the output results. Depending on the number of hidden layers, this situation continues until the output layer and the result from the output layer come out to the outside world. This means that information is constantly fed forward and never fed back. Therefore, such architectures are called feedforward neural networks.

In the following sub-title, we will discuss the Backpropagation method, which is frequently used in the training of ANNs, in which the information is fed back from the output layer. Activation functions play a vital role in the excellent performance of ANNs. The most used activation functions will be discussed below. In more straightforward classification problems, Sigmoid or Logistics, ReLu or Leaky ReLU activation function is used in problems where verification is essential.

3.1.4.3. The Most Common Types of Activation Functions

Sigmoid Activation Function: Used for mathematical equations and classification problems, this function produces values between 0 and 1 for each input value. Equation 3.1 and Figure 3.5 show the Sigmoid function:

$$F(x) = \frac{1}{1+e^{-x}} \quad \text{(Eq 3.1)}$$

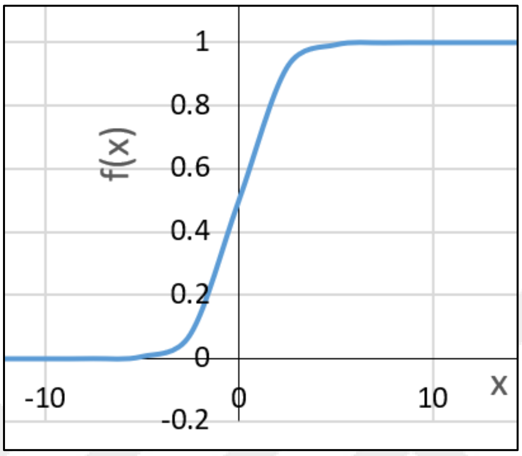


Figure 3. 5. The graphical equivalent of the sigmoid function

Tangent activation function: The corresponding function scales the input values between -1 and +1 using the threshold value. The following equation 3.2 and Figure 3.6 show the Tangent function.

$$F(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1 \quad \text{(Eq3.2)}$$

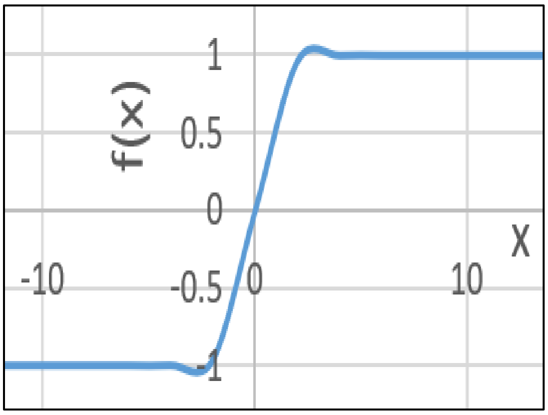


Figure 3. 6. The graphical equivalent of the tangent function.

ReLU (Rectified Linear Unit) Activation Function: It is a powerful function that only allows positive values to pass and resets all negative values. It is the most widely used activation function in Deep Learning and can only be applied in hidden layers (Krizhevsky, Sutskever, & Hinton, 2012). Equation 3.3 and Figure 3.7 represent the ReLU function.

A common problem with the ReLU activation function is that the gradient is zero for negative inputs, which means that the weights will not be updated. Therefore, this will create cells that will not be sensitive to any changes and will not become active again. Thus, a part of the network will become passive. Leaky ReLU has been proposed to solve this problem. Leaky ReLU gets very low values instead of 0 at negative values.

$$F(x) = max(0, x) \tag{Eq3.3}$$

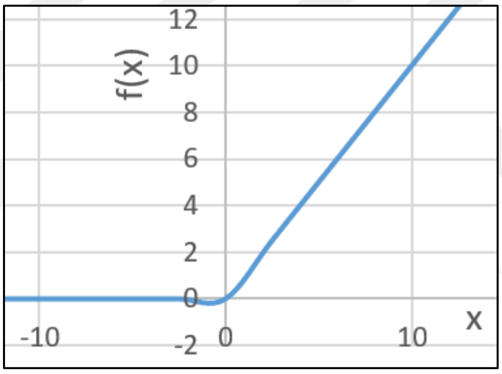


Figure 3. 7. The graphical equivalent of the ReLU function.

Choosing which activation function to use in an ANN is not always trivial. It depends on the problem to be solved; in some cases, it is necessary to combine 2 or 3 different activation functions to solve a problem.

Since it is not fully understood in detail what is going on in the hidden layers of the ANN, that is, how the transactions take place, it is referred to as a "black box." It is known how each activation function works but understanding how they work when thousands or millions of neurons are combined to produce the desired output is quite challenging.

In general, when designing ANNs to solve a problem, the number of layers to be used, the number of neurons to be used, and the type or types of activation functions to be used are the most critical decisions. Every problem is different, so no one network architecture can be an absolute fit for all problems or two similar problems. Once the ANN architecture has been determined, a good strategy is required to train the network. The following sub-title will be given information on how to train ANN.

3.1.4.4. Training Artificial Neural Networks

To train a properly functioning ANN, a large amount of data must be available. It is impossible to train an ANN to solve the related problems without sufficient data. As explained above, this situation was seen as an open problem and solved by data augmentation techniques.

The learning process starts by taking inputs from the external environment to the input layer in ANN, and the weights are randomly determined. After the received, inputs are subjected to mathematical processing in the activation function, one or more outputs are obtained in the output layer.

In the next step, the result obtained from the system is compared with the expected result, and the error rate is found by using the loss function or cost function. After the residual error rate is determined, it appears as an optimization problem, and it is aimed to minimize the error rate with the feedback method by using various optimization algorithms.

The most widely used algorithm in the training of ANN is the feedback algorithm. In feedback ANNs, the output of a cell can be fed as input to any cell in the previous or same layer. The feedback method consists of three main functions; feedforward to calculate the result, gradient taking to backward the error rate, and updating the weights with any optimization algorithm. Recently famous and frequently used optimization algorithms: Gradient Descent, Gradient descent with momentum, Scaled Conjugate Gradient, Broyden Fletcher Goldfarb Shanno Quasi-Newton, Levenberg-Marquardt, and Square Information about Route means square prop is given later in the article.

3.1.4.5. The Most Famous and Frequently Used Optimization Algorithms

Gradient Descent algorithm: Gradient Descent algorithm is one of the most popular and widely used optimization algorithms. The gradient descent algorithm is also known as the steepest descent in the literature.

The gradient descent algorithm is an iterative optimization algorithm used to find the minimum value. The primary purpose of the algorithm is to reset the parameters to random values and then take small steps in the direction of the gradient at each iteration.

This algorithm is used in deep learning models to update the weights of the ANN via backpropagation. As shown in Figure 3.8, the backpropagation algorithm sets the weights towards the negative of the gradient, that is, in the direction where the performance function decreases the fastest and tries to find the optimum point by calculating the error gradient.

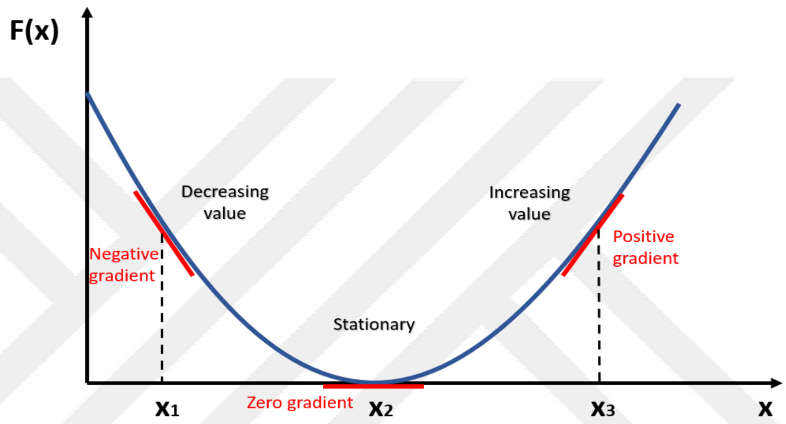


Figure 3. 8. Example of the Gradient Descent algorithm.

Gradient Descent algorithm with Momentum: Calculates the average of the exponential weights of the existing gradients and then uses the same gradient to update the weights. It helps to speed up gradient vectors by ignoring small features on the surface. It also considers previous gradients to make updating easier.

Conjugate Gradient Descent algorithm: Current-based algorithms show linear convergence in various problems. Compared to the two other algorithms mentioned above, it is faster thanks to the step size scaling mechanism. The search paths of the steepest descent and Conjugate Gradient methods are shown in Figure 3.9.

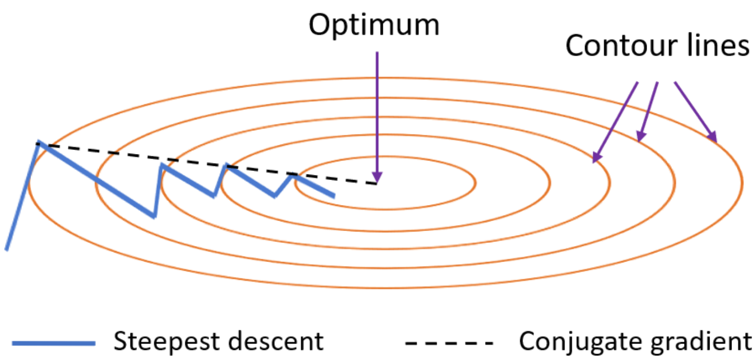


Figure 3. 9. Search paths of steepest descent and conjugate gradient methods.

BFGS, Quasi-Newton algorithm: Another widely used algorithm in network training is the BFGS Quasi-Newton algorithm. The BFGS quasi algorithm is notable for its resemblance to Newton's hill-climbing techniques, which seek a fixed function point. This technique has long been known to perform well, even in non-deep networks (Curtis and Que, 2015).

Levenberg-Marquardt algorithm works explicitly on the sum of squared error type loss functions. Instead of calculating the entire Hessian matrix, it calculates the gradient vector and the Jacobian matrix. Its dependence on Jacobian computation and the large Jacobian matrix requires much memory, making it difficult to perform well on networks and large datasets.

The root of the square mean algorithm: This algorithm was first introduced by University of Toronto member Geoffrey Hinton in Coursera lecture slides, an online education platform on ANNs. Hinton has not published the current algorithm in an official academic paper, but it is still one of the most popular gradient descent optimization algorithms for deep learning today.

The root-square-mean algorithm aims to solve the rapidly decreasing learning rates in the Adagrad algorithm using the moving average of the square gradient. It takes advantage of the magnitude of the final gradient descents to normalize the gradient. The learning rate is adjusted automatically in the current algorithm, and a different learning rate is selected for each parameter. The performance comparison of some optimization algorithms mentioned above can be seen in Figure 3.10.

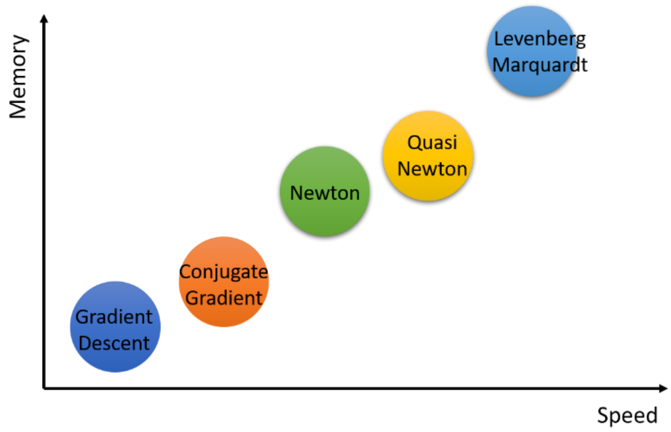


Figure 3. 10. Comparison of optimization algorithms in terms of speed and memory

As we mentioned before, the main purpose of feedback networks is to minimize the error rate by updating the weights during training. In minimizing the error rate, the weights of the ANNs are renewed, and it is aimed to use the activation function more effectively. Depending on the problem, this process is repeated hundreds, thousands, or even millions of times. Each repetition is called the round training number (epoch). The period until the weights are constantly renewed and the expected result is obtained called learning.

After fine-tuning all weights to give a near-zero error rate, the ANN is trained and expected to solve the related problem accurately. After the ANN is trained, input data that the network has never encountered before is given to the trained ANN. Then, the connection between the results it produces, and the desired result is examined.

If the desired-expected result is produced from the newly given input data, it means that the ANN has been trained correctly, and when the opposite results are produced, corrections in the hyper-parameters are required. Correct selection of hyper-parameters affects training success in feedback networks.

Therefore, hyper-parameters must be carefully selected to achieve good performance. In the continuation of the article, information will be given about the most frequently used hyper-parameters in deep learning applications.

Data set size: As mentioned earlier, data set size is one of the most critical factors for successfully training ANNs. The larger the size of our data set, the better the learning rate for the ANN architecture. However, the size of the data set may not be sufficient for a well-functioning model, and it is also crucial that the data set be more diverse. Because as the data set increases, the success rate increases somewhat.

Batch size: Processing all the data in our dataset simultaneously is very costly in time and memory. Because as mentioned above, the gradient is computed through the backpropagation process. Therefore, the more data in the gradient calculation process, the longer the calculation will take.

It is proposed to process the data in the dataset piece by piece to solve this problem. For this reason, the learning process takes place through these parts. Processing a data set in parts is called batch size in the literature. The value specified as the batch size during model creation means that the model will process as much data as that value at the same time.

The specified batch size value must be specified in proportion to the video card's memory is used. The batch size value is 2,4,8,16,32,64,128..., 512 and so on. When not determined by these values, a sudden drop in performance may occur. At the same time, the random selection of data in batch size selection will make the model more resistant to potential fraud that may occur during the training phase.

Learning rate: The learning rate controls how quickly the model adapts to the current problem. If the learning rate value is set too large, it will cause oscillation. If it is small, the learning time will take longer because it will progress step by step. A large learning rate value will result in good results, but then the results decline. It will take longer to learn with a lower learning rate, but the result will be more transparent. Therefore, the desired results will be obtained in the learning phase if the learning rate is chosen initially high and reduced with increasing iterations.

The number of training Rounds (Epoch): Two learning methods are used to calculate the data set in the backpropagation method. These methods are called online training and group training in the literature. In individual training, the weights will be updated with the backpropagation based on the error rate that will be obtained after every single element of dataset is loaded into the network.

But as we mentioned before in batch training, the weights will be updated with the backpropagation based on the error rate that will be obtained after a part of the data set is loaded into the network as a segment. Then the model is trained by piece again, and the weights are updated again. This process is repeated until the optimal weight values for the model are found. It usually takes a long time to train a model; it could take days, weeks, or even months, depending on the problem.

The number of training rounds varies according to the problem, but the number of training rounds should still be higher in the models learned from the models than in the other models. With the increase in the number of training rounds, the model's success rate will also increase because, after a specific training round, the success rate will be meager, the training process can be terminated.

Momentum coefficient: In general, it provides fast network recovery. The momentum coefficient plays an essential role in reducing the error rate. It is vital to use the momentum parameter for this reason and because it prevents network fluctuation during the learning process. However, let us stress that using the momentum coefficient is not a panacea. The value of the momentum coefficient must be between 0 and 1.

3.2. Fuzzy Logic

3.2.1. Intoduction to Fuzzy Logic

In digital systems, it is based on zero and one in classifying data or input, meaning that it is either within or outside the range, or in other words, it can be said with the logic of true and false. So, we know from this matter that a boundary clearly and purely differentiates between two groups, one belonging to a special section and another group outside it. So, in this theory, we know a sharp, clear, crisp, and unambiguous separation between the two groups.

Specifically, in the theory of numerical systems mentioned earlier, the element is not allowed to be in a set and not in the set simultaneously, and we cannot place the element in an intermediate set between the two sets. Thus, many real problems that we experience in real life cannot be described and dealt with previously. On the contrary, fuzzy set theory accepts inter-solutions, and therefore, in a sense, we can say that this method includes the previous pattern with an increased possibility of classifying some of the data between the two groups.

At the same time, in FL, we can dispense with numerical data and accept Linguistic or non-numerical data and work to classify and benefit from them to facilitate the expression of rules and facts.

FL is an extension of Boolean logic proposed by Lutfi Zadeh in 1965 based on the mathematical theory of fuzzy sets. The principle works by introducing the concept of degree into verifying a condition, thus enabling the condition to be in an incorrect or false state. FL provides invaluable flexibility in thinking. FL is an easy way to describe and represent human experience, and it offers practical solutions to real-world problems, making it possible to account for inaccuracies and uncertainties.

In order to introduce the concept of fuzzy sets, we first review the elementary set theory of numerical systems. We will find that fuzzy set theory is a natural extension of numerical system theory and a rigorous mathematical concept.

3.2.2. Basic Concepts of Ordinary Sets and Fuzzy Sets

Ordinary Sets: is defined as sharp or crisp boundaries; there is no vagueness or uncertainty in the boundaries or determinants of the group.

3.2.2.1. Operations on Ordinary Set

1. **Union:**

$$\mathrm{A} \cup \mathrm{B} = \{ \mathrm{X} \mid \mathrm{X} \in \mathrm{A} \text{ or } \mathrm{X} \in \mathrm{B}\} \quad \text{(Eq 3.4)}$$

2. **Intersection:**

$$A \cap B = \{ X \mid X \in A \; and \; X \in B \} \quad \text{(Eq 3.5)}$$

3. **Complement:**

$$A` = \{ X \mid X \notin A, X \in X \} \quad \text{(Eq 3.6)}$$

4. **Difference:**

$$A \mid B = \{ X \mid X \in A \; and \; X \notin B\} \quad \text{(Eq 3.7)}$$

3.2.2.2. Properties of Ordinary (Crisp) Sets

1. **Commutativity:**

$$A \cup B = B \cup A \quad \text{(Eq 3.8)}$$

$$A \cap B = B \cap A \quad \text{(Eq 3.9)}$$

2. Associativity:

$$A \cup (B \cup C) = (A \cup B) \cup C \quad \text{(Eq 3.10)}$$

$$A \cap (B \cap C) = (A \cap B) \cap C \quad \text{(Eq 3.11)}$$

3. Distributivity:

$$A \cup (B \cap C) = (A \cup B) \cap (A \cup C) \quad \text{(Eq 3.12)}$$

$$A \cap (B \cup C) = (A \cap B) \cup (A \cap C) \quad \text{(Eq 3.13)}$$

4. Idempotency:

$$A \cup A = A \quad \text{(Eq 3.14)}$$

$$A \cap A = A \quad \text{(Eq 3.15)}$$

5. Identity:

$$A \cup \emptyset = A \quad \text{(Eq 3.16)}$$

$$A \cap X = A \quad \text{(Eq 3.17)}$$

$$A \cap \emptyset = \emptyset \quad \text{(Eq 3.18)}$$

$$A \cup X = X \quad \text{(Eq 3.19)}$$

6. Transitivity:

$$If\ A \subseteq B\ and\ B \subseteq C, then\ A \subseteq C \quad \text{(Eq 3.20)}$$

7. Involution:

$$A'' = A \quad \text{(Eq 3.21)}$$

3.2.3. Fuzzy Sets

Fuzzy Logic: is defined as a Multivalued Logic with various degrees of values for its member elements. FL is based on "degrees of truth" than the (1 or 0) Boolean logic on which the modern computer is based.

Fuzzy set: is a group with imprecise and unclear boundaries. Hence, FL depends on the theory of fuzzy sets, and as we explained earlier, if the classical set is divided into zero and one or true and false as in numerical systems, it will become clear to us that the classical set is a particular case of the fuzzy set as shown in Figure 4.1. So, the fuzzy set can be defined as a set containing elements with varying degrees of membership values in the range from zero to one.

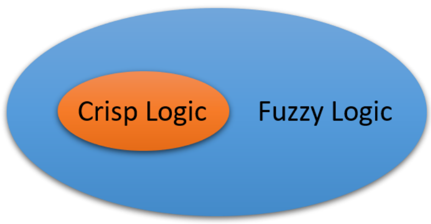


Figure 3. 11. The classical set theory is a subset of the theory of fuzzy sets

3.2.3.1 Fuzzy Set Operations

The following operations are commonly used on fuzzy sets and see their representation in Figure 4.2:

1. **Inclusion:**

$$A \subseteq B \leftrightarrow \mu_A (X) \leq \mu_B (X) \qquad \text{(Eq 3.22)}$$

2. **Equality:**

$$A = B \leftrightarrow \mu_A (X) = \mu_B (X) \qquad \text{(Eq 3.23)}$$

3. **Complement:**

$$\mu_{A'} (X) = 1 - \mu_A (X) \qquad \text{(Eq 3.24)}$$

4. **Intersection:**

$$\mu_{A \cap B}(x) = \min \{\mu_A (X), \mu_B (X)\} \qquad \text{(Eq 3.25)}$$

5. **Union:**

$$\mu_{A \cup B}(x) = \max \{\mu_A (X), \mu_B (X)\} \qquad \text{(Eq 3.26)}$$

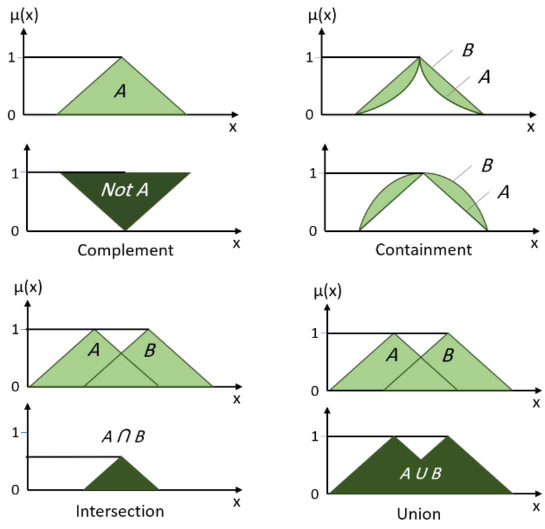


Figure 3. 12. Representation Fuzzy Set Operations

It is known in classical logic that the variable takes one of the two values (0,1) or (T, F). If the universal set X is taken, for example, A is a subset of set X, then any element of the constituent set either belongs to the subset A or does not belong to this group. If a group of people is taken as a comprehensive group, the group of children aged ≤ 10 years is taken as a subgroup A of the group of persons, then the person either belongs to children group A or does not belong, so a ten-year old person will suddenly lose his childhood within a few days.

The FL presents a suitable solution for cases where the variable is assigned a degree of belonging to the actual field [0,1] instead of the group (0,1). This helps in determining the affiliation of the element to the subgroup. For example, a person assigns a three-year-old child group affiliation score of 0.8, 10 years old assigns a 0.4, and 13 years old 0.1.

3.2.4. Difference between Classical Set and Fuzzy Set

3.2.4.1. Classical set

Crisp boundaries define a classical set. There is no uncertainty in the prescription or location of the boundaries of the set. Therefore, if there is an element of the universe that either belongs to the set or does not, as shown in Figure 3.13.

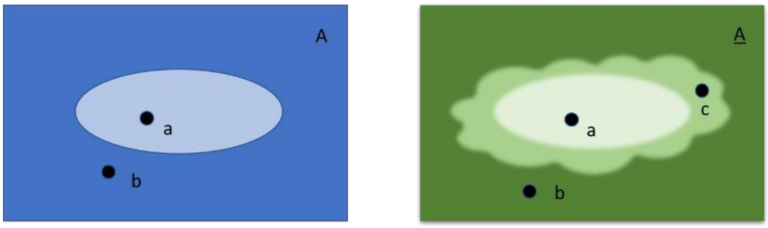


Figure 3. 13. Diagrams for (A) crisp set boundary and (A) fuzzy set boundary

The total number of elements in a universe X is called its cardinal number, denoted nx, where x is a label for individual elements in the universe.

Collections of elements within a universe are called sets, and collections of elements within sets are called subsets. We define the null set Ø as the set containing no elements, and the whole set, X, as the set of all elements in the universe.

3.2.4.2. Fuzzy Set

Vague or ambiguous properties prescribe a fuzzy set; hence its boundaries are ambiguously specified. Fuzzy set theory permits the gradual assessment of the membership of elements in a set, described with the aid of an MF valued in the actual unit [0,1]. A membership degree is a real number on [0, 1]. In extreme cases, if the degree is 0, the element does not belong to the set, and if one, the element belongs 100% to the set.

The excluded middle axioms and De Morgan's principles are two unique properties of set operations. Let us suggest we have two sets, A and B. We use the excluded middle axioms to describe the given sets that are not valid for classical and fuzzy sets. We have two excluded middle axioms. The first one, called the axiom of the excluded middle, deals with the union of a set A and its complement. The second one, called the axiom of contradiction, represents the intersection of a set A and its complement.

All Properties of classical and fuzzy sets are similar, except for two excluded middle axioms mentioned above. In the fuzzy sets, can the set and its complement overlap. For ordinary extended sets, we can express it by the excluded middle axioms as follows:

$$A \cup A` \neq X \qquad \text{(Eq 3.27)}$$

$$A \cap A` \neq \emptyset \qquad \text{(Eq 3.28)}$$

All other operations on classical sets also apply to fuzzy sets, except for the excluded middle axioms. This is because fuzzy sets can overlap their boundaries, and this also makes the possibility that a set can overlap its complement. For extended fuzzy sets, we can express it by the excluded middle axioms as follows:

$$A \cup A` \neq X \qquad \text{(Eq 3.29)}$$

$$A \cap A` \neq \emptyset \qquad \text{(Eq 3.30)}$$

3.2.5. Fuzzy Membership Functions

Based on the foregoing, it became clear that there is often overlap between ambiguous groups. Therefore, there was an urgent need to define relationships that control the element's affiliation to any group and the degree of its association with that group, which was expressed by the fuzzy relationships.

Using the Cartesian plane and fuzzy relations, we can determine the affiliation of element A, for example, to the X or Y group. Then we give a degree representing the strength of the relationship between the element and the group with an organic function on the unit interval [0,1]. And then we get the fuzzy relationship R that shows the exact and correct placement of the element in the Cartesian plane where the power of assignment is expressed through the MF $\mu_R(X, Y)$

The type of the MF is one of the following functions depending on statistical studies: polynomial, hyperbolic, triangular, sigmoid, trapezoidal, exponential, tangent, generalized bell-shaped, Gaussian, and any other functions can be used or could be chosen depending on the advice of the experts.

The MF is defined as mapping elements in a domain of concern into their membership value in a set.

Triangular depends on three parameters a, b, and c and are given by:

$$f(X; a, b, c) = \begin{cases} 0 & for\ X < a \\ \frac{X-a}{b-a} & for\ a \leq X < b \\ \frac{c-X}{c-b} & for\ b \leq X < c \\ 0 & for\ X > c \end{cases} \quad \text{(Eq 3.31)}$$

Trapezoidal curves depend on four parameters and are given by:

$$f(X; a, b, c, d) = \begin{cases} 0 & for\ X < a \\ \frac{X-a}{b-a} & for\ a \leq X < b \\ 1 & for\ b \leq X < c \\ \frac{d-X}{d-c} & for\ c \leq X < d \\ 0 & for\ d \leq X \end{cases} \quad \text{(Eq 3.32)}$$

The π-shaped MFs are given by (Giarratano and Riley, 1993):

$$f(X; b, c) = \begin{cases} S\left(X; c-b, c-\frac{b}{2}, c\right) & for\ X \leq c \\ 1 - S\left(X; c, c+\frac{b}{2}, c+b\right) & for\ X > c \end{cases} \quad \text{(Eq 3.33)}$$

Where S (X; a, b, c) represents a MF defined as:

$$S(X;a,b,c) = \begin{cases} 0 & for\ X < a \\ \frac{2(X-a)^2}{(c-a)^2} & for\ a \le X < b \\ 1 - \frac{2(X-c)^2}{(c-a)^2} & for\ b \le X \le c \\ 1 & for\ X > c \end{cases} \quad \text{(Eq 3.34)}$$

In the previous equation, a, b, and c are the parameters that are adjusted to fit the desired membership data. Gaussian curves depend on two parameters σ and c and are represented by:

$$f(X;\sigma,c) = \exp\left[\frac{-(X-c)^2}{2\sigma^2}\right] \quad \text{(Eq 3.35)}$$

MFs are associated with term sets that appear in the antecedent or consequent of rules when designing a fuzzy inference system.

3.2.6. Fuzzy Cartesian Product and Composition

Let we have two fuzzy sets A and B on two universes X and Y Respectively, then the Cartesian product between the two fuzzy sets A and B will give in fuzzy relation R, which is represented by the following equation:

$$A \text{ x } B = R \subset X \text{ x } Y \quad \text{(Eq 3.36)}$$

Where relation R has MF given as:

$$\mu_R(X,Y) = \mu_{A\times B}(X,Y) = \min(\mu_A(X), \mu_B(Y)) \quad \text{(Eq 3.37)}$$

In equation (Eq4.33), the Cartesian product is applied in the same way we apply the cross-product of two vectors. It is not the same as the arithmetic product. So, for example, if we have two fuzzy sets, A and B, and the fuzzy set A has three elements, and the fuzzy set B has two elements, then we will notice that a matrix of size 3 × 2 represents the resulting fuzzy relation R.

The fuzzy composition can be obtained through crisp relations. Suppose we have three fuzzy relations R, S, and T on the different Cartesian spaces (X x Y), (Y x Z), and (X x Z) respectively, then we can represent the fuzzy max-min composition as shown below:

$$T = R\ o\ S \quad \text{(Eq 3.38)}$$

$$\mu_T(X,Z) = \vee_{y\in Y}(\mu_R(X,Y) \wedge \mu_s(Y,Z)) \quad \text{(Eq 3.39)}$$

Also, fuzzy max - product composition can be written in terms of MF theoretically as follows:

$$\mu_T(X,Z) = \vee_{y\in Y}(\mu_R(X,Y) \bullet \mu_s(Y,Z)) \qquad \text{(Eq 3.40)}$$

It should be noted out that neither crisp nor fuzzy compositions are commutative in general so:

$$R\ o\ S \neq S\ o\ R \qquad \text{(Eq 3.41)}$$

Different types of composition are (1) MAX-MIN (2) MAX –PRODUCT (3) MAX-MAX (4) MIN- MIN (5) MIN-MAX etc. Composition provides more information which reduces the impreciseness present in the problem.

3.2.7. Fuzzy Inference System

A fuzzy inference system (FIS) is a nonlinear system using fuzzy rules to map the input data vector and converts them into a scalar output.

The mapping process consists of:

1. Input and output MFs

2. FL operators

3. Fuzzy if-then rules

4. Aggregation of output sets

5. Defuzzification.

Figure 3.14 displays four FIS components: the fuzzifier, inference engine, rule base, and defuzzifier. Figure 3.15. shows chematic diagram of a fuzzy inference system.

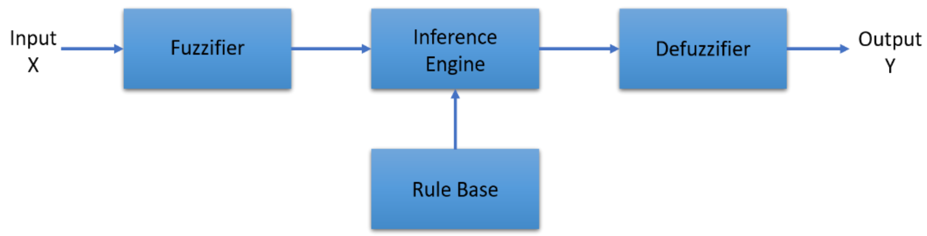


Figure 3. 14. Block diagram of a fuzzy inference system

The rule base contains linguistic rules that experts provide. Once the rules are set, FIS can set the input vector and get the output vector from it.

The fuzzifier maps input numbers into corresponding fuzzy memberships. This is required to activate rules that are in terms of linguistic variables.

The fuzzifier's role is to get input values then determine the degree of belonging to each fuzzy set that we have by using the MFs. The inference engine defines the mapping from fuzzy input sets into fuzzy output sets. It determines the degree to which the antecedent is satisfied for each rule. If the antecedent of a given rule has more than one clause, fuzzy operators are applied to obtain one number representing the result of that rule's antecedent. One or more rules may operate at the same time.

Then the Outputs for all rules are aggregated. The fuzzy output sets obtained from each rule are merged into a single fuzzy set in this process.

The role of the defuzzifier converts fuzzy output sets into a crisp number. It converts the fuzzy set that contains a range of output values to a single number so that the fuzzy set turns into a precise number.

Several methods for defuzzification are used in practice, including the centroid, maximum, mean of maxima, height, and modified height defuzzifier. The most popular defuzzification method is the centroid, which calculates and returns the center of gravity of the aggregated fuzzy set.

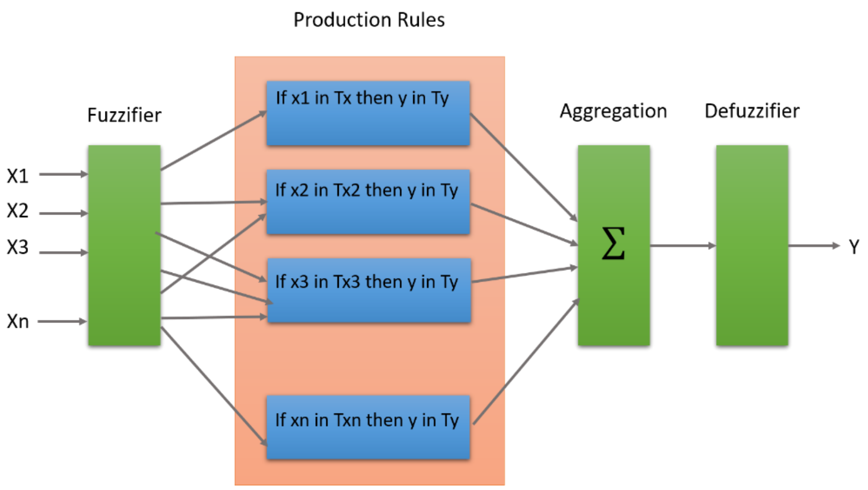


Figure 3. 15. Schematic diagram of a fuzzy inference system.

3.2.8. Fuzzification

Fuzzification is the process of converting the crisp values into a fuzzy value, meaning if we say that a student has a mark of 17, it will be converted to the maximum mark and the minimum mark or to pass and fail and so on, of course within the specified range from zero to one after specifying the MFs.

Some methods are used to generate membership values, which in turn are used to transform crisp values into fuzzy ones, including inference, intuition, rank-ordering, using GA, using ANN, inductive reasoning, Meta rules, and fuzzy statistics.

3.2.9. Fuzzy Rules

In FL systems, a rule is created that controls the outputs, and this rule is based on a simple principle (conditional if-then). After working on this rule, the results are extracted.

IF x is A THEN y is B, this statement represents a fuzzy rule depending on a conditional statement form.

where x and y are linguistic variables; A is a linguistic value on the universe of discourse X, and B is linguistic value on the universe of discourse Y, which is determined by fuzzy sets.

There are many ways to represent knowledge in the field of artificial intelligence and ML. One of the most common ways of doing this is the "if-then" hypothesis that translates to a large extent the human way of thinking.

This method usually helps to reach conclusions if we have some facts (antecedent, premise, hypothesis), in that case, we can understand the above or reach new conclusions that were not known before, and this is necessary in the context of linguistics because we do not have numerical values in some cases. It refers to knowledge practical and empirical close to human language.

Despite this, it cannot understand some of the deep things usually associated with feelings, intuition, and behavior because these are among the things that are difficult to express and reduce into linguistic phrases that we can benefit from correctly.

Therefore, we find that systems based on fuzzy rules are more realistic and effective in representing complex systems because they are based on linguistic variables that give them an advantage due to their proximity to human language.

3.2.10. Defuzzification

Defuzzification is the reverse process of the fuzzification process, which converts linguistic values into quantitative values that can be measured to be used in machines because they only understand two numerical values, namely zero and one. This can be done in one of the following ways: Centroid method, weighted average method, the maximum method, Mean-max membership method, height method, modified height method, Centre of sums method, Centre of largest area method, and First (or last) of maxima method, etc.

Five methods of the above could be described as below:

1. Centroid defuzzification method: By this method, the center of gravity (centroid) yi' of B is determined by the defuzzifier then that value is used as the output of the FLS. So, if we have an aggregated fuzzy set, the centroid will be given by:

$$y` = \frac{\int_s y_i \mu_B(y)\, dy}{\int_s \mu_B(y)\, dy} \tag{Eq 3.42}$$

2. Maximum-decomposition method: The maximum value that output y for which $\mu_B(y)$ of the aggregated fuzzy set is examined and chosen by the defuzzifier. The maximum-decomposition method has properties better than the centroid method and is more applicable to a narrower class of problems.

3. Centre of maxima: This method could be used in a multimode fuzzy region, by this technique could find the highest plateau and the next highest plateau. After that, the midpoint between the centers of these plateaus must be determined.

4. Height defuzzification: By this method, firstly, the $\mu_{B_i}(y)$ at y'1 is evaluated, and then the output of the FLS is computed by the defuzzifier, where Bi is the center of gravity of fuzzy sets. Output yh, in this case, is given by:

$$y_h = \frac{\sum_{i=1}^{m} y_i' \mu_B(y_i)}{\sum_{i=1}^{m} \mu_B(y_i)} \tag{Eq 3.43}$$

Where m represents the number of fuzzy output sets obtained after implication, and y'i represents the centroid of fuzzy region i.

CHAPTER IV

FINDINGS & DISCUSSION

4.1 Calculations depending on Fuzzy Logic

In this chapter, the inputs and outputs that have been worked on using FL and ANN will be reviewed, and three suggested scenarios will be made to compare the results and indicate some possibilities that may occur in practice.

4.1.1. The Used Dataset

The basic idea of this work is that the machine is purely managerial decision-making. Administrative decisions may not often contain numerical statistics but rather be based on linguistic variables only. This may relate to senior management positions in most cases, as these positions may be compelled to decide despite the lack of data that helps them do so. That is why we often say that they are ambiguous estimated values that do not have specific numbers.

Table 4. 1: The used dataset

Strength of Interest	Inclusion of Interest	Expectation Of Interest	Fields of Interest				
			Religion	Soul	Brain	Race	Money
Essential	General	Current	120	119	118	117	116
Essential	General	Expected	115	114	113	112	111
Essential	Partially General	Current	110	109	108	107	106
Essential	Private Transitive	Current	105	104	103	102	101
Requirement	General	Current	100	99	98	97	96
Essential	Private minor	Current	95	94	93	92	91
Essential	Partially General	Expected	90	89	88	87	86
Requirement	General	Expected	85	84	83	82	81
Essential	Private Transitive	Expected	80	79	78	77	76
Essential	Private minor	Expected	75	74	73	72	71
Requirement	Partially General	Current	70	69	68	67	66
Requirement	Private Transitive	Current	65	64	63	62	61

Requirement	Private minor	Current	60	59	58	57	56
Requirement	Partially General	Expected	55	54	53	52	51
Improvement	General	Current	50	49	48	47	46
Improvement	General	Expected	45	44	43	42	41
Requirement	Private Transitive	Expected	40	39	38	37	36
Requirement	Private minor	Expected	35	34	33	32	31
Improvement	Partially General	Current	30	29	28	27	26
Improvement	Partially General	Expected	25	24	23	22	21
Improvement	Private Transitive	Current	20	19	18	17	16
Improvement	Private minor	Current	15	14	13	12	11
Improvement	Private Transitive	Expected	10	9	8	7	6
Improvement	Private minor	Expected	5	4	3	2	1

Therefore, this problem was one of the most critical problems that we faced in this thesis: obtaining comprehensive and complete administrative data that can be used in ML to take administrative decisions, especially since the higher administrative positions are sensitive positions in all institutions. So, it is difficult to share and obtain such data so easily because of the privacy and confidential information it contains regarding the affairs of the institution.

The other thing is that in some institutions, there may not be archiving of these administrative decisions in the form of tabular data that can be used in the research and engineering field.

Therefore, work has been done by communicating with the departments of humanities and administration to obtain some studies that may help the director in the DM process and identify priorities in the administrative process. Table 4.1 has been obtained from those departments. This table and the idea of dividing it were reviewed in a book called “Rules in the Classification of Priorities and their Applications in the Palestinian Issue" by Dr. Muhammad Melhem (Muhammad Melhem, 2019). This Arabic reference contained this table and the order of life priorities based on four variables: the Strength of Interest (SOI), the Inclusion of Interest (IOI), the Expectation of Interest (EOI), and the Field of Interest (FOI).

In this table, a numerical scale appears from one to one hundred and twenty, and this scale represents the Degree of Priority (DOP) in DM, as the lowest priority is the case that carries the value one and which corresponds to the four variables as follow: (SOI: improvement, IOI: special minor, EOI: expected, and FOI: money).

As for the highest priority, the case has the value one hundred and twenty, which corresponds to the four variables as follows: (SOI: essential, IOI: general, EOI: current, and FOI: religion).

These datasets, which was taken from the metioned book previously, is formed from a set of fundamental rules based on the religious science of the Islamic religion. These rules are concerned with determining the priority of the religious judgment which their priority arranged by the Islamic religion.

These rules, some of them depend on the degree of strength of the interest, others depend on the degree of expectation of their occurrence, other rules depend on the degree of their spread and other rules depend on the sectors of their effectiveness.

These bases are divided into different sectors. Each of the factors was taken and correlated with factors from other sectors. And since these rules are overlapping and interdependent with each other, each case consisting of these factors has become a case with a specific degree in the priority scale.

4.1.2. The outputs of the system

It was proposed to divide the outputs into five fuzzy sets based on the experts' recommendations. These five categories represent the system's outputs, called the DOP. The five ranks are, respectively: lowest priority, low priority, medium priority, high priority, and the highest priority.

Table 4.2 shows this division, which has been adopted, and this table has been applied and worked on using the MATLAB program, and the results obtained will be shown in the upcoming sections.

Table 4. 2: The degree priority with fuzzy sets for the entered variables

Strength of Interest	Inclusion of Interest	Expectation Of Interest	Fields of Interest					Degree of Priority
			Religion	Soul	Brain	Race	Money	
Essential	General	Current	120	119	118	117	116	highest priority
Essential	General	Expected	115	114	113	112	111	
Essential	Partially General	Current	110	109	108	107	106	
Essential	Private Transitive	Current	105	104	103	102	101	
Requirement	General	Current	100	99	98	97	96	high priority
Essential	Private minor	Current	95	94	93	92	91	
Essential	Partially General	Expected	90	89	88	87	86	
Requirement	General	Expected	85	84	83	82	81	
Essential	Private Transitive	Expected	80	79	78	77	76	
Essential	Private minor	Expected	75	74	73	72	71	
Requirement	Partially General	Current	70	69	68	67	66	medium priority
Requirement	Private Transitive	Current	65	64	63	62	61	
Requirement	Private minor	Current	60	59	58	57	56	
Requirement	Partially General	Expected	55	54	53	52	51	
Improvement	General	Current	50	49	48	47	46	low priority
Improvement	General	Expected	45	44	43	42	41	
Requirement	Private Transitive	Expected	40	39	38	37	36	
Requirement	Private minor	Expected	35	34	33	32	31	
Improvement	Partially General	Current	30	29	28	27	26	
Improvement	Partially General	Expected	25	24	23	22	21	
Improvement	Private Transitive	Current	20	19	18	17	16	lowest priority
Improvement	Private minor	Current	15	14	13	12	11	
Improvement	Private Transitive	Expected	10	9	8	7	6	
Improvement	Private minor	Expected	5	4	3	2	1	

4.1.3. Application on the MATLAB Program

A MATLAB program was used (© 1994-2019 The MathWorks, Inc.) to represent the data practically, and the MFs for each variable will be presented, and the results discussed.

4.1.3.1. Membership Function (MF)

As we defined earlier, the MF is a function that maps elements in a domain of concern into their membership value in a set.

The type of MF worked on Trapezoidal curves depend on four parameters and are given by:

$$f(X; a, b, c, d) = \begin{cases} 0 & for\ X < a \\ \frac{X-a}{b-a} & for\ a \le X < b \\ 1 & for\ b \le X < c \\ \frac{d-X}{d-c} & for\ c \le X < d \\ 0 & for\ d \le X \end{cases} \qquad \text{(Eq 4.1)}$$

a) The Membership Function of the Strength Of Interest (SOI)

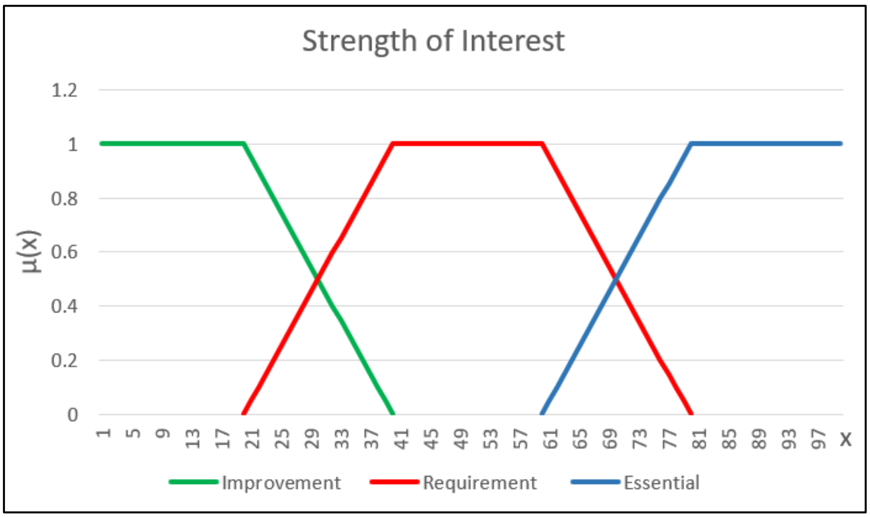


Figure 4. 1. The MF of the SOI

1. Improvement – SOI = (1/20, 0.5/30, 0/40)
2. Requirement – SOI = (0/20, 0.5/30, 1/40, 1/60, 0.5/70, 0/80)
3. Essential – SOI = (0/60, 0.5/70, 1/80)

b) The Membership Function of Inclusion Of Interest (IOI)

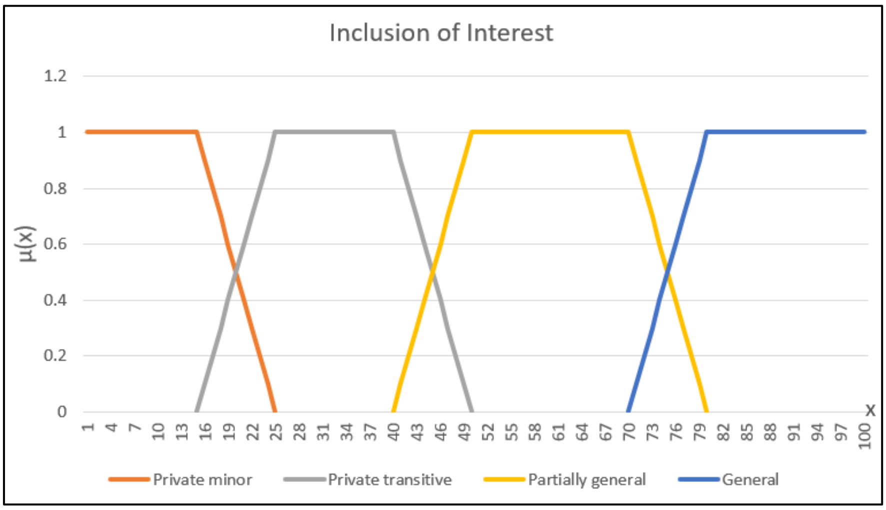


Figure 4. 2. The MF of IOI

1. Private minor – IOI = (1/15, 0.5/20, 0/25)
2. Private transitive – IOI = (0/15, 0.5/20, 1/25, 1/40, 0.5/45, 0/50)
3. Partially general – IOI = (0/40, 0.5/45, 1/50, 1/70, 0.5/75, 0/80)
4. General – IOI = (0/70, 0.5/75, 1/80)

c) The Membership Function of Expectation Of Interest (EOI)

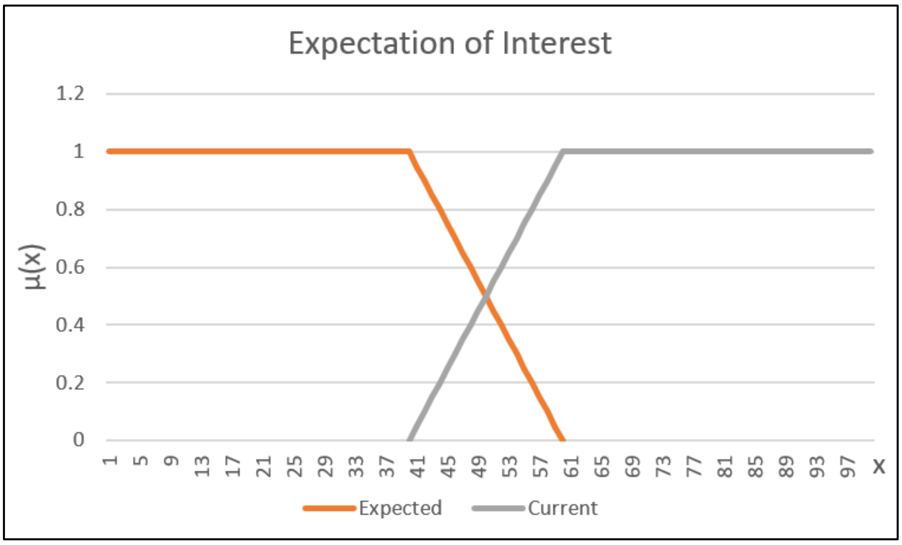


Figure 4. 3. The MF of EOI

1. Expected – EOI = (1/40, 0.5/50, 0/60)
2. Current – EOI = (0/40, 0.5/50, 1/60)

d) The Membership Function of Fields Of Interest (FOI)

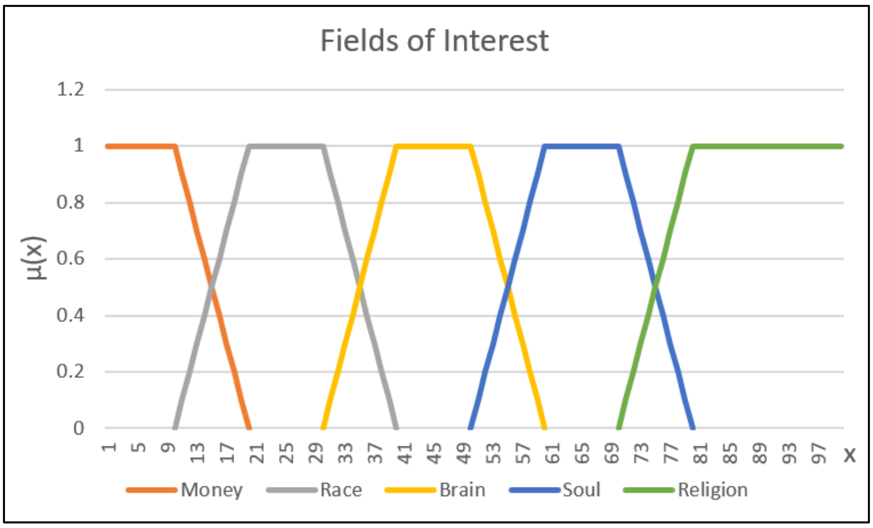


Figure 4. 4. The MF of FOI

1. Money – FOI = (1/10, 0.5/15, 0/20)
2. Race – FOI = (0/10, 0.5/15, 1/20, 1/30, 0.5/35, 0/40)
3. Brain – FOI = (0/30, 0.5/35, 1/40, 1/50, 0.5/55, 0/60)
4. Soul – FOI = (0/50, 0.5/55, 1/60, 1/70, 05/75, 0/80)
5. Religion – FOI = (0/70, 0.5/75, 1/80)

e) The Membership Function of Degree of Priority (DOP)

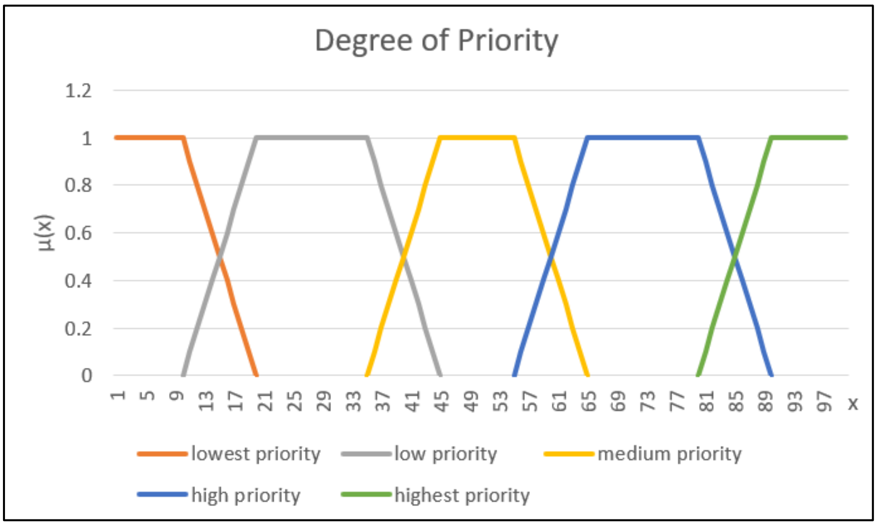


Figure 4. 5. The MF of DOP

4.1.3.2. The Used Rules

The used rules depend mainly on the used data table, as the rules were developed to include all cases based on the suggested division in Table 4.3.

Three scenarios will be made to show the impact of the inputs on the obtained results if the used weights or the entered data are different.

The basic rules that were used in the basic scenario are as follows:

Table 4. 3: The representation of the used rules

	Strength of Interest		**Inclusion of Interest**		**Expectation Of Interest**	**Fields of Interest**						**Degree of Priority**
						Religi	**Soul**	**Brain**	**Race**	**Mone**		
IF	Essential	AND	General	AND		ALL WEIGHTS ARE EQUAL (1)					THEN	highest priority
	Essential		Partially General		Current							
	Essential		Private Transitive		Current							
	Requirement		General			ALL WEIGHTS ARE EQUAL (1)						high priority
	Essential		Private minor									
	Essential		Partially General		Expected							
	Essential		Private Transitive		Expected							
	Requirement		Partially General			ALL WEIGHTS ARE EQUAL (1)						medium priority
	Requirement		Private Transitive		Current							
	Requirement		Private minor		Current							
	Improvement		General			ALL WEIGHTS ARE EQUAL (1)						low priority
	Requirement		Private Transitive		Expected							
	Requirement		Private minor		Expected							
	Improvement		Partially General									
	Improvement		Private Transitive			ALL WEIGHTS ARE EQUAL (1)						lowest priority
	Improvement		Private minor									

4.1.4. Suggested Scenarios

The idea of the proposed scenarios is to review these different scenarios that could affect the results to reach the best scenario that simulates human thinking. Therefore, the machine will be able to reach the same or similar human decisions.

4.1.4.1. First Scenario

In this scenario, the weights related to the FOI are proposed to be the same ,which equals one, meaning that no one has preference over the other, and they are all of the same ranks of priority.

We proposed twenty samples. These samples were carefully selected to include all possible and expected cases to compare the three scenarios through these samples and find out which one is closer to simulating human thinking. The samples are shown in Table 4.4 below.

In this scenario, the previously mentioned rules in Table 4.3 will be used without any changes and will be tested by the twenty samples that we refer to before, and the results will be observed and then compared with other scenarios later. Figures 4.6,4.7 show the simulation of first scenario by MATLAB.

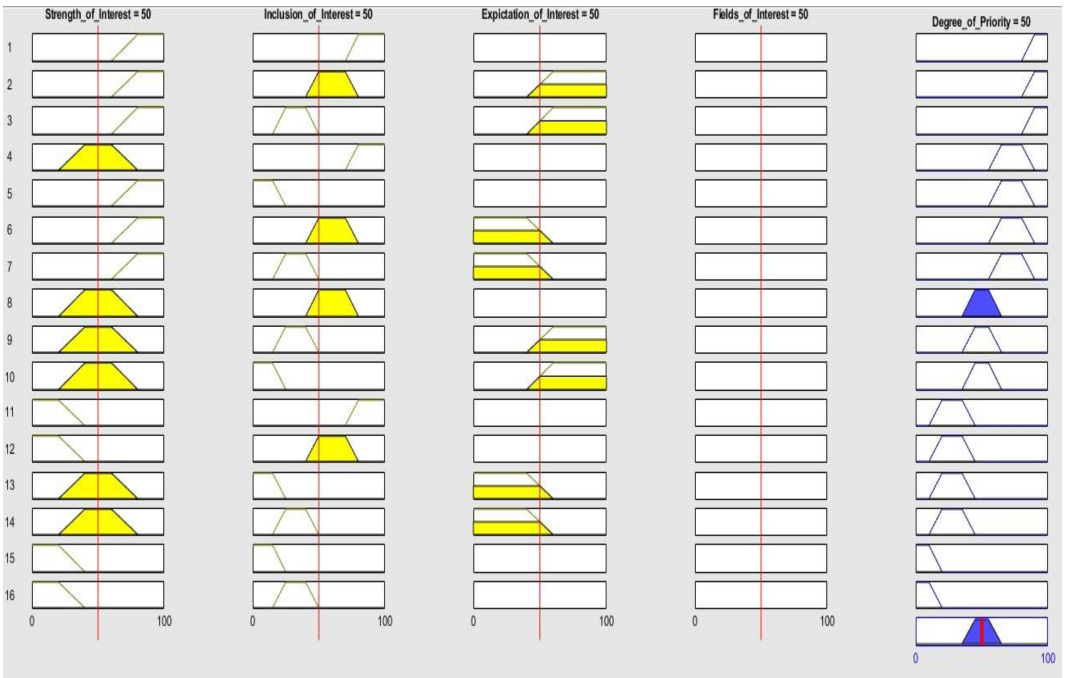


Figure 4. 6. The Rules of MFs of all systems for a special case (1st scenario)

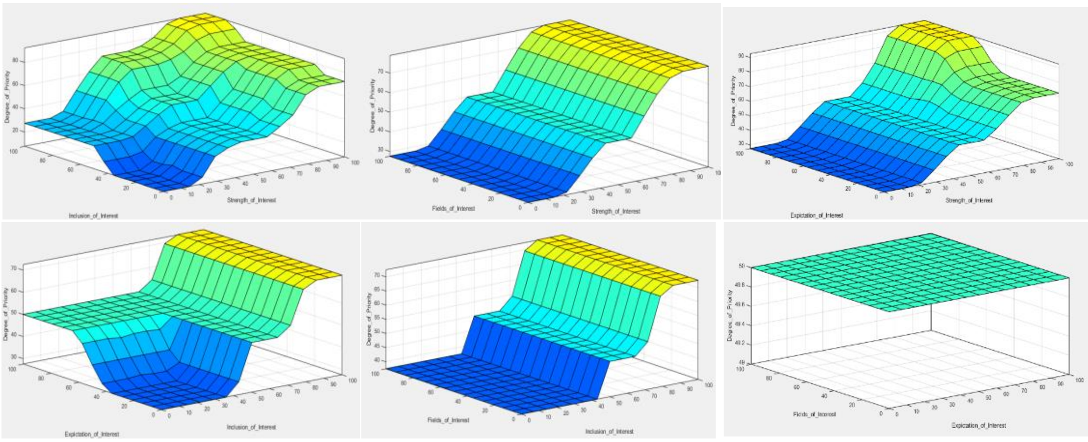


Figure 4. 7. The representation of MFs of all systems for a special case as a surface (1st scenario)

Table 4. 4: The proposed cases of twenty inputs (1st scenario)

Case no.	Strength of Interest	Inclusion of Interest	Expectation Of Interest	Fields of Interest	Degree of Priority
1.	20	10	30	10	7.52
2.	30	20	50	15	31
3.	50	30	70	25	50
4.	70	45	30	35	50
5.	80	60	50	45	78.8
6.	20	75	70	55	27.5
7.	30	90	30	65	49.9
8.	50	10	50	75	37.5
9.	70	20	70	85	69
10.	80	30	30	10	72.2
11.	20	45	50	15	21
12.	30	60	70	25	37.4
13.	50	75	30	35	62.5
14.	70	90	50	45	78.9
15.	80	10	70	55	72.4
16.	20	20	30	65	8.56
17.	30	30	50	75	31
18.	50	45	70	85	50
19.	70	60	30	10	62.4
20.	80	75	50	15	78.8

4.1.4.2. Second Scenario

In this scenario, the weights of the FOI will be determined according to the strength of its influence in the DM and the priority of the decision.

The religion will be given a weight of 1, the soul 0.7, the mind 0.5, the race 0.3, and the money 0.2. Figures 4.8 and 4.9 show the simulation of second scenario by MATLAB.

The obtained results by applying second scenario could be seen in Table 4.5.

Figure 4. 8. The Rules of MFs of all systems for a special case (2nd scenario)

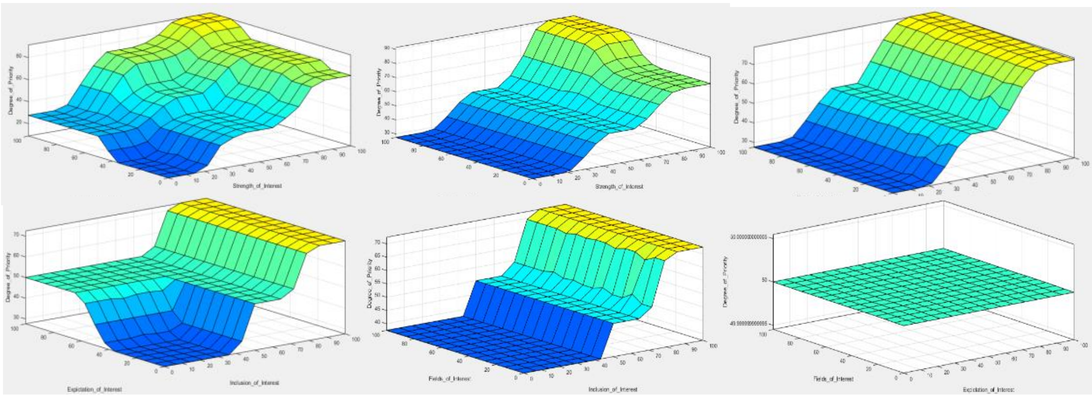


Figure 4. 9. The representation of MFs of all systems for a special case as a surface (2nd scenario)

Table 4. 5: The proposed cases of twenty inputs (2nd scenario)

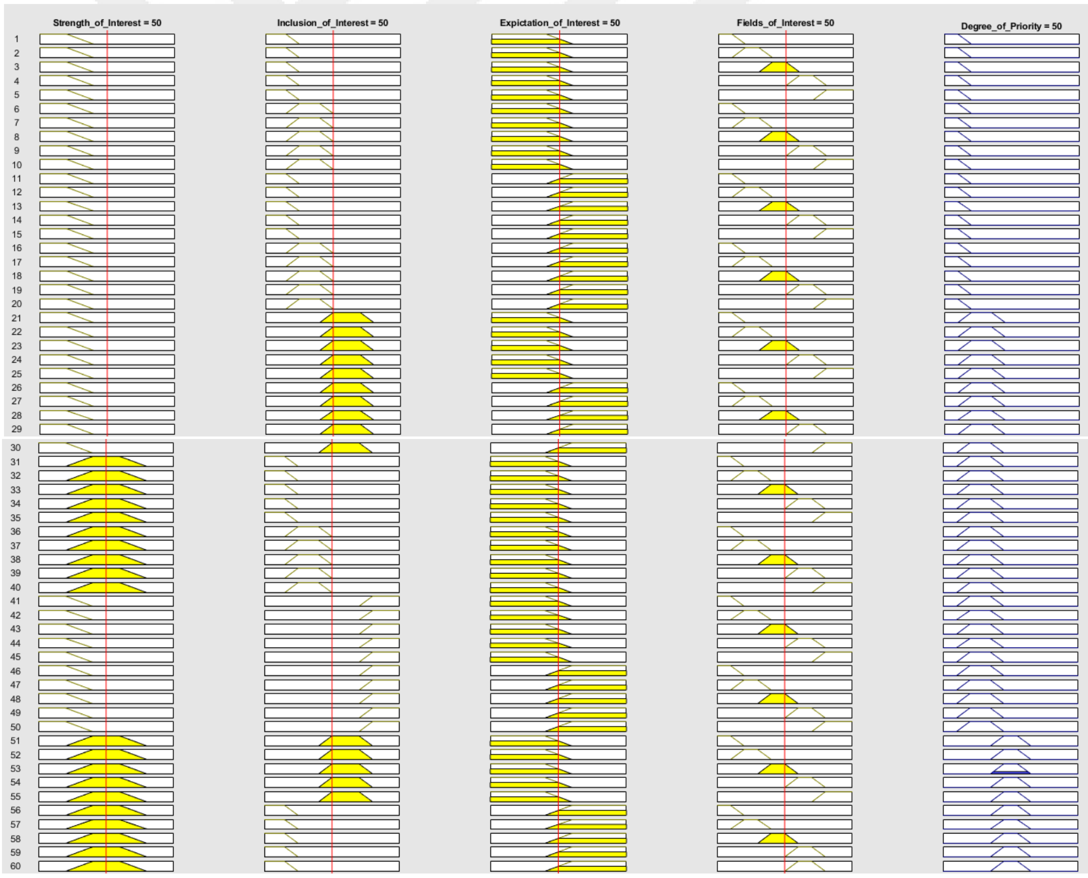
Case no.	Strength of Interest	Inclusion of Interest	Expectation Of Interest	Fields of Interest	Degree of Priority
1.	20	10	30	10	9.26
2.	30	20	50	15	31.8
3.	50	30	70	25	50
4.	70	45	30	35	50
5.	80	60	50	45	78.2
6.	20	75	70	55	27.5
7.	30	90	30	65	49.9
8.	50	10	50	75	37.5
9.	70	20	70	85	69
10.	80	30	30	10	72.3
11.	20	45	50	15	21.8
12.	30	60	70	25	37.4
13.	50	75	30	35	62.5
14.	70	90	50	45	78.4
15.	80	10	70	55	72.3
16.	20	20	30	65	8.89
17.	30	30	50	75	31
18.	50	45	70	85	50
19.	70	60	30	10	62.4
20.	80	75	50	15	78

4.1.4.3. Third Scenario

In this scenario, weights were imposed in proportions appropriate to each case, meaning that each rule for the hundred and twenty cases we are studying took a different weight. The obtained results by applying these weights are seen in Table 4.6.

This scenario calculated the weights by dividing the weight from one hundred by one hundred and twenty existing cases and then converting it to a percentage as shown in Eq 4.2. The first case, which represents the minor priority cases in our study, was taken, and the weight was 0.00833333, and each case bears the same difference from the following case. The highest priority condition was carrying one full weight, meaning one hundred percent. Figures 4.10, 4.11 show the simulation of third scenario.

Weight of case = (100/120) % x case no (Eq 4.2)



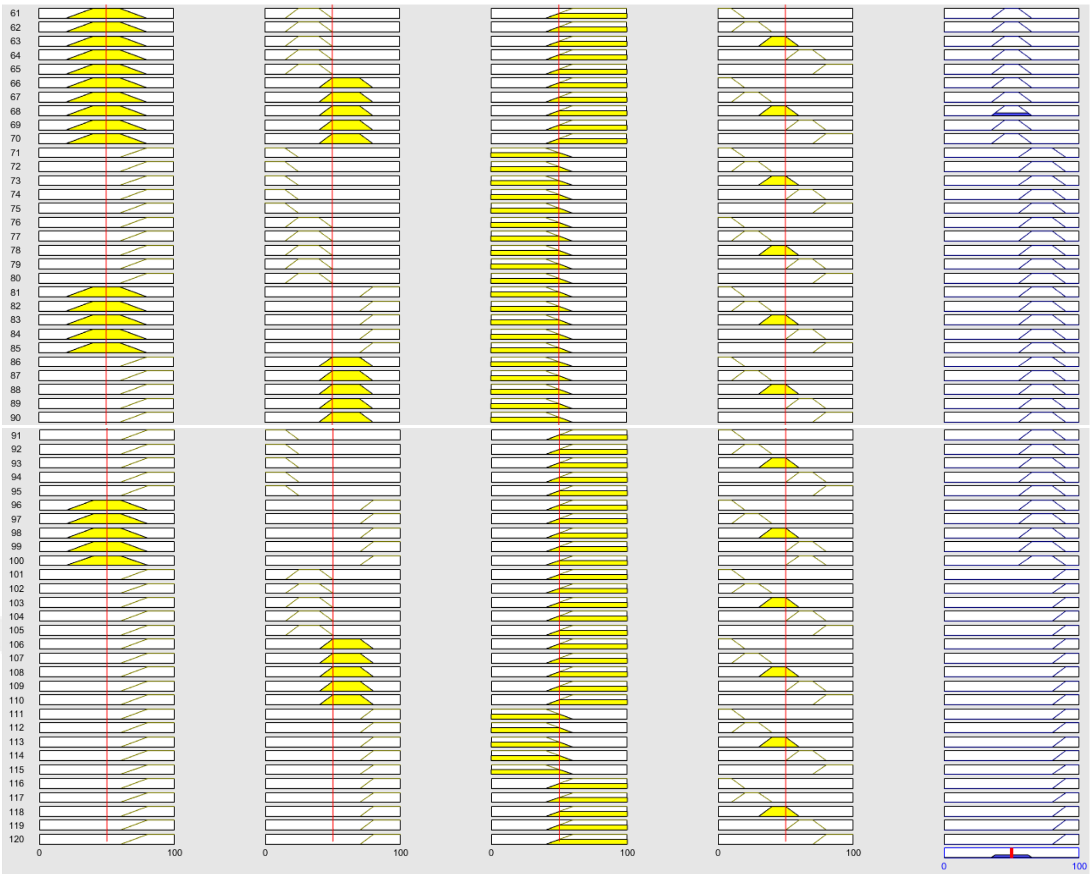


Figure 4. 10. The Rules of MFs of all systems for a special case (3rd scenario)

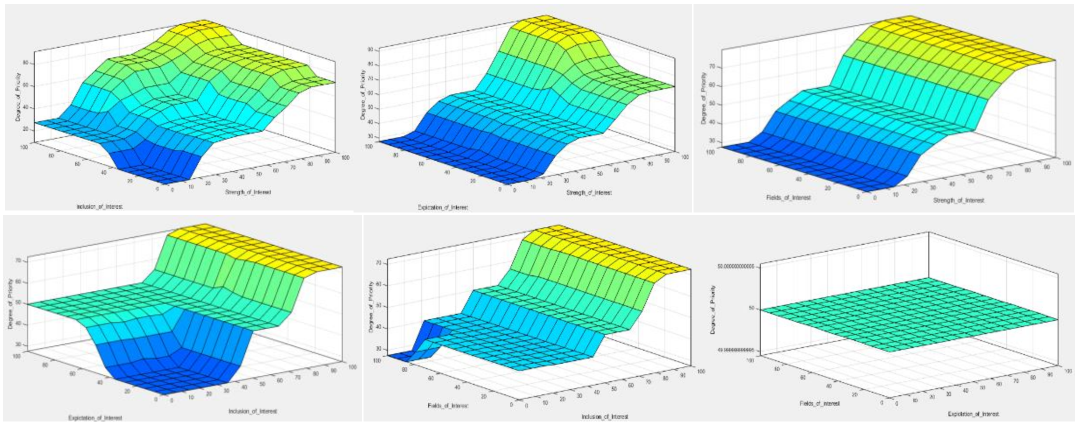


Figure 4. 11. The representation of MFs of all systems for a special case as a surface (3rd scenario)

Table 4. 6: The proposed cases of twenty inputs (3rd scenario)

Case no.	Strength of Interest	Inclusion of Interest	Expectation Of Interest	Fields of Interest	Degree of Priority
1.	20	10	30	10	9.5
2.	30	20	50	15	38.2
3.	50	30	70	25	50
4.	70	45	30	35	56.8
5.	80	60	50	45	79.6
6.	20	75	70	55	27.5
7.	30	90	30	65	56.4
8.	50	10	50	75	40.7
9.	70	20	70	85	71.6
10.	80	30	30	10	72.4
11.	20	45	50	15	23.7
12.	30	60	70	25	42.7
13.	50	75	30	35	64.9
14.	70	90	50	45	79.7
15.	80	10	70	55	72.4
16.	20	20	30	65	9.5
17.	30	30	50	75	37.8
18.	50	45	70	85	50
19.	70	60	30	10	65.2
20.	80	75	50	15	80.1

4.1.5. Results

Table 4. 7: The comparison between the three scenarios

Case no.	Degree of Priority			The result as a fuzzy value
	1st scenario	2nd scenario	3rd scenario	
1	7.52	9.26	9.5	lowest priority
2	31	31.8	38.2	low priority
3	50	50	50	medium priority
4	50	50	56.8	medium priority
5	78.8	78.2	79.6	high priority
6	27.5	27.5	27.5	low priority
7	49.9	49.9	56.4	medium priority
8	37.5	37.5	40.7	low priority
9	69	69	71.6	high priority
10	72.2	72.3	72.4	high priority
11	21	21.8	23.7	low priority
12	37.4	37.4	42.7	medium priority
13	62.5	62.5	64.9	high priority
14	78.9	78.4	79.7	high priority
15	72.4	72.3	72.4	high priority
16	8.56	8.89	9.5	lowest priority
17	31	31	37.8	low priority
18	50	50	50	medium priority
19	62.4	62.4	65.2	high priority
20	78.8	78	80.1	high priority

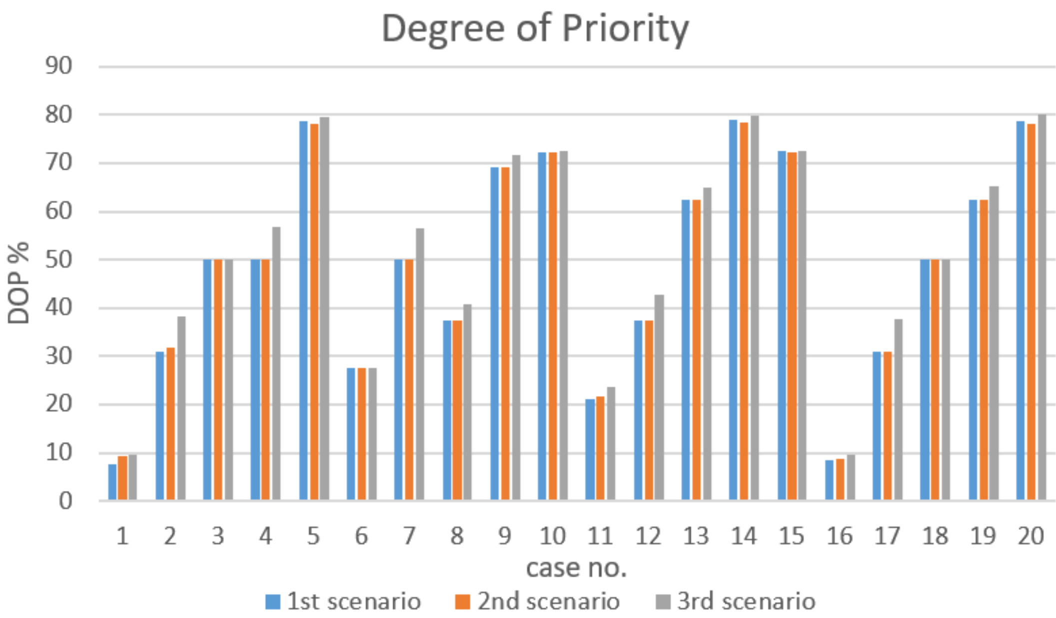


Figure 4. 12. The representations of the three scenarios as column chart

Based on Table 4.7 and Figure 4.12, we find that the difference between the first and second scenarios is negligible and straightforward, based on the selected cases, because there is no difference between the weights in the FOI factor in the first scenario. All domains have the same weight, whose value is one. We understand that the FOI does not influence the decision, so the priority does not change if the FOI changes.

In the second scenario, the weights are differed according to the values that we explained earlier in the second scenario section, but we note that some of the cases shown were less than the first scenario, some of them completely equal, and some slightly higher than them.

The difference in the results between the first and second scenarios is due to the location of the twenty samples for the membership functions and the suggested weights for each scenario. This is clear in that the second scenario is higher than the first example of case No. 11.

When the results are equal between the first and second scenarios, as in case No. 18, for example, we find that the weights are equal between the two scenarios, but in the case that the second scenario is less than the first, as in case number 20, because the weights in the first scenario are all equal to one, but in the second scenario, only the debt domain is equal to one.

In the last scenario, we do not find this fluctuation present, but the cases take constant non-vibrating values because each case had the weight that affects the case itself only. So, the more accurate the used weights and the more accurate classification of cases for user data that we get from the experts, we will be able to simulate human decisions better and get better results. The machine will have the ability to determine which decisions are first in the implementation based on which gets the highest value according to our proposed model.

4.2. Calculations Depending on Artificial Neural Network Principle

We will study the impact of using ANN technology and its effectiveness in prioritizing administrative DM and then work on the design of a proposed ANN that uses the same data that was used before in the chapter of FL so that we can compare the two cases and the effectiveness of each of them.

4.2.1. The Used Inputs

As we mentioned earlier that the dataset that we will use in this chapter is the same as the previous data for comparison purposes, but we made some modifications to the data, meaning that we converted the linguistic variables into numerical variables so that the ANN can understand and study the data correctly.

We have made several attempts to represent linguistic data numerically, but the most correct and more reality is presented in the following Table 4.8, which helped us reach the desired results highly accurately.

The modifications that we made consisted in giving each variable within each factor affecting DM a value that represents it under this factor and not others. Our study included four main factors that affect DM: the SOI, the IOI, the EOI, and the FOI.

For example, we took the first factor, which is the SOI, which contains three classifications, namely Essential, Requirement and Improvement, and we gave each of them a number of its own according to its importance, so we gave the Essential a value of 3, the Requirement a value of 2 and the Improvement a value of 1.

Furthermore, in the FOI, we gave religion a value of 5, Soul a value of 4, Brain a value of 3, Race a value of 2, and Money a value of 1.

Likewise, the results were divided into numbers, so the Highest Priority took a value of 5, High Priority a value of 4, Medium Priority a value of 3, Low Priority a value of 2 ,and Lowest Priority a value of 1, as shown in Table 4.8.

Table 4. 8: New representation of the same data

Strength of Interest		Inclusion of Interest		Expectation Of Interest		Fields of Interest		Degree of Priority		Degree of Priority
Essential	3	General	4	Current	2	Religion	5	120	5	highest priority
Essential	3	General	4	Current	2	Soul	4	119	5	
Essential	3	General	4	Current	2	Brain	3	118	5	
Essential	3	General	4	Current	2	Race	2	117	5	
Essential	3	General	4	Current	2	Money	1	116	5	
Essential	3	General	4	Expected	1	Religion	5	115	5	
Essential	3	General	4	Expected	1	Soul	4	114	5	
Essential	3	General	4	Expected	1	Brain	3	113	5	
Essential	3	General	4	Expected	1	Race	2	112	5	
Essential	3	General	4	Expected	1	Money	1	111	5	
Essential	3	Partially General	3	Current	2	Religion	5	110	5	
Essential	3	Partially General	3	Current	2	Soul	4	109	5	
Essential	3	Partially General	3	Current	2	Brain	3	108	5	
Essential	3	Partially General	3	Current	2	Race	2	107	5	
Essential	3	Partially General	3	Current	2	Money	1	106	5	
Essential	3	Private Transitive	2	Current	2	Religion	5	105	5	
Essential	3	Private Transitive	2	Current	2	Soul	4	104	5	
Essential	3	Private Transitive	2	Current	2	Brain	3	103	5	
Essential	3	Private Transitive	2	Current	2	Race	2	102	5	
Essential	3	Private Transitive	2	Current	2	Money	1	101	5	
Requirement	2	General	4	Current	2	Religion	5	100	4	high priority
Requirement	2	General	4	Current	2	Soul	4	99	4	
Requirement	2	General	4	Current	2	Brain	3	98	4	
Requirement	2	General	4	Current	2	Race	2	97	4	
Requirement	2	General	4	Current	2	Money	1	96	4	
Essential	3	Private minor	1	Current	2	Religion	5	95	4	
Essential	3	Private minor	1	Current	2	Soul	4	94	4	

Essential	3	Private minor	1	Current	2	Brain	3	93	4	
Essential	3	Private minor	1	Current	2	Race	2	92	4	
Essential	3	Private minor	1	Current	2	Money	1	91	4	
Essential	3	Partially General	3	Expected	1	Religion	5	90	4	
Essential	3	Partially General	3	Expected	1	Soul	4	89	4	
Essential	3	Partially General	3	Expected	1	Brain	3	88	4	
Essential	3	Partially General	3	Expected	1	Race	2	87	4	
Essential	3	Partially General	3	Expected	1	Money	1	86	4	
Requirement	2	General	4	Expected	1	Religion	5	85	4	
Requirement	2	General	4	Expected	1	Soul	4	84	4	
Requirement	2	General	4	Expected	1	Brain	3	83	4	
Requirement	2	General	4	Expected	1	Race	2	82	4	
Requirement	2	General	4	Expected	1	Money	1	81	4	
Essential	3	Private Transitive	2	Expected	1	Religion	5	80	4	
Essential	3	Private Transitive	2	Expected	1	Soul	4	79	4	
Essential	3	Private Transitive	2	Expected	1	Brain	3	78	4	
Essential	3	Private Transitive	2	Expected	1	Race	2	77	4	
Essential	3	Private Transitive	2	Expected	1	Money	1	76	4	
Essential	3	Private minor	1	Expected	1	Religion	5	75	4	
Essential	3	Private minor	1	Expected	1	Soul	4	74	4	
Essential	3	Private minor	1	Expected	1	Brain	3	73	4	
Essential	3	Private minor	1	Expected	1	Race	2	72	4	
Essential	3	Private minor	1	Expected	1	Money	1	71	4	
Requirement	2	Partially General	3	Current	2	Religion	5	70	3	
Requirement	2	Partially General	3	Current	2	Soul	4	69	3	
Requirement	2	Partially General	3	Current	2	Brain	3	68	3	
Requirement	2	Partially General	3	Current	2	Race	2	67	3	medium priority
Requirement	2	Partially General	3	Current	2	Money	1	66	3	
Requirement	2	Private Transitive	2	Current	2	Religion	5	65	3	
Requirement	2	Private Transitive	2	Current	2	Soul	4	64	3	

Requirement	2	Private Transitive	2	Current	2	Brain	3	63	3	
Requirement	2	Private Transitive	2	Current	2	Race	2	62	3	
Requirement	2	Private Transitive	2	Current	2	Money	1	61	3	
Requirement	2	Private minor	1	Current	2	Religion	5	60	3	
Requirement	2	Private minor	1	Current	2	Soul	4	59	3	
Requirement	2	Private minor	1	Current	2	Brain	3	58	3	
Requirement	2	Private minor	1	Current	2	Race	2	57	3	
Requirement	2	Private minor	1	Current	2	Money	1	56	3	
Requirement	2	Partially General	3	Expected	1	Religion	5	55	3	
Requirement	2	Partially General	3	Expected	1	Soul	4	54	3	
Requirement	2	Partially General	3	Expected	1	Brain	3	53	3	
Requirement	2	Partially General	3	Expected	1	Race	2	52	3	
Requirement	2	Partially General	3	Expected	1	Money	1	51	3	
Improvement	1	General	4	Current	2	Religion	5	50	2	low priority
Improvement	1	General	4	Current	2	Soul	4	49	2	
Improvement	1	General	4	Current	2	Brain	3	48	2	
Improvement	1	General	4	Current	2	Race	2	47	2	
Improvement	1	General	4	Current	2	Money	1	46	2	
Improvement	1	General	4	Expected	1	Religion	5	45	2	
Improvement	1	General	4	Expected	1	Soul	4	44	2	
Improvement	1	General	4	Expected	1	Brain	3	43	2	
Improvement	1	General	4	Expected	1	Race	2	42	2	
Improvement	1	General	4	Expected	1	Money	1	41	2	
Requirement	2	Private Transitive	2	Expected	1	Religion	5	40	2	
Requirement	2	Private Transitive	2	Expected	1	Soul	4	39	2	
Requirement	2	Private Transitive	2	Expected	1	Brain	3	38	2	
Requirement	2	Private Transitive	2	Expected	1	Race	2	37	2	
Requirement	2	Private Transitive	2	Expected	1	Money	1	36	2	
Requirement	2	Private minor	1	Expected	1	Religion	5	35	2	
Requirement	2	Private minor	1	Expected	1	Soul	4	34	2	
Requirement	2	Private minor	1	Expected	1	Brain	3	33	2	

Requirement	2	Private minor	1	Expected	1	Race	2	32	2	
Requirement	2	Private minor	1	Expected	1	Money	1	31	2	
Improvement	1	Partially General	3	Current	2	Religion	5	30	2	
Improvement	1	Partially General	3	Current	2	Soul	4	29	2	
Improvement	1	Partially General	3	Current	2	Brain	3	28	2	
Improvement	1	Partially General	3	Current	2	Race	2	27	2	
Improvement	1	Partially General	3	Current	2	Money	1	26	2	
Improvement	1	Partially General	3	Expected	1	Religion	5	25	2	
Improvement	1	Partially General	3	Expected	1	Soul	4	24	2	
Improvement	1	Partially General	3	Expected	1	Brain	3	23	2	
Improvement	1	Partially General	3	Expected	1	Race	2	22	2	
Improvement	1	Partially General	3	Expected	1	Money	1	21	2	
Improvement	1	Private Transitive	2	Current	2	Religion	5	20	1	lowest priority
Improvement	1	Private Transitive	2	Current	2	Soul	4	19	1	
Improvement	1	Private Transitive	2	Current	2	Brain	3	18	1	
Improvement	1	Private Transitive	2	Current	2	Race	2	17	1	
Improvement	1	Private Transitive	2	Current	2	Money	1	16	1	
Improvement	1	Private minor	1	Current	2	Religion	5	15	1	
Improvement	1	Private minor	1	Current	2	Soul	4	14	1	
Improvement	1	Private minor	1	Current	2	Brain	3	13	1	
Improvement	1	Private minor	1	Current	2	Race	2	12	1	
Improvement	1	Private minor	1	Current	2	Money	1	11	1	
Improvement	1	Private Transitive	2	Expected	1	Religion	5	10	1	
Improvement	1	Private Transitive	2	Expected	1	Soul	4	9	1	
Improvement	1	Private Transitive	2	Expected	1	Brain	3	8	1	
Improvement	1	Private Transitive	2	Expected	1	Race	2	7	1	
Improvement	1	Private Transitive	2	Expected	1	Money	1	6	1	
Improvement	1	Private minor	1	Expected	1	Religion	5	5	1	

Improvement	1	Private minor	1	Expected	1	Soul	4	4	1
Improvement	1	Private minor	1	Expected	1	Brain	3	3	1
Improvement	1	Private minor	1	Expected	1	Race	2	2	1
Improvement	1	Private minor	1	Expected	1	Money	1	1	1

4.2.2. The Outputs of the System

As work was done in the fuzzy logic system, we used ANNs to determine the degree of priority of each of the input cases.

As shown in the previous table, the learning method of the network that we used here is supervised learning.

We also used the MATLAB program to simulate the ANNs applied to the attached data, and its details will be discussed successively.

4.2.3. Application ANN Mathematically

4.2.3.1. Architecture for Given Data

In the input layer, we need at least four neurons, each node representing one of the inputs. As for the outputs, one output is sufficient because there is only one value that the system must give us, which is the DOP.

We will also need a hidden layer because the classification of our data is not linear, but there are many overlaps so that we will need a more complex classification process than the linear pattern, which makes us need hidden layers, as given in Figure 4.13.

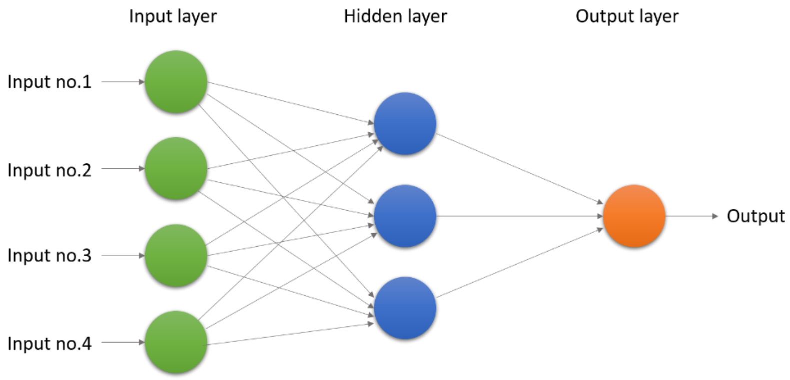


Figure 4. 13. Architecture for given data

4.2.3.2. The weights values of the inputs data

In addition to the above, we need the ANN system to determine the values of weights as shown in Figure 4.14, which have an essential role in the classification process and obtaining results, which can be imposed starting and after the work of the system, it will modify the values of the weights based on the operations that the system will use to reach the desired results.

In our case, we use the Mean Squared Errors (MSE) algorithm to help us determine weights and modify them. Moreover, we must not forget that in the inputs, the value of the Bais must be added, which its role gives the activation function freedom of movement with decision boundary in the classification mission.

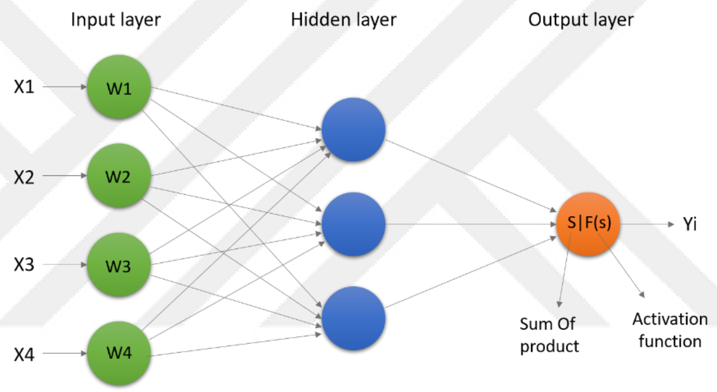


Figure 4. 14. Representation of weights

$$S = SOP\ (X_i, W_i) \tag{Eq. 4.3}$$

$$S = \sum_{1}^{m} X_i\ W_i \tag{Eq. 4.4}$$

Where X_i represents inputs and W_i represents weights of inputs, Bias can be added to eq 4.4.

4.2.3.3. Components of Output Layers

The output layer consists of two parts, the first one is the Sum of Product (SOP) for the input values with weights, and the second one is the activation function. The activation function is a function to match the SOP with the classification of the categories that represent the output. It means this function obtains a value from the SOP and then determines which class of output it belongs to.

We have many activating functions, for example, Base Weiss Linear, Sigmoid, and Signum. The activation function is chosen based on the number of classes for the outputs that will be obtained, which in our case, we are studying are five classes.

4.2.3.4. Learning Rate and Epoch

The learning rate is a parameter representing the speed of the network's response in dealing with the changes that occur. This rate has a value ranging between zero and one. If its value is closer to one, it will learn faster and interact very quickly with changes, but this negatively affects the stability of the system and the occurrence of an error. However, if the value decreases, it will take more time, but the noise will be less, and the system will be more stable.

Moreover, as we explained earlier in the ANNs chapter, the epoch represents the number of times the network learned and reached a state with no or significantly reduced error.

4.2.3.5. Artificial neural network training steps

The steps of training an ANN are:

1. Weight’s initialization.
2. Inputs application.
3. Sum of inputs-weights products.
4. Activation function response calculation.
5. Weight’s adaptation in case of wrong output value.
6. Back to step 2 and repeat until no error.

If the predicted output is not the same as the desired output, then the weights are to be adapted according to the following equation:

$$W(n+1) = W(n) + \eta \left[y_d\,(n) - y_p\,(n)\right] X(n) \qquad \text{(Eq. 4.5)}$$

Where $W(n+1)$: The new weight to be calculated, $W(n)$: The current weight that did not pass the classification process, η: learning rate, $y_d\,(n)$: desired output, $y_p\,(n)$: predicted output, and $X(n)$: input value.

4.2.4. Application on the MATLAB Program

A MATLAB program was used (© 1994-2019 The MathWorks, Inc.) to represent the data practically.

The Prototype of the Implemented Neural Network: The properties of the network were used; network type: Feed-Forward Propagation, the training algorithm type was chosen Levenberg-Marquardt TRAINLM, the type of the adaption learning function LEARNGDM, the performance function MSE, the number of layers selected 2, the number of neurons for hidden layer 10, and the transmission function is TANSIG.

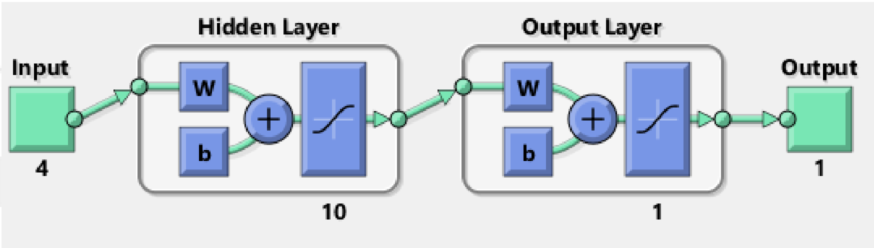


Figure 4. 15. Graphic representation of the selected ANN

After the main characteristics to be applied to the network were selected, as shown in Figure 4.15, the network was trained on the entered data, and the results were as follows: The network took an estimated 427 epoch until it reached the stage where there is no error between the obtained output and the desired output, by adjusting the weights in each error case. As we can see, the results were satisfactory, and this shows the degree of small error obtained from this network as shown in Table 4.9.

Table 4. 9: The results for the training of the ANN (test scenario)

Scenario no.	Test
Epoch	427
Time	14 sec
Performance	5.39E-11
Gradient	9.98E-08
µ	1.00E-08
Validation Checks	0

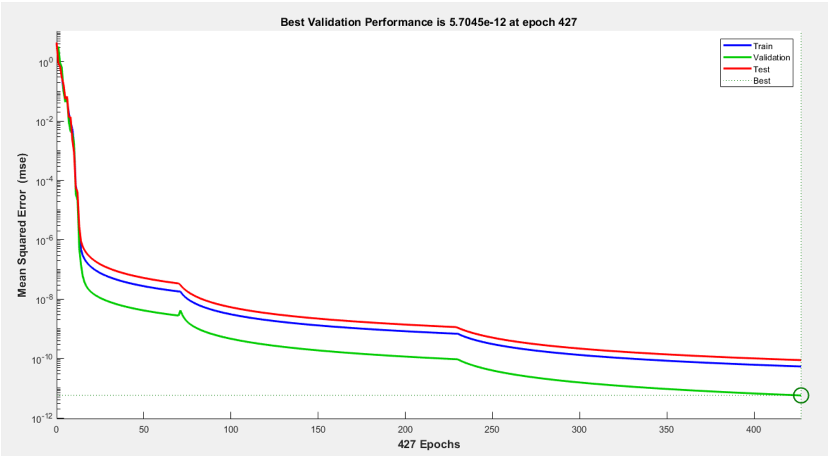


Figure 4. 16. Graphical representation of errors for validation, training, and testing (test scenario)

In Figure 4.16, we can note that the error with continuous training of the network decreases, and the difference between the obtained outputs and the desired outputs is minimal to the point of zero, as its values are reduced, as shown, to 5e-12. This means that the training is excellently effective. In addition to that, it increases in accuracy with every epoch until it reaches the knowledge of the exact weights.

4.2.5. Dividing the data into three sections :learning, validation, and testing

Knowing that the data available to us is very little for the ML process and to obtain the necessary accuracy, we are forced to work with it only due to the lack of administrative data that we have tried to obtain and the problems that we encountered that we previously explained.

Therefore, the data will be divided into three parts, training, validation, and testing.

As shown below in Table 4.10, our data was divided into three sections: a training section with 70%, which is equivalent to 84 samples of the data, a 15% validation section, which is equivalent to 18 samples, and a testing section by 15%, which is equivalent to 18 samples. The results of the base scenario are shown in Tables 4.11, 4.12 and Figure 4.17.

Table 4. 10: Dividing data into three sections

Training	70%	84 Samples
Validation	15%	18 Samples
Testing	15%	18 Samples

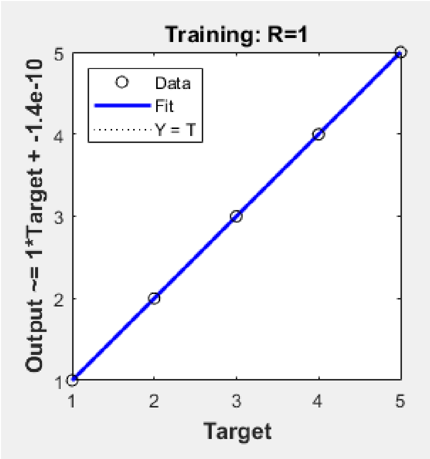
Table 4. 11: The results of MSE and Regression for all samples (base scenario)

	Samples	MSE	R
Training	84	3.0687E-19	1
Validation	18	7.8462E-19	1
Testing	18	1.42968E-18	1

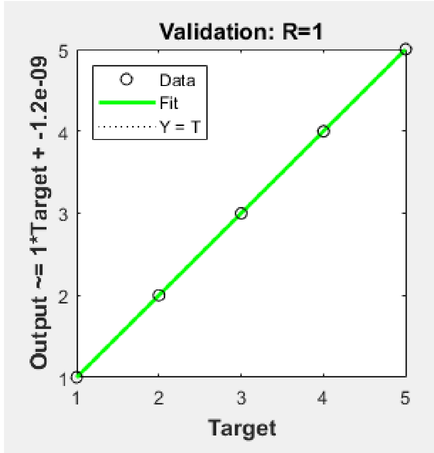
Table 4. 12: The results for the training of the ANN (base scenario)

Scenario no.	Base
Epoch	19
Time	3 sec
Performance	3.07E-19
Gradient	9.64E-10
μ	1.00E-08
Validation Checks	0
No. of Neurons in the hidden layer	10

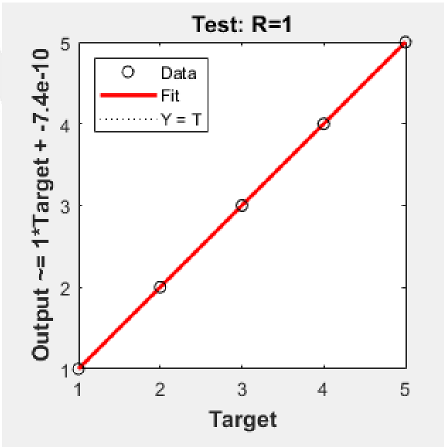
It is important to note that our results will change because of the change in the initial conditions and samples used whenever we repeat the learning process. For example, in the first case, the number of epochs was 427 see Table 4.9, while in this attempt, it was 19 see Table 4.12.



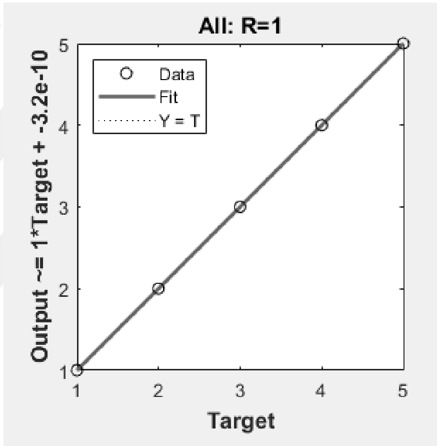
(a)



(b)



(c)



(d)

Figure 4. 17. The results of dividing data (base scenario)

Mean Squared Error (MSE): is the average squared difference between outputs and targets. This means, when the MSE values are low, it indicates that the expected results approximate the desired results, and zero means that there is no error. Values of Regression R measure the correlation between outputs and targets. An R-value of 1 means a close relationship, 0 a random relationship.

In Figure 4.17 (a), we can see that the error between the obtained outputs and the desired outputs in the case of training is tiny, as well as in the case of validation as shown in Figure 4.17 (b) and the testing case as shown in Figure 4.17 (c), and we see in Figure 4.17 (d) the sum of the three cases. The obtained output is equal to the desired output which is required.

4.2.5.1. The Second Scenario

We only changed the number of neurons in the hidden layer in the second scenario and selected only one. We kept the last division of the data in the same proportions between training, validation, and testing. The results are shown in Tables 4.13, 4.14.

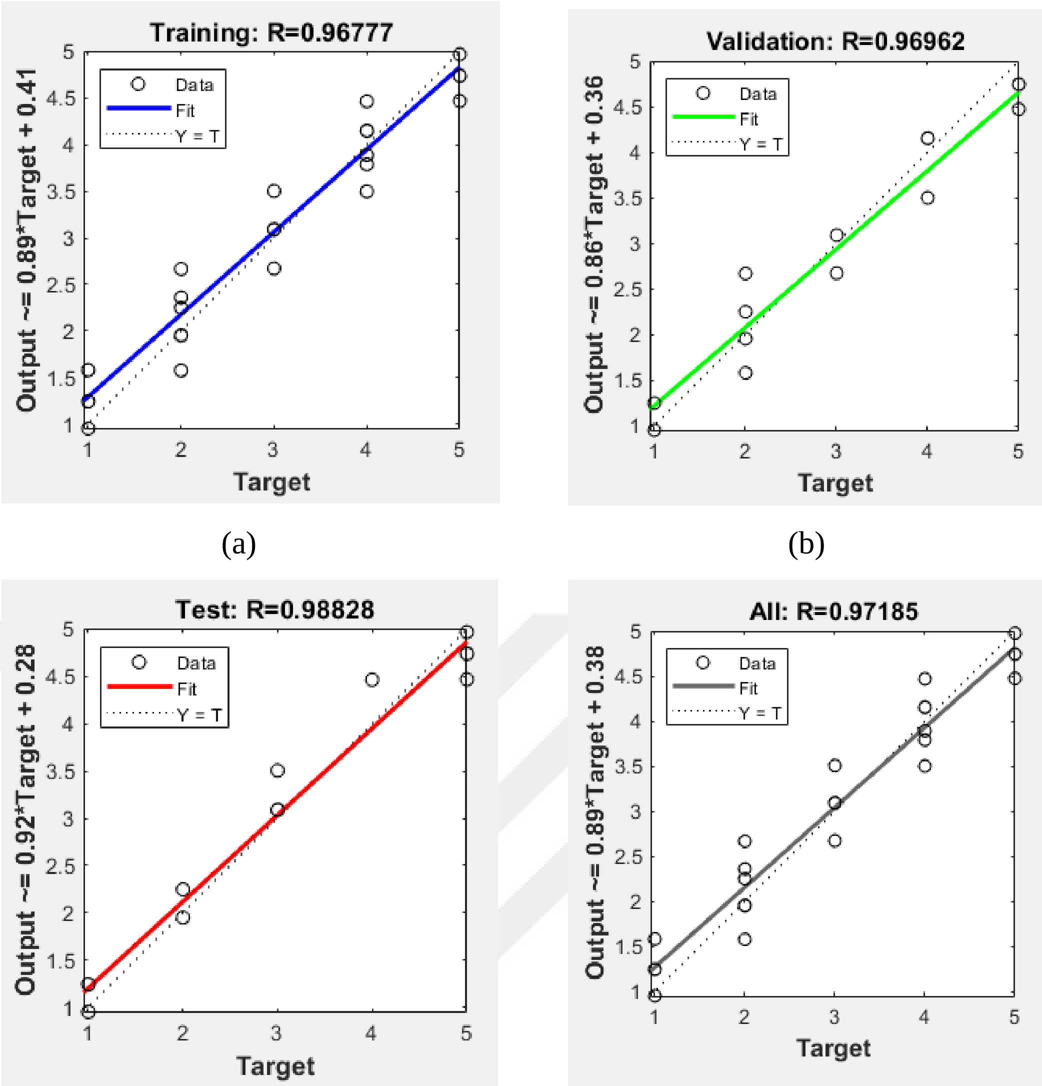
Table 4. 13: MSE and Regression results for all samples (2nd scenario)

	Samples	MSE	R
Training	84	1.12E-01	9.68E-01
Validation	18	1.42E-01	9.70E-01
Testing	18	6.84E-02	9.88E-01

Table 4. 14: The results for the training of the ANN (2nd scenario)

Scenario no.	Second
Epoch	11
Time	2 sec
Performance	1.00E-01
Gradient	2.48E-06
μ	1.00E-11
Validation Checks	6
no. of neurons in the hidden layer	1

We note from the above that there is a big difference between the obtained results and the desired results. This matter is clear in the results of the error in the three cases in training, validation and testing that shown in Figures 4.18 a, b, c, and d, and we note that the obtained curve does not match the desired curve.



(a) (b)

(c) (d)

Figure 4. 18. The results of the second scenario

4.2.5.2. The Third Scenario

In this scenario, we changed the percentage of data distribution on the training as shown below in Table 4.15, validation, and testing sectors, so the training share was 80%, the validation share was 10%, and the testing share was also 10%. The number of neurons for the hidden layer was kept at ten. The results are shown in Tables 4.16, 4.17.

Table 4. 15: Dividing data into three sections (3rd scenario)

Training	80%	96 Samples
Validation	10%	12 Samples
Testing	10%	12 Samples

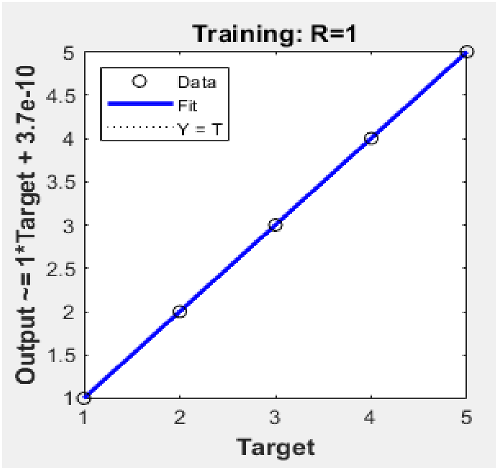
Table 4. 16: The results of MSE and Regression for all samples (3rd scenario)

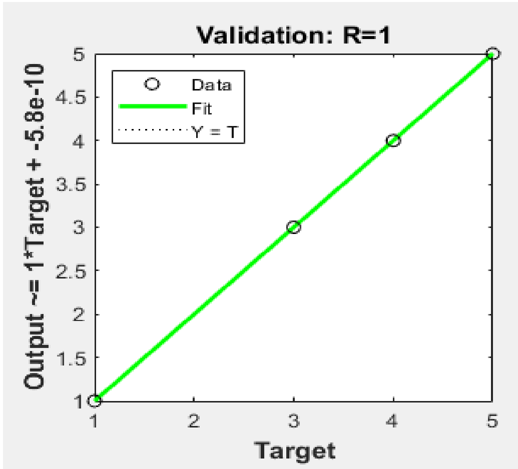
	Samples	MSE	R
Training	96	5.06E-19	1
Validation	12	1.45E-18	1
Testing	12	2.40E-18	1

Table 4. 17: The results for the training of the ANN (3rd scenario)

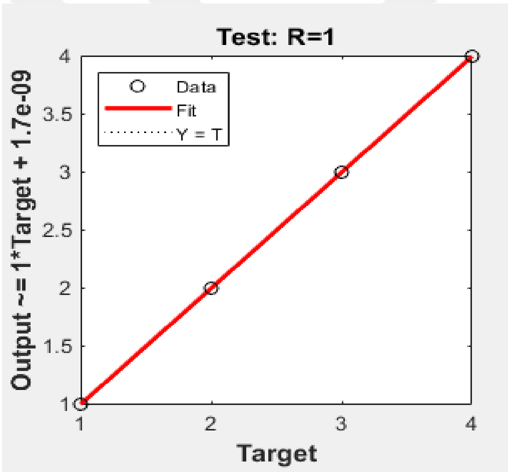
Scenario no.	Third
Epoch	24
Time	0.12 sec
Performance	5.06E-19
Gradient	1.27E-09
µ	1.00E-08
Validation Checks	0
No. of Neurons in the hidden layer	10

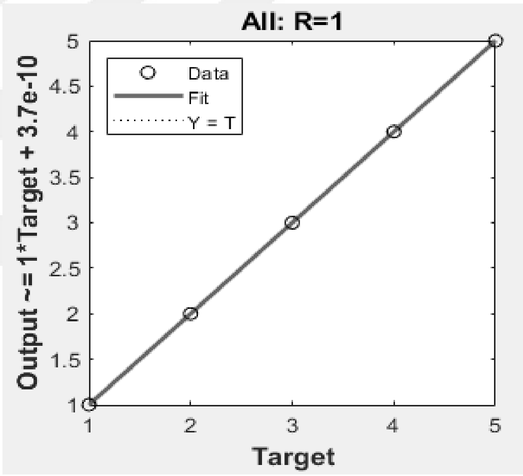
From Figure 4.19, we can notice that the results we obtained with changing the ratios were also satisfactory, as the error rate is small, but we cannot accurately compare between the scenarios due to the small amount of data used, as slight differences may not appear in such a quantity of data. In any case, we were able to show the changes that occurred on the network by changing the proposed scenario graphically.





(a) (b)





(c) (d)

Figure 4. 19. The results of the third scenario

4.2.6. Results

4.2.6.1. Comparing the Three Scenarios

From Table 4.18 below, we can note that the first and third scenarios, despite changing the distribution of data between training for the machine, validation, and testing, these two scenarios gave the best results, and this is evident in the value of the performance, which represents a minimal value for the error made from the training process according to the proposed scenarios.

We note that the more neurons in the hidden layer, the more accurate the results are. Based on the studied data, we found that five neurons or more gave acceptable results with the experiment.

Table 4. 18: The results of three scenarios

Scenario no.	Base	Second	Third
Epoch	19	11	24
Time	3 sec	2 sec	0.12 sec
Performance	3.07E-19	1.00E-01	5.06E-19
Gradient	9.64E-10	2.48E-06	1.27E-09
μ	1.00E-08	1.00E-11	1.00E-08
Validation Checks	0	6	0
no. of neurons in the hidden layer	10	1	10
Data distribution (training, validation, testing)%	(70, 15, 15) %	(70, 15, 15) %	(80, 10, 10) %

4.2.6.2. The Obtained Results of Twenty Samples

In this section, the 20 samples used in the FL section were tested, and their results were presented, and the results were compared according to the three scenarios to find out which one was better. The used values before having been converted to their equivalent data entered into the ANN system, as shown in Table 4.19.

Table 4. 19: The results of the proposed cases of twenty inputs by using ANN

Case no.	Strength of Interest		Inclusion of Interest		Expectation Of Interest		Fields of Interest		Degree of Priority	
1	20	1	10	1	30	1	10	1	1	Lowest
2	30	1	20	1	50	1	15	1	1	Lowest
3	50	2	30	2	70	2	25	2	3	Medium
4	70	3	45	2	30	1	35	2	4	High
5	80	3	60	3	50	1	45	3	4	High
6	20	1	75	3	70	2	55	3	2	Low
7	30	1	90	4	30	1	65	4	2	Low
8	50	2	10	1	50	1	75	4	2	Low
9	70	3	20	1	70	2	85	5	4	High
10	80	3	30	2	30	1	10	1	4	High
11	20	1	45	2	50	1	15	1	1	Lowest
12	30	1	60	3	70	2	25	2	2	Low
13	50	2	75	3	30	1	35	2	3	Medium
14	70	3	90	4	50	1	45	3	5	Highest
15	80	3	10	1	70	2	55	3	4	High
16	20	1	20	1	30	1	65	4	1	Lowest
17	30	1	30	2	50	1	75	4	1	Lowest
18	50	2	45	2	70	2	85	5	3	Medium
19	70	3	60	3	30	1	10	1	4	High
20	80	3	75	3	50	1	15	1	4	High

From the previous table, it becomes clear to us the accuracy of the obtained results according to the data dealt with. More than the values shown in the table have been tried, and the results are accurate. It is worth noting that the neural network system does not deal with data as it deals with fuzzy logic, as neural networks deal with data as sharp or clear data without blurring, unlike the fuzzy logic that can deal with it.

However, if numerical rather than linguistic data is obtained that accurately represents each case of the input, we will arrive at accurate results in the output. The results obtained from both systems will be compared in the next section.

4.3. Comparing Results between Fuzzy Logic and Artificial Neural Networks

4.3.1. Analayzing Obtained Results from FL & ANNs Systems

In Table 4.20, shown below, we show the results obtained from both studies: the results obtained after using FL and the results obtained after using ANNs. This table shows the twenty samples tested in the past after applying both the FL system and the ANN system.

Table 4. 20: Comparison of results between FL systems and ANNs

Case no.	Strength of Interest		Inclusion of Interest		Expectation Of Interest		Fields of Interest		Degree of Priority	
									FL	ANN
1	20	1	10	1	30	1	10	1	1	1
2	30	1	20	1	50	1	15	1	2	1
3	50	2	30	2	70	2	25	2	3	3
4	70	3	45	2	30	1	35	2	3	4
5	80	3	60	3	50	1	45	3	4	4
6	20	1	75	3	70	2	55	3	2	2
7	30	1	90	4	30	1	65	4	3	2
8	50	2	10	1	50	1	75	4	2	2
9	70	3	20	1	70	2	85	5	4	4
10	80	3	30	2	30	1	10	1	4	4
11	20	1	45	2	50	1	15	1	2	1
12	30	1	60	3	70	2	25	2	2	2
13	50	2	75	3	30	1	35	2	4	3
14	70	3	90	4	50	1	45	3	4	5
15	80	3	10	1	70	2	55	3	4	4
16	20	1	20	1	30	1	65	4	1	1
17	30	1	30	2	50	1	75	4	2	1
18	50	2	45	2	70	2	85	5	3	3
19	70	3	60	3	30	1	10	1	3	4
20	80	3	75	3	50	1	15	1	4	4

When we look at this table and Figure 4.20 below, it becomes clear to us in the cases that carry the numbers 2, 4, 7, 11, 13, 14, 17, and 19 that we have a difference between the results we obtained from the FL system ANNs. This difference means that each value is in a different rank, as we have previously shown that the rank with number one in the results means the lowest priority, the number two means low priority, three means medium priority, four is a high priority, and five is the highest priority.

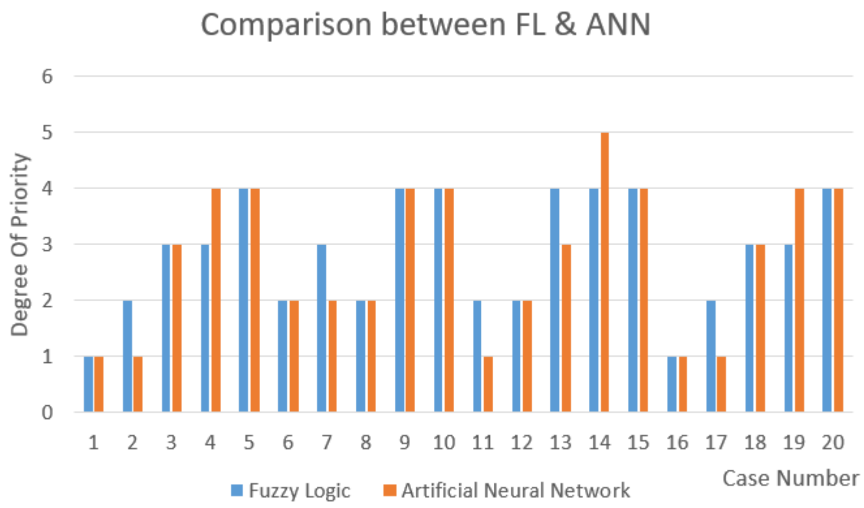


Figure 4. 20. Comparison between FL & ANN

Therefore, we note a clear disparity between the priority ranks in each system in the cases mentioned above. For example, the 13th case, the FL system, gave us rank four that this case is considered high priority, while in the ANN system, it gave us rank three that this case is considered a medium priority.

This disparity is due to several factors; the most important is the principle of these two systems' operations. FL gives a blurry space in the transition from one state to another or from one rank to another. This pattern does not exist in ANNs; it moves sharply from one rank to another without this Gradient transition.

Therefore, in our study of administrative decisions and giving priority when a group of decisions conflict, we need to give the exact order of the entered values to get the correct and accurate decision of the case. This is the most crucial mission in the border areas for each rank.

We have this disparity in results for some of the cases listed in Table 4.20 because those cases are located in intersection areas, where they belong to more than one sector simultaneously, as we explained in this chapter (refer to Figures 4.1-4.5). Moreover, these samples were chosen in order to ensure that all levels of expected decisions are represented.

Therefore, some samples were selected from the Essential range, Rquerment or Improvement only. In contrast, other samples were selected from the intersection areas between the Essential and Requirement and the intersection areas between Requirement and Improvement, as a sample.

This mechanism was applied in selecting samples with the other factors affecting DM.

So, we will see this difference in the results between the FL systems and the ANNs. This is because these systems interact with the data located in the intersection areas differently.

The second reason for this disparity is the lack of data used on the one hand - we mentioned the reasons for this before - and the lack of specific and clear parameters to separate the cases located in the intersection areas in administrative matters.

Of course, this does not mean the ANN system's inefficiency in prioritizing administrative decisions, but rather this system showed a considerable correspondence with the FL system despite the mentioned obstacles.

The efficiency of both systems will be high if there is an accurate scale that gives each case its classification. This is considered an essential matter in the DM process and the presentation of any decision over another. So, the differences between the priorities of one decision over another may be minimal. In such cases, the ANN system can give us as accurate results as we could get from the FL system that we worked on.

4.3.2. Practical Example

We will show an illustrative practical example of the DM mechanism, prioritizing it, and how the systems we proposed work within this procedure.

4.3.2.1. Steps for Determining Priority in Decisions

As shown in Figure 4.21, we show the steps of the DM process, and what are the stages of the DM process and prioritization:

1. Identifying Problem: We mean the stage during which the user enters data related to the matters to be prioritized by answering a set of questions; through that, the SOI, the IOI, the EOI, and the FOI will be determined.

2. Establishing Decision Criteria: At this stage, the system is provided with reference values obtained from the specialists and the experts.

3. Weighing Decision Criteria: In this stage, the input values are compared with the reference values, processed, and converted into values that fit each system used by us, whether FL or ANNs.

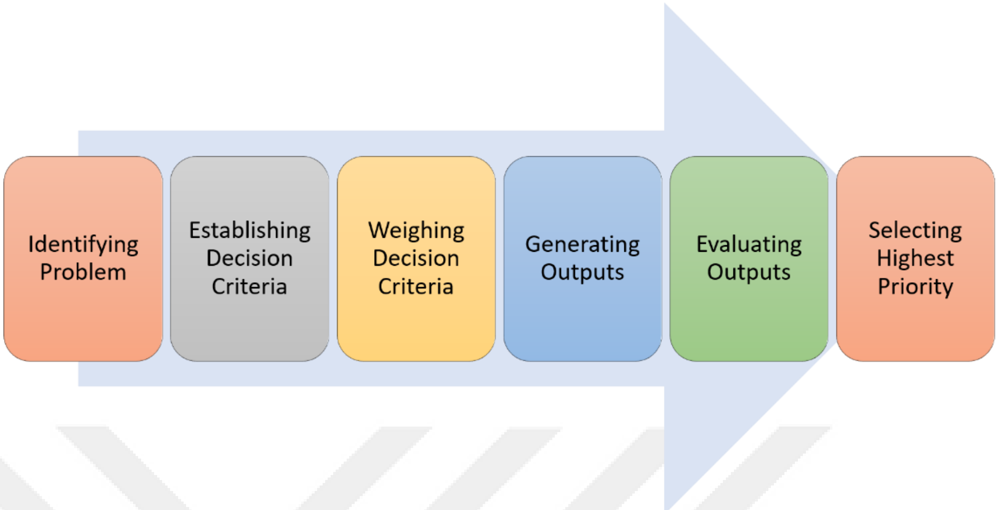


Figure 4. 21. Steps for determining priority in a decisions

4. Generating Outputs: This stage generates outputs for each input case.

5. Evaluating Outputs: In this stage, the values obtained from the previous stage are evaluated and compared. Determining which the highest value means the highest priority is.

6. Selecting Highest Priority: At this stage, the highest priority status is selected and shown to the user.

4.3.2.2. Practical Example: The Corona Epidemic in Turkey

In this part, we will study the situation of the Corona epidemic in Turkey and how the Turkish government has taken the appropriate decisions to deal with each case and each circumstance the country has gone through, taking into calculation the political, economic, and health conditions that the country is going through.

Initially, when the epidemic began to spread in the country in March of the year 2020, the government closed the country because of the spread of the disease, the large number of infections, and the lack of vaccines.

So, almost all institutions were closed except for hospitals, bakeries, and necessary places that are indispensable to people.

If we look, for example, on the one side of the problem, which represents: what is the reason for some institutions remaining working, but others have stopped in same time. We note that if we measure the matter according to our study, we will find that the institutions that remained operating during the general closing are hospitals, which lies in the rank of essential of SOI. In contrast, the institutions lying in the rank of requirement, such as education (universities and schools), were closed, as were the institutions lying in the rank of improvement, such as tourism, which were closed.

Let us return to the situation that we talked about as a first case regarding the spread of the epidemic, which is shown below in Figure 4.22. We see that the degree of the SOI in protecting people from the epidemic (closing) reaches the rank of Essential. As the IOI for closing, we see that it comes at the rank of the General. Furthermore, for the EOI, which is to protect people, it is Current. In the FOI that benefits this closure, we will find that it is the protection of the Soul.

So, we find that the priority rank of this case is Highest Priority, as it took the rank of Essential, General, Current, and Soul. The rank of this case, based on our study, was 119 out of 120, which represnts a high rank, and high in importance.

Moreover, if someone says that in this case, if the country is closed, the economy will collapse. We say to him, let us do the process of priority to this matter according to our study.

In case: the country is closed so that the economy will be at the rank of Essential, General, Expected, and Money, which takes the value of 111 out of 120.

So, we will find that the decision taken at that time was the right one because the value of 119 greater than 111 shows the priority of the decision.

Then conditions changed after a while; let us call it the second case, shown below in Figure 4.22, as the number of disease cases decreased due to the preventive procedures taken and the activation of vaccines. But the disease did not end yet.

This matter transformed the previous case from the general in the rank of IOI to a partially general. So, closing of country has become at the rank of essential, partially general, Current, and Soul, so this rank represents the value of 109 out of 120 for our study.

At the same time, the economy was negatively affected by the closing procedures, meaning that the disease transformed the economy from the rank of the Expected to the rank of Current.

So, its rank became Essential, General, Current, Money, and this is equivalent to the value of 116 out of 120.

So, we find that the priority is not to close and open the way to let the economy recover once again. We see that the value of 116 is more significant than 109, meaning that it has priority in the administrative decision.

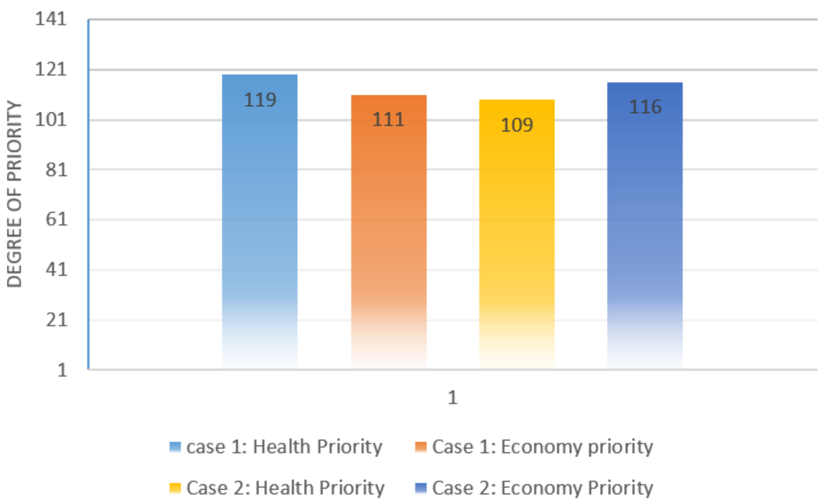


Figure 4. 22. Comparing the DOP of two cases in DM

CHAPTER V

CONCLUSION

5.1. Conclusion

Both FL systems and ANNs have proven their efficiency in dealing with administrative data and determining the priority of the input case with the possibility of comparing it with others. From the results we obtained, it was clear that the FL system is better in dealing with linguistic variables than ANNs, and despite that, ANNs also showed highly satisfactory results.

The FL system showed a high ability to deal with linguistic variables, especially when defining the fuzzy groups accurately, and the degree of affiliation of the elements to these groups.

Also, ANNs system showed high accuracy in determining the degree of priority, and it appeared that in case of a more accurate and detailed classification of the data, this system would outperform other systems.

To increase the efficiency of the two systems in the process of priorities determination in administrative decisions, a massive number of administrative decisions must be obtained, accurately categorized, and represented in numbers in addition to linguistics as this step will strengthen both systems and their ability to learn and judge, based on the supervised learning.

5.2. Future works

This thesis can be extended in different ways such as: working on a hybrid system of fuzzy system and ANNs together, as well as making an application for smartphones or a computer program that enables the user to interact appropriately to reach the best decisions based on the data he enters, and this application or program can simulate any level of management, whether at the personal level or corporates or institutions level, and even countries level.

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CURRICULUM VITAE

Education

- 2022 - Master degree in Computer Science and Engineering, Istanbul Sabahattin Zaim University, Istanbul – Turkey.
- 2003 – B.Sc. in Electro Mechanical Engineering, Al-Balqa' Applied University, Amman – Jordan, rated Good.

Training Courses

- Modern Vehicles Control Modules (Design and Repair), (24) hours, Automotive Technology Academy (ATA), Amman – Jordan, June 2007.
- Programmable logic controller (PLC), (18) hours, F.A. KETTANEH (SEMINES AGENT), Amman – Jordan, March 2010.
- PIC microcontrollers, (30) hours, Momentum Technology, Amman – Jordan, October 2010.
- Wireless Communication and Sensor Network, (30) hours, Engineering Training Center, Amman – Jordan, September 2014.

Professional Experience

- March 2014 – April 2016 Working at an educational institution as executive Director, responsible for:
  - 17 educational centers spread over different regions.
  - Develop plans and follow up their implementation.
  - training and development.
  - Financial follow-up of the branches.
  - Hiring the right talent.
- June 2011 - 2013: establishing a computer and electronic devices selling and maintenance company.
  - The project based on the marketing, sale and maintenance of electronic devices.
- Nov. 2010 – June 2011: Project Execution Administrator (private project).
  - The project based on building and establishment of football stadiums and facilities.
- Oct. 2008 – Nov. 2010: Working at Central Trade and Auto Company, TOYOTA dealership in Jordan as technical support engineer, responsible for:

- Delegating the daily workload between a team of technicians in order to maximize the workshop efficiency, and make follow-ups on works done.
- Troubleshooting of the mechanical and electrical problems using wiring diagrams.
- Extending technical support to the technicians as well as making quality assurance tests.
- Training for a technicians and an outside people who needs training.

Personal Skills

- The ability to good planning, time management, management of material and human resources and the development of alternative plans (contingency plans).
- The ability to lead and direct the work teams.
- The ability to meet the challenges and find appropriate solutions within what is available.
- Creativity and the ability to enter what is new to the surrounding environment.
- The ability to persuasion and influence with others
- Ability to troubleshoot and extend Technical Support on various electromechanical systems and ensuring customer satisfaction through prompt redressing of their problems.
- Good background in designing control systems using microcontrollers and interface them with sensors and actuators.
- Power Presentation Skills as well as efficient time-management techniques.
- Strongly Familiar with the most common-used computer operating system (MS Windows), with high-level proficiency on the most common used software package (MS Office).
- Mastering many computer programs like: Engineering softwares, graphic design, editing, sounds, office and others.

Languages

- Arabic: Mother language.
- English: Very good.
- Turkish: Good.