CHAPTER ONE

INTRODUCTION

1.1- General view

Intensive care medicine frequently involves making rapid decisions on the basis of a large and disparate array of information. To make medical decisions, intensive care unit (ICU) physicians often rely on conventional wisdom and personal experience to arrive at subjective assessments and judgments.

In the human body, blood is pumped in to the arteries and then travels through the circulatory system. Blood pressure (BP) is the pressure exerted by the blood on the walls of the arteries. The term BP as generally used in the medical area refers to arterial blood pressure (ABP). During each heartbeat, BP varies between systolic pressure (SP) and diastolic pressure (DP). SP is defined as the highest value of pressure that occurs when the heart contracts and ejects the blood in to the arteries. DP is determined as the lowest pressure value occurring between the each systole. Mean arterial pressure (MAP) is defined as the average arterial pressure during a single cardiac cycle. The pulse pressure (PP) is defined as the difference between SP and DP. One ABP pulse is determined from the end of one heart contraction to the start of the next one. BP is not constant in the body, and it differs at various places. The pressure of the circulating blood decreases as blood passes through arteries, arterioles, capillaries, and veins. BP used in clinical practice without further specification normally refers to the arterial pressure measured at the patient’s upper arm. The BP value is not always constant and can change during 24 hr according to an individual’s activity such as stress, nutritional factors, drugs or diseases. We find this process of a diastole and a systole control by the human brain.

Compared with the human brain, computers are well suited to making rapid calculations and recalling large numbers of facts, permitting the creation of decision networks that support near limitless complexity. For many situations, however, the variable nature of disease and patient characteristics makes it difficult, even impossible, to decide exactly what should be done in every conceivable set of circumstances. In such situations, the physician must depend on intuitive decision making, sometimes described as the art of medicine. Intuitive decision making is usually described as being poorly suited to computerization. Certainly, subjective judgment generally defies description in terms of the kinds of deterministic mathematical equations that computers are well suited to solving.

However, the methods of fuzzy logic are suited to this kind of endeavor and can lead to algorithms that mirror the inexplicit nature of clinical decision making.

In this perspective, fuzzy logic works will be described by illustrating its application in the regulation of blood pressure. After clinicians appreciate the kinship of fuzzy logic with expert clinical thinking, we anticipate that fuzzy logic may become widely embraced for use in some aspects of clinical decision making.

1.2 - Problem statement

If blood pressure is controlled and oscillations in the hemodynamic variables are reduced, patients experience fewer complications after surgery. In clinical practice, this is usually achieved using manual drug delivery, various automatic control techniques have been used to control the hemodynamic variables by infusion of two agent, dopamine and sodium nitroprusside. Given that different patients have different sensitivity and reaction time to drugs, determining manually the right drug infusion rates may be difficult. This is a problem where automatic drug delivery can provide a solution.

1.3- Objectives

The objectives of this research are to:

1. Introduce various design approaches for the purpose of multivariable control applications.
2. Control blood pressure by infusion the dopamine and sodium nitropressuide to regulate the hemodynamic variables automatically.
3. Present the beneficiary application of Artificial Intelligent (AI) in the medical field.

1.4- Methodology

The method is proposed to control non-liner multi-input and multi-output process. A rule-base construction system which is aimed at extracting control rules from the process of the iterative learning is proposed. This means that the correct control actions are progressively learned by operating the system repeatedly. Clearly, this process is similar to the learning process possessed by a human being.

The rule-base can be initially empty and is constructed on-line. The coupling between input and output variables is handled through a number of rules that constitute defuzzification mechanism and results in a decoupled strategy. The fuzzification and inference stages use the concept of adaptive similarity factor in multi-input and multi-output framework.

So the system will include a neural system to be training with the blood pressure to be control, then our neural system will be connected to a fuzzy system with blood pressure data in different number of membership function with different terms, then the next step is be created the rules of our fuzzy system with different situations of patients with different weights, then fuzzy system will complete the lack of knowledge, that the neural system has no ability to measure it.

The overall system composes four functional models: the reference inputs and outputs, the learning network, the rule-base mechanism of fuzzy system and the controlled process which is assumed to have numbers of inputs and numbers of outputs.

1.5- The thesis layout

This research consists of five chapters. Chapter one is an introduction. The previous studies are given in chapter two. The theoretical background in chapter three, chapter four the proposed system, "Modeling and Simulation Results", Finally conclusion and recommendations are presented in chapter five.

CHAPTER TWO

Previous studies

This chapter contains about five previous studies are:

1. Fuzzy Based High Blood Pressure Diagnosis

Vishal Chandra, IIPinki Singh (India 2014)

A methodology for the automated development of fuzzy expert systems is presented. The idea is to start with a crisp model described by crisp rules and then transforms them into a set of fuzzy rules, thus creating a fuzzy model .Nowadays the use of computer technology in the fields of medicine area diagnosis, treatment of illnesses and patient pursuit has highly increased. Despite the fact that these fields, in which the computers are used, have very high complexity and uncertainty and the use of intelligent systems such as fuzzy logic, artificial neural network and genetic algorithm have been developed. This research based thesis focused on the use of Computer Science and Engineering (CSE) to design a web-based fuzzy expert system for the management of hypertension (High Blood Pressure) using the fuzzy logic approach. In this thesis, systolic blood pressure, diastolic blood pressure, age, and body mass index (BMI) were taken as input parameters to the fuzzy expert system and “hypertension risk” was the output parameter. The resultant hypertension risk was based on fuzzy rules that were developed for the expert system. The input trapezoidal membership functions are normal, high, and very high for blood pressure. The output triangular membership functions are mild, moderate and severe. The expert system was designed based on clinical observations, medical diagnosis, and the experts’ knowledge. The expert system provides a web-based interface that was designed using ASP as a scripting language with Microsoft Access as a database under Windows operating system platform, and using ASP.NET to archive the system design. . We selected the records of 500 patients with hypertension provided by Dr. Kaushal Kishore (MBBS,MS)-M.G.M. Hospital, Jamshedpur. And computed the results that were in the range of predefined limit by the domain experts. The diagnosis of hypertension involves several levels of uncertainty and imprecision. The taskof hypertension diagnosis and management is complex because of the numerous variables involved i.e. imprecision and uncertainties. Patients cannot describe exactly how they feel; doctors and nurses cannot tell exactly what they observe; and laboratories results are dotted with some errors caused either by the carelessness of technicians or malfunctioning of the instruments. Medical researchers cannot precisely characterize how diseases alter the normal functioning of the body (Szolvits, 1988). Hypertension can become so complex and unpredictable that physicians sometimes must make decisions based on intuition. All of these complexities in medical practice make traditional quantitative approaches of analysis inappropriate. Fuzzy logic plays an important role in medicine. Fuzzy logic is a method that renders precise what is imprecise in the world of medicine using natural language. Fuzzy logic systems are excellent in handling ambiguous and imprecise information prevalent in medical diagnosis. Fuzzy set and fuzzy logic founded by (Zadeh, 1965) makes it possible to define inexact medical entities as fuzzy set. Hypertension (High Blood Pressure) is one of the known cardiac diseases believed to be the cause of the “sudden death” syndrome prevalent in Nigeria today (Ogah, 2006). Complications of hypertension could lead to stroke or heart failure (Hobbs and Boyles. 2004). Such complications may be caused by improper diagnosis and or improper management of the disease, due to inaccessibility of experienced medical personnel at all times. This necessitated the dire need for a tool that is readily available to render up-to-date medical information to the patient.

Developments of expert system For developing an expert system at first the crisp sets are converted into fuzzy sets .Elements of crisp sets are real World object. Linguistic variables are declared. According to nature of elements

Membership function is given. Its result will generate rules for solving the problem. The rules are if. Then rule. Further the fuzzy output is defuzzified and gives the result to user.These are major factors which affects the blood pressureBut these factors are directly related to it and contain some degree of

Membership for all.SBP (Systolic blood pressure), DBP (Diastolic blood pressure), Age, BMI (Body mass index). Linguistic Variable and Membership Function Graph For all factors these are the linguistic variable and membership Function graph. These graphs are trapezoidal and also contain L type and R type. Graphs are trapezoidal because the membership functions for some range are same. Systolic blood pressure{mild ,moderate ,severe } Diastolic blood pressure{mild ,moderate ,severe } Age{Young, Middle-aged, Old, Very old} Body mass index{Low, Normal, High, Very high}.

2. Human Blood Pressure Classification Analysis Using Fuzzy Logic Control System In Data mining

Mayilvaganan M and K.Rajeswari (India 2014)

High blood pressure is usually referred to as hypertension due to the high level of blood pressure classification is not appropriate fuzzy logic system classifies between 0 and 1 . The high blood pressure classification (BP) Eg : normal low or high . The blood pressure has been tested as systolic diastolic blood pressure. In this paper, al fuzzy logic system is introduced in order to help users in providing accurate information. In fuzzy logic control system is to diagnose the heart disease and kidney damage of a patient.

FlS rules are extracted from the numerical data depend on input and output. Each rule has to parts;" IF" part; is called consequent the extracted FLS ruled are given below;

Rule1: IF HR is "low" THEN BP IS "low"

Rule2: IF HR is "medium" THEN BP is "medium".

Rule3: IF HR is "high" THEN BP is "high"

There are huge data management tools available within health care systems, but analysis tools are not sufficient to discover hidden relationships amongst the data. Most of the medical information is vague, imprecise and uncertain. Extracting correct information from this data is considered an art. It can be said to be an art because it is complicated by many factors and its solution involves literally all of a human's abilities including intuition and subconscious [2]. Medical diagnosis is a complicated task that requires operating accurately and efficiently. According to the World Health Organization, 12 million deaths occur each year due to heart diseases. It is the primary reason behind deaths in adults. In the United States, 50% of deaths occur due to cardio vascular disease. In fact, one person dies every 34 seconds due to cardiovascular diseases in the United States [2]. Similarly, in other developed countries heart disease is one of the main reasons behind adult death. In order to decrease the mortality rate of cardiovascular disease, it is necessary for the disease to be diagnosed at an early stage. HBP causes artery damage and kidneys are packed with arteries. Kidneys are supplied with dense blood vessels and high volumes of blood flow through them. Damaged kidney arteries do not filter blood well. Kidney has small, finger-like nephrons that filter your blood. Damaged kidneys fail to regulate blood pressure. Healthy kidney produces a hormone to help the body regulate its own blood. Having fuzzy data management capability in a database

Is important to be able to store vague data. Ignoring vague data management means the risk of losing important information, which may be useful for some applications. A database that supports vague, imprecise and uncertain

Information is called a fuzzy database. It is based on fuzzy logic and fuzzy set theory which is introduced by Zadeh [3][4].

3. Fuzzy Logic in Heart Rate and Blood Pressure Measuring System

Iman Morsi and Yahia Zakria Abd El Gawad (Egyp 2012)

Healthcare sector quality demands are exponentially rising to design expert systems for medical diagnosis. Likewise there is growing capture of biological, clinical, administrative data and integration of distributed and heterogeneous databases. Those previous mentioned branches create a completely new base for medical quality and cost management. In this paper fuzzy logic model is designed and practically tested. A group of 105 patients is use to develop this model and another group of same count patients was used to test it. All results are compared using fuzzy logic model in MATLB.

Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth - truth values between "completely true" and "completely false". It is especially suited to medical applications, since much of the information required for medical decision-making is uncertain. Kalmanson and Stegall performed an extensive analysis of medical decision-making and concluded that the classic, formal, quantitative approach to medical research and clinical decision threatens us with the danger of drowning in excessive data, and that a new conceptual and methodological approach based on the concept of fuzzy sets offers an alternative decision making path [4]. Hudson and Cohen outlined the sources of uncertainty in medical decision-making and concluded that fuzzy logic could provide the adequate approach to handle medical problems [6]. Costin, H and Rotariu, Cr described the use of fuzzy logic and semantic knowledge for edge detection and segmentation of magnetic resonance (MR) images of brain [7]. Allahverdi presented a survey of the fuzzy set and fuzzy control theory in the medicine area in general as well as on some concrete applications [8]. Gal, N. proposed a system that can mimic the thinking of a human medic. The system consists of a fuzzy frication engine that converts the numerical data in to linguistic data. A medical knowledge database is implemented and a fuzzy inference engine is used [9].Sivasankar and E. Rajesh, R.S. assessed the role of the data mining techniques namely Fuzzy Logic rule based classifier in the diagnosis of severity of appendicitis in patients presenting with right iliac fossa (RIF) pain [10].

By using MATLAB 7.9.0 results are analyzed and using the fuzzy tools to make the comparison between the different results. The linear equations from Equation 1 to Equation 3 are produced based on the comparison between the reference device results and the generated results by the IR sensor and the LDR sensor . Which indicate that the IR sensor and the LDR sensor results are very close to the results of (HEM-907XL) reference device, with a slight difference in some of the results (with effort condition).

To confirm the validity of the derived equations, a random value on the curve results has been chosen, and a comparison has been done for this value between the reference device and the proposed design.

$y = 9*z + 5.51$ (1)

Where $z = (x - 5.24) / 10$ (2)

$y = 8.8*z + 5.51$ (3)

$z = (x - 5.25) / 10$ (4)

Tests are applied of all equations to detect the accuracy. If the value X from the device (HEM-907XL) is 122. The model is found to be accurate for classification and, when compared; it is proved to be at least as accurate as the reference values. By comparison the predicted output using fuzzy logic values, and the reference values of IR sensor for measuring heart beat rate, gave a the percentage error of 0.1116%. But when comparison the predicted output using fuzzy logic values and the reference values of LDR sensor for measuring heart beat rate, gave a percentage error of 1.511%. From this comparison conclude that using IR sensor is achieving the required accuracy. While by comparison the predicted output using fuzzy logic values and the reference values of strain gauge sensor for measuring blood pressure, gave a percentage error of 0.812%.

The usage of fuzzy logic rule-based classifiers is an effective tool for accurate diagnosis of heart and blood pressure measurements.

4. Design and Development of Fuzzy Expert System for Diagnosis of Hypertension

Azian Azamimi Abdullah, Zulkarnay Zakaria and Nur Farahiyah Mohammad (MALAYSIA 2011)

The aim of this study is to design a Fuzzy Expert System (FES) for diagnosis of hypertension risk for patients aged between 20's, 30's and 40's years and is divided into male and female gender. The input data is collected from a total of 10 people which consists of male and female with different working background. The parameters used as input for this fuzzy expert system were age, Body Mass Index (BMI), blood pressure and heart rate. Hypertension is diagnosed if blood pressure is over than 140/90mmHg. Hypertension is called the silent killer because it has no symptoms and can cause serious disease if left untreated for a long time [11]. Thus, an intelligent and accurate diagnostic system is needed in order to threat the hypertension patient. In this study, we have proposed an expert system using fuzzy for diagnosis of hypertension. The diagnosis process, linguistic variables and their values were modeled based on expert's knowledge and from existing literature. It is expected that our proposed Fuzzy Expert System can provide a faster, cheaper and more accurate result compared with other traditional methods.

Nowadays the methods of artificial intelligence have largely been used in the medical applications. In the medicine area, many expert systems were designed to diagnose and treatment the disease [12]. Hence, a rule-based fuzzy expert system that simulates an expert-doctors behavior for diagnosis of the disease is developed. Fuzzy logic is a true extension of conventional logic, and fuzzy logic controllers are a true extension of linear control models. Hence anything that was built using conventional design techniques can be built with fuzzy logic, and vice-versa. However, in a number of cases, conventional design
Methods would have been overly complex and, in many cases, might prove simpler, faster and more efficient. On the other hand, high blood pressure or hypertension is a condition that occurs when the pressure in our arteries is consistently above the normal range.
Fuzzy expert system is designed to determine the risk of hypertension by using fuzzy inference system (FIS) tool [13]. This design consists of 4 inputs and 1 output whereas for the fuzzification, Mamdani method is used. The inputs consist of blood pressure, BMI, heart rate and age while the output is the risk of

hypertension (%). The variables are used like low, middle, medium and high for input and low, middle and high for output. 9 rules are designed using fuzzy rule. The rules have been developed using if-then method. For example, if Age is Young and BMI is Low and BP is Low and HR is low then the output risk is Low. Using these rules, the result risk in term of percentage (%) has been computed. Figure 8 shows the result for the subject at the age of 23 years old, BMI is 20.3 kg/m^2, blood pressure is 112/68 mmHg and heart rate is 82 bpm. Hence, the output result obtained for this subject is 50%. This means that the subject has 50% risk to get hypertension based on the factor of age, BMI, blood pressure and heart rate.
The result for the risk of hypertension, It is consisted of age from 20’s to 40’s for males and females. For the age 20’s the risk to get the hypertension isabout 50%, for the age 30’s the risk is about 39% and finally for the age of 40’s is 50%. From the result, subject number 2 have a high reading for heart rate and the risk to get the hypertension is 50%. For the age around 20’s, all the subjects have 50% risk to get the hypertension. It is maybe because the pressure in their study and not having a healthy life style such as lack of exercises, depression and stress.

Fuzzy expert system design is very appropriate compared to the Bayesian Statistics, Statistical and other methods. This is because fuzzy expert system can simulate as an expert doctors behavior in order to diagnose diseases. This

Study is aimed to design a fuzzy expert system for diagnosis of hypertension. For current progress, age, BMI, heart rate and blood pressure are used as input for the fuzzification method while risk of hypertension (%) is used as output. For the next progress, we will add ECG waves as another input to give further analysis of the condition of patient hypertension. More fuzzy rules will be developed in order to get a better result and determine the risk factor of hypertension. The designed fuzzy expert system is then, will be tested to the samples taken from the hypertension database of Hospital Tuanku Fauziah, Kangar, and Perlis.

5. Fuzzy Expert System for the Management of Hypertension

X.Y. Djam, M.Sc. and Y.H. Kimbi, MBBS (Nigeria 2011)

This paper focused on the use of information and communication technology (ICT) to design a web-based fuzzy expert system for the management of hypertension using the fuzzy logic approach. In this paper, systolic blood pressure, diastolic blood pressure, age, and body mass index (BMI) were taken as input parameters to the fuzzy expert system and “hypertension risk” was the output parameter. The resultant hypertension risk was based on fuzzy rules that were developed for the expert system. The input triangular membership functions are Low, Normal, High, and Very High for blood pressure. The output triangular membership functions are mild, moderate and severe. The defuzzification method used in this paper is the Root Sum Square. The expert system was designed based on clinical observations, medical diagnosis, and the experts’ knowledge. The expert system provides a web-based interface that was designed using PHP as a scripting language with MySQL relational database on Apache Sever under Windows operating system platform, and using Java Script and HTML to archive the system design. Unified Modeling Language was used to describe the logical design of the system. We selected 50 patients with hypertension and computed the results that were in the range of predefined limit by the domain experts.

The complexity of medical practices makes traditional quantitative approaches of analysis inappropriate (Rahim et al., 2007). Every trust worthy expert knows that his/her medical knowledge and resulting diagnosis are pervaded by uncertainty with imprecise formulations. Medical processes can be so complex and unpredictable that physicians sometimes must make decisions based on intuition. Computers are capable of making calculations at high and constant speed and of recalling large amounts of data and can, therefore, be used to manage decision networks of high complexity (Merouani et al., 2009).

UML, as an object oriented tool, was used to capture and model some of the functionalities in the system. UML is an excellent tool for modeling objects and the relationship between the objects and classes. (Kendall and Kendall, 2002). The UML approach helps to depict the system in many different views thus giving a quick structural representation of the system. There are two types of UML diagrams: the structural diagram and the behavioral diagram. Structural diagrams are used to describe the relationship between classes. They include class diagrams, object diagram, use-case diagrams, component diagrams, and deployment diagrams. Behavioral diagrams on the other hand can be used to describe the interaction between objects. They include sequence diagram, collaboration diagrams, state chart and activity diagram (Alhir, 2000). In this paper, we made used of three UML diagrams: use-case diagram, sequence diagram and class diagram. The use-case diagram is the description of the systems behavior from a user’s point of view.

This diagram is a valuable tool during system analysis and design as developing use-cases help to understand system requirements. The use-case diagram is shown in Figure 1. The actors are the patient and the medical expert as they are the individuals that interact with the system.

Based on RSS, hypertension risk was computed for 50 patients' data. The example below shows sample values of 5 patient data: From the fuzzy rules predefined above and using RSS, hypertension risk can be computed .Based on RSS, the computed value for hypertension risk for the first sample of patient data is 0.61. The crisp output of 0.61 show that the patient has moderate risk of hypertension; thus, the patient needs close monitoring and possible indication fo treatment of hypertension. The main objective of this study is to determine hypertension risk based on the linguistics description of the input parameters SBP, DBP, BMI, and age. Hypertension risk will be based on fuzzy rules, which have different antecedent parts but with the same consequence. The problem is that we have to work out a final numerical value with the fuzzy inputs. This can be achieved only with defuzzification process.

On the basis of the all presented, it can be concluded that there is no doubt whether Expert Systems should be applied for hypertension management. Our results based on real patient data confirms that the fuzzy logic expert system can represent the expert's thinking in a satisfactory manner in handling complex tradeoffs. Fuzzy logic systems are excellent in handling ambiguous and imprecise information prevalent in medical diagnosi

CHAPTER THREE

The Theoretical Background

3.1.1- Introduction

Fuzzy logic control is equivalent to have computers reason like humans do, just much faster. Normally when we think of computers making decisions, the output would be true or false. However, fuzzy logic is a way of letting the computer say little, big, bigger, not so big, and so forth, and have an output decided upon from these vague inputs. Often biological systems are nonlinear, difficult, or impossible to model mathematically. However, fuzzy logic control is empirically-based and model free thus opens doors for control systems that would normally be deemed unfeasible for automation. Furthermore, fuzzy logic control is very robust and does not need precise and noise-free inputs to generate usable outputs. Finally, it can easily be modified and fine tuned during operation.

3.1.2- Fuzzy logic

Fuzzy logic seems closer to the way our brains work. Fuzzy logic is an approach to computing based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic on which the modern computer is based. The idea of fuzzy logic was first advanced by Lotfi A.Zadeh, professor of computer science at the University of California in Berkeley in the 1960s; it is a superset of conventional Boolean logic with extensions to cater for imprecise information [1]. Fuzzy logic later developed to account for imprecision of natural language quantities e.g. (many) and statements (e.g. not very likely), in fuzzy logic, a statement can be both true or false and also can be neither true nor false [2]. Fuzzy logic permits vague information, knowledge and concepts to be used in at exact mathematical manner. Words and phrases such as ‘fast’, ’slow’, ’very fast’, ’quite slow’, ‘not very fast’ are used to describe continuous, overlapping states, this enables qualitative and imprecise reasoning statements to be incorporated within rule-bases so producing simpler, more intuitive and better behaved models. Fuzzy logic is non monotonic logic; it can use to solve paradoxes (e.g. RUSSELL’S paradox) that well known cannot be solved using classical logic, The main idea behind fuzzy systems is that truth values (in fuzzy logic) or membership values are indicated by a value in the range 0-1 with 0 for absolute falsity and 1 for absolute truth[2]. Fuzzy logic is based on the principle that every crisp value belongs to all relevant fuzzy sets to various extents called the degrees of membership [3]. These range from 0(definitely not a member) to 1(definitely is a member), with values between generated by a membership function. This contrasts with conventional, Boolean logic, where membership of a set is either false or true, i.e. 0 or 1. This graduation from 0-1 enables us to smooth out and overlap the boundaries between sets, unlike Boolean logic where sets are mutually exclusive, fuzzy logic allows crisp values to belong to more than one fuzzy set.

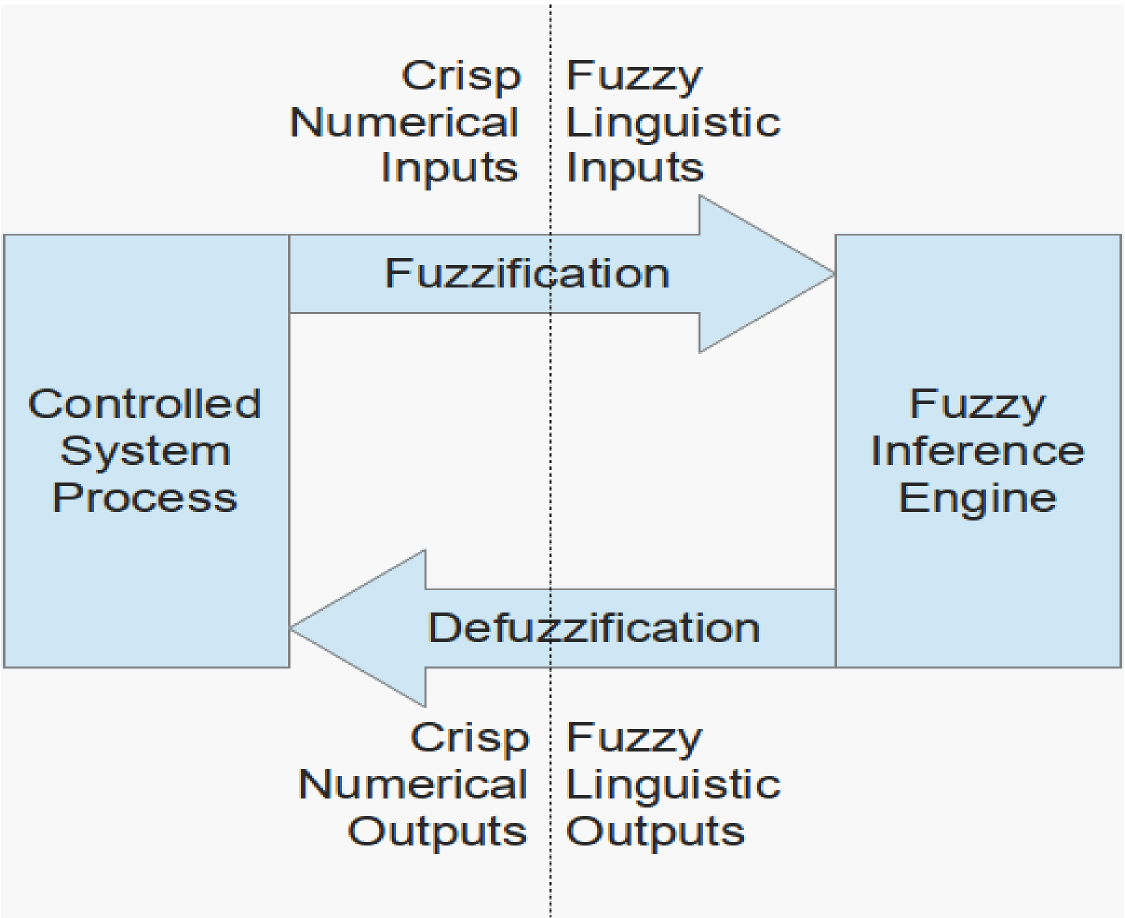


Figure (3.1) the fuzzy system

3.1.2.1- Fuzzy set

A fuzzy set is a class of object with a continuum of grades of membership [3]. In mid 60's zadeh developed the concept of 'fuzzy sets' to account for numerous concepts used in human reasoning which are vague and imprecise e.g. tall, old etc. The aim is to use fuzzy sets in order to make computers more 'intelligent'. Such a set is characterized by a membership (characteristic) function which assigns to each object a grade of membership ranging between zero and one. Fuzzy set is very convenient method for representing some form of uncertainty [2]. Example: if we have two sets, one consist of all the temperatures in the world (A), and the other set consist of temperatures that are cold for the humans (U), if we take x=-100, it consider very cold so we can say it belong to the (U)or (1), if x=+500, it consider very hot, so not belong for (U) or (0), it still like conventional logic, but if x=12, this is cool temperature so it can be not very cold and not very hot so it can be belong to (U) with (0.5) and this is the concept of fuzzy set.

3.1.2.2- Linguistic variables

In 1973, professor lotfi A.zadeh proposed the concept of linguistic [1] or "fuzzy" variables. It is a variable that assume a value consisting of words or sentences rather than numbers, which is use in classical logic. To illustrate the concept of linguistic variable can consider the word age in natural language; it is a summary of the experience of enormously large number of individuals; it cannot be characterized precisely. Employing fuzzy sets (usually fuzzy number), we can describe age approximately. Age is a linguistic variable consisting of fuzzy set like very young, young, middle age, old, and very old. They are called terms of the linguistic variable age. Each term (set) is defined by an appropriate membership function. We can apply temperature (cold, cool, normal, warm, hot), and a car speed (very fast, not very fast, fast, slow, quite slow) etc, as a linguistic variables, with their terms.

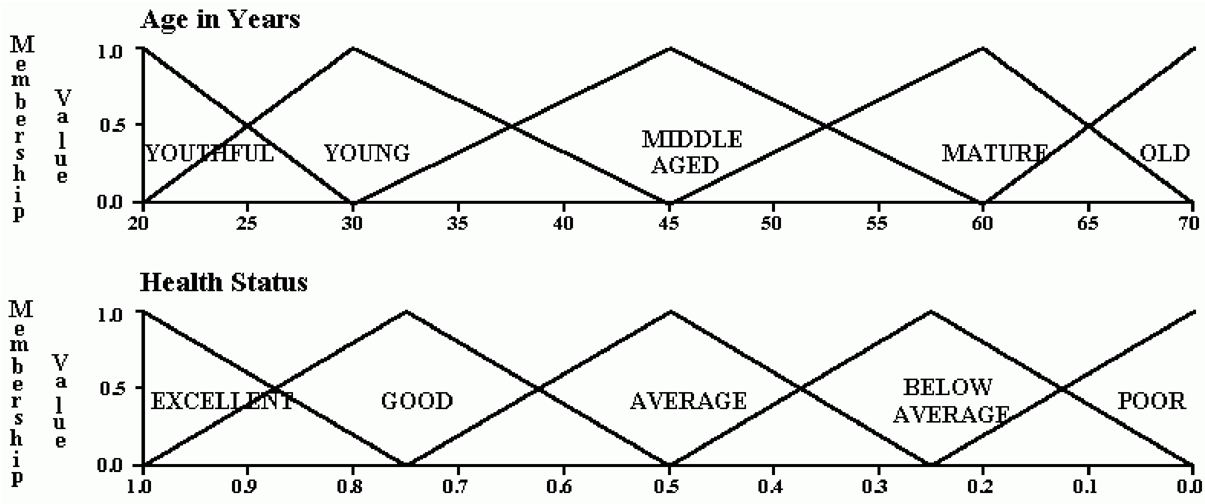


Figure (3.2) linguistic variables and their terms

3.1.2.3- Membership function

The membership function is a graphical representation of the magnitude of participation of each input[4]. The membership function has a condition to be identify, it must has extents with a range from zero to one only. It associates a weighting with each of the inputs that are processed, define functional overlap between inputs, and ultimately determines an output response.

There are different membership functions, triangle (□), trapezoidal (□), singleton, sigmoid, and Gaussian types. The simplest ones in calculations are the triangular which is a collection of three points forming a triangle and trapezoidal which is a truncated triangle curve.

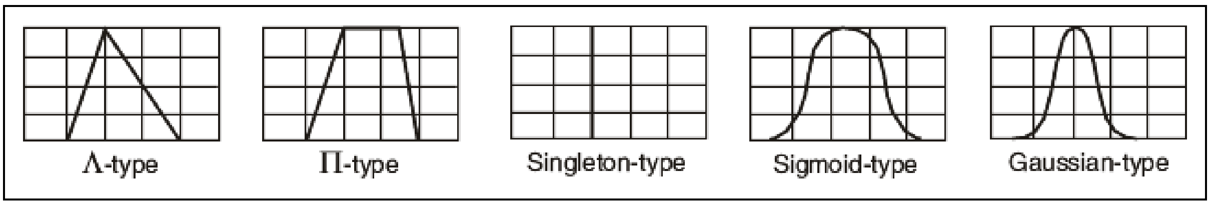


Figure (3.3) shapes of standard membership functions

3.1.2.4- Logical operations

To build system depends on fuzzy logic, we needs for numbers of logical operations, there are four logical operations are:

- Intersection
- Union
- Complement

-The intersection:

The membership function of the Intersection of two fuzzy sets A and B with membership functions (μA) and (μB) respectively is defined as the minimum of the two individual membership functions. This is called the minimum criterion.

$\mu A\cap B=\min(\mu A, \mu B)$

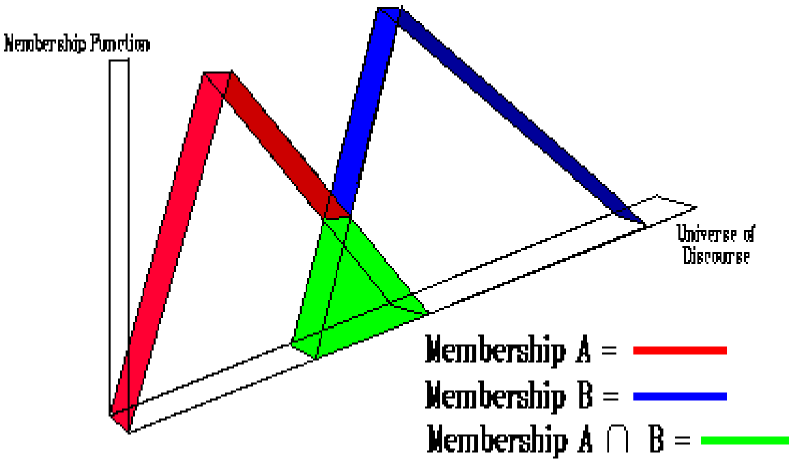


Figure (3.4) the intersection operation

The Intersection operation in Fuzzy set theory is the equivalent of the **AND** operation in Boolean algebra.

-The union:

The membership function of the Union of two fuzzy sets A and B with membership functions (μA) and (μB) respectively is defined as the maximum of the two individual membership functions. This is called the maximum criterion.

μAUB=max (μA, μB)

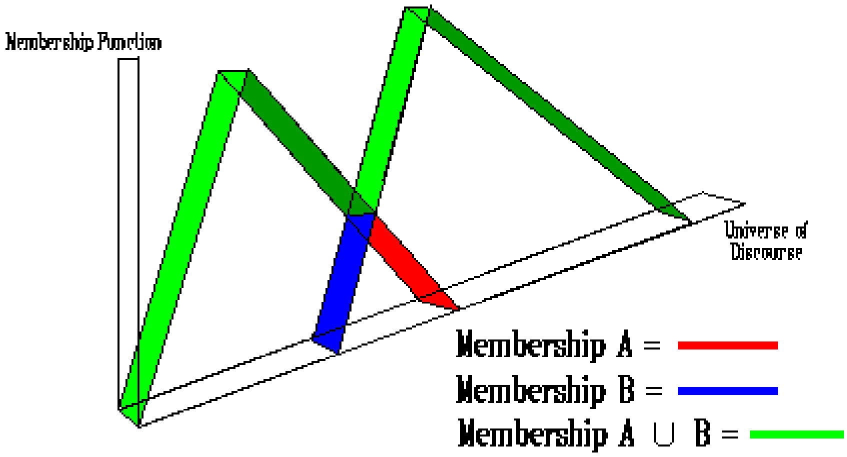


Figure (3.5) the union operation

The Union operation in Fuzzy set theory is the equivalent of the **OR** operation in Boolean algebra.

-The complement:

The membership function of the Complement of a Fuzzy set A with membership function (μA) is defined as the negation of the specified membership function. This is called the negation criterion.

$\mu_{\bar{A}} = 1 - \mu_A$

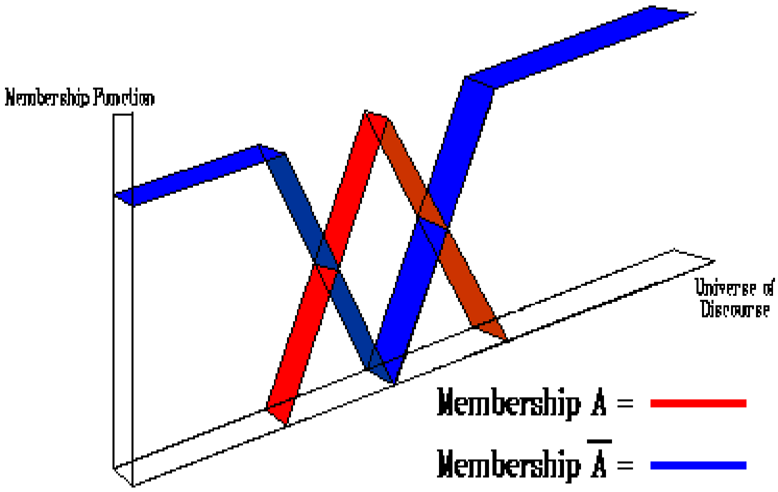


Figure (3.6) the complement operation

The Complement operation in Fuzzy set theory is the equivalent of the **NOT** operation in Boolean algebra.

3.1.2.5- Rules

Human being making decisions based on rules [5]. Even we may not be aware of it, all decisions we make are based on computer like if-then statements. Rules associate ideas and relate one event to another. Fuzzy machines, which always tend to mimic the behavior of man, work the same way. Only this time the decision and the means of choosing that decision are replaced by fuzzy sets and rules are replaced by fuzzy rules. Fuzzy rules are small chunks of knowledge expressed in the form of if-then statements each one contain of two parts called left part(represents the antecedent or conditional part) and right part(represents the conclusion or action or result part). The implication can be defined as set of rules, or conditional sentences (if-then), the first case of the rule represents the condition, and the other represent the result. For example if the temperature is med and the humidity is low then the weather is cool, in this simple law there is three logical variables, two represent the condition of rule (temperature and humidity), and the third is the result of rule (weather). So there is a fuzzy sets for this variable are: “med” refers to the temperature, “low” refers to humidity, and “cool” refers to the weather, if we have a certain values of temperature and humidity, then we need for two steps to identify the weather. In the first step must identify the extents of member value that was given for fuzzy sets, and use the logic operations(intersection), because we use (and), then in the second step we must evaluating the result. If the condition was available with a certain ratio then the decision will be correct with the same ratio. If we supposes the temperature is 30 degree of Celsius, and the humidity is 40%, and let us suppose the degree of temperature that was be belong to fuzzy set was 0.8, for the humidity 0.6, so while we was use the intersection, then the condition will be available by degree of member 0.6(mini), for that the degree of the weather to be belong to fuzzy set (cool) is 0.6 too.

3.1.2.6- Inference

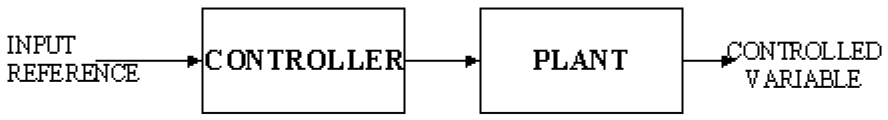
Fuzzy interference also called “reasoning or decision making” it is a process of making decisions by using fuzzy logic, or is the process of formulating from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves Membership function, Logical operations, and If-Then rules [5]. The inference can be achieved through the following steps:

1. **Fuzzification**: compare the input variables with the membership function on the first part to obtain the membership degree of each linguistic variable.
2. **Knowledge base**: consist of the rules (if-then), the first part of this rule may have one or more condition in the sentence. The knowledge base does not use to store the rule only, but it can make the condition of the first part in the rule to be available by evaluate them from all rules, by using the implication operation that will ably all logical operation (intersection, union, complement).
3. **Decision making**: this step can be considered as humans reasoning in decision making, it is very important, and simple. Decision making depend on the following rule: if the condition is be available by a certain ratio, and then the result of that condition will be available with same ratio.
4. **Defuzzification**: aggregate the qualified consequent to produce a crisp output, this means convert from fuzzy value to crisp value to be easy for computer and machine to deal with it.

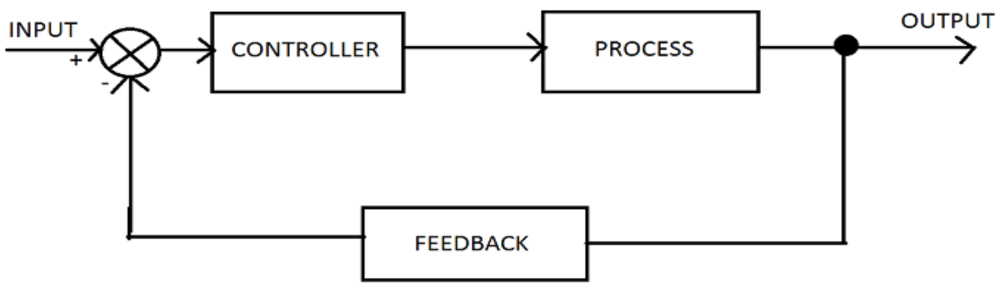
3.1.3- Control system

A control system is an arrangement of physical components designed to alter, to change, or to regulate through a control action. Control systems are two types: open loop control system, in which the control action is independent of physical system output, and closed loop control systems (also known as feedback control system) which feedback the physical system output.

The physical system under control is called a plant certain physical forcing signals (called inputs) are determined by the responses of the system (called outputs). To obtain satisfactory responses and characteristics for the closed loop control system, it is necessary to connect an additional system, known as a controller, or a compensator, into the loop.



OPEN-LOOP CONTROL



CLOSE-LOOP CONTROL

Figure (3.7) type of control system

3.1.3.1- Fuzzy logic control system

Most traditional control algorithms require a mathematical model of the system you want to control; however many physical systems are difficult or impossible to model mathematically [6]. Fuzzy logic control (FLC) is best utilized in complex ill-defined processes that can be controlled by skilled human operator without much knowledge of their underlying dynamics. The basic idea behind FLC is to incorporate the "expert experience" of a human operator in the design of the controller in controlling a process whose input-output relationship is described by collection of fuzzy control rules (e.g. if-then rules) involving linguistic variables rather than a complicated dynamic model. During the past decade, fuzzy logic control has emerged as one of the most active research areas in the application of fuzzy set theory. Especially in the area of industrial process which is very complex to control by conventional methods because of lack of quantitative data regarding the input-output relations, the fuzzy logic control proved to be effective and reliable, and much closer in spirit to human thinking and natural language than traditional logical systems. The ability of FLCs to translate the information supplied in linguistic terms into a computer-usable form has made fuzzy logic systems popular for implementing complex process control.

The design of the fuzzy logic controllers is differ from the conventional controllers in two ways: first, the fuzzy logic control uses linguistic rules rather than mathematical equations to model the system. Second, the fuzzy logic control models the behavior of the operator rather than that of the process.

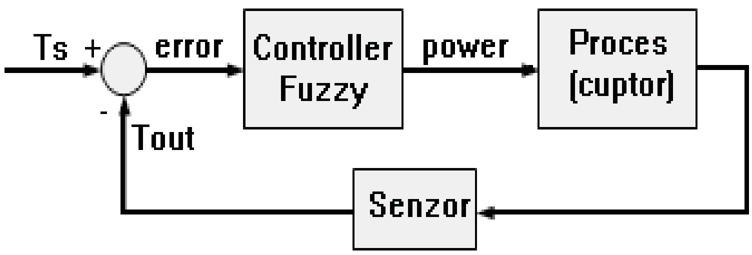


Figure (3.8) fuzzy control system

1- Theoretical reasons for the use of fuzzy controller

The mathematical model is too difficult to obtain, then most important information comes from sensors or human experts who provide linguistic description about the system and control instructions.

Fuzzy logic control is model free approach it does not require a mathematical model of the system under control.

2- Practical reasons for the use of fuzzy controller

The following reasons make the fuzzy controller desirable because:

a. It is easy to understand because fuzzy control emulates human control strategy of the control specialists.
b. Very robust.
c. It is simple, quick, and cheaper to implement.
d. Can be easily modified.

Because fuzzy control is easy to understand; the time necessary to learn the approach is short.

3- Generic configuration of fuzzy controller

The basic components of fuzzy logic controller are shown in the block diagram blew, in four steps: fuzzification, inference mechanism, rule-base, defuzzification.

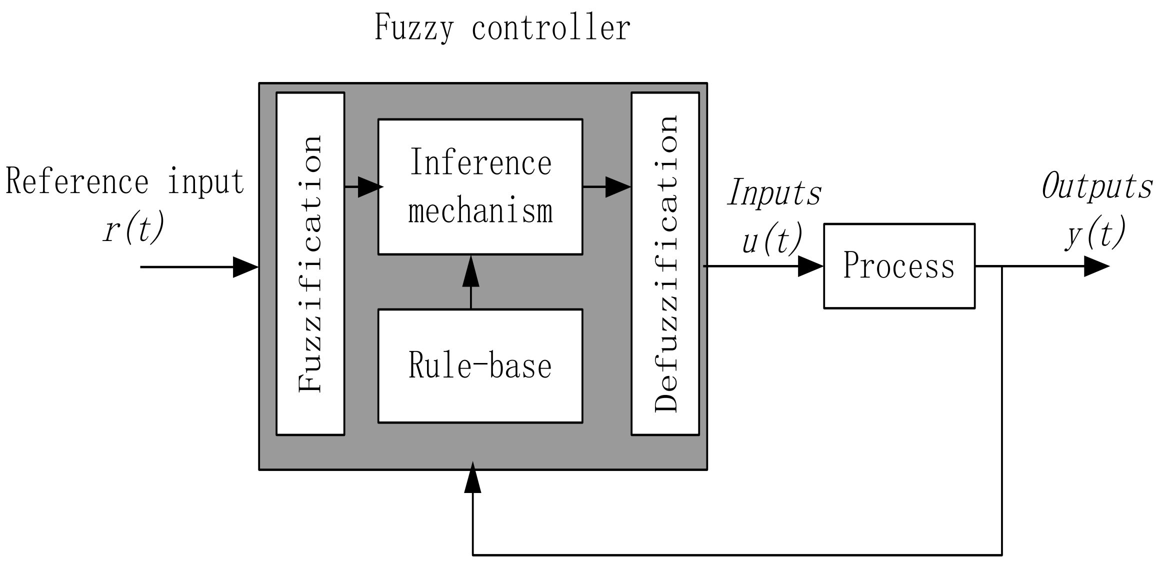


Figure (3.9) fuzzy controller architecture

Basically, you should view the fuzzy controller as an artificial decision maker that operates in a closed-loop system in real time. It gathers plant output data y(t), compares it to the reference input r(t), and then decides what the plant input u(t) should be to ensure that the performance objectives, will be met. The fuzzy controller has four main components:

1) The fuzzification interface simply modifies the input, it process of associating crisp, or numerical, input values with the linguistic terms of the corresponding input linguistic variables. So that they can be interpreted and compared to the rules in the rules in the rule-base.

   For example, a fuzzy controller might associate the temperature reading from a thermometer with the linguistic terms cold, moderate, and hot for the current temperature linguistic variable. Depending on the membership functions for the linguistic terms, the temperature value might correspond to one or more of the linguistic terms [5].
2) The inference mechanism evaluates which control rules are relevant at the current time and then decides what the input to the plant should be.

   After a fuzzy control fuzzifies the input values of a fuzzy system, the fuzzy controller uses the corresponding input linguistic terms and rule-base to determine the resulting linguistic terms of the output linguistic variables.

   For example, suppose the current temperature of a room is 50 degrees, which corresponds to a linguistic term of cold with a degree of member ship of 0.4. Also suppose the desired temperature is 70, which corresponds to a linguistic term of moderate with a degree of membership of 0.8. Then fuzzy controller invokes the following rule of the fuzzy system: If current temperature is cold AND desired temperature is moderate, THEN heater setting is low [5].
3) The rule-base holds the knowledge, in the form of a set of rules, of how best to control the system.
4) The difuzzification interface converts the degrees of membership of output linguistic variables within their linguistic terms into crisp numerical values [5], by the inference mechanism into the inputs to the plant.

4- Design parameters of fuzzy controller

A fuzzy system consists of three main parts: linguistic variables, membership function, and rules.

- **Creating linguistic variables**

  Linguistic variables represent in words, the input variables and output variables of the system you want to control. When you create a linguistic variable to represent an input or output variable, decide how many linguistic terms, or categories of values of the linguistic variable, you want to create. Linguistic variables usually have an odd number of linguistic terms, at each extreme. In most applications, three to seven linguistic terms are sufficient for categorizing the values of a linguistic variable [5].

- **Creating membership functions**

  Membership functions are numerical functions corresponding to linguistic terms. A membership function represents the degree of membership of linguistic variables within their linguistic terms [6].

- **Creating a rule base**

  Rules describe in words, the relationships between input and output linguistic variables based on their linguistic terms. A rule base is the set of rules for a fuzzy system. To create a rule, you must specify the antecedents, or IF portions, and consequents, or THEN portions, of the rule. Associate an input linguistic variable with a corresponding linguistic term to form an antecedent. Associate an output linguistic variable with a corresponding linguistic term to form a consequent. The consequent of a rule represent the action you want the fuzzy controller to take if the linguistic terms of the input linguistic variable in the rule are met. When constructing a rule base, avoid contradictory rules, or rules with the same IF portion but different THEN portions. A consistent rule base is a rule base that has no contradictory rules. The total number N of possible rules for a fuzzy system is defined by the following equation:

$$\boldsymbol{N}=\boldsymbol{P_1}+\boldsymbol{P_2}+\ldots\ldots\ldots\ldots\ldots+\boldsymbol{P_n}$$

Where P_n is the number of linguistic terms for the input linguistic variable n. if each input linguistic variable has the same number of linguistic terms, the total number $\boldsymbol{N}$ of possible rules is defined by the following equation:

$$N = p^m$$

Where $\boldsymbol{p}$ is the number of linguistic terms for each input linguistic variable, and $\boldsymbol{m}$ is the number of input linguistic variables. For example, for three input linguistic variables with five linguistic terms each, the total number of possible rules is $N = 5^3 = 125$

A rule base with at least one active rule for each possible combination of input linguistic variables and linguistic terms is a complete rule base. If you define an in complete rule base, you must specify a default linguistic term for each output linguistic variable so the fuzzy controller can handle situation in which no rules are active [6].

3.1.3.2- Application of fuzzy logic

- Control system
  - consumer system
    - -Automatic transmissions
    - - Washing machines
    - -Camera autofocus
  - industrial system
    - - Aircraft engines
    - -Power supply regulation
    - -Steam turbine start-up
- Artificial intelligence
  - -Robot motion planning
  - -Image segmentation
  - -Medical diagnosis system

2-multivariable blood pressure control system

3.2.1-introduction

Fuzzy systems have been successfully applied to various control and classification problems. In many application tasks, fuzzy rules are manually derived from human expert knowledge, and the resulting system is then tuned by monitoring its performance through trial and error. However, this approach becomes impractical for large dimension problems. To solve this problem, several methods are used to construct rule bases by means of self-learning algorithms; this research will present new methodologies which can be used to construct rule-bases for multivariable fuzzy controllers via self-learning. The controlled object proposed, the multivariable process, is assumed to be characterized by strong interaction between variables and pure time delay in control, [14]. The aim of the proposed system is to construct independent and decoupled rule-bases those can be used for several individual control loops. The basic idea may be simply stated as follows. By introducing a reference model and employing an iterative learning control scheme, desired control actions are learned. At the same time, the rule-bases are formed by observing, recording and properly processing the learned actions those used subsequently.

The automatic control of physiological parameters has been considered as important point for several years. One of the particular problems that have been subjected is the control of hemodynamic variables such as mean arterial pressure (MAP) and cardiac output (CO), The cardiac output is the amount of blood that is pumped by the heart per unit time, while mean arterial pressure is the average pressure reached inside the arteries. The implementation of automatic control system is very essential to improve the patient care in order to minimizing the workload of the physicians and reducing the costs. The Cardiovascular system has been used to designs control systems for blood pressure control[6].E. Furutani et al. have developed and implemented a state-predictive servo controller for continuous feedback control of MAP and inference fuzzy rules to avoid the risk and make the patients in safe side during surgical operation [7]. Over the past several years, different approaches have been investigated. Many have focused on the single-input single-output (SISO) control systems to lower the patients' blood pressure and maintain it at desired level using single drug particularly sodium nitropressied (SNP). So regulation of blood pressure (BP) and cardiac output (CO) is needed in some clinical situations, for instance congestive heart failure. It is desirable to maintain or increase CO and, at the same time, to decrease the blood pressure. This can be achieved by simultaneous infusions of a positive of inotropic agent, which increases the heart's contractility and cardiac output, and with vasodilator agent which dilates the vasculature and lowers the arterial pressure. To maintain the desired blood pressure, nurse has to frequently check the blood pressure and change the drug infusion rate accordingly. So there is a clear requirement to develop an automated feedback control system which hybrid technology, where blood pressure sensor reads a signal to a blood pressure controller, which will adjust the speed of a drug infusion pump accordingly. The control system has to control the flow of two agents to maintain the outputs (mean arterial pressure (MAP) and cardiac output (CO)) at their desired range or set points [15].

The objective of the control system is to decrease the patient's mean arterial pressure and increase the cardiac output to desired value by tracking the reference signals. Two frequently used drugs in clinical practice are the inotropic drug dopamine (DPM) and vasoactive drug sodium nitroprusside (SNP), DPM increases both cardiac outputs (CO) and main arterial pressure (MAP) while SNP increases cardiac outputs (CO) and decreases main arterial pressure (MAP). The drug infusion rates are measured in (mg/min.kg). Cardiac output is measured in (ml/min.kg). Mean arterial pressure is measured in millimeters of mercury (mmHg).

3.2.2-Factual knowledge

Fact and relations regard as the primitives of an information-processing from which all other informational structure can be defined. Although facts and relations are very simple notions, they are powerful enough to provide a lever into understanding what are normally to as knowledge.

The basic structure of the domain factual knowledge which contains seven facts represents the basic entities of the proposed system.

1. Reference inputs

   It is the desired inputs of the reference models y_{co}^{d} and y_{map}^{d} subject to step command signals.

2. Process outputs

   They are the outputs of the drug dynamics model ΔCO_d andΔRA_d.

3. Rule

   Gives the relation between the blood pressure scale and the Amount of the drug should be infused in order to keep the desired blood Pressure set point stable.

4. Rule-base

It is a collection of rules that covers the dopamin and sodium nitro pressuide of the blood Pressure control knowledge.

5. Learning interval

   It is the time that taken to generate rule-bases.

6. Fuzzy output

   It is the output that obtained by the fuzzy controller.

7. Set-point

   It is the scale of the blood pressure that should be stabilized by Proposed system.

The proposed system is modeled as taxonomy of units and subunits. The system output is the result of combining the functions of two main subunits, rule-base and fuzzy control, the first contains the rules that constitute the expert knowledge model which formulated using conclusions from facts and rule-base.

3.3- Neural network

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements**.**

Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network.

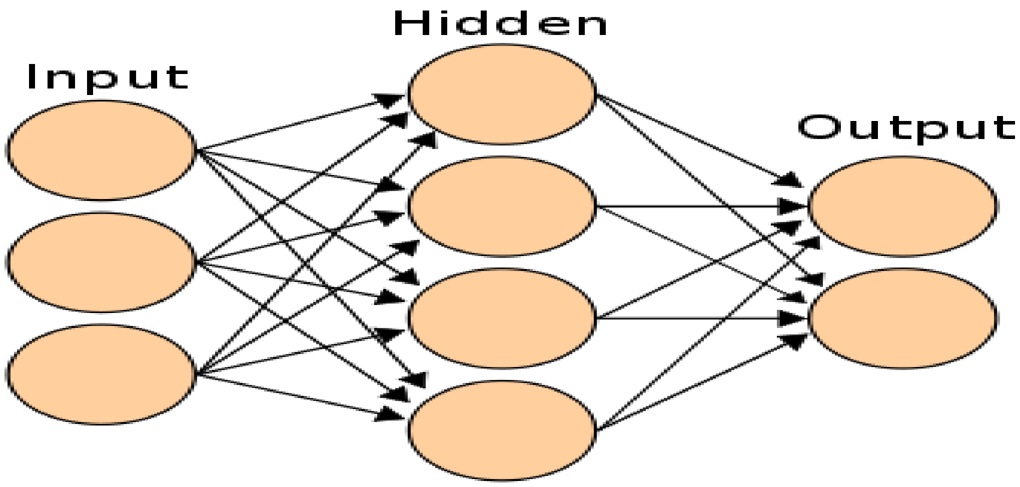


Figure (3.10) framework of network

Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems.

Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings. Throughout the toolbox emphasis is placed on neural network paradigms that build up to or are themselves used in engineering, financial and other practical applications**.**

The supervised training methods are commonly used, but other networks can be obtained from *unsupervised training* techniques or from direct *design* methods. Unsupervised networks can be used, for instance, to identify groups of data. Certain kinds of linear networks and Hopfield networks are designed directly. In summary, there are a variety of kinds of design and learning techniques that enrich the choices that a user can make**.**

-Back-propagation network

it used for learning Which contains two input units, four hidden units , and two outputs units , the outputs of the hidden units and output units use a sigmoid function to compute the activation value of each unit.

The back propagation learning algorithm is a supervised learning algorithm that provides a method to adjust the weights (W) in a multi-layer network of connected processing units. The purpose of the weight adjustment a gain to produce the correct outputs for a given training set, where the training set Consists of patterns of inputs and desired outputs. You give the algorithm examples of what you want the network to do and it changes the network's weights so that, when training is finished, it will give you the required output for a particular input.

Back Propagation networks are ideal for simple Pattern Recognition and Mapping Tasks. As just mentioned, to train the network you need to give it examples of what you want – the output you want (called the Target) for a particular input .The network is first initialized by setting up all its weights to be small random numbers – say between –1 and +1. Next, the input pattern is applied and the output calculated (this is called the forward pass). The calculation gives an output which is completely different to what you want (the Target), since all the weights are random. We then calculate the Error of each neuron, which is essentially:

Target - Actual Output. This error is then used mathematically to change the weights in such a way that the error will get smaller. In other words, the Output of each neuron will get closer to its Target (this part is called the reverse pass). The process is repeated again and again until the error is minimal.

The learning algorithm is described as follows:

1. First apply the inputs to the network and work out the output – remember this initial output could be anything, as the initial weights were random numbers.

2. Next work out the error for neuron B. The error is what you want – What you actually get, in other words: Error B= Output B (1-Output B) (Target B– Output B). The "Output (1-Output)"term is necessary in the equation because of the Sigmoid Function.

3. Change the weight. Let W"AB be the new (trained) weight and WAB be the initial weight. W"AB= WAB+ (Error B x Output A).

4. Calculate the Errors for the hidden layer neurons. Unlike the output layer we can't calculate these directly (because we don't have a Target), so we Back Propagate them from the output layer (hence the name of the algorithm). This is done by taking the Errors from the output neurons and running them back through the weights to get the hidden layer errors. Error A= Output A(1 – Output A)(Error B WAB + Error C WAC) .

5. Having obtained the Error for the hidden layer neurons now proceed as in stage 3 to change the hidden layer weights. By repeating this method we can train a network of any number of layers.

The correct way to train the network is to apply the first pattern and change all the weights in the network once. Next apply the second pattern and do the same, then the third and so on. Once you have done all four patterns, return to the first one again and repeat the process until the error becomes small.

We could stop it once the network can recognize all the patterns successfully, but in practice it is usual to let the error fall to a lower value first. This ensures that the patterns are all being well recognized. You can evaluate the total error of the network by adding up all the errors for each individual neuron and then for each pattern in turn to give you a total error, once the network has been trained, it should be able to recognize not just the perfect patterns but also corrupted or noisy versions In fact if we deliberately add some noisy versions of the patterns into the training set as we train the network we can improve the network's performance in this respect.

In other words, the network keeps training all the patterns repeatedly until the total error falls to some pre-determined low target value and then it stops [16].

CHAPTER FOUR

The proposed system

(Modeling and Simulation Results)

A framework was introduced on neural network, such as a way that the rule-base can be constructed automatically also the fuzzy reasoning mechanism can be implemented easily and the required knowledge prior knowledge about the controlled environment should be as little as possible. The starting point is to structurally map a simplest fuzzy control algorithm in to a counter propagation network [5, 6].

Back propagation is very Simple Structure and is used here in such a way that control knowledge is explicitly represented in the form of connection weights, by introducing a valid radius it providing an on-line learning teacher.

4.1- the interaction between BP net and blood pressure data

Described as follows:

-Apply back propagation network

-Apply BP data

-Calculate desired output

-Input initial control

-Repeat

-Calculate process output

-Calculate learning- error

-Until learning-error close to zero

4.2.1-Training back propagation network with blood pressure data:

Each network requires a data to be created or implemented, network that will be acceptable for the results.

Networks will be try to make a connection between the inputs data and the target output, in the end of training operation, a minimum possible values of error will be calculate that will be best if that values became zero.

In the first must create the network back propagation with a real data about blood pressure include hypertension, hypotension and weights data, and then must be define our inputs.

Network input include the medians for very low, low, normal, high and very high of systolic and diastolic pressure[78 90 125 145 165], [58 68 85 95 105] .

Then defined the target, which include values of medians for sodium nitro pressued (SNP) and dopamine (DPM) [20 15 0 8 12].

After network training with the above data, our system must be created to infuse the drugs with different rate for different patient with different weights

Therefor the patient's weights consider the basis factor for our calculate, the value[78/58] refers to a very low blood pressure from very low range of BP [70-81/50-61]systolic and diastolic BP, when any value from this range consider lower BP and the infusion of drugs will be constant to each weight, so when any value of the range insert to the system, the system take it as one value[78/58], and the drug infusion (target)will take [20] from dopamine range[10.5-31],so the low BP with value[90/68] from range[80-101/60-71], normal BP with value[125/85] from range[100-140/70-91] high [145/95] from range [139-156/90-100] very high [165/105] from rang [155-180/99-110], will be measure with the same method above.

So this method provides time when the physician decided how many rates of drugs must be infusion to patient to control the cases, this use manual method to decide the rate by applying the input data in this formula.

$$= \frac{\text{mcg x weight x 60}}{mg/mL}$$

-Mcg: physician order for drugs (microgram). For sodium nitro pressure SNP (0.3—10) mcg/kg/min, while for dopamine DPM (5—20) mcg/kg/min.

- Weight: patient's weight.

- 60: to convert from minute to hour.

- Mg/mL: concentration of drugs per ml.

4.2.2-Simulation Results

Creating a Network (newff):

The first step in training a feedforward network is to create the network object. The function newff creates a feedforward network. It requires three arguments and returns the network object. The first argument is a matrix of sample R-element input vectors. The second argument is a matrix of sample S-element target vectors. The sample inputs and outputs are used to set up network input and output dimensions and parameters. The third argument is an array containing the sizes of each hidden layer. (The output layer size is determined from the targets.)

To create a network, you provide typical input and output values that initialize weight and bias values and determine the size of the output layer.

$$p = [x_1, x_2, \ldots\ldots, x_n]$$

$$t = [x_1, x_2, \ldots\ldots\ldots, x_m]$$

where (X), represent any number, (n) is numbers of input, (m) numbers of target If There are three neurons in one hidden layer. The default transfer functions for hidden layers is tan-sigmoid, and for the output layer is linear.

net = newff(p,t,3);

This command creates the network object and also initializes the weights and biases of the network; therefore the network is ready for training.

Initializing Weights (init):

Before training a feedforward network, you must initialize the weights and biases. The newff command automatically initializes the weights, but you might want to reinitialize them. You do this with the init command. This function takes a network object as input and returns a network object with all weights and biases initialized. Here is how a network is initialized (or reinitialized):

```
net = init(net);
```

-Feed forward Back propagation Code:

-part of the code

```
 p= [78 90 125 145 165;58 68 85 95 105];
 t= [20 15 0 8 12 ];
net=newff(p,t,10);
net=train(net,p,t);
 y=sim(net,p)

y =
  Columns 1 through 4
 20.0000   12.2432   -0.0000    8.0000
 Column 5
  4.3561
>> net=init(net);
>> net=train(net,p,t);
>> y=sim(net,p)

y =
 Columns 1 through 4
 -6.6693   -7.5864    2.2222   -6.6374
Column 5
 11.5491
>> net=init(net);
>> net=train(net,p,t);
>> y=sim(net,p)

y =
  Columns 1 through 4
   18.6627   23.6106   28.2676   37.1033
  Column 5
  19.9658
>> net=init(net);
>> net=train(net,p,t);
>> y=sim(net,p)

y =
```

Columns 1 through 4
19.5579   15.0692   0.0270   8.0734
Column 5
11.7944

In the final network was be trained with a desired outputs as [19.5579 15.0692 0.0270 8.0734 11.7944], after training, the error reduced to minimum value as possible about(10^{-30}), so it is acceptable result, as show in a below figure (4.1). That shows the maximum acceptable ratio of error to be10^{0}, and can be decrease more than 1.

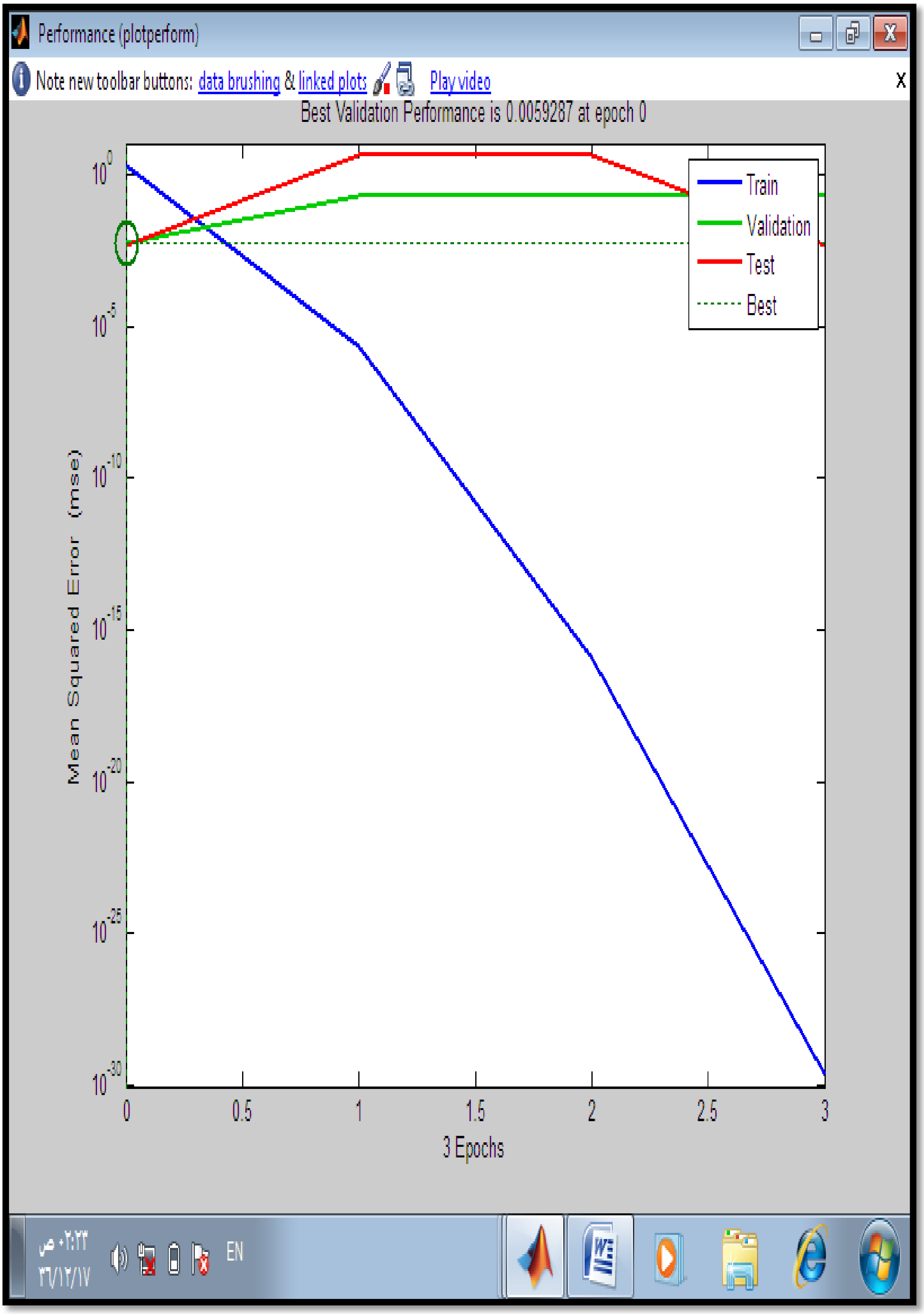


Figure (4.1) training network error

-Simulation Model

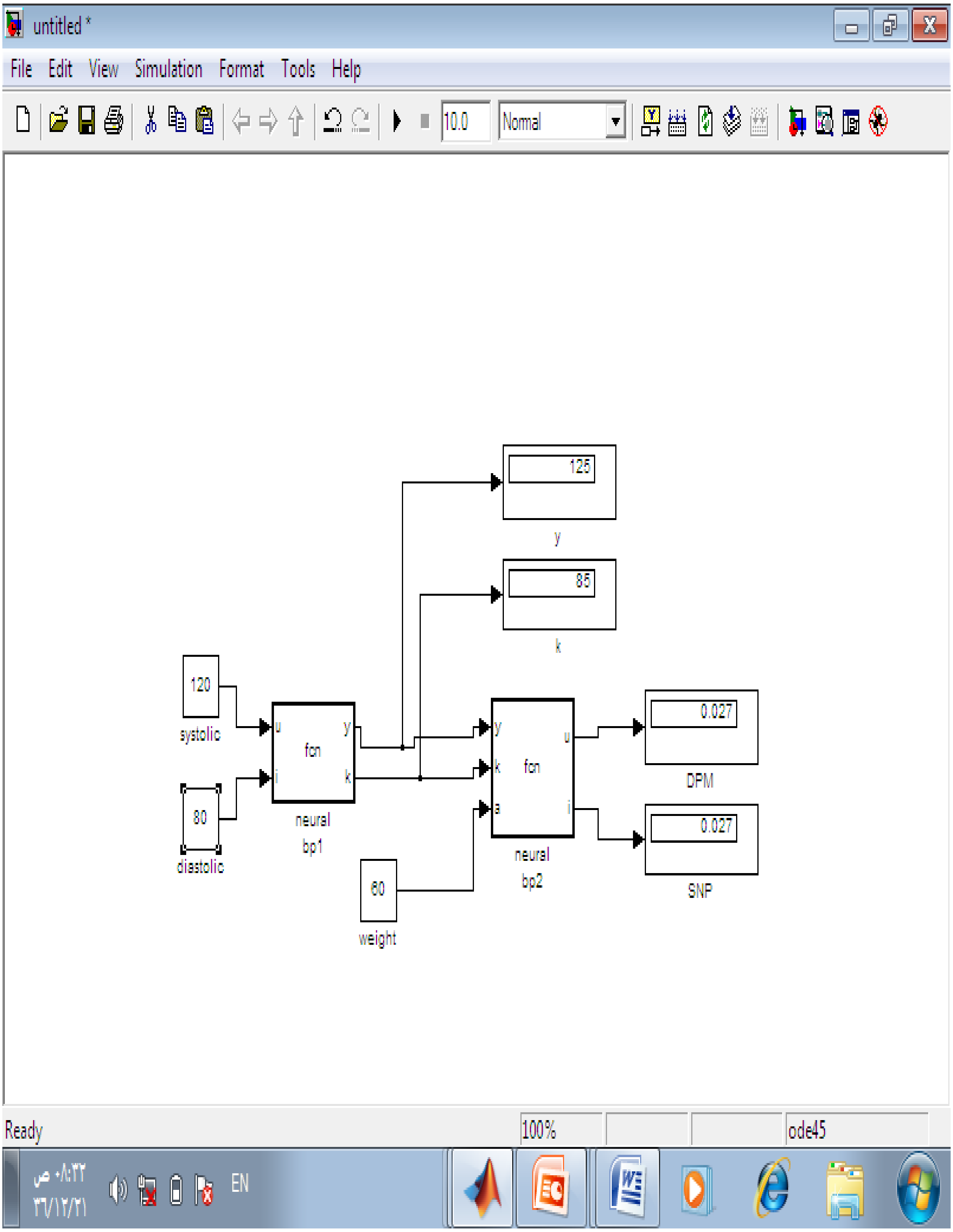


Figure (4.2) network simulation system

-The collection data that are used in a proposed system had gathered from both Haj Alsafi Hospital (Baheri/Sudan) and King Fahad Cenral Hospital (juizan/Sudia Arabia), as show as:

-Without depend of the weight

Table (4.1) collection data from haj alsafi hospital

Blood pressure state	Hypertension	Hypotension
Drugs infusion rate	(4-12)ml/hour	(8-22)ml/hour

-With depended of the weight

$$= \frac{\text{mcg x weight x 60}}{mg/mL}$$

Table (4.2) collection data from King fahed central hospital

Blood pressure state	Hypertension	Hypotension
Drugs infusion rate	(4-22)ml/hour	(8-31)ml/hour

The results as shown as:

A below table will show the result of training network with blood pressure data with different weights of patients

Table (4.3) the blood pressure network results

Weights	**Blood Pressure data**				
	Very low [70-81/50-61]	**Low [80-101/60-76]**	**Normal [100-138/75-89]**	**High [139-156/90-100]**	**Very High [155-180/99-110]**
40	10.0579	8.0692	0.0270	4.0734	5.7944

45	11.5579	8.0692	0.0270	4.5734	6.7944
50	12.5579	9.0692	0.0270	5.0734	7.2944
55	13.5579	10.0692	0.0270	5.5734	7.7944
60	15.5579	10.5692	0.0270	6.0734	8.7944
65	16.5579	11.0692	0.0270	6.5734	9.7944
70	17.5579	12.0692	0.0270	7.0734	10.2944
75	19.0579	13.0692	0.0270	7.5734	10.7944
80	20.5579	14.0692	0.0270	8.0734	11.7944
85	21.5579	15.0692	0.0270	8.5734	12.7944
90	23.0579	16.0692	0.0270	9.0734	13.2944
95	24.5579	17.0692	0.0270	9.5734	13.7944
100	25.5579	18.0692	0.0270	10.0734	14.7944
105	27.0579	19.0692	0.0270	10.5734	15.7944
110	28.5579	20.0692	0.0270	11.0734	16.2944
115	29.5579	21.0692	0.0270	11.5734	16.7944
120	30.5579	22.0692	0.0270	12.0734	17.7944

4.3.1- fuzzy logic with blood pressure data

This is the basic part of the system; because all process will be define with same degree of target as human brain.

Each value will be calculated with more efficient of degree.

Fuzzy logic (FL) can able to work for higher degree of acceptable data (±zero) means it can be able to define the output for any input without define this value directly to the system.

Example if we apply data to both fuzzy logic and network to give same output , fuzzy logic consider more efficiently than network, network need to define every and each value that you need to measure and give only that output for that value only, means if you increase or decrease that value to minimum values(±0.0000) the network will not be apple to give you your measure , because you are not insert that value for network, network doesn't work by degree of approximation, while fuzzy logic can apply that process easily and with number of degree as you want, because is like human brain has a degree of approximation to measure, just define the parameter range for your input and outputs then it can work efficiently with (±zero), so fuzzy logic more acceptable for clinical decided and any other need to identical result for work not be able to endures the increases or decreases in certain values.

-work concept of fuzzy logic:

(IF A THEN Z)

Firstly must insert inputs, and output to the system then apply the rules.

Input 1: high systolic [139—180] mmHg.

Input 2: high diastolic [90—110] mmHg.

Input 3: weight [40—120] kg.

Output: nitro pressed (SNP) [4—18] mL/hour.

-rules:

If any value in systolic range and any value of diastolic range and any value of weight have a certain value of output range.

Example: if (input1 150) and (input2 100) and (input3 69) then (output 7).

Input1 is a first term in the high systolic pressure member ship.

Input2 the first term in the high diastolic pressure member ship.

Input3 is the third term in weight member ship, because the first will be 40 set and second for 50 set, and so.

4.3.2- simulation result for fuzzy logic:

First must define how many input variables and output variables we applied fuzzy logic Simulation for hypertension and hypotension values, then we have 3 input variable and only one output variable for each one.

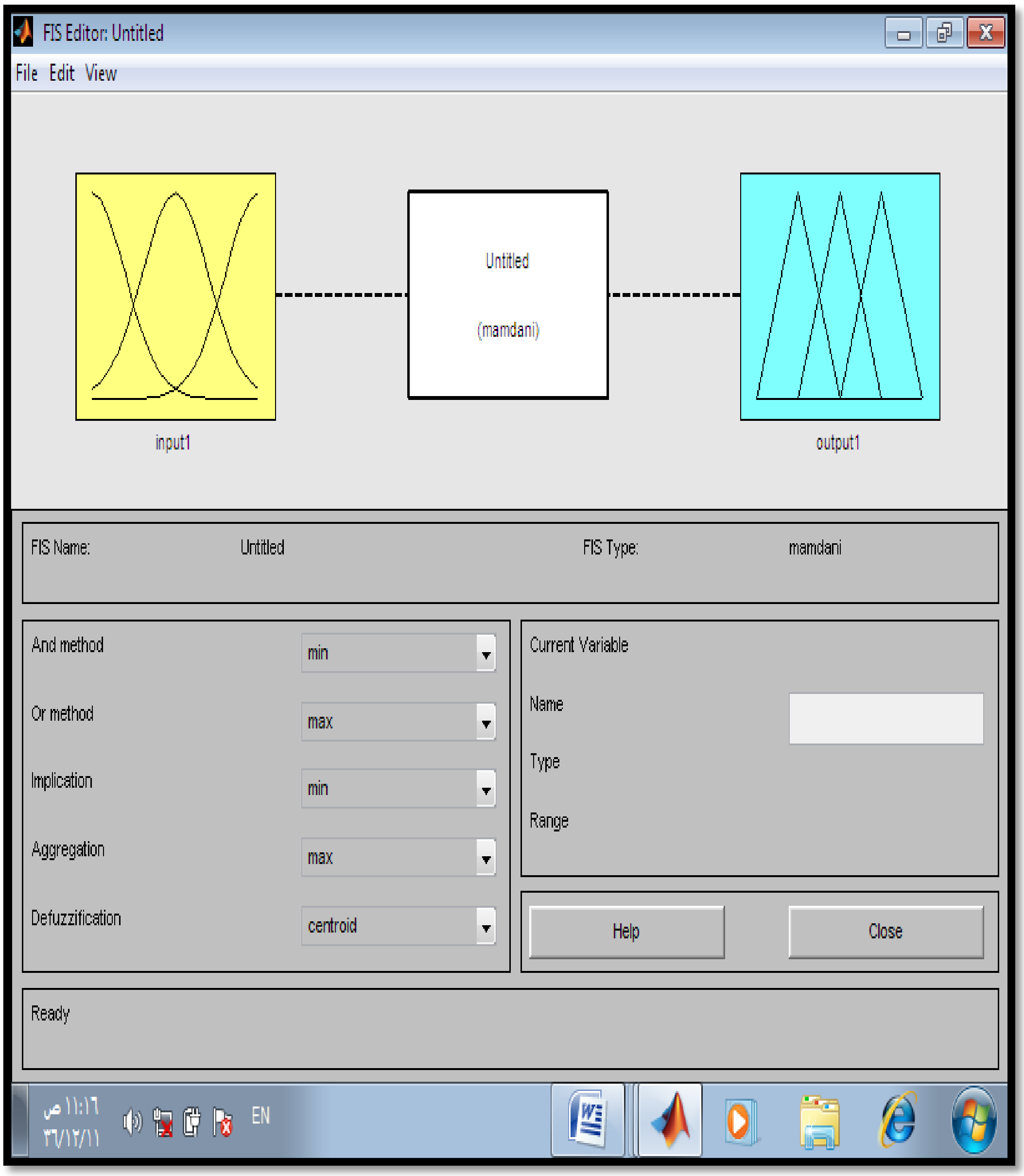


Figure (4.3) the framework of fuzzy logic system

4.3.3-The hypertension fuzzy logic parameters

And method (min).

Or method (max).

Implication (max).

Aggregation (max).

Deffuzzification (centroid).

-Member ship 1:

Name (systolic)

Type (input)

Range [70—180]

Display range [70—180]

Number of terms (3)

Normal with range [60—140]

Normal PARAM's [60-70-140]

High with range [139—156]

High PARAM's [139-148-156]

Higher with range [155—180]

Higher PARAM's [155-180-190]

Type of terms (tri mf)

- Member ship 2:

Name (diastolic)

Type (input)

Range [50—110]

Display range [50—110]

Number of terms (3)

Normal with range [40—91]

Normal PARAM's [40-50-91]

High with range [90—100]

High PARAM's [90-95-100]

Higher with range [99—120]

Higher PARAM's [99-110-120]

-Member ship 3:

Name (weight)

Type (input)

Range [40—120]

Display range [40—120]

Number of terms (17)

Mf1 with range [37—43]

Mf1 PARAM's [38-40-43]

Mf2 with range [42—48]

Mf2 PARAM's [42-45-48]

Mf3 with range [47—53]

Mf3 PARAM's [47-50-53]

Mf4 with range [52—58]

Mf4 PARAM's [52-55-58]

Mf5 with range [57—63]

Mf5 PARAM's [57-60-63]

Mf6 with range [62—68]

Mf6 PARAM’s [62-65-68]

Mf7 with range [67—73]

Mf7 PARAM’s [67-70-73]

Mf8 with range [72—78]

Mf8 PARAM’s [72-75-78]

Mf9 with range [77—83]

Mf9 PARAM’s [77-80-83]

Mf10 with range [82—88]

Mf10 PARAM’s [82-85-88]

Mf11 with range [87—93]

Mf11 PARAM’s [87-90-93]

Mf12 with range [92—98]

Mf12 PARAM’s [92-95-98]

Mf13 with range [97—103]

Mf13 PARAM’s [97-100-103]

Mf14 with range [102—108]

Mf14 PARAM’s [102-105-108

Mf15 with range [107—113]

Mf15 PARAM’s [107-110-113]

Mf16 with range [112—118]

Mf16 PARAM’s [112-115-118]

Mf17 with range [117—123]

Mf17 PARAM’s [117-120-123]

Member ship 4:

Name (SNP)

Type (output)

Range [0—18]

Display range [0—18]

Number of terms (26)

Mf1 with range [0—0]

Mf1 PARAM's [0-0-0]

Mf2 with range [3.7—4.3]

Mf2 PARAM's [3.7-4-4.3]

Mf3 with range [4.2—4.8]

Mf3 PARAM's [4.2-4.5-4.8]

Mf4 with range [4.7—5.3]

Mf4 PARAM's [4.7-5-5.3]

Mf5 with range [5.2—5.8]

Mf5 PARAM's [5.2-5.5-5.8]

Mf6 with range [5.7—6.3]

Mf6 PARAM's [5.7-6-6.3]

Mf7 with range [6.2—6.8]

Mf7 PARAM's [6.2-6.5-6.8]

Mf8 with range [6.7—7.3]

Mf8 PARAM's [6.7-7-7.3]

Mf9 with range [7.2—7.8]

Mf9 PARAM’s [7.2-7.5-7.8]

Mf10 with range [7.7—8.3]

Mf10 PARAM’s [7.7-8-8.3]

Mf11 with range [8.2—8.8]

Mf11 PARAM’s [8.2-8.5-8.8]

Mf12 with range [8.7—9.3]

Mf12 PARAM’s [8.7-9-9.3]

Mf13 with range [9.2—9.8]

Mf13 PARAM’s [9.2-9.5-9.8]

Mf14 with range [9.7—10.3]

Mf14 PARAM’s [9.7-10-10.3]

Mf15 with range [10.2—10.8]

Mf15 PARAM’s [10.2-10.5-10.8]

Mf16 with range [10.7—11.3]

Mf16 PARAM’s [10.7-11-11.3]

Mf17 with range [11.2—11.8]

Mf17 PARAM’s [11.2-11.5-11.8]

Mf18 with range [11.7—12.3]

Mf18 PARAM’s [11.7-12-12.3]

Mf19 with range [12.7—13.3]

Mf19 PARAM’s [12.7-13-13.3]

Mf20 with range [13.2—13.8]

Mf20PARAM’s [13.2-13.5-13.8]

Mf21 with range [13.7—14.3]

Mf21 PARAM’s [13.7-14-14.3]

Mf22 with range [14.7—15.3]

Mf22 PARAM’s [14.7-15-15.3]

Mf23 with range [15.7—16.3]

Mf23 PARAM’s [15.7-16-16.3]

Mf24 with range [16.2—16.8]

Mf24 PARAM’s [16.2-16.5-16.8]

Mf25 with range [16.7—17.3]

Mf25 PARAM’s [16.7-17-17.3]

Mf26 with range [17.7—18.3]

Mf26 PARAM’s [17.7-18-18.3]

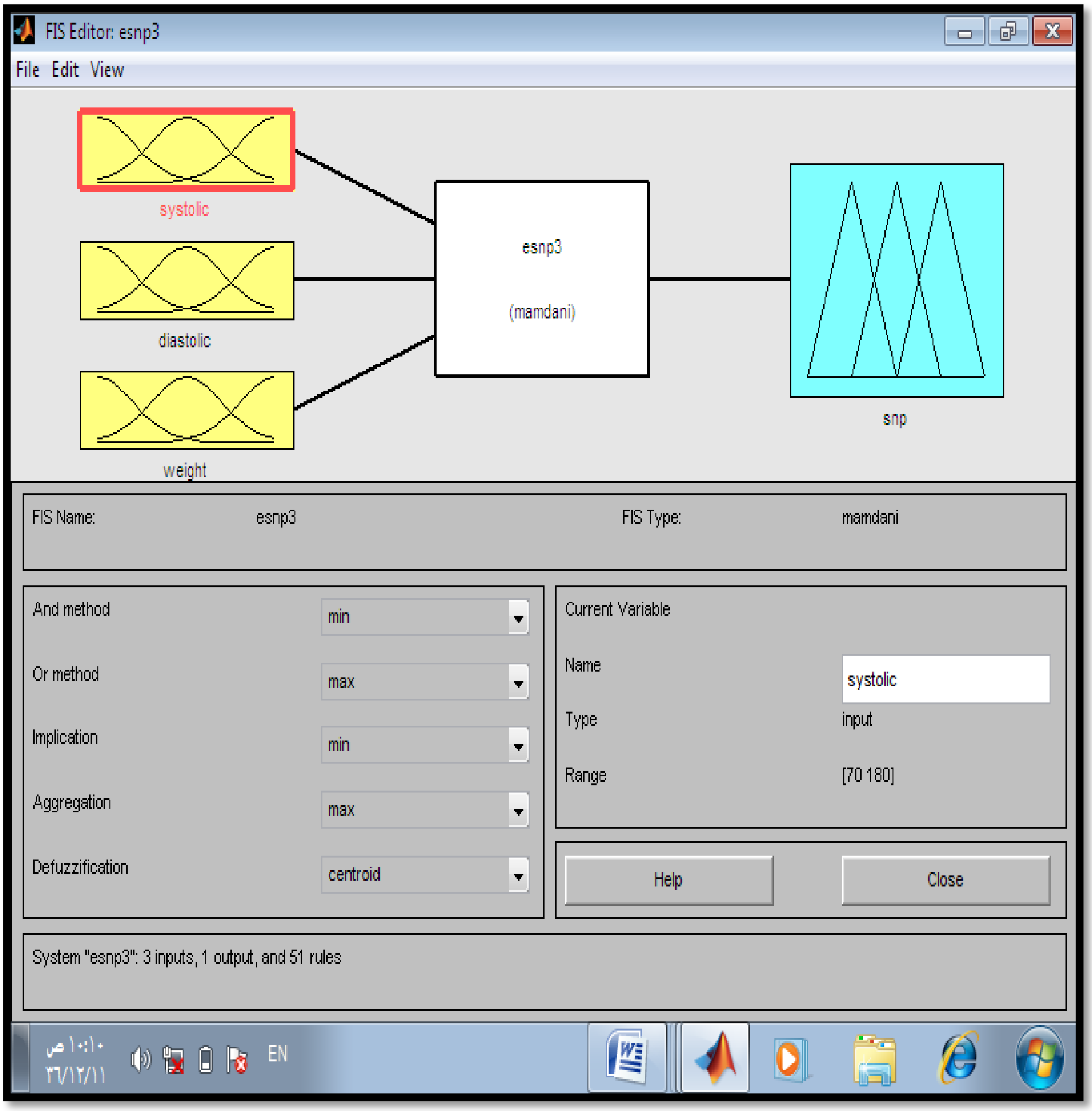


Figure (4.4) the total membership functions of hypertension blood pressure

4.3.4-The rules

IF A THEN Z

Here we have three inputs and one output.

IF A and B and C then Z

If (systolic is normal) and (weight is 40) then (SNP is 0)

The value of SNP will be zero for all weight value when systolic and diastolic are normal if (systolic is high) and (diastolic is high) and [weight (40-120)] then [SNP is (4-12)].

If (systolic is higher) and (diastolic is higher) and [weight (40-120)] then [SNP (6-18)]

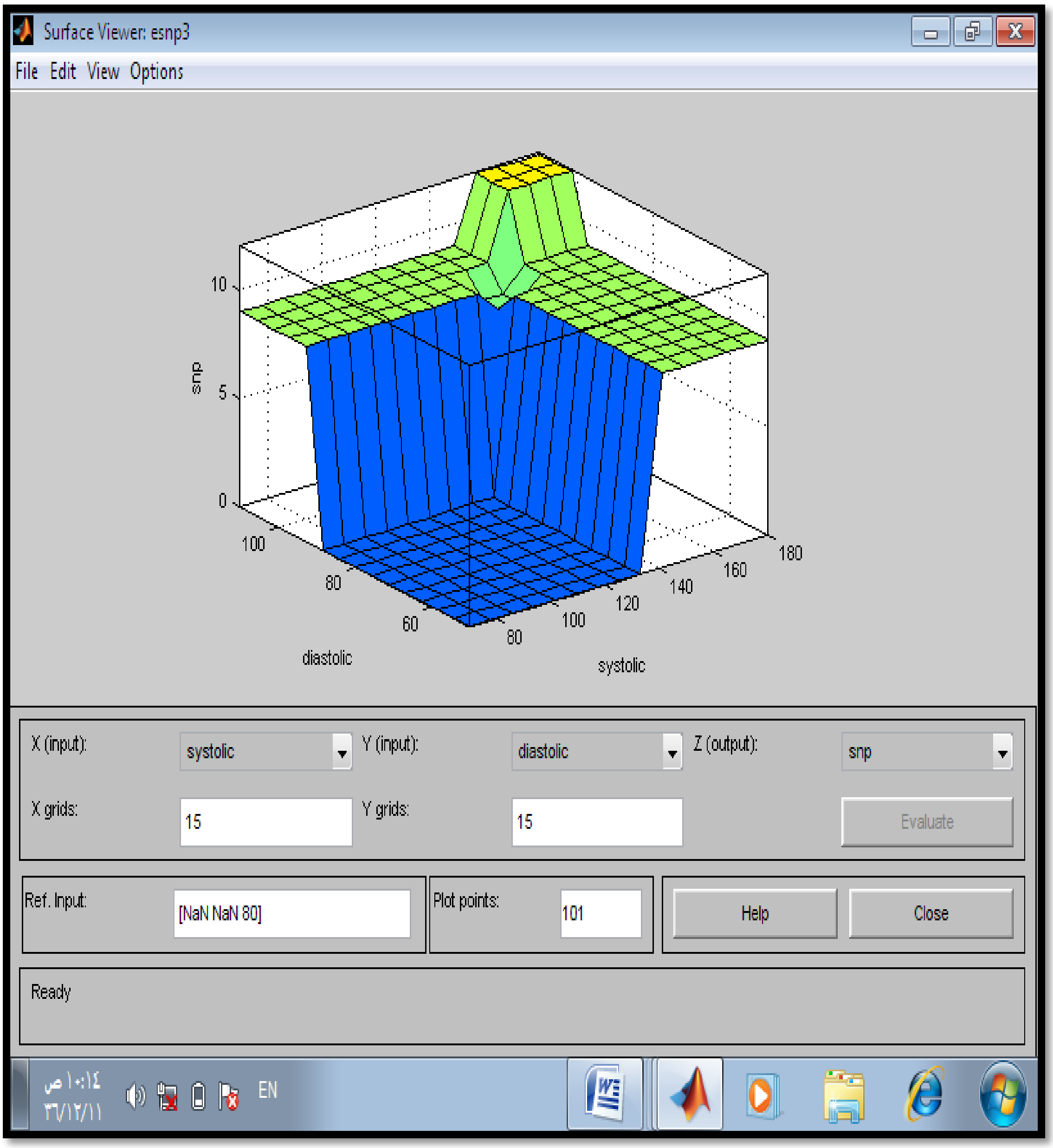


Figure (4.5) rules of hypertension

4.3.5-while for hypotension

Member ship 1

Name (systolic)

Type (input)

Range (70—180)

Display range (70—180)

Number of terms (3)

Lower [60—81]

Lower PARAM's [60-70-81]

Low [80—101]

Low PARAM's [80-90-101]

Normal range [100—180]

Normal PARAM's [100-180-190]

Type of terms (tri mf)

-member ship2:

Name (diastolic)

Type (input)

Range [50—110]

Display range [50—110]

Number of terms (3)

Lower range [40—61]

Lower PARAM's [40-50-61]

Low range [60—71]

Low PARAM's [60-65-71]

Normal range [70—110]

Normal PARAM’s [70-110-120]

Member ship3:

Name (weight)

Type (input)

Range [40—120]

Display range [40—120]

Number of terms (17)

Mf1 with range [37—43]

Mf1 PARAM’s [38-40-43]

Mf2 with rang [42—48]

Mf2 PARAM’s [42-45-48]

Mf3 with range [47—53]

Mf3 PARAM’s [47-50-53]

Mf4 with range [52—58]

Mf4 PARAM’s [52-55-58]

Mf5 with range [57—63]

Mf5 PARAM’s [57-60-63]

Mf6 with range [62—68]

Mf6 PARAM’s [62-65-68]

Mf7 with range [67—73]

Mf7 PARAM’s [67-70-73]

Mf8 with range [72—78]

Mf8 PARAM’s [72-75-78]

Mf9 with range [77—83]

Mf9 PARAM’s [77-80-83]

Mf10 with range [82—88]

Mf10 PARAM’s [82-85-88]

Mf11 with range [87—93]

Mf11 PARAM’s [87-90-93]

Mf12 with range [92—98]

Mf12 PARAM’s [92-95-98]

Mf13 with range [97—103]

Mf13 PARAM’s [97-100-103]

Mf14 with range [102—108]

Mf14 PARAM’s [102-105-108

Mf15 with range [107—113]

Mf15 PARAM’s [107-110-113]

Mf16 with range [112—118]

Mf16 PARAM’s [112-115-118]

Mf17 with range [117—123]

Mf17 PARAM’s [117-120-123]

Member ship4:

Name (dpm)

Type (input)

Range [0—33]

Display range [0—33]

Number of terms (26)

Mf1 with range [0—0]

Mf1 PARAM’s [0-0-0]

Mf2 with range [7.2—8.3]

Mf2 PARAM’s [7.2-8-8.3]

Mf3 with range [8.7—9.3]

Mf3 PARAM’s [8.7-9-9.3]

Mf4 with range [9.7—10.3]

Mf4 PARAM’s [9.7-10-10.3]

Mf5 with range [10.2—10.8]

Mf5 PARAM’s [10.2-10.5-10.8]

Mf6 with range [10.7—11.3]

Mf6 PARAM’s [10.7-11-11.3]

Mf7 with range [11.7—12.3]

Mf7 PARAM’s [11.7-12-12.3]

Mf8 with range [12.7—13.3]

Mf8 PARAM’s [12.7-13-13.3]

Mf9 with range [13.7—14.3]

Mf9 PARAM’s [13.7-14-14.3]

Mf10 with range [14.7—15.3]

Mf10 PARAM’s [14.7-15-15.3]

Mf11 with range [15.7—16.3]

Mf11 PARAM’s [15.7-16-16.3]

Mf12 with range [16.7—17.3]

Mf12 PARAM’s [16.7-17-17.3]

Mf13 with range [17.7—18.3]

Mf13PARAM's [17.7-18-18.3]

Mf14 with range [18.7—19.3]

Mf14 PARAM's [18.7-19-19.3]

Mf15 with range [19.2—19.8]

Mf15 PARAM's [19.2-19.5-19.8]

Mf16 with range [19.7—20.3]

Mf16 PARAM's [19.7-20-20.3]

Mf17 with range [20.7—21.3]

Mf17 PARAM's [20.7-21-21.3]

Mf18 with range [21.7—22.3]

Mf18 PARAM's [21.7-22-22.3]

Mf19 with range [22.7—23.3]

Mf19 PARAM's [22.7-23-23.3]

Mf20 with range [23.2—23.8]

Mf20 PARAM's [23.2-23.5-23.8]

Mf21 with range [24.7—25.3]

Mf21 PARAM's [24.7-25-25.3]

Mf22 with range [25.7—26.3]

Mf22 PARAM's [25.7-26-26.3]

Mf23 with range [27.2—27.8]

Mf23 PARAM's [27.2-27.5-27.8]

Mf24 with range [28.7—29.3]

Mf24 PARAM's [28.7-29-29.3]

Mf25 with range [29.7—30.3]

Mf25 PARAM’s [29.7-30-30.3]

Mf26 with range [30.7—31.3]

Mf26 PARAM’s [30.7-31-31.3]

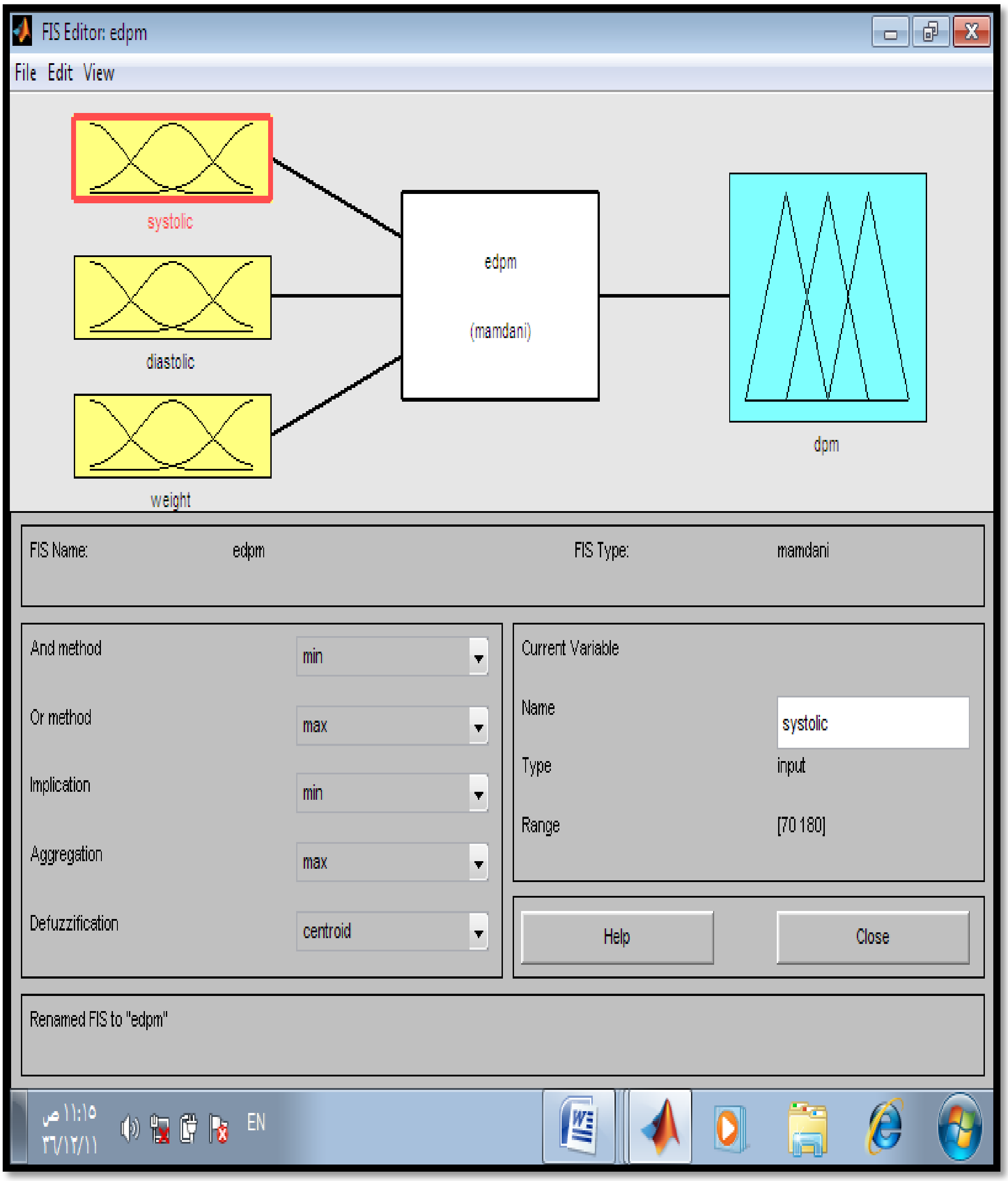


Figure (4.6) total membership functions for Hypotension blood pressure

4.3.6 -The rules:

If A then Z

If A and B and C then Z if(systolic is normal) and (diastolic is normal) and [weight is (40-120)] then (dpm is zero)

If (systolic is low) and (diastolic is low) and [weight is (40-120)] then [dpm is (8-23)]

If (systolic is lower) and (diastolic is lower) and [weight is (40-120)] then [dpm is (10.5-31)].

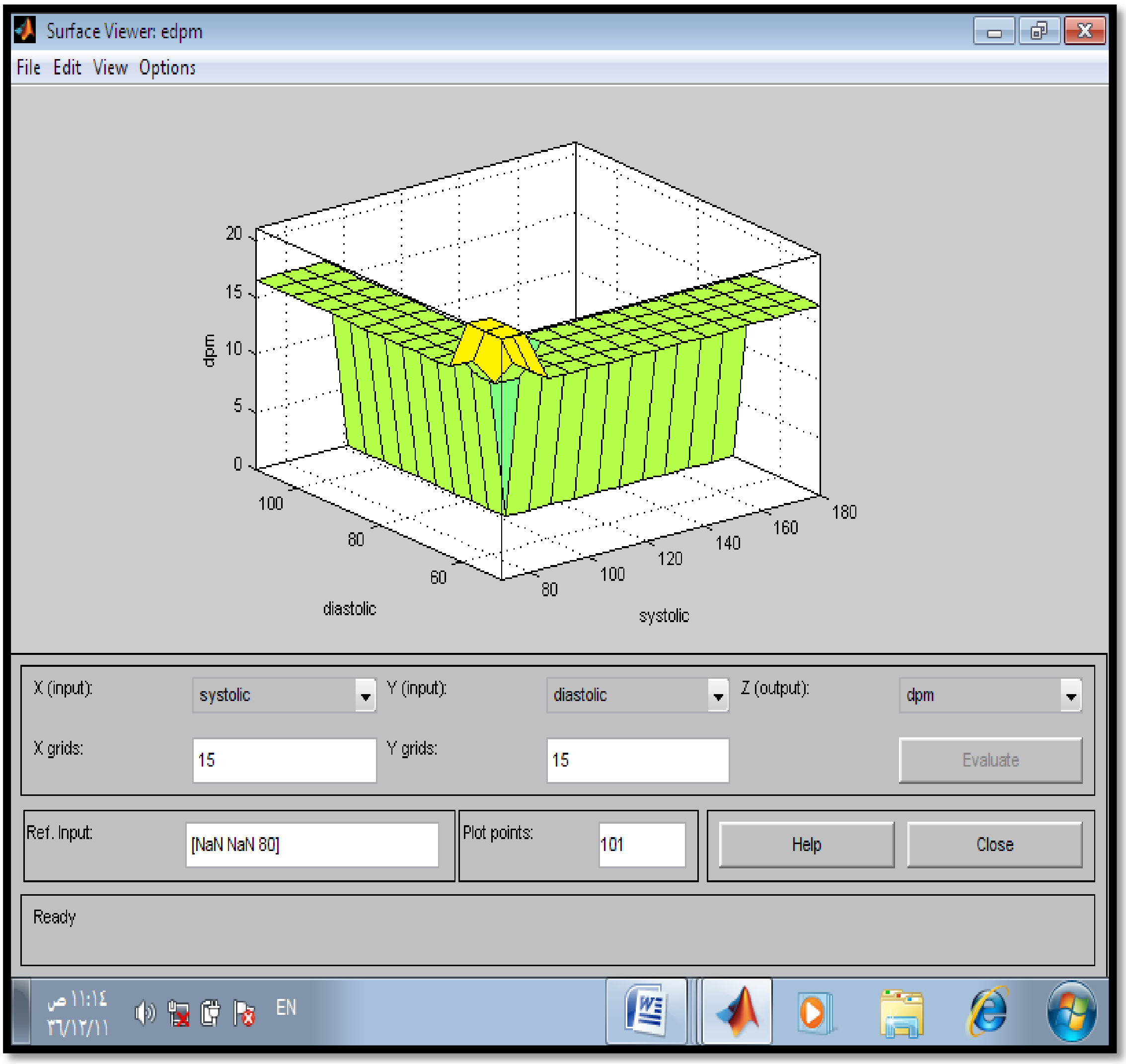


Figure (4.7) rules of hypotension

After all this operations fuzzy logic will be able to calculate any value about blood pressure and regulate it by give a degree of output regulate the given inputs.

Then fuzzy logic was being simulation to give results by using fuzzy controller in Simulation program as shown in table (4.7).

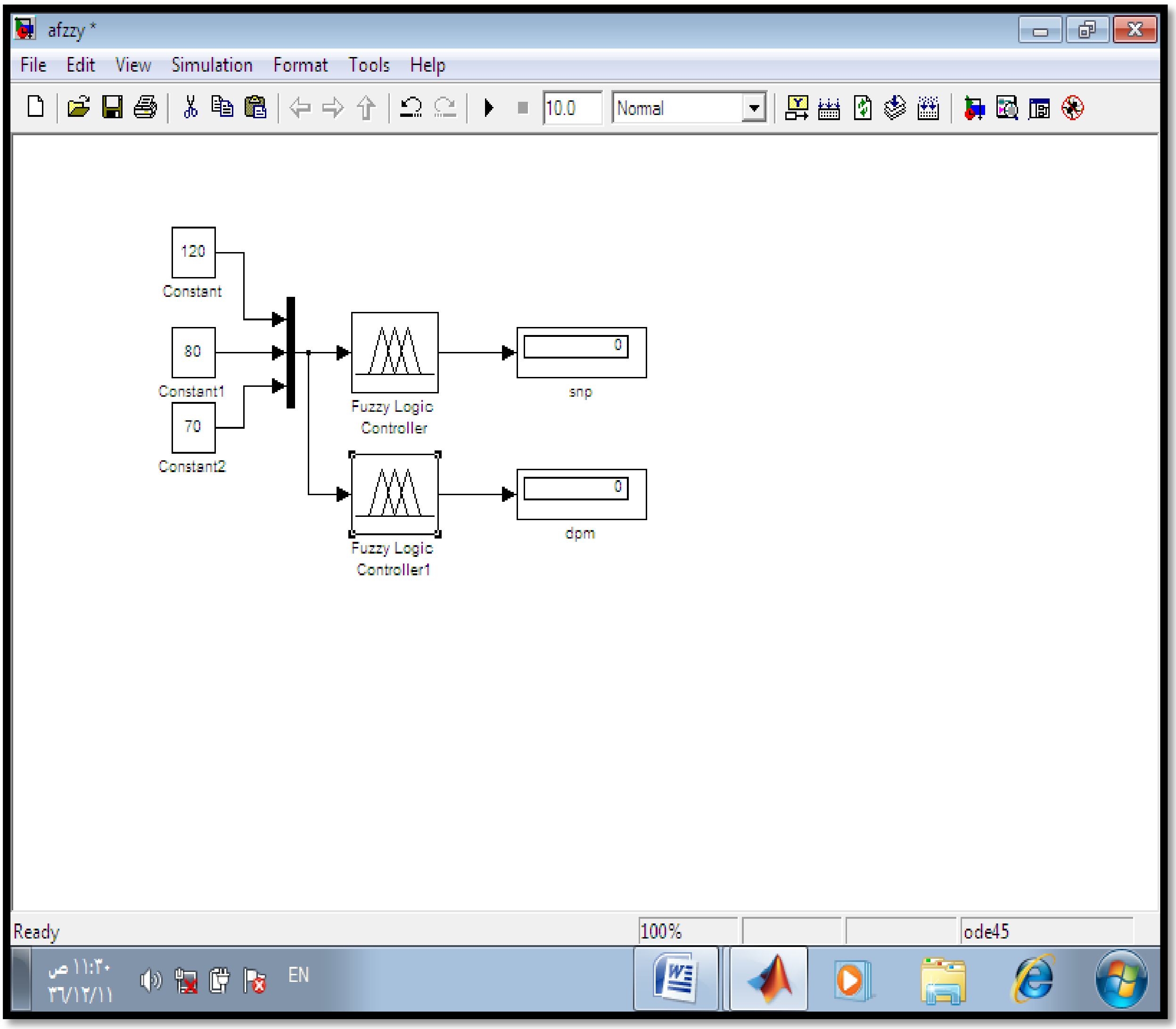


Figure (4.8) simulation of fuzzy logic system

4.4.1- Fuzzy-neural system

Fuzzy neural system is a combination between both of a neural networks and fuzzy logic control system (FLC), to be work under one framework to control the blood pressure (BP).

Neural networks does not deal with a degree of approximation to be measure the desired outputs as human brain, but it be train to be decide if the input of the system is consider lower, low, high, higher and normal blood pressure. While fuzzy logic system consider a inverse of neural network, it does not decide what type of blood pressure are be in a inputs, it just deal with the number in the input to be calculate follow to what rule include that number and what is the situation about that number, but fuzzy logic system has a degree of approximation to deal with it in his measurement, it can decide the results as a human brain, means fuzzy logic can be apple to calculate all values with all degree of increase or decrease of our inputs values.

So fuzzy neural system combine between two above system, the inputs of the system comes from the neural system to define the situation of the blood pressure, after that fuzzy logic take the outputs of neural system as inputs of fuzzy logic, then our desired outputs will be calculate, to control the blood pressure of the patients inside the surgical operations.

4.4.2-Simulation results

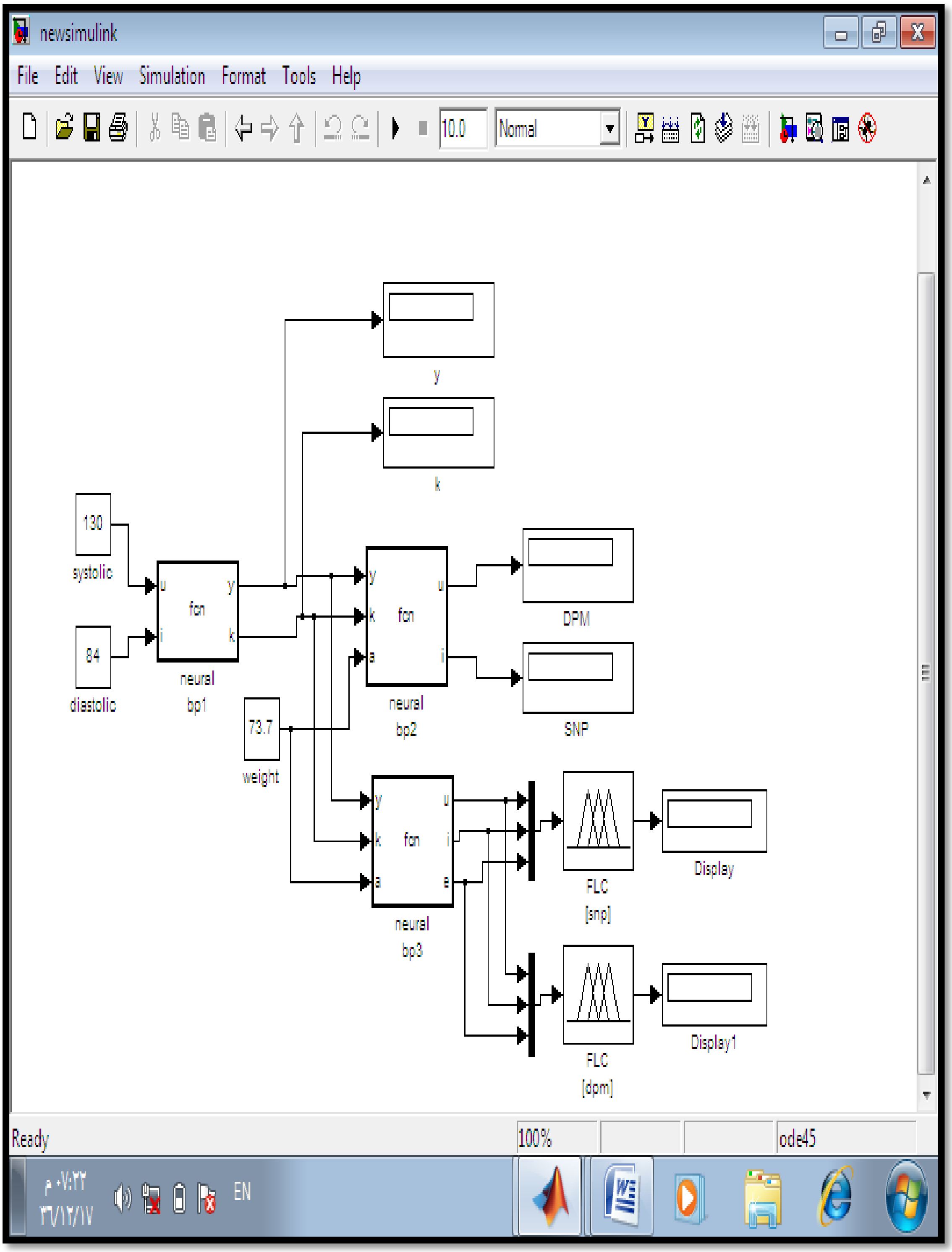


Figure (4.9) simulation of fuzzy neural system

Above Figure (4.9) show how fuzzy systems that combine with the neural systems under one system to regulate the blood pressure control.

So when the inputs be insert to the system, neural system as apart one of the system, will deal with the variables, to decide for what set of blood pressure sets consider that values, then the neural system give the results of it calculation, to the outputs, that outputs will be consider as a inputs for the second part of the system (FLC), that inputs will be compare to all rules that are saved in fuzzy system, so when all inputs meet it rules the outputs will be measure, to give the final results of the system.

-The result as show as:

Table (4.4) blood pressure fuzzy neural system results

Weights	**Blood Pressure data**				
	Very Low [70-81/50-61]	**Low [80-101/60-76]**	**Normal [100-138/75-89]**	**High [139-156/90-100]**	**Very High [155-180/99-110]**
40	10.47	7.997	0	3.989	5.988
45	12.05	7.997	0	4.5	7.002
50	13.04	8.99	0	5.011	7.512
55	14.02	9.99	0	5.505	7.996
60	16.01	10.51	0	5.985	9
65	17	11	0	6.494	10
70	17.98	12	0	7.006	10.49
75	19.47	13	0	7.515	11

80	20.96	13.99	0	7.995	12.01
85	21.95	15	0	8.489	13
90	23.54	16	0	9	13.5
95	24.95	17	0	9.511	14
100	25.96	18	0	10	14.99
105	27.55	19.01	0	10.49	16
110	29	20	0	10.99	16.51
115	30.03	21	0	11.51	17
120	31.02	22	0	12.01	17.92

4.5-Compares between the results of both proposed systems

Table (4.5) compares of very low blood pressure data

Weights	**Very low (neural)**	**Very low (fuzzy neural)**	**Stander infusion drugs**	**Difference (Neural)**	**Difference (Fuzzy neural)**
40	10.0579	10.47	10.5	-0.4421	-0.03
45	11.5579	12.05	12	-0.4421	-0.05
50	12.5579	13.04	13	-0.4421	-0.04
55	13.5579	14.02	14	-0.4421	+0.02
60	15.5579	16.01	16	-0.4421	-0.01
65	16.5579	17	17	-0.4421	0
70	17.5579	17.98	18	-0.4421	-0.02
75	19.0579	19.47	19.5	-0.4421	-0.03
80	20.5579	20.96	21	-0.4421	-0.04
85	21.5579	21.95	22	-0.4421	-0.05

90	23.0579	23.54	23.5	-0.4421	+0.04
95	24.5579	24.95	25	-0.4421	-0.05
100	25.5579	25.96	26	-0.4421	-0.04
105	27.0579	27.55	27.5	-0.4421	+0.05
110	28.5579	29	29	-0.4421	0
115	29.5579	30.03	30	-0.4421	+0.03
120	30.5579	31.02	31	-0.4421	+0.02

Above table show the different between two system's results to the stander drug for all cases with very low blood pressure. As was show the neural system decreased from stander infusion drugs with a constant value (0.04421), while the fuzzy neural system was both increased and decreased with a minimum value than the neural system, and in some situations the system had the same stander values, which that results indicated to the fuzzy neural system as appropriate system that can be use.

Table (4.6) compares of low blood pressure data

Weights	**Low (neural)**	**Low (fuzzy neural)**	**Stander infusion Drugs**	**Difference (neural)**	**Difference (fuzzy neural)**
40	8.0692	7.997	8	+0.0692	-0.003
45	8.0692	7.997	8	+0.0692	-0.003
50	9.0692	8.99	9	+0.0692	-0.01
55	10.0692	9.99	10	+0.0692	-0.01
60	10.5692	10.51	10.5	+0.0692	+0.01
65	11.0692	11	11	+0.0692	0
70	12.0692	12	12	+0.0692	0
75	13.0692	13	13	+0.0692	0
80	14.0692	13.99	14	+0.0692	-0.01
85	15.0692	15	15	+0.0692	0
90	16.0692	16	16	+0.0692	0
95	17.0692	17	17	+0.0692	0
100	18.0692	18	18	+0.0692	0
105	19.0692	19.01	19	+0.0692	+0.01
110	20.0692	20	20	+0.0692	0

115	21.0692	21	21	+0.0692	0
120	22.0692	22	22	+0.0692	0

Above table show the different between two system's results to the stander drug for all cases with low blood pressure. As was show the neural system increased from stander infusion drugs with a constant value (0.0692), while the fuzzy neural system was both increased , decreased with a minimum value than the neural system and in some situations the system had the same stander values, which that results indicated to the fuzzy neural system as appropriate system that can be use**.**

Table (4.7) compares of normal blood pressure data

Weights	**Normal (neural)**	**Normal (fuzzy neural)**	**Stander infusion Drugs**	**Difference (neural)**	**Difference (fuzzy neural)**
40	0.0270	0	0	+0.0270	0
45	0.0270	0	0	+0.0270	0
50	0.0270	0	0	+0.0270	0
55	0.0270	0	0	+0.0270	0
60	0.0270	0	0	+0.0270	0
65	0.0270	0	0	+0.0270	0
70	0.0270	0	0	+0.0270	0
75	0.0270	0	0	+0.0270	0
80	0.0270	0	0	+0.0270	0
85	0.0270	0	0	+0.0270	0
90	0.0270	0	0	+0.0270	0
95	0.0270	0	0	+0.0270	0
100	0.0270	0	0	+0.0270	0
105	0.0270	0	0	+0.0270	0
110	0.0270	0	0	+0.0270	0
115	0.0270	0	0	+0.0270	0
120	0.0270	0	0	+0.0270	0

Above table show the different between two system's results to the stander drug for all cases with normal blood pressure. As was show the neural system increased from stander infusion drugs with a constant value (0.0270), while the fuzzy neural system was had the same stander values, which that result indicated to the fuzzy neural system as a most appropriate system for normal pressure to be use.

Table (4.8) compares of high blood pressure data

weights	**High (neural)**	**High (fuzzy neural)**	**Stander infusion Drugs**	**Difference (neural)**	**Difference (fuzzy neural)**
40	4.0734	3.989	4	+0.0734	-0.011
45	4.5734	4.5	4.5	+0.0734	0
50	5.0734	5.011	5	+0.0734	+0.011
55	5.5734	5.505	5.5	+0.0734	+0.005
60	6.0734	5.985	6	+0.0734	-0.015
65	6.5734	6.494	6.5	+0.0734	-0.006
70	7.0734	7.006	7	+0.0734	+0.006
75	7.5734	7.515	7.5	+0.0734	+0.015
80	8.0734	7.995	8	+0.0734	-0.005
85	8.5734	8.489	8.5	+0.0734	-0.011
90	9.0734	9	9	+0.0734	0
95	9.5734	9.511	9.5	+0.0734	+0.011
100	10.0734	10	10	+0.0734	0
105	10.5734	10.49	10.5	+0.0734	-0.01
110	11.0734	10.99	11	+0.0734	-0.01
115	11.5734	11.51	11.5	+0.0734	+0.01
120	12.0734	12.01	12	+0.0734	+0.01

Above table show the different between two system's results to the stander drug for all cases with high blood pressure. As was show the neural system increased from stander infusion drugs with a constant value (0.0734), while the fuzzy neural system was both increased , decreased with a minimum value than the neural system and in some situations the system had the same stander values, which that results indicated to the fuzzy neural system as appropriate system that can be use**.**

Table (4.9) compares of very high blood pressure data

weights	Very High (neural)	Very High (fuzzy neural)	Stander infusion Drugs	Difference (neural)	Difference (fuzzy neural)
40	5.7944	5.988	6	-0.2056	-0.012
45	6.7944	7.002	7	-0.2056	+0.002
50	7.2944	7.512	7.5	-0.2056	+0.012
55	7.7944	7.996	8	-0.2056	-0.004
60	8.7944	9	9	-0.2056	0
65	9.7944	10	10	-0.2056	0
70	10.2944	10.49	10.5	-0.2056	-0.01
75	10.7944	11	11	-0.2056	0
80	11.7944	12.01	12	-0.2056	+0.01
85	12.7944	13	13	-0.2056	0
90	13.2944	13.5	13.5	-0.2056	0
95	13.7944	14	14	-0.2056	0
100	14.7944	14.99	15	-0.2056	-0.01
105	15.7944	16	16	-0.2056	0
110	16.2944	16.51	16.5	-0.2056	+0.01
115	16.7944	17	17	-0.2056	0
120	17.7944	17.92	18	-0.2056.	-0.08

Above table show the different between two system's results to the stander drug for all cases with high blood pressure. As was show the neural system decreased from stander infusion drugs with a constant value (0.2056), while the fuzzy neural system was both increased , decreased with a minimum value than the neural system and in some situations the system had the same stander values, which that results indicated to the fuzzy neural system as appropriate system that can be use**.**

So all above compares was refers to a fuzzy neural system as acceptable system that can be used to regulate the blood pressure, than neural system.

CHAPTER FIVE

Conclusion and Recommendations

5.1-Conclusion

This research based on three steps to design the proposed system, to regulate the blood pressure for a patient in a surgical operation, to reduce the complication that will affect in the patient's health.

In the first step, a feed forward back propagation network was used to training the blood pressure data with different rate, medians of blood pressure taken to represent the input of the network, [78 90 125 145 165], [58 68 85 95 105] Then defined the target, which include values of medians for sodium nitro pressured (SNP) and dopamine (DPM) [20 15 0 8 12]. After network been trained a minimum error was obtained, as show in figure (4.1). In the final network was be trained with a desired outputs as [19.5579 15.0692 0.0270 8.0734 11.7944].

Then a simulation of back propagation neural system was made as show in figure (4.2), a desired results was obtained as show in table (4.3), from collected data as show in both tables (4.1) and (4.2).

The second step was included a fuzzy logic system with number of membership functions that was consist of number of terms, as show in figures (4.3), (4.4) and (4.6),that was trained with the patient's weights, then a based rules was been created to control the system as show in figures (4.5) and (4.7). Finally a fuzzy system was be simulated in mat lab as show in figure (4.8).

The last step was included a combination of both back propagation network and fuzzy system to created a proposed system as show in figure (4.9), then a desired results was obtained , as show in table (4.4).

Finally the compare between the neural network and a fuzzy neural network, that was show the most acceptable system that can be use to regulate blood pressure control, was show in tables (4.5), (4.6), (4.7), (4.8) and (4.9).

5.2-Recommendations

This research needs to:

1-Training with more blood pressure data.

2-Training with real direct medical cases.

3-apply a practically.