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DEPARTMENT OF BIOMEDICAL ENGINEERING

A Project Submitte In Partial fulfillment for the Degree of B. Sc. In Biomedical Engineering

Implementation of artificial neural networks and fuzzy logic for hypovolemia monitoring in the operation theatre.

تطبيق الشبكة العصبية الإصطناعية والمنطق الغامض لمراقبة نقص حجم السوائل للمريض في غرفة العمليات.

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DEDICATION

We guide this research to those who contributed in our arrival to the path of the end to whom it was credited after God to us , to our parents and our families.

To all of us taught something new and fed our ideas of science and knowledge and stood by us and helped us overcome all the difficulties , to our professors and our doctors in the university.

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Abstract

The objective of this research is to improve the patient safety during surgical procedures by providing a system for detection and classification of hypovolemia event on the basis of a vital parameters. This system analyzes three physiological data which related to blood volume in the body and regarding all this data it'll give output .it'll empower doctors to take their decision quickly.

In this research used two systems to satisfy objective and evaluate between them, the first system is artificial neural network which trained by back propagation learning algorithm to diagnosis hypovolemia critical event, it simulated system by Graphical user interface tool(GUI).the proposed system obtained the physiological data from patient monitoring devices as testing data to artificial neural network and then give two output which indicate to the hypovolemia stage and the compensation volume of blood ,water or plasma.

The second system has been designed using fuzzy logic controller which consist rule–base mechanism of fuzzy system and the controlled process to diagnosis hypovolemia critical event ,these system is simulated by using simulation program .the proposed system obtained the physiological data from patient monitoring devices as inputs to fuzzy control system which decide depend on rule-base and the degree of member ship function of each input value to fuzzy set or linguistic term and then give two output which indicate to the hypovolemia stage and the compensation volume of blood ,water or plasma.

The simulation results show an acceptable performance or those two systems compared to the doctor decision in the hospital.

المستخلص

إن الهدف من هذا البحث هو تحسين سلامة المرضى أثناء العمليات الجراحية من خلال توفير نظام للكشف وتصنيف حالة نقص حجم السوائل على أساس البيانات الحيوية، هذا النظام يحلل ثلاثة بيانات فسيولوجية والتي تتعلق بحجم الدم في الجسم وهي معدل ضربات القلب وضغط الدم وكمية البول المخرجة، وبناء على هذه البيانات سوف يعطي النظام الخرج ، هذا النظام سوف يمكن الأطباء من إتخاذ القرار بصورة أسرع فيما يتعلق بحجم التعويض.
هذا البحث تضمن نظامين من انظمة الذكاء الاصطناعي لتحقيق الهدف وتطبيق النظامين ، النظام الاول هو الشبكات العصبية الإصطناعية التي تم تدريبها بخوارزمية الإنتشار الخلفي بغرض تشخيص نقص حجم السوائل الحرج، ومن ثم تم تطبيق هذا النظام علي برنامج واجهة المستخدم الرسومية، تم الحصول على البيانات من أجهزة مراقبة المرضى لإختبار الشبكة ومن ثم الحصول على الخرج في صورتين هما نقص حجم الدم وحجم التعويض سواء كان دم أو ماء أو بلازما.
النظام الثاني تم تصميمه باستخدام المنطق الغامض الذي يشتمل على مجموعة من القواعد التي تحكم النظام وعملية التحكم لتشخيص حالة نقص حجم السوائل، وتمت محاكاة هذا النظام باستخدام برنامج المحاكاة ، تم الحصول على البيانات من أجهزة مراقبة المرضى كمدخلات لنظام التحكم الغامض والذي يعطي الخرج بناء على مجموعة من القواعد ودرجة إنتماء كل دخل إلى المجموعة الغامضة المعينة ويكون الخرج في صوتين أيضا وهما نقص الدم وحجم التعويض سواء كان دم أو ماء أو بلازما.
هذان النظامين أعطيا نتائج مقبولة مقارنة مع قرار الطبيب في المستشفى.

CHAPTER ONE

INTRODUCTION

1.1- General view

The world we live in is full of uncertainty and imprecision in so many ways. In particular the domain of medical decision making is one driven by problems of vagueness and uncertainty. The doctor makes decisions on treatment based not simply on matching precise symptoms or measurements to diagnosis.

Smart computer algorithms have led to rapid development in the field of patient monitoring , Accelerated growth in the field of medical science has made data analysis more demanding and thus the complexity of decision-making procedures [1] . Doctor working in the operating theatre are responsible for carrying out a multitude of tasks which requires constant vigilance, thus a need for a smart decision support system has arisen , The decision support tools capable of detecting pathological events thus can enhance the Doctor performance by providing the diagnostic information [2] in an interactive and ergonomic display format. monitoring of patients under surgery involves the interpretation of data related to the physiologic conditions of the patient [3] but it requires cautious attention by doctor who are monitoring clinical critical event and performing patient management tasks simultaneously, often in a state of unconsciousness patients cannot directly communicate with the doctor and have to be monitored using a multitude of parameters producing a significant amount of data. all patients undergoing major surgery are at risk from complications caused by a reduction in circulating blood volume. Hypovolemia can occur during longer surgical procedures as a result of the blood lost during surgery [4]. there are a number of embarrassing events that occur to the patients inside the operating room, the most important and most serious of these events is a Hypovolemia , Hypovolemia is a decrease of the volume of circulating blood which frequently involves making rapid decisions on the basis of a large physiological information.

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.

The introduction of fuzzy logic for setting up Decision support systems (DSSs) is founded on the ability of fuzzy logic in dealing with the incompleteness and vagueness that often characterize medical data and knowledge. Computer programs employing fuzzy logic are intended to imitate human thought processes in complex circumstances like hypovolemia but to function at greater speed[5]. In this perspective, fuzzy logic works will be described by illustrating its application in the monitoring of hypovolemia in operation room. 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

Doctor should control and detect all complications that occur during any surgery in the operation room and give right and rapid decisions in order to obtain integrated healthcare to the patient and increasing the safety, The big problem in hospitals is that they deplete a great time and few precision to detect hypovolemia and determine compensation value to the patient because the human has a limited ability to accurately and continuously analyze large amounts of data. The calculation of the lost blood volume is difficult and taking long time because they calculate the number of saturated lawn and then they compensate approximate value of blood to patient this can lead to complications to patient and also can lead to death , So we must avoid giving the patients too little or too much compensation volume.

1.3- Objective

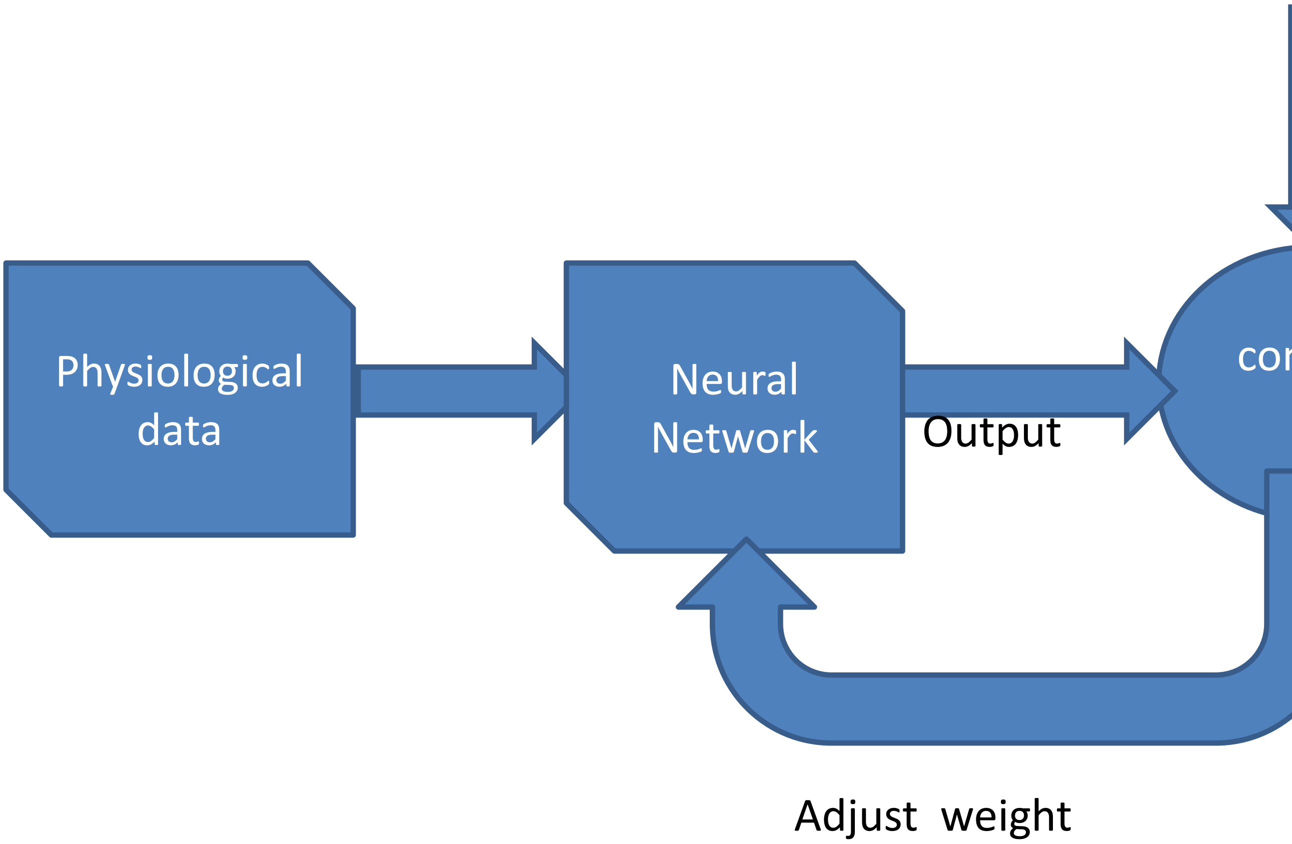
The main objective of this research is to:

Implementation of artificial neural networks and fuzzy logic for detecting and classification of hypovolemia and give the compensation volume in the operation theatre**.**

1.4- Methodology

The method of artificial neural network and fuzzy logic monitoring systems is proposed to control, monitoring and classification the hypovolemia class level to hypovolemic patients in the operation theatre.

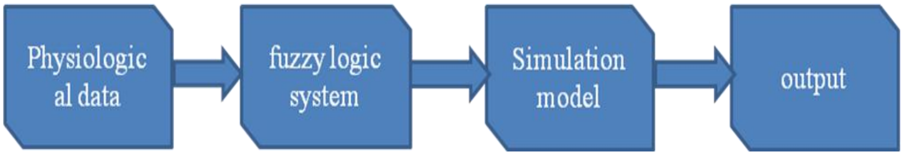
- Firstly system neural network to be training to give two output the stage of hypovolemia and the quantity of compensation according to inputs are heart rate, blood pressure and urine output with a different situations of patients .



Figure(1.1) neural network diagram

- Secondly in fuzzy the rule-base is initially empty and is constructed. 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. The inputs are heart rate, blood pressure and urine output with a different situations of patients and two output the stage of hypovolemia and the quantity of compensation.
- The overall system composes three functional models: the reference inputs and outputs the rule-base mechanism of fuzzy system and the controlled process which is assumed to have

numbers of inputs and numbers of outputs.



Figure(1.2) fuzzy logic diagram

1.5- The project 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 consist the proposed system "Modeling and Simulation Results". Finally conclusion and recommendations are presented in chapter five.

CHAPTER TWO

PREVIOUS STUDIES

This chapter consist of five previous studies are

2.1- Artificial Neural Networks in Medical Diagnosis

Qeethara Kadhim Al-Shayea (March 2011)

Artificial neural networks are finding many uses in the medical diagnosis application. The goal of this paper is to evaluate artificial neural network in disease diagnosis. Two cases are studied. The first one is acute nephritis disease; data is the disease symptoms. The second is the heart disease; data is on cardiac Single Proton Emission Computed Tomography (SPECT) images. Each patient classified into two categories:
infected and non-infected. Classification is an important tool in medical diagnosis decision support. Feed-forward back propagation neural network is used as a classifier to distinguish between infected or non-infected person in both cases. The results of applying the artificial neural networks methodology to acute nephritis diagnosis based upon selected symptoms show abilities of the network to learn the patterns corresponding to symptoms of the person.
The data is separated into inputs and targets. The targets for the neural

network will be identified with 1's as infected and will be identified with 0's as non-infected. In the diagnosis of acute nephritis disease; the percent correctly classified in the simulation sample by the feed-forward back propagation network is 99 percent while in the diagnosis of heart disease; the percent correctly classified in the simulation sample by the feed-forward back propagation network is 95 percent.

The Proposed Diagnosis Model

Feed-forward neural networks are widely and successfully used models for classification, forecasting and problem solving. A typical feed-forward back propagation neural network is proposed to diagnosis diseases. It consists of three layers: the input layer, a hidden layer, and the output layer. A one hidden with 20 hidden layer neurons is created and trained. The input and target samples are automatically divided into training, validation and test sets. The training set is used to teach the network. Training continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy. The information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. There are no cycles or loops in the network.

Feed-forward neural network allows signals to travel one-way only; from source to destination; there is no feedback. The hidden neurons are able to learn the pattern in data during the training phase and mapping the relationship between input and output pairs. Each neuron in the hidden layer uses a transfer function to process data it receives from input layer and then transfers the processed information to the output neurons for further processing using a transfer function in each neuron.

Experimental Results

A. Acute Nephritis Diagnosis Data

The data was created by a medical expert as a data set to test the expert system, which will perform the presumptive diagnosis of one of the urinary system diseases. The main idea of this data set is to construct the neural network model, which will perform the presumptive diagnosis of acute nephritis. Acute nephritis of renal pelvis origin occurs considerably more often at women than at men. It begins with sudden fever, which reaches, and sometimes exceeds 40C. The fever is accompanied by shivers and one- or both-side lumbar pains, which are sometimes very strong. This dataset contains 120 patients. The dataset contains 120 samples. 90 sample used in training the network while 30 samples used in testing the network

B. Heart Disease Diagnosis Data

The dataset describes diagnosing of cardiac Single Proton Emission Computed Tomography (SPECT) images. Each of the patients is classified into two categories: normal and abnormal. The dataset contains 267 samples. 80 sample used in training the network while 187 samples used in testing the network.

C. Performance Evaluation

Neural network toolbox from Matlab 7.9 is used to evaluate the performance of the proposed networks. Acute nephritis of renal pelvis origin is the first disease to be diagnosed. A two-layer feed-forward network with 6 inputs and 20 sigmoid hidden neurons and linear output neurons was created. The results of applying the artificial neural networks methodology to distinguish between healthy and unhealthy person based upon selected symptoms showed very good abilities of the network to learn the patterns corresponding to symptoms of the person. The network was simulated in the testing set (i.e. cases the network has not seen before). The results were very good; the network was able to classify 99% of the cases in the testing set Heart disease is the second disease to be diagnosed. A two-layer feed-forward network with 22 inputs and 20 sigmoid hidden neurons and linear output neurons was created The results were very good; the network was able to classify 95% of the cases in the testing set. Fig.6 shows the training state value.

This study aimed to evaluate artificial neural network in disease diagnosis. The feed-forward back propagation neural network with supervised learning is proposed to diagnose the disease. Artificial neural networks showed significant results in dealing with data represented in symptoms and images. Results showed that the proposed diagnosis neural network could be useful for identifying the infected person.

2.2- Towards Non-Invasive Monitoring of Hypovolemia in Intensive Care Patients

Alexander Roederer, James Weimer, Joseph Dimartino and Jacob Gutsche, and Insup Lee (April 2015).

Hypovolemia caused by internal hemorrhage is a major cause of death in critical care patients. Novel non-invasive methods for detecting hypovolemia in the literature utilize the photoplethysmogram (PPG) waveform generated by the pulse oximeter attached to a finger or ear. Until now, PPG-based alarms have been evaluated only on healthy patients under ideal testing scenarios (e.g: motionless patients). the PPG is sensitive to patient health and significant artifacts manifest when patients move. Since patient health varies within the intensive care unit (ICU) and ICU patients typically do not remain motionless, this work introduces a PPG-based monitor designed to be robust to waveform artifacts and health variability in the underlying patient population. the monitor detects hypovolemia within a twelve hour window of nurse documentation of hypovolemia when it is present. they present a detector for hypovolemia which can be run continuously using only PPG. Over a set of five ICU patients (two with hypovolemia, three without) the detector alerts for hypovolemia within a twelve hour window of documented hypovolemia in patients who had it, and with only two false alarms over three and a half days of monitoring non-hypovolemic patients. they present a detector for hypovolemia which can be run continuously using only PPG. Over a set of five ICU patients (two with hypovolemia, three without) the detector alerts for hypovolemia within a twelve hour window of documented hypovolemia in patients who had it, and with only two false alarms over three and a half days of monitoring non-hypovolemic patients.

Physiological Model

The mechanism behind hypovolemia involves a reaction to a drop in oxygenation caused by reduced blood volume. As the volume of blood circulating in the body decreases, the amount of oxygen reaching the control centers of the brain goes down. In an attempt to maintain perfusion to the vital organs, the brain engages hemodynamic compensation mechanisms whereby the heart rate increases (to pump more blood more quickly through the system), respiration rate increases (to deliver more oxygen to the blood), and peripheral vasoconstriction occurs, along with increased sympathetic nerve activity [6].

PPG Sensor

Photoplethysmography (PPG) is an optical measurement technique most commonly used within a pulse oximeter to detect blood volume changes in the micro vascular bed of tissue. the current approach to detecting hypovolemia involves closely monitoring patients' heart rate, blood pressure, respiration rate, and visual status [7,8]. an elevated heart rate coupled with dehydration and changes in the patient's skin condition may rouse suspicion of hypovolemia. If these signs are present and a patient's blood pressure is low, fluids are typically administered [9,10]. Patients who respond to fluids by returning to more normal blood pressures are considered likely to have been suffering from hypovolemia, but the diagnosis is often left unclear.

CFAR Detector

Over a series of values extracted from the DC signal, they build a parameter-invariant statistic to distinguish between signal patterns indicative of hypovolemia and those which are not indicative of hypovolemia. they aim to construct models to test for hypovolemia by observing that the PPG signal of a non-hypovolemic patient drifts naturally over time, while a hypovolemic patient experiences a decrease in PPG [11]. To capture the effects of these hypotheses we establish a null hypothesis H0 representing a non-hypovolemic patient, in which the patient's DC signal experiences simple Brownian motion, and an alternative hypothesis H1, in which a patient's DC signal experiences first- order decay:

$$H0 : \quad y(k+1) = y(k)+\sigma 0 n(k) \; H1 : y(k+1) = \alpha\, y(k)+\beta+\sigma 1 n(k) \qquad (2.1)$$

with $0 < \alpha < 1$ representing the rate of decay in the DC signal, $\beta < 0$, and $\sigma 0$ and $\sigma 1$ representing the unknown variances of the noise under each hypothesis. in both of the hypovolemic patients. their detector presented a higher-than average number of alarms within a 24 hour envelope of hypovolemia was first documented.

This paper describes a method for creating a robust detector of hypovolemia in critically ill patients by creating a parameter invariant statistic over a patient's photoplethysmogram waveform after filtering artifact from the data. Pre- liminary tests on a small set of retrospective patient data show that the proposed detector produces alarms near and before time of diagnosed hypovolemia while producing few false alarms in healthy patients.

2.3- Fuzzy Logic Analysis of Physiological Data for Hypovolemia Class Level Detection

Shumit Saha **(**2014)

Hypovolemia is a dangerous and acute disease for mankind which results form a decreased level of blood volume or a loss of blood. In extreme case, it can cause an irreversible cellular damage which can cause death. In this paper, a fuzzy control system is proposed to detect this hypovolemia class level. The four classes of hypovolemia can be detected by this proposed system for adult persons. This system analyzes five physiological data which come from the devices that are used for monitoring the patients and regarding all these data it'll give the hypovolemia class level of the patients. It'll empower the doctors to take quick decisions in case of surgeries and seizures.

In this paper, there is a system proposed based on fuzzy logic to detect this hypovolemia class level in any conditions. This system accumulates all the possibilities of hypovolemia by five physiological parameters which are respiratory rate, pulse rate, blood pressure, pulse pressure and capillary refill. All the basic clinical evaluation processes of hypovolemia are taking into account in the proposed system. Thirty eight fuzzy rules are set up for classifying the 4 levels of hypovolemia.

Their proposed system based on fuzzy logic to detect this hypovolemia class level in any conditions. This system accumulates all the possibilities of hypovolemia by five physiological parameters which are respiratory rate, pulse rate, blood pressure, pulse pressure and capillary refill. All the basic clinical evaluation processes of hypovolemia are taking into account in the proposed system. Thirty eight fuzzy rules are set up for classifying the 4 levels of hypovolemia. The proposed system correctly predicts the hypovolemia class levels so that all the classes can be determined and it can empower the doctors in case of surgeries and seizures a lot. Specially, in all critical surgeries, doctors must have to consider the extreme cases of hypovolemia. By this system, the doctors can easily monitor the class of hypovolemia so that they can take decisions much quickly. This algorithm can also be incorporated with any medical devices as an extra feature. A new device can also be implemented by using this system. This system will help the doctors to determine how much electrolytes can be needed to be infused in the patient. Moreover, this system can be used in rural areas and in the third world countries as these areas are deprived of expert doctors. Another advantage of this system is it can be used in telemetry also. As this system works on PC based now, this system can easily transmit the patient’s condition from remote places.

The proposed design consists of seven monitors which will monitor various signals from patients. there are seven monitors. They are Respiratory Rate monitor, Blood Pressure Monitor, Pulse Rate Monitor, Capillary Refill Detector and Pulse Pressure Monitor. All the input from these monitor directly feed into fuzzy inference system. Then the Fuzzy inference system determines the hypovolemia class level by the fuzzy rules gives the final output.

A. RR Monitor

RR monitor is respiratory rate monitor. Respiratory rate is the breathing frequency which can be calculated within a range of time. An adult person with healthy body has an RR of 12 to 20 breaths per minute. So, this 12 to 20 is termed as normal rate. This rate will increase when there is an acute hypovolemia occurs and rate can go to at most 60 per minute.

B. Blood Pressure Monitor

Blood pressure monitor or sphygmomanometer is the most used device in the medical science. As now digital blood pressure machines are available, it will use as another input. Mainly human blood pressure is the arterial blood pressure which is varies between systolic and diastolic pressure. For a healthy adult person, the normal systolic pressure varies from 100 to 140 mmHg and diastolic pressure varies between 60 and 90 mmHg. So for the proposed system, the normal ranges for systolic and diastolic pressure are being set up as those values. Also, it will vary with the hypovolemic shock level.

C. Pulse Rate Monitor

Pulse is another important parameter for determine the hypovolemia. Mainly, pulse denoted as the arterial palpation of the heartbeat. It is mainly the systolic blood pressure observation. A normal healthy adult's pulse rate is 60 to 99 beats per minute at rest. In this system, this range is termed as normal pulse rate. In case of acute hypovolemia, this pulse rate goes around 120 to 160 beats per minute. So that, the pulse rate with 120 to 139 beats per min. is termed as very high and greater than 140 beats per minute is termed as extremely high rate. These values are strictly followed with the adult person.

D. Capillary Refill Monitor

The elapsed time for colour to comeback to an external capillary bed after some pressure is enforced to cause blanching or turn pale is Capillary refill time. For normal adult, this time is 2 seconds. So, the time range 0 to 2 seconds is termed as normal in capillary refill. Capillary refill goes low if then it takes 2 to 4 seconds.

E. Pulse Pressure Monitor

Pulse pressure is the pressure that is felt when feeling the pulse. Formally it is the systolic pressure minus the diastolic pressure. So, this pressure can also be calculated from the blood pressure meter. As normal blood pressure for an adult person is 120 by 80 mmHg, so the normal pulse pressure would be 40 mmHg. In this system, 30 to 40 mmHg is termed as normal range. After collecting data from all these monitors, data are feed into a fuzzy system developed by Matlab which determines the hypovolemia class level.

In this paper, a fuzzy system is proposed to detect the hypovolemic shock levels. All the physiological parameters for this intelligent system are clinically evaluated. By this system, the doctors can easily determine the hypovolemic shock level and give proper medication. This fuzzy system is designed for adult people only. This system is not suitable for children as their normal respiratory rate are not same as a normal adult person. Their usual respiratory rate is higher than adult person. In future, the author will develop a new algorithm with considering all the ages of people and also tries to determine the specific amount of electrolytes loss from human body. This will aid the doctors to determine the specific amount of electrolytes needed by the patients.

2.4- Detection and Classification of Hypovolaemia during Anaesthesia

Mirza Mansoor Baig, Hamid Gholam Hosseini , Si-Woong Lee and

Michael J. Harrison (January 2012).

In recent years, there has been a rapid growth in patient monitoring and medical data analysis using decision support systems, smart alarm monitoring, expert systems and many other computer aided protocols. The main goal of this study was to enhance the developed diagnostic alarm system for detecting critical events during anesthesia. The proposed diagnostic alarm system is called Fuzzy logic monitoring system-2 (FLMS-2). The performance of the system was validated through a series of off-line tests. When detecting hypovolaemia a substantial level of agreement was observed between FLMS-2 and the human expert and it is shown that system has a better performance with sensitivity of 94%, specificity of 90% and predictability of 72%.

Their prototype diagnostic system, fuzzy logic monitoring system-2 (FLMS-2), was developed using three physiological features; heart rate (HR), blood pressure (BP) and pulse volume (PV) [12] . The system detects hypovolaemia and classifies it into mild, moderate and severe. hypovolaemia refers to a decrease in volume of blood plasma. The heuristic relationship of hypovolaemia is identified by the transformation in observable physiological variables like BP, HR and PV. The patients" data were collected from the existing S/5 Datex-Ohmeda anesthesia monitor in the operating theatre with ethical approval from the local ethics committees. The collected data were converted into a readable format using DOMonitor.net [13]. The accuracy of the diagnostic results from the proposed system was analyzed using Kappa analysis. Kappa [14] gives a statistical measure for evaluating inter-observer variability, that is, how often two or more observers agree/disagree in their interpretation. In this research project, the expert (anesthetist) and FLMS-2 are the two observers interpreting the diagnoses for the pathological events using the physiological data.

Their system structure (FLMS-2) and the major component works as follows:

1- Signal processing – Multi rate data processing (using an interpolation technique to increase the sampling period from 10 sec to 30 sec), smoothing, filtering and calculating descriptive statistics.

2- Data analysis – using a time series tool for multiple plots in real time.

3- Adaptive neuro fuzzy inference system (ANFIS) – training the model with 10 patients‟ data and testing with 20 patients data selected randomly (Mamdani type model) [15].

4- Fuzzy inference system (FIS) – is used to train the fuzzy model (Sugeno type model) [16].

5- Membership functions (MFs) –The MFs for each input are set as mild, moderate, and severe. The selection of the MFs limits is set after analyzing the data statistics, time series analysis and ANFIS outputs.

6- Rules –These are set using all MFs and all possible levels of hypovolemia which were detected throughout the training sessions.

7- Sugeno Model – This model is used for ANFIS training and testing.

8- Mamdani Model – This model is used for testing.

The FLMS-2 Configuration The test conditions for the detection of hypovolaemia were classified as: mild, moderate, and severe.The following three principles were set before the generation of alarms in the system:

Principle 1- Sampling period*:* The system checks the sampling period of the input data which should be 30sec.

Principle 2- Three Inputs*:* The system is set to accept only three inputs which are HR, BP, and PV. Therefore, if any input data set is missing, the system will return the present alarm status as false, and wait for the next 15 minutes of the data set.

Principle 3- Membership Functions: the limits of the membership functions were set after considering the following points:

1- The limits are set so that the FLMS-2 can detect the changes in the parameters, rather than the crisp numerical values and filtered data were divided into five-minute intervals.
2- The relative value of each parameter (such as HR) is found by removing its average and dividing the result by its standard deviation for each fiveminute interval.
3- The SDs were calculated for the whole parameter values which include both hypovolaemic data as well as data that was normal.
4- Considering the limits of SD in the whole data set**.**

Principle 4- Ten Rules*:* The rules are set for testing of the patients data with their MFs.

According to these principles the system checks whether each parameter is true with the input values (principle 1 & 2) and each parameter exceeds the standard deviation limit (principle-3). If both conditions are true, then principle-4 with ten rules will be checked. The system generates alarm/warning in one of the three hypovolaemia levels of : mild, moderate or severe.the developed diagnostic alarm system has shown that evidence-based expert diagnostic systems can accurately diagnose a hypovolemia and could be useful in providing decision support to anesthetists.

5. Urine Flow Is a Novel Hemodynamic Monitoring Tool for the Detection of Hypovolemia

Micha Y. Shamir, MD, Leonid Kaplan, MD, Rachel S. Marans, MD, Dafna Willner, MD, Yoram Klein and MD (March 2011).

Hemorrhagic shock is among the leading causes of death after trauma. Early diagnosis of hypovolemia is thus of the utmost importance. Clinical diagnosis of hemorrhagic shock and measurements of its severity are based on traditional vital signs including heart rate, arterial blood pressure, respiratory rate, level of consciousness, and urine output (ml/h). these variables change only after 15% of the estimated blood volume is lost and become strikingly apparent only after a 30% loss which is a life-threatening situation. Hypovolemia can be diagnosed earlier using invasive monitoring tools such as: pulmonary capillary wedge pressure, cardiac output, and arterial systolic pressure variation (SPV). Obtaining these variables and their interpretation is cumbersome and therefore are not considered standard of care at the early phase of patient evaluation.

Urine output is a sensitive variable reflecting the patient’s effective blood volume and tissue perfusion. Urinary catheters are routinely inserted very early in the resuscitation phase in trauma victims so that urine output can be used as a diagnostic tool [17] , Because small volumes are difficult to measure, initial information only becomes available 15 to 20 minutes after catheter insertion and the initial measurement of urine output is extrapolated to record the average value for urine output per hour (ml/h).

URINFO™ is a novel urine collecting and measurement system , This monitor incorporates dynamic optical flow-sensing technology, providing real-time continuous automated measurements of urine flow. Urine volume measurement errors are small because flow is optically measured. This is in contrast to traditional urino meters, which do not permit the display of minute urine flow.

Their methodology was Patients were pre medicated with diazepam 0.15

mg/kg. Upon arrival to the operating room, the patients were connected to standard monitoring (electrocardiogram, noninvasive arterial blood pressure, pulse oximeter, and capnography). General anesthesia was induced with IV fentanyl 1 g/kg, IV propofol 2 mg/kg, and IV vecuronium 0.1 mg/kg. After tracheal intubation, anesthesia was maintained with isoflurane 0.5% in an O2/N2O mixture at a 1:1 ratio. Patients' lungs were ventilated at a rate of 10 to 12 breaths/min and tidal volume of 6 to 8 mL/kg adjusted to keep end-tidal CO2 at approximately 40 mm Hg. After induction of anesthesia, the radial artery was cannulated using a 20-gauge catheter and a urinary catheter introduced to the urinary bladder. This catheter was connected to the URINFO 2000™ system for continuous measurements, which were downloaded to a laptop computer for analysis.

They found that an average of 614 -143 ml (mean SD) of blood was shed. During phlebotomy, the mean urine flow rate decreased from (5.7-8) ml/min to (1.07-2.5) ml/min. Systolic blood pressure and hemoglobin also decreased. down increased. After rehydration, urine flow, blood pressure, and down values returned to baseline. The hemoglobin concentration decreased whereas other variables did not change significantly.

Decreased Urine Flow as a Sign of Hypovolemia in this study, they evaluated the utility of using urine flow rate as an early sign of hypovolemia due to hemorrhage. their results demonstrated significant changes in urine flow rate associated with bleeding. These findings are in agreement with those of Sondeen et al. who found that urine flow rate decreased significantly in conscious bleeding pigs when the amount of blood loss was between 10% and 20% of estimated blood volume. In addition, the first variable to change in relation to renal blood flow was urine flow. These changes were attributed to decreased renal perfusion during hypovolemia.

Study Limitations Systolic blood pressure and hemoglobin decreased slightly after 15% blood loss, an unanticipated change in grade 1 hemorrhage Because systolic blood pressure changes were not clinically significant (10%) they do not consider them as meaningful clinical change. The same is true for the 0.5 g/dl decrease in hemoglobin after phlebotomy. Alternatively, the combination of preoperative fasting and removing 15% of the blood volume (upper volume limit for class I hemorrhagic shock) might result in a deeper hypovolemia than intended. In combination with general anesthesia, some susceptible patients might react in a more pronounced way.

The method for creating a robust detector of hypovolemia in critically ill patients by creating a parameter invariant statistic over a patient's photoplethysmogram waveform after filtering artifact from the data. Preliminary tests on a small set of retrospective patient data show that the proposed detector produces alarms near and before time of diagnosed hypovolemia while producing few false alarms in healthy patients. Future work will include incorporating more features, either through extracting new dimensions from the PPG waveform or by using other waveforms, to improve predictive power. Future work will also involve expanding our test set of patients by identifying more cases of clear hypovolemia to improve our confidence in the technique and provide clearer estimates of specificity/sensitivity.

CHAPTER THREE

The Theoretical Background

3.1- Neural network

3.1.1- Introduction

Artificial neural systems or neural networks are physically cellular systems which can acquire, store and utilize experimental knowledge [18]. Neural networks are inspired by the way human brains and nervous systems process and store information. They have been studied from as early as 1943 when McCulloch, W. S. et al [19] described ANNs as adaptive nonlinear information processing systems consisting of multiple processing units (neurons) that could self-adapt, self organize and learn real time. In general, artificial neural networks consist of neurons which are interconnected to each other and work together to solve a given problem. Ding, S., et al. [20] suggest each neuron is a transfer function which is generally multi input and single output. The number of neurons, the weight associated with each connection and the activation function of each layer defines the network behavior. Using experimental data ANNs can be trained to achieve generalizations and extract complex non-linear relationships between the given inputs and outputs.

Neural networks learn or train by iteratively changing the connection weights. The learning process can be carried out in three basic ways: supervised learning, unsupervised learning and reinforcement learning [20]. Neural networks can also be categorized as Feedforward Neural Networks (FNN) and Recurrent Neural Networks (RNN). In an FNN, the network architecture consists of subsequent layers, each consisting of neurons which are connected to the neurons of the previous and next layer while neurons in the same layers are not connected to each other. Parallel processing of inputs in such a setup is therefore layer dependent but neuron independent. RNNs consist of additional backward connections or time delayed outputs fed back into the network as inputs to capture time varying dynamics of a system [21]

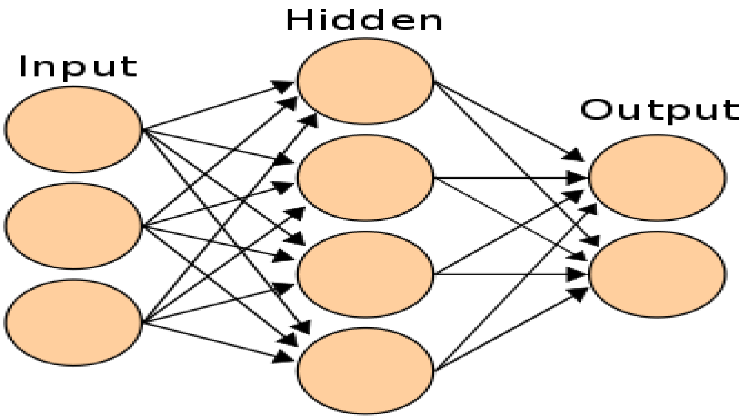


Figure (3.1) form of neural network

3.1.2- Back-propagation network

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 [22].

3.2- Fuzzy logic control technique

3.2.1- Introduction

The complexity of medical practice makes traditional quantitative approaches of analysis inappropriate [23].Fuzzy Logic Systems (FLS) produce acceptable but definite output in response to incomplete, ambiguous, distorted, or inaccurate (fuzzy) input. "fuzzy" is defined as blurred, indistinct, imprecisely defined confused, vague. 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 trials and errors. The aim of the proposed system is to construct independent and decoupled rule-bases those can be used for several individual control loops to diagnosis and treatment purposes.

The Fuzzy logic (FL) control is equivalent to have computers reason like humans do but in faster pattern. often the output of computers making decisions would be true or false but fuzzy logic is a way of making the computer say little, big, bigger, not so big .fuzzy logic control is very robust and does not need precise and noise-free inputs to generate usable outputs. also it can easily be modified during operation . (FL) is a multi-valued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computers, in order to apply a more human-like way of thinking in the programming of computers [24].

Fuzzy systems have been applied to a wide variety of fields ranging from control, signal processing, communications, integrated circuit manufacturing, and expert systems to business, medicine, psychology, etc. However, the most applications have concentrated on control problems. in the world of medicine fuzzy logic play an important role for effective diagnosis of medical problems because Fuzzy Logic is conceptually simple and easy to understand and the mathematical concepts behind fuzzy logic are very easy [25].

3.2.2- Fuzzy logic and Fuzzy set

The idea of Fuzzy logic was invented by Professor L. A. Zadeh of the University of California at Berkeley in 1965 [26]. This invention was not well recognized until Dr. E. H. Mamdani, who is a professor at London University, applied the fuzzy logic in a practical application to control an automatic steam engine boiler combination in 1974 [27].Dr. Zadeh was working on the problem of computer understanding of natural language. natural language (like most other activities in life and indeed the universe) is not easily translated into the absolute terms of 0 and 1.

Fuzzy logic is an approach to soft computing method based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic on which the modern computer is based. Fuzzy logic includes 0 and 1 as extreme cases of truth (or "the state of matters" or "fact") but also includes the various states of truth in between so that for example, the result of a comparison between two things could be not "tall" or "short" but 0.24 of tallness. Fuzzy logic seems closer to the way our brains work we aggregate data and form a number of partial truths which we aggregate further into higher truths which in turn, when certain thresholds are exceeded cause certain further results such as motor reaction. A similar kind of process is used in artificial , neural network and expert systems.

Fuzzy systems are knowledge-based or rule-based systems. the heart of a fuzzy system is a knowledge base consisting of the so-called Fuzzy if-then rules. 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. 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.

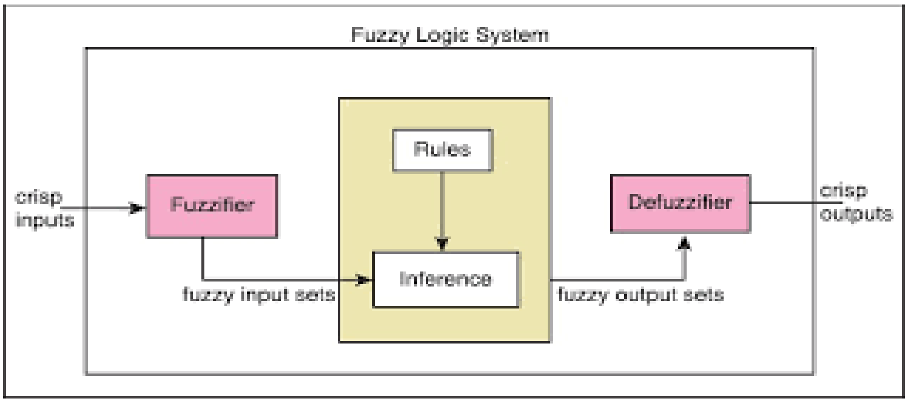


Figure (3.2) the Fuzzy logic system

Unlike classical logic which requires a deep understanding of a system, exact equations and precise numeric values. fuzzy logic incorporates an alternative way of thinking, which allows modeling complex systems using a higher level of abstraction originating from our knowledge and experience. fuzzy Logic has emerged as a profitable tool for the controlling and steering of systems and complex industrial processes, as well as for household and entertainment electronics, as well as for other expert systems [28].

Fuzzy set is an extension of the classical or crisp set [28]. in 1965 zadeh developed the concept of ‘fuzzy sets’ to account for numerous concepts used in human reasoning which are vague and imprecise [26], e.g. tall, old etc. Fuzzy sets can be used for representing information where the boundaries of the set are not clearly defined.

The classical set only considers a limited number of degrees of membership such as 0 or 1, or a range of data with limited degrees of membership [29]. For instance, if a temperature is defined as a crisp high its range must be between 80˚F and higher and it has nothing to do with 70˚ F or even 60˚F but the fuzzy set will consider a much larger temperature range such as from 0˚ F to higher degrees as a high temperature. The exact degree to which the 0˚F can contribute to that high temperature depends on the membership function. This means that the fuzzy set uses a universe of discourse (UOD) as its base and it considers an infinite number of degrees of membership in a set. In this way the crisp set can be considered as a subset of the fuzzy set [25]. The aim is to use fuzzy sets in order to make computers more ‘intelligent’. in conventional Boolean logic where membership of a set is either false or true. i.e. 0 or 1. This graduation from 0 to 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.

3.2.2.1- Linguistic variables

In 1973, professor lotfi A.zadeh proposed the concept of linguistic or “fuzzy” variables [26]. It is a variable that assume a value consisting of words or sentences rather than numbers which is use in classical logic. e.g. 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. We can apply temperature (cold, cool, normal, warm, hot), and a car speed (very fast, not very fast, fast, slow, quite slow) they are called terms of the linguistic variable for temperature or car speed Each term (set) is defined by an appropriate membership function.

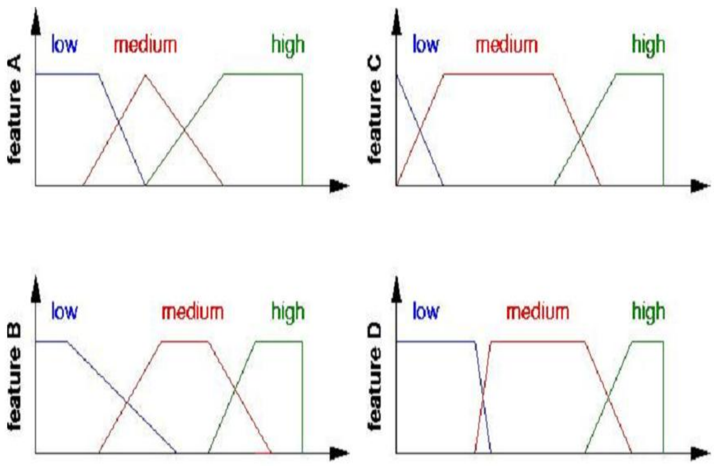


Figure (3.3) Linguistic Variables and their terms

3.2.2.2- Membership Function

Membership function is the mathematical function which defines the degree of an element's membership in a fuzzy set. Also The membership function is a graphical representation of the magnitude of participation of each input [24]. it associates a weighting with each of the inputs that are processed define functional overlap between inputs, and ultimately determines an output response. The rules use the input membership values as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion. It maps each point in the input space to a membership value in a closed unit interval [0,1] [28]. the figure below show general membership function curve

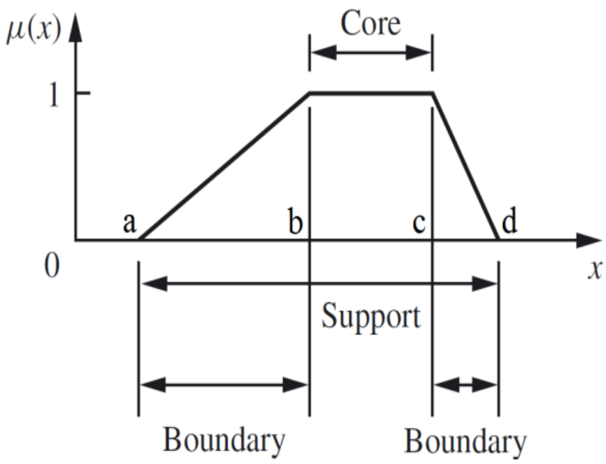


Figure (3.4) sample of membership function

The horizontal axis represents an input variable *x*, and the vertical axis defines the corresponding membership value *μ(x)* of the input variable *x*. The Support of membership function curve explains the range where the input variable will have nonzero membership value. In this figure, $(x) \neq 0$ when *x* is any point located between point a and point d. While the Core of membership function curve interprets the range where the input variable *x* will have full degree of membership ($(x) = 1$).

The Fuzzy Logic Toolbox includes 11 built in membership function types. Generally There are five common shapes of membership function: Triangle MF, Trapezoidal MF, Gaussian MF, Generalized Bell MF, and Sigmoid MF. the exact type depends on the actual applications. For those systems that need significant dynamic variation in a short period of time, a triangular or trapezoidal waveform should be utilized. For those system that need very high control accuracy, a Gaussian or S-curve waveform should be selected [29].

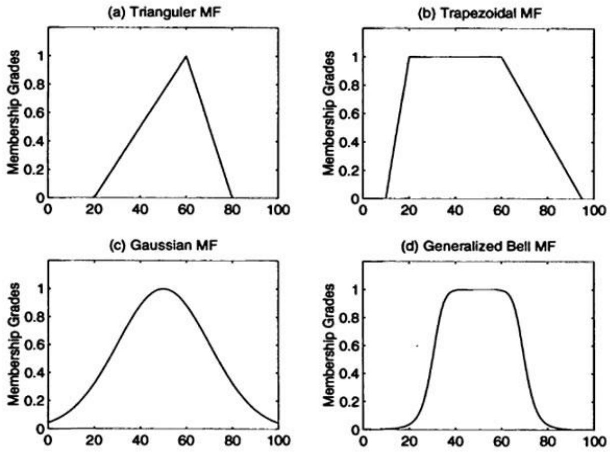


Figure (3.5) shapes of standard membership functions

3.2.2.3- The knowledge base

Human knowledge in any related field of application is represented in terms of fuzzy IF-THEN rules**.** The Fuzzy rule base represents the collection of fuzzy IF-THEN rules [30]**.** the if-then rules is represented leading to algorithms describing what action or output should be taken in terms of the currently observed information, which includes both input and feedback if a closed-loop control system is applied. The law to design or build a set of fuzzy rules is based on a human being's knowledge or experience which is dependent on each different actual application [29].

A fuzzy IF-THEN rule associates a condition described using linguistic variables and fuzzy sets to an output or a conclusion. The IF part is mainly used to capture knowledge by using the conditions and the THEN part can be utilized to give the conclusion or output in linguistic variable form. This IF-THEN rule is widely used by the fuzzy inference system to compute the degree to which the input data matches the condition of a rule. the fuzzy approach requires a sufficient expert knowledge for the formulation of the rule base, the combination of the sets and the defuzzification [30]. The inputs are combined logically using the and operator to produce output response values for all expected inputs. The active conclu sions are then combined into a logical sum for each membership function. a strength for each output membership function is computed. All that remains is to combine these logical sums in a defuzzification process to produce the crisp output.

3.2.2.4- Fuzzy Inference System

Generally Fuzzy inference is the process of mapping the given input variables to an output space via fuzzy logic based deducing mechanism which is comprised by If-Then rules, membership functions and fuzzy logical operations [28]. in other hand the conclusion or control output derived from the combination of input, output of membership functions and fuzzy rules it is still a vague or fuzzy element and this process in called fuzzy inference. The control rule is the core of the fuzzy inference process, and those rules are directly related to a human being’s intuition and feeling [29].the domain and range of the mapping could be fuzzy sets or points in a multidimensional space.

FIS is also known as

1-Fuzzy models.

2-Fuzzy associate memory.

3-Fuzzy-rule-based systems.

4-Fuzzy expert systems.

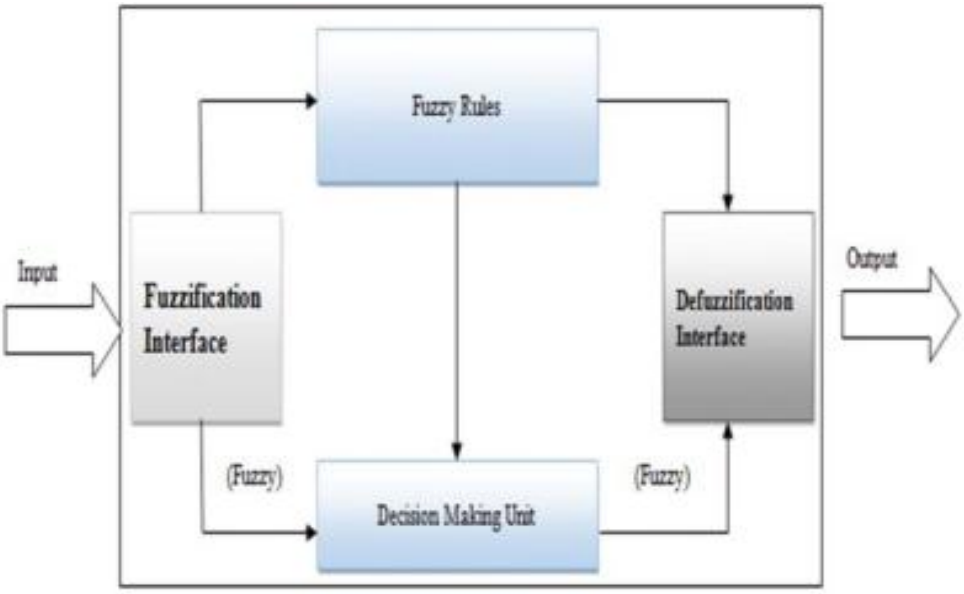


Figure (3.6) the Fuzzy Inference System

Generally three types of fuzzy inference methods are proposed in literature: Mamdani fuzzy inference, Sugeno fuzzy inference, and Tsukamoto fuzzy inference**.** Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology and it expects the output membership functions to be fuzzy sets.

Mamdani Fuzzy inference system:

In 1975, Professor Ebrahim Mamdani of London University built one of the first fuzzy systems to control a steam engine and boiler combination [27]. He applied a set of fuzzy rules supplied by experienced human operators.

Mamdani-type fuzzy inference process consists of five steps:

Step1: Fuzzification of input variables: transformation of the crisp numerical values of input variables into the equivalent membership values of the appropriate fuzzy sets via membership functions.

Step2: Rule Evaluation (matching):Taking the fuzzified inputs and apply them to the antecedents of the fuzzy rules.

If a given fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent evaluation. This number (the truth value or firing strength) is then applied to the consequent membership function.

Step3: Apply aggregation method: Aggregation is the process of unification of the outputs of all rules**.** the input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable.

Step4: Defuzzification: The input for the defuzzification process is the aggregate output fuzzy set and the output is a single number.

Defuzzification operates on the implied fuzzy sets produced by the inference mechanism and combines their effects to provide the “most certain” output.

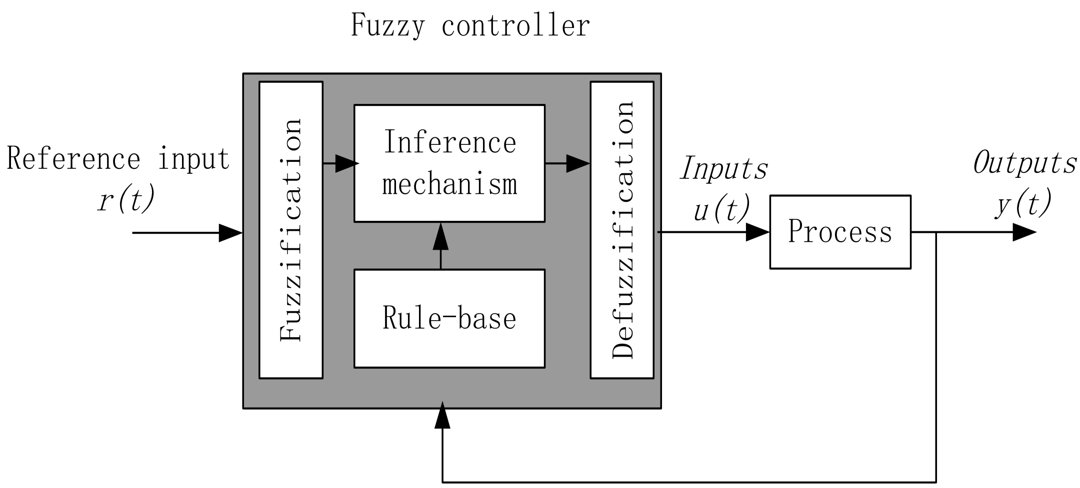


Figure (3.7) show the Fuzzy controller architecture

3.2.3- Control system

A control system is an arrangement of physical components designed to change or to regulate through a control action. control systems can be used either as open-loop controllers or closed-loop controllers as shown in Fig (3.8) and (3.9) respectively. When used as an open-loop controller, the fuzzy system usually sets up some control parameters and then the system operates according to these control parameters. Many applications of fuzzy systems in consumer electronics belong to this category. When used as a closed-loop controller, the fuzzy system measures the outputs of the process and takes control actions on the process continuously. Applications of fuzzy systems in industrial processes belong to this category.

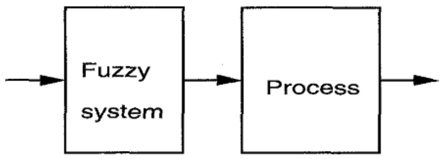


Figure (3.8) fuzzy system as open-loop controller

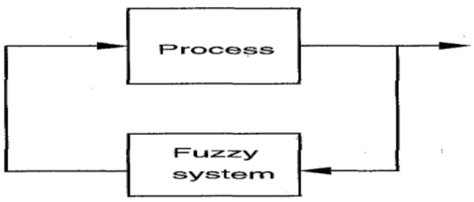


Figure (3.9) fuzzy system as closed-loop controller

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.

The Characteristic of Fuzzy logic

1- Fuzzy logic is conceptually easy to understand because fuzzy control emulates human control strategy**.**
2- Fuzzy logic is flexible with any given system.
3- The mathematical concepts behind fuzzy reasoning are very simple.
4- Very accurate , quick and cheaper to implement.
5- Can be easily modified.

3.2.4- Application of Fuzzy logic

1) The general application are

1- Simplified control of robots.
2- Camera-aiming for the telecast of sporting events.
3- Efficient and stable control of car engines.
4- Cruise-control for automobiles .
5- Automatic transmission of automobiles.
6- Optimised planning of bus timetables.
7- Prediction system for early recognition of earthquakes.

2) Application in medical field

Fuzzy logic algorithms have been used in the classification of:

1- EEG patterns .
2- ECG patterns.
3- Hypertension.
4- Abdominal diseases.
5- Chromosomes and of leukocytes.

also it is used to diagnosis of

1- Heart diseases.

2- Asthma.
3- Diabetes.
4- Cancer.
5- Tuberculosis.
6- Malaria.
7- Menigioma.

3.3- Hypovolemia

3.3.1- Introduction

Blood and fluid management is an important part of patient monitoring in hospital operation theatre in part to mitigate the risk of hypovolemia .Early detection of hypovolemia is clinically important because severe hypovolemia, blood loss of more than 1 liter can lead to rapid decline and cardiovascular collapse, this occur to Patients present in emergency room, patients undergoing surgery and post-operative patients in intensive care units.

Hypovolemia (hypo=low, volemic = volume) is a dangerous and acute disease for mankind which results form a decreased level of blood volume or a loss of blood. In extreme case it can cause an irreversible cellular damage which can cause death [31]. Persistent internal hemorrhage can over time cause a decrease in the volume of blood in the circulatory system. Unfortunately assessment of decreasing volume status is one of the most difficult tasks in clinical medicine. the reduced circulating blood volume is unable to carry sufficient oxygen to the major organs and tissues which can lead to serious post operative complications, delayed recovery time and a longer hospital stay for the patient [4]. if shock is prolonged the cell membrane loses its integrity, the normal electrical gradient is lost and swelling and damage occur and eventual cell death.

Symptoms of hypovolemia are: pale, cool and moist skin, increased heart rate, weak pulse, decreased urine output, Hypotension may not be present until the blood volume decreases for more than 10-20% (0.5-1 liter blood) when hypovolemic shock starts to develop [31].

Hypovolemia have two type:

1 - Absolute Hypovolemia refers to a decreased volume of the fluid or blood within the circulatory system in which the fluid leaves the body, for example in bleeding.Causes**:** lost of blood (external bleeding) ,lost of plasma (Burns), lost of water from the body.

2- Relative hypovolemia means the fluid from the circulatory system does not leave the body and it can refer to two different situations: increases the volume of the circulatory system due to wide spread vasodilation in neurogenic shock and the volume of the fluid or blood within the circulatory system remains the same but becomes insufficient. also some fluid leaves the circulatory system but not the body such in ascites where the fluid accumulates in the abdominal cavity.

Hypovolemia does not already mean hypovolemic shock. For example donation of 500 mL blood causes hypovolemia but usually not shock. Hypovolemia and Dehydration are closely related but dehydration means a decrease in total body water it can be associated with hypovolemia, normovolemia or even hypervolemia but hypovolemia means a decrease in the volume of fluid within the vascular system with or without whole body water depletion ,hypovolemia can be caused by dehydration. Hypovolemia causes hypotension when the blood volume loss is greater than 30% this is called decompensated hypovolemic shock

[31]. So continuous monitoring to patient fluid inputs and outputs should be present because the change in it can reflect changes in blood volume.these changes only occur after significant blood is lost.

After 15-30% of total blood volume is lost the patient is at high risk of experiencing hypovolemic shock [31]. shock occurs when the heart can no longer pump enough blood to the body, the heart can no longer pump enough blood to the body. blood pressure plummets and tissue perfusion is not capable of sustaining aerobic metabolism leading to wide spread ischemic tissue damage. at the onset of hypovolemia a patient's body will attempt to compensate by increasing heart rate to continue to deliver oxygen to the extremities with the diminished amount of blood. However, heart rate alone is not sufficient to determine the need for emergent interventions as it is a specific. Respiratory rate may rise but this is often a late change and can be masked by mechanical ventilation.

3.3.2- Hypovolemia class level

There are four classes of hypovolemia is determined by the volume of blood loss:

a. Class 1: the blood loss is less than 750 ml. Here, heart rate is <100 bpm, blood pressure is almost normal. There is no cardiovascular sign occurs in this case, this class called no-hypovolemia.but this small lost blood should be compensated.

b. Class 2: the blood loss is 750 to 1500 ml. Here, heart rate is greater than 100 bpm ,the blood pressure remains normal but the pulse pressure goes low and the urine output is 20-30 ml\h. Here, the skin becomes pale, moist, cool, this class called mild.

c. Class 3: The blood loss in is 1500 to 2000 ml. Here, heart rate is greater than 120 bpm, both pulse pressure and blood pressure goes low and the urine output is 5-20 ml\h. This stage stimulates anxiety and confusion in patients ,this class called moderate.

d. Class 4: the blood loss is greater than 2000 ml. Here, heart rate is greater than 140 bpm, blood pressure goes very low and the urine output is .Confusion, drowsiness, and coma are the state of this class, this class called severe.

Confounding factors in Response to Hypovolemia are: Patients age, Pre-existing disease / meds, Severity of injury, Access to care, Duration of shock, Amount pre-hospital fluid, Presence of hypothermia.

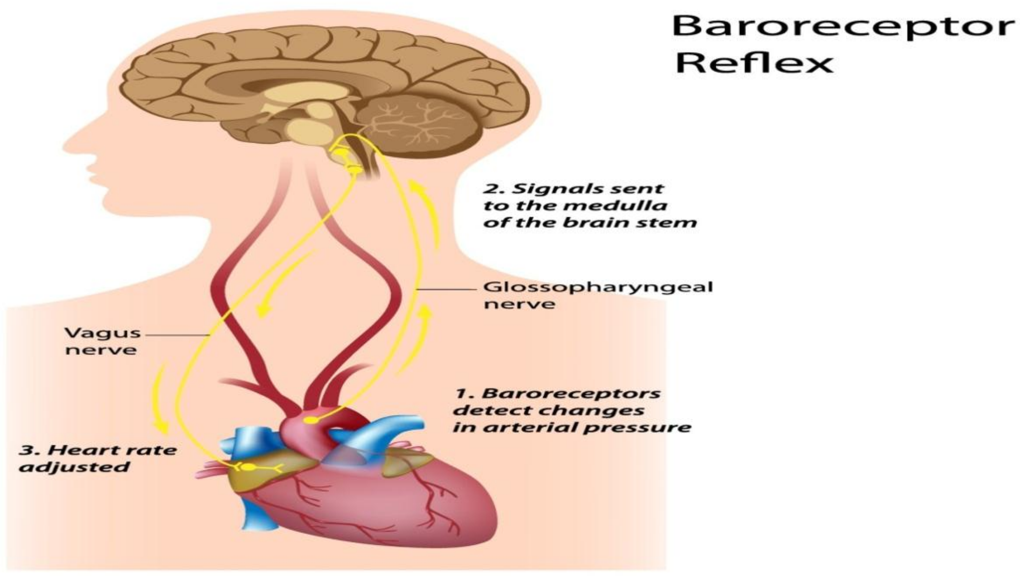


Figure (3.10) the response of brain to shock

Important Hormones in Shock

1. Catecholamine: Epinephrine & Nor epinephrine:

Increased heart rate & contractility, Vasoconstriction & narrowed pulse pressure.

1. Renin-Angiotensin Axis: Aldosterone and ADH:

Water and sodium conservation & vasoconstriction , increase in blood volume and blood pressure and decreased urine output.

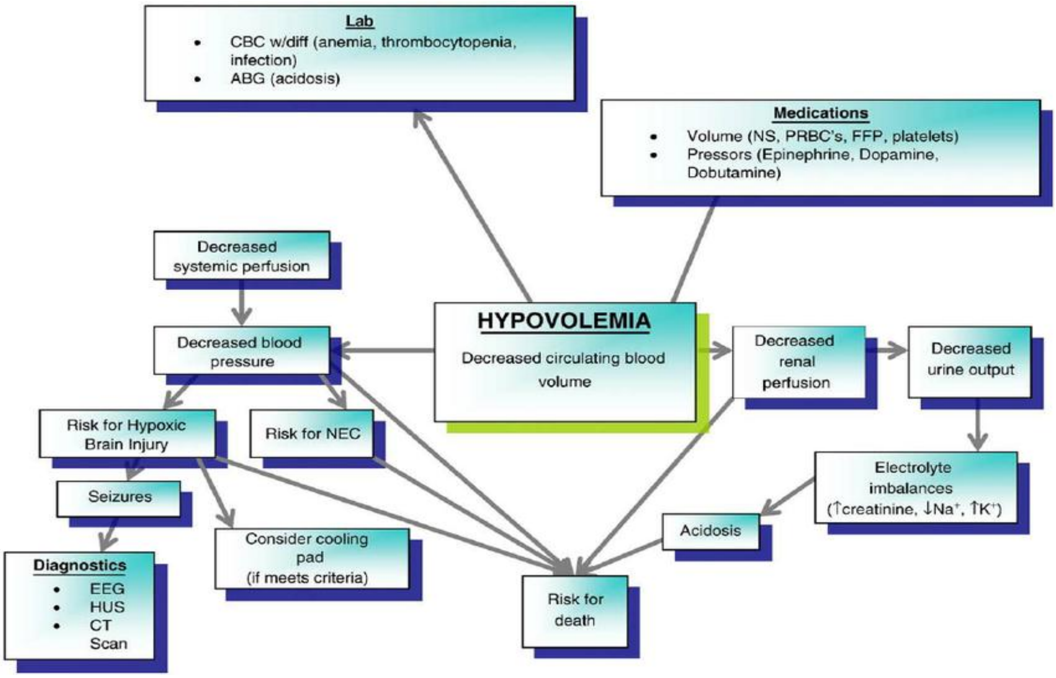


Figure (3.11) the concept map of hypovolemia

CHAPTER FOUR

The Proposed System

The proposed control systems for diagnosis hypovolemia will described below with all components and the modeling of the systems by using simulink and then applying ideal data of the hypovolemia in the two systems to specify the hypovolemia class level and the compensation volume of blood or fluids.

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4.1 – System description

4.1.1- Neural network

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 .

Back propagation is of a 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.

4.1.1.1- The interaction between parameters (HR ,BP,UO) network and (HR, BP,UO) data

Described as follows:

-Apply back propagation network

-Apply (HR, BP and UO)data

-Calculate desired output

-Input initial control

-Repeat

-Calculate process output

-Calculate learning- error

-Until learning-error close to zero

4.1.1.2-Training back propagation network with 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.

Network input include the medians for no hypo, mid, moderate and severe of heart rate (HR), blood pressure (BP) and urine output (UO) [75 107.5 128 168], [140 115 83 60], [43.5 22 9.5 2.5] (table A). Then defined the target compensate volume [375 1120 1740 2730].

After network training with the above data, our system must be created to obtain volume of compensate blood for different cases .

The values (75 140 43.5) refer to no hypo, from range of heart rate [50-100] , blood pressure [130-150] , urine output [27-60] . when any value of the range insert to the system, the system take it as one value (75 140 43.5) ,then compensate volume [375].

so the mild parameters with value[107.5 115 22] from range of heart rate [95-120] , blood pressure [95-135] , urine output [15-27] , the moderate parameters with value [128 83 9.5] from range of heart rate [115-140] , blood pressure [65-100] , urine output [4-15] and the severe parameters with value [168 60 2.5] from range of heart rate [135-200] , blood pressure [50-70] , urine output [0-5] .

4.1.1.3- 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. There are three requirements and returns the network object . The first requirement is a matrix of input . The second requirement is a matrix of target vectors. The inputs and outputs are used to set up network input and output dimensions and parameters. The third requirement 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 = [ ];

t = [ ];

If There are ten 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,10);

This command creates the network [Network code B] object and also initializes the weights and biases of the network, therefore the network is ready for training.

Sim: Simulate neural network is usually called implicitly by calling the neural network as a function

Round: round to nearest integer

Y= round(x), round the elements of x to the nearest integers

load: Load data from m-file into work space(load network from m.file)

load ('file.mat' , 'net');

Newpr: To analyze the network response, examine the confusion matrix by considering the outputs of the trained network and comparing them to the expected results (target)

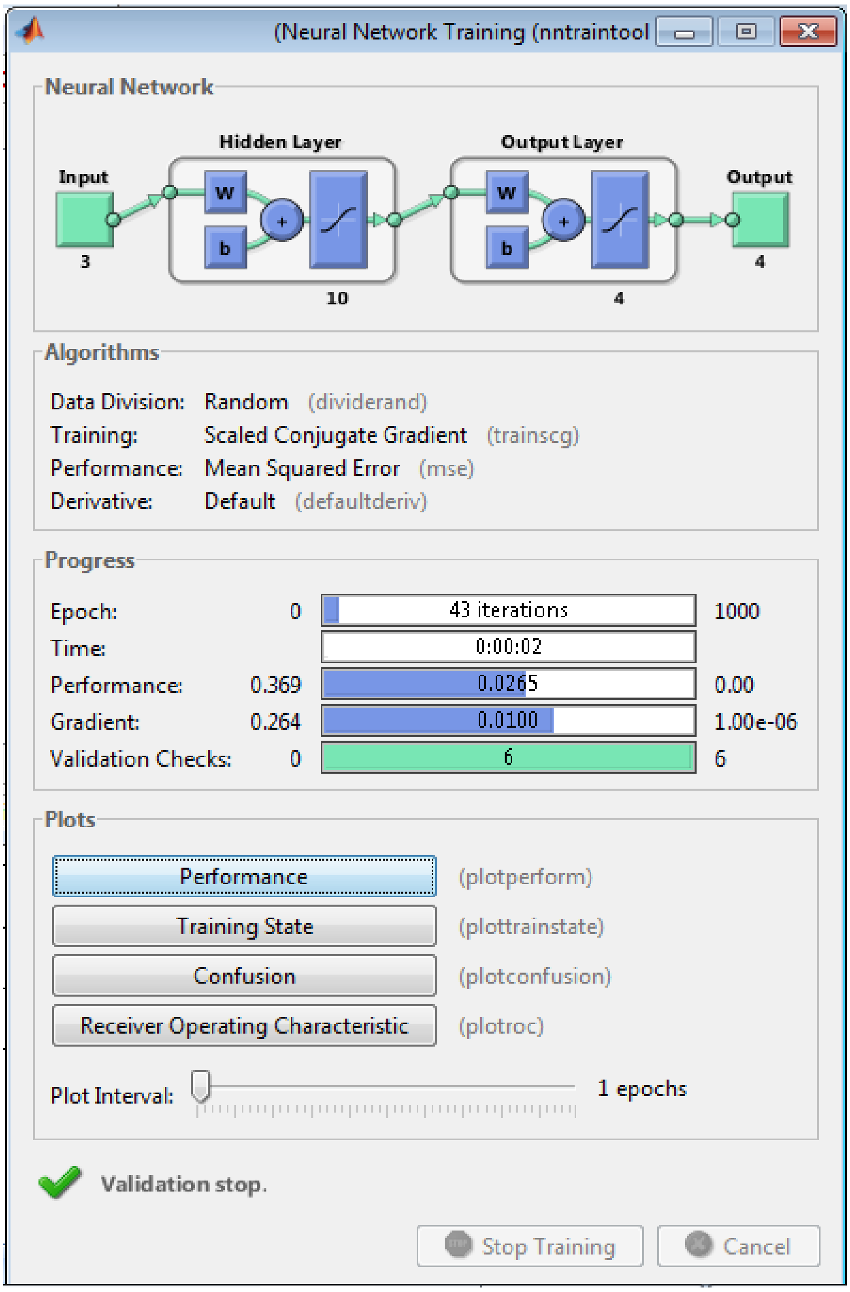


Figure (4.1) artificial neural network

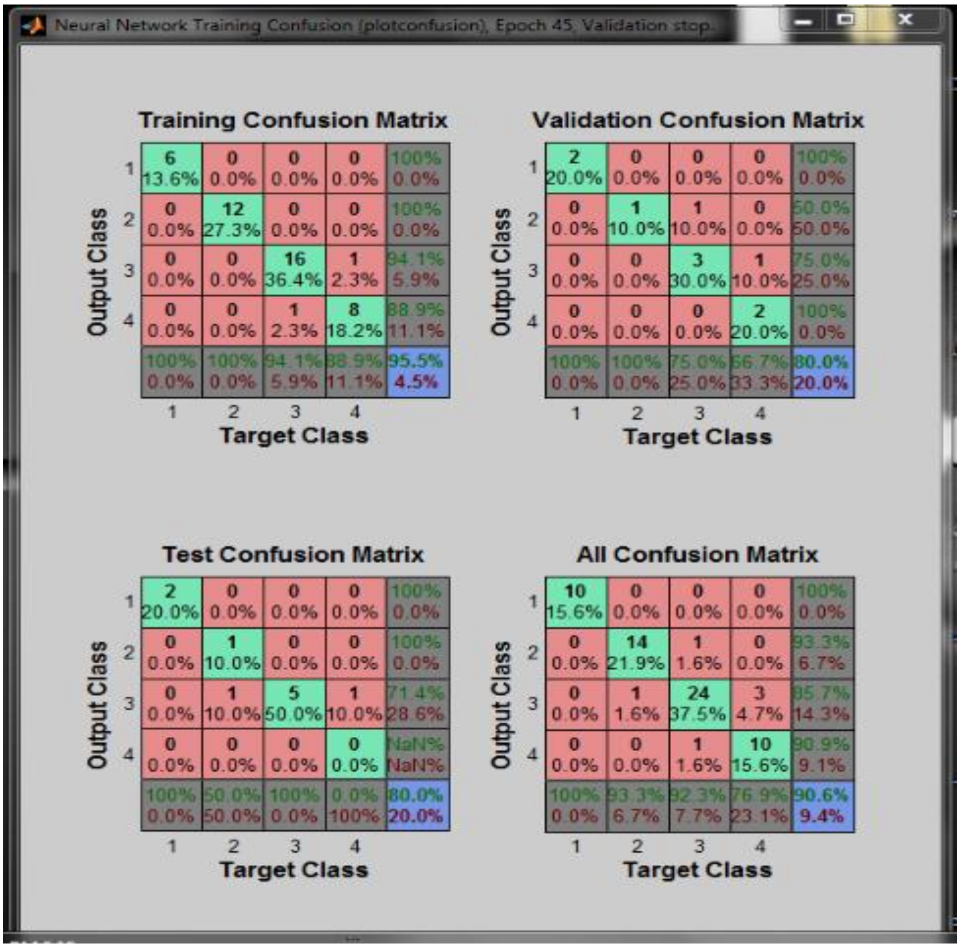


Figure (4.2) neural network training

Test data

```
TT=[160  70  5]
No=[1;0;0;0];
MI=[0;1;0;0];
MO=[0;0;1;0];
S=[0;0;0;1];
load( 'test.mat' , 'net');
simul=sim(net,TT');
simul2=round(simul);
if simul2==No;
   text(0.5,0.4,'No-
hypo','FontSize',14,'EdgeColor','red');
else
if simul2==MI;
 text(0.5,0.4,'Mild','FontSize',14,'EdgeColor','red');
else.3
if simul2==MO;

text(0.5,0.4,'Moderate','FontSize',14,'EdgeColor','red');
else
```

```
if simul2==S;
 text(0.5,0.4,'Severe','FontSize',14,'EdgeColor','red');
end
end
end
end
display (text),figure;
```

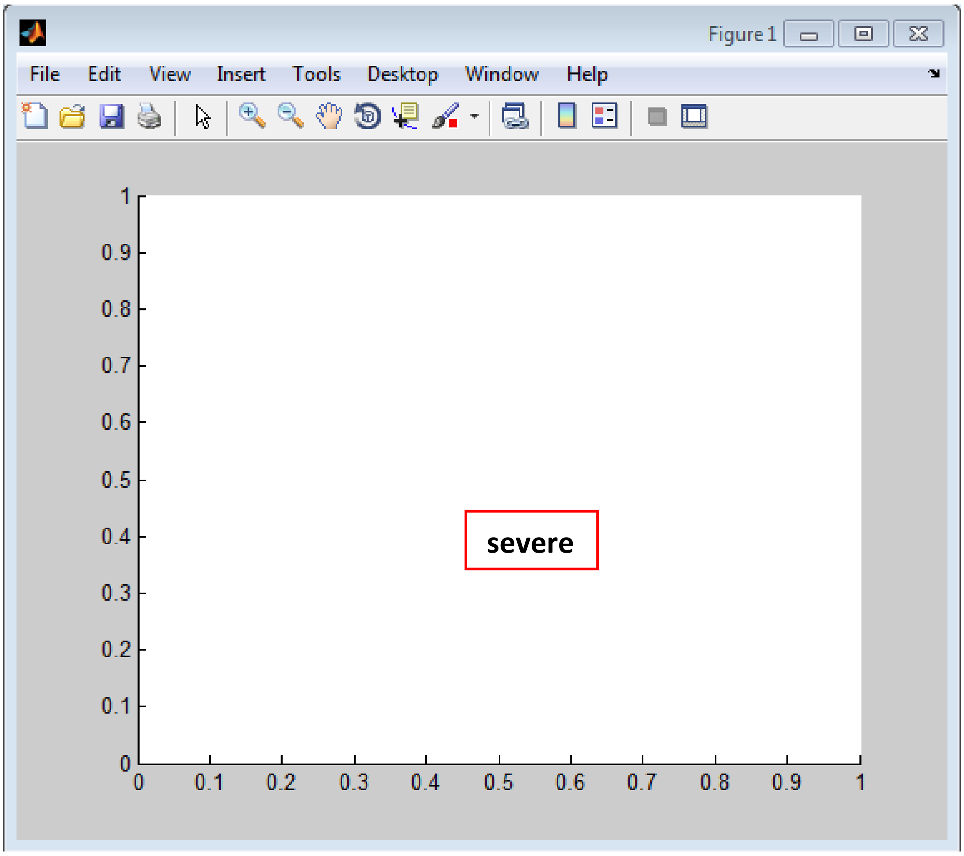


Figure (4.3) result obtain of severe case

The Graphical User Interface (GUI)

Is type of user interface that allows users to interact with electronic devices through graphical icon and visual indicator, instead of text-based user interfaces, typed command labels or text navigation. (code (C))

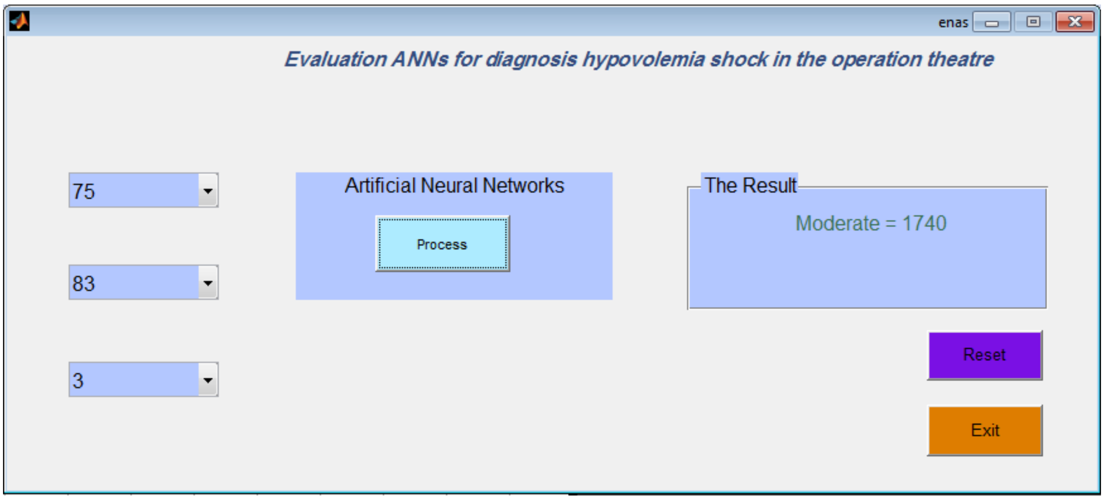


Figure (4.4) the result obtained of moderate case

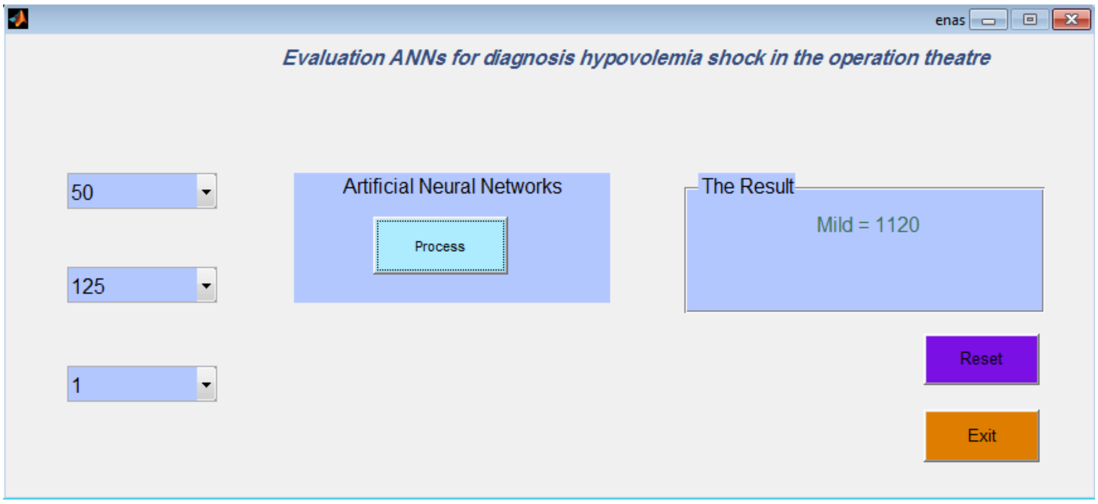


Figure (4.5) the result obtained of mild case

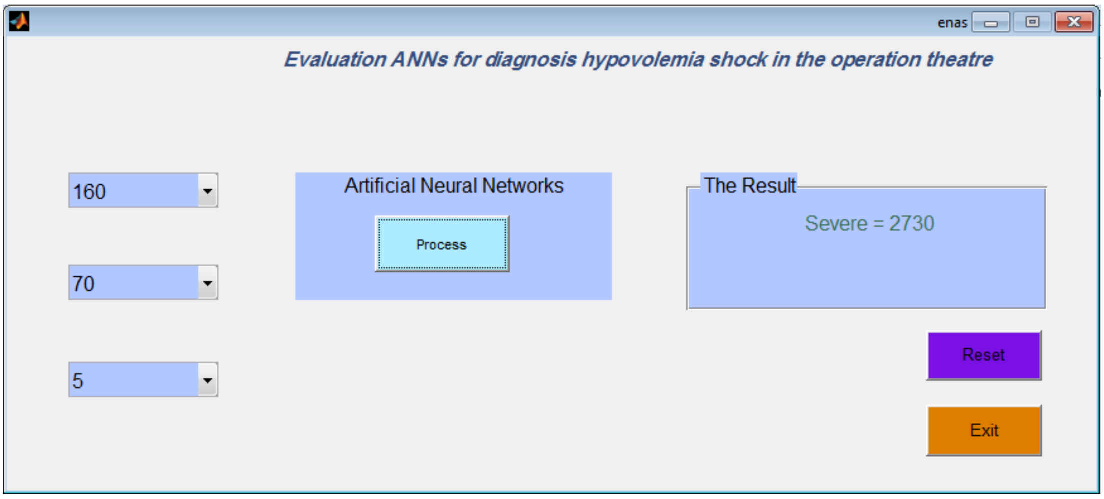


Figure (4.6) the result obtained of severe case

4.1.2- Fuzzy logic

Fuzzy logic (FL) can be able to define the output for any input without define this value directly to the system. depending on the system it may not be necessary to evaluate every possible input combination since some may rarely or never occur. by this way fewer rules can be evaluated, thus simplifying the processing logic and perhaps even improving the fuzzy logic system performance. generally fuzzy logic can apply that work with number of degree as we want because is like human brain has a degree of approximation to measure just we define the parameter range for our inputs and outputs then it can work efficiently, so fuzzy logic more acceptable for clinical decided and any other need to identical results for work not be able to endures the increases or decreases in certain values.

The overall fuzzy system composes four functional models: The reference inputs and outputs , the rule-base mechanism of fuzzy system and the controlled process.

Fuzzy control system is obtained by writing a set of rules in the form of

IF [situation] THEN [action]

Steps of building process of FLC systems

the first step is insertion of inputs and output range (table A)

Input 1: Heart rate [50—200] beat per minute (bpm).

Input 2: blood pressure [50—150] mmHg.

Input 3: urine output [0—60] ml/h.

Output1:the hypovolemia class level [0—40].

Output2: compensation volume [0—3500] ml .

The second step is construct the rules for each input(heart rate ,blood pressure and urine output) and each output (the stages and compensation value).Example : if (HR is 80) and (BP is 150) and (UR is 17) then (CLASS is 5).

5 is indicate to no hypovolemia

e.g if (HR is 80) and (BP is 150) and (UR is 17) then (VOLUME is 375.3).

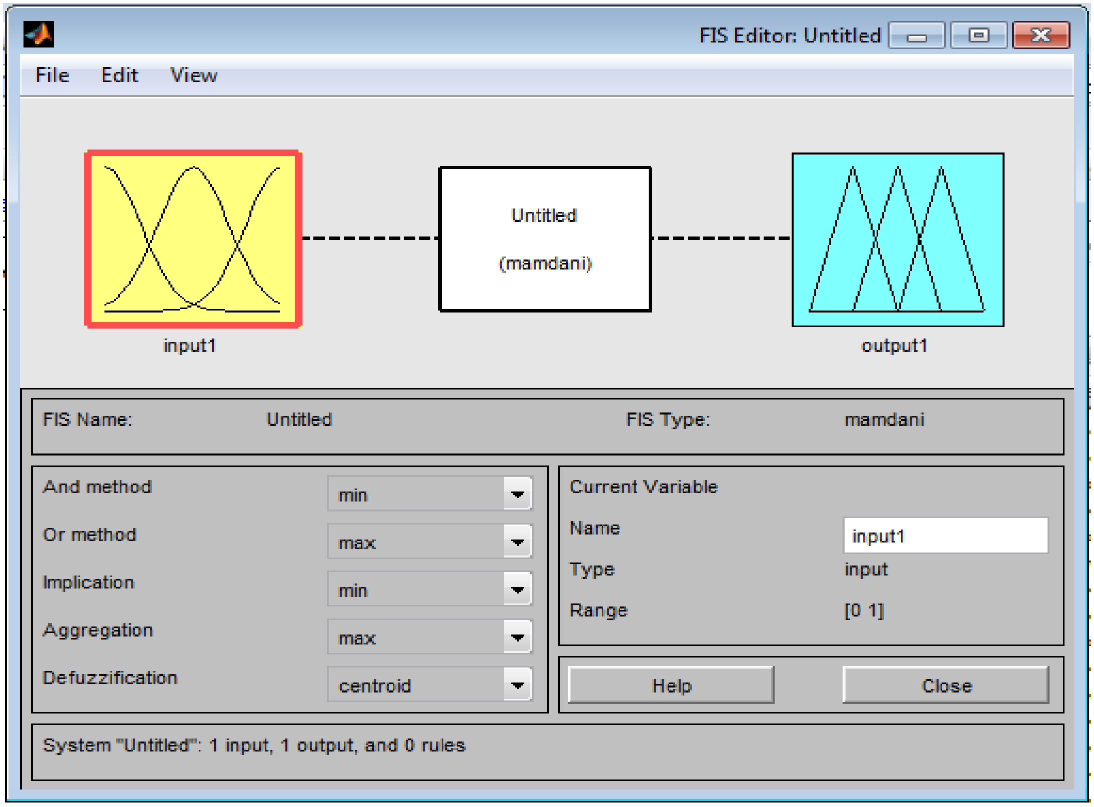


Figure (4.7) the framework of fuzzy logic system

4.1.2.1- System modeling

Firstly we define an ideal data of hypovolemia to the Fuzzy logic system which consists of three input variable (heart rate , blood pressure and urine output), two outputs (the classification of hypovolemia and compensation volume). there are two system but the input is the same in both. each input and output consists of four linguistics terms (no hypo , mild , moderate ,severe) each input and output have a certain range to specify hypovolemia class level and compensation volume.

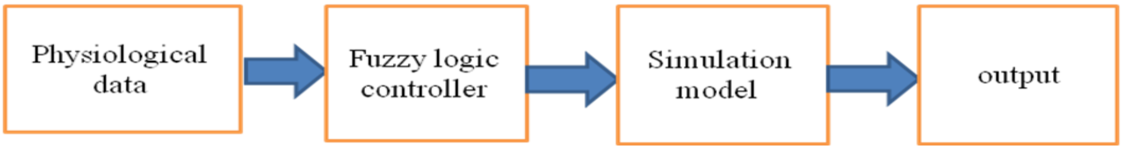
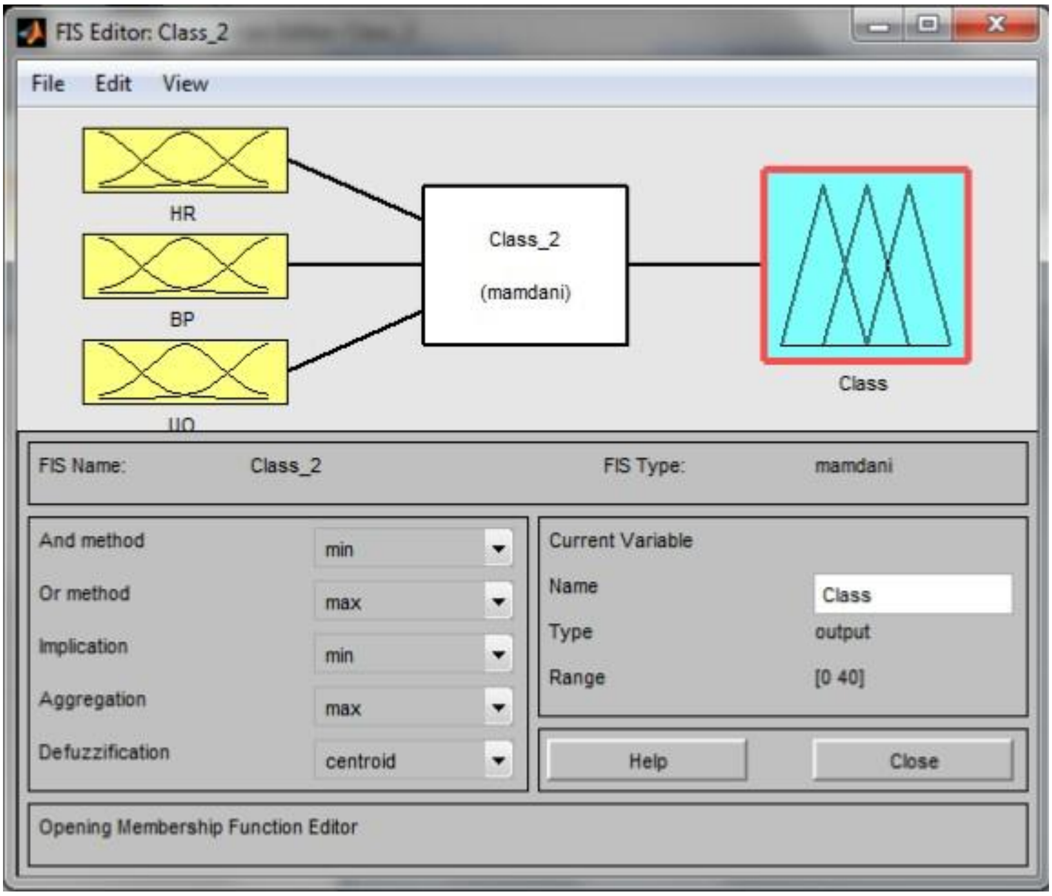


Figure (4.8) The general flow diagram of proposed diagnostic system

4.1.2.2- The FLC system for hypovolemia class level

In this system the output is the classification of hypovolemia (no hypo , mild , moderate , severe).



Figure(4.9) The total system input and output

Linguistic variables:

1. Name (HR)

Type (input)

Range [50 —200]

Display range [50—200]

Number of terms (4)

Its membership functions:

-Membership Function1:

Name (no-hypo)

PARAM [50-75-100]

Type of terms (trimf)

-Membership Function 2:

Name (mild)

PARAM [95-107.5-120]

Type of terms (trimf)

-Membership Function 3:

Name (moderate)

PARAM [115-128-140]

Type of terms (trimf)

-Membership Function 4:

Name (severe)

PARAM [135-168-200]

Type of terms (trimf)

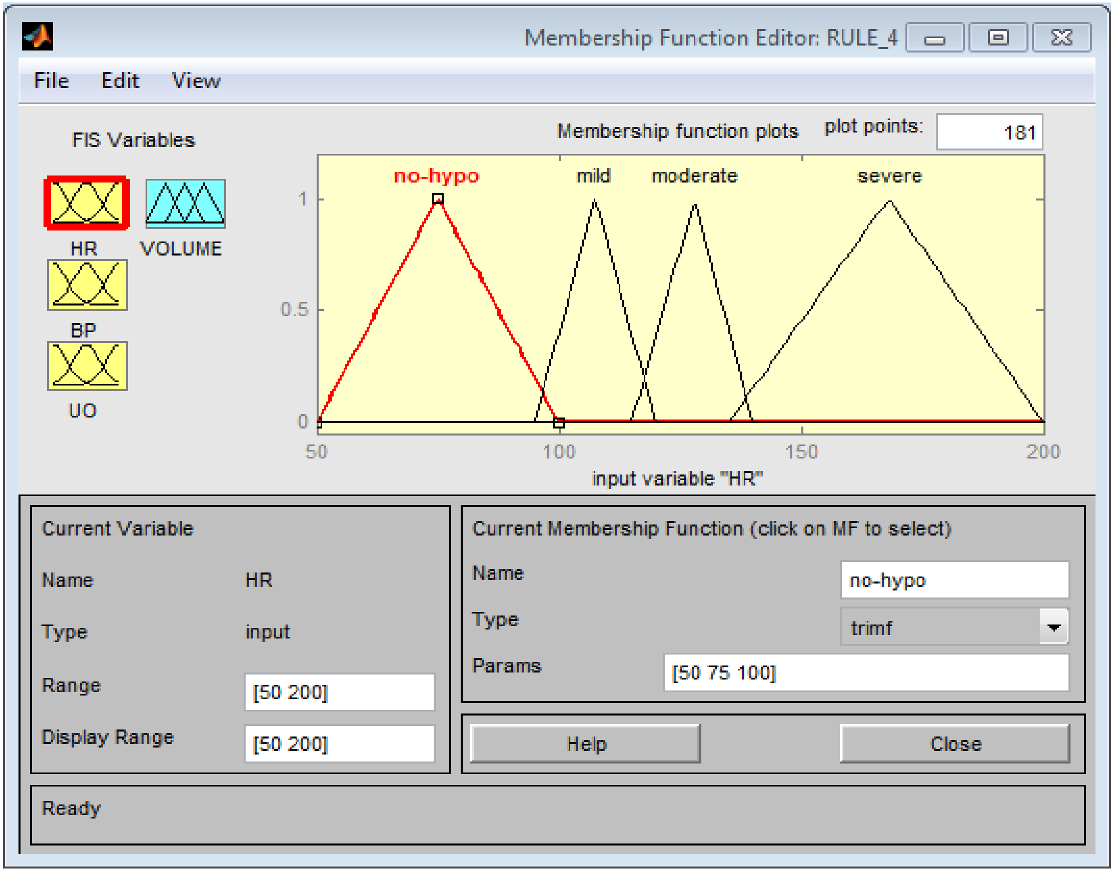


Figure (4.10) plot of total membership functions for the input variable "HR"

2. Name (BP)

Type (input)

Range [50—150]

Display range [50—150]

Number of terms (4)

Its membership function:

-Membership Function 1:

Name (severe)

PARAM [50-60-70]

Type of terms (trimf)

-Membership Function 2:

Name (moderate)

PARAM [65-83-100]

Type of terms (trimf)

-Membership Function 3:

Name (mild)

PARAM [95-115-135]

Type of terms (trimf)

-Membership Function4:

Name (no-hypo)

PARAM [130-140-150]

Type of terms (trimf)

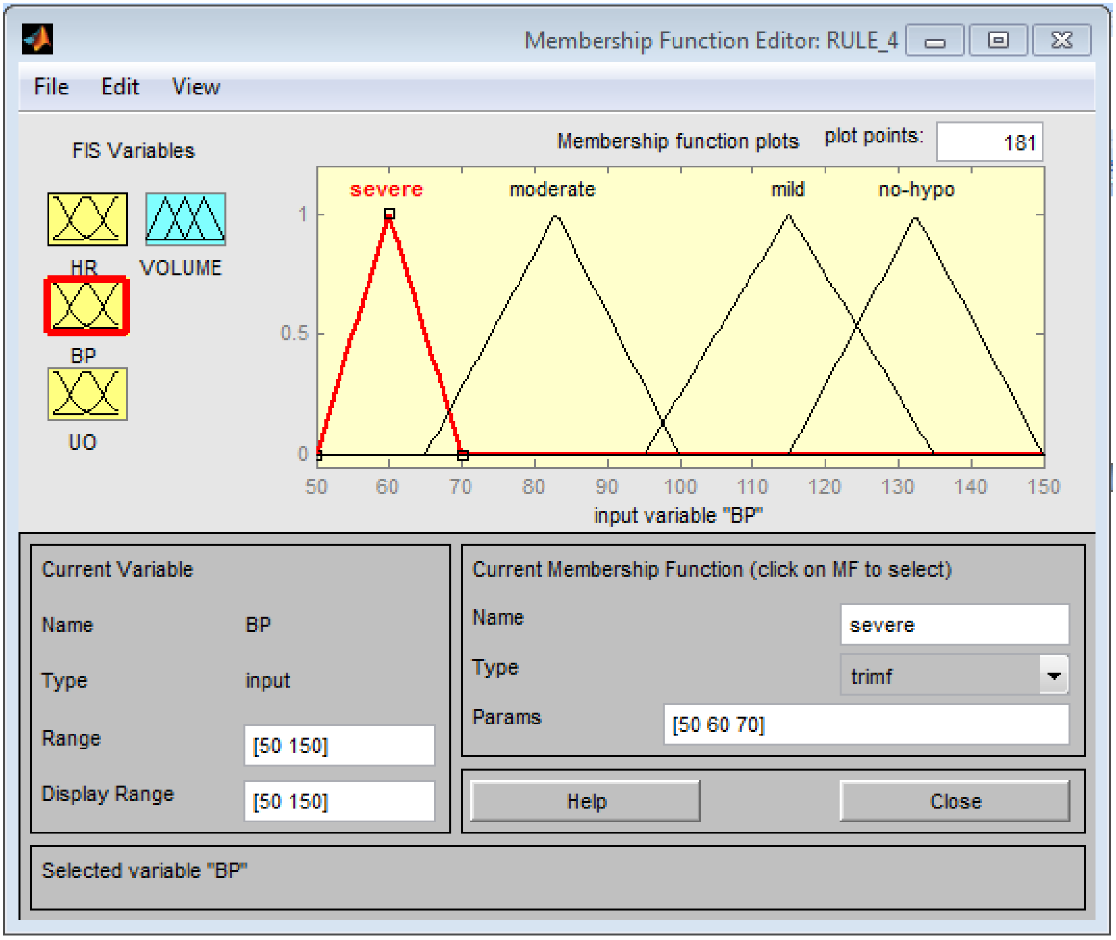


Figure (4.11) plot of total membership functions for the input variable "BP

3. Name (UO)

Type (input)

Range [0—60]

Display range [0—60]

Number of terms (4)

Its membership function:

-Membership Function1:

Name (severe)

PARAM [0-2.5-5]

Type of terms (trimf)

-Membership Function 2:

Name (moderate)

PARAM [4-9.5-15]

Type of terms (trimf)

-Membership Function 3:

Name (mild)

PARAM [14-22-30]

Type of terms (trimf)

-Membership Function 4:

Name (no-hypo)

PARAM [27-43.5-60]

Type of terms (trimf)

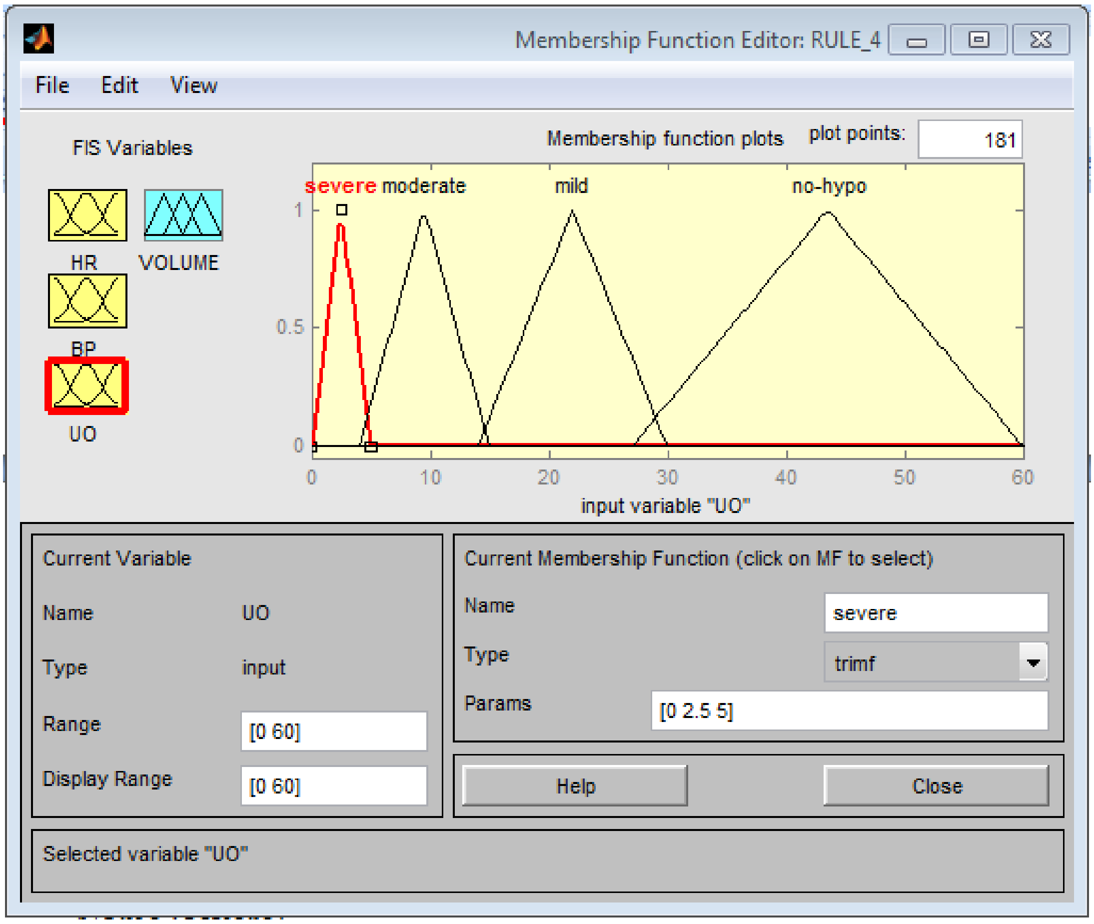


Figure (4.12) Plot of total membership functions for the input variable "UO"

4. Name (CLASS)

Type (output)

Range [0—40]

Display range [0—40]

Number of terms (4)

Its membership function:

-Membership Function 1:

Name (no-hypo)

PARAM [0-5-10]

Type of terms (trimf)

-Membership Function 2:

Name (mild)

PARAM [9-14.5-20]

Type of terms (trimf)

-Membership Function 3:

Name (moderate)

PARAM [19-24.5-30]

Type of terms (trimf)

-Membership Function 4:

Name (severe)

PARAM [29-34.5 -40]

Type of terms (trimf)

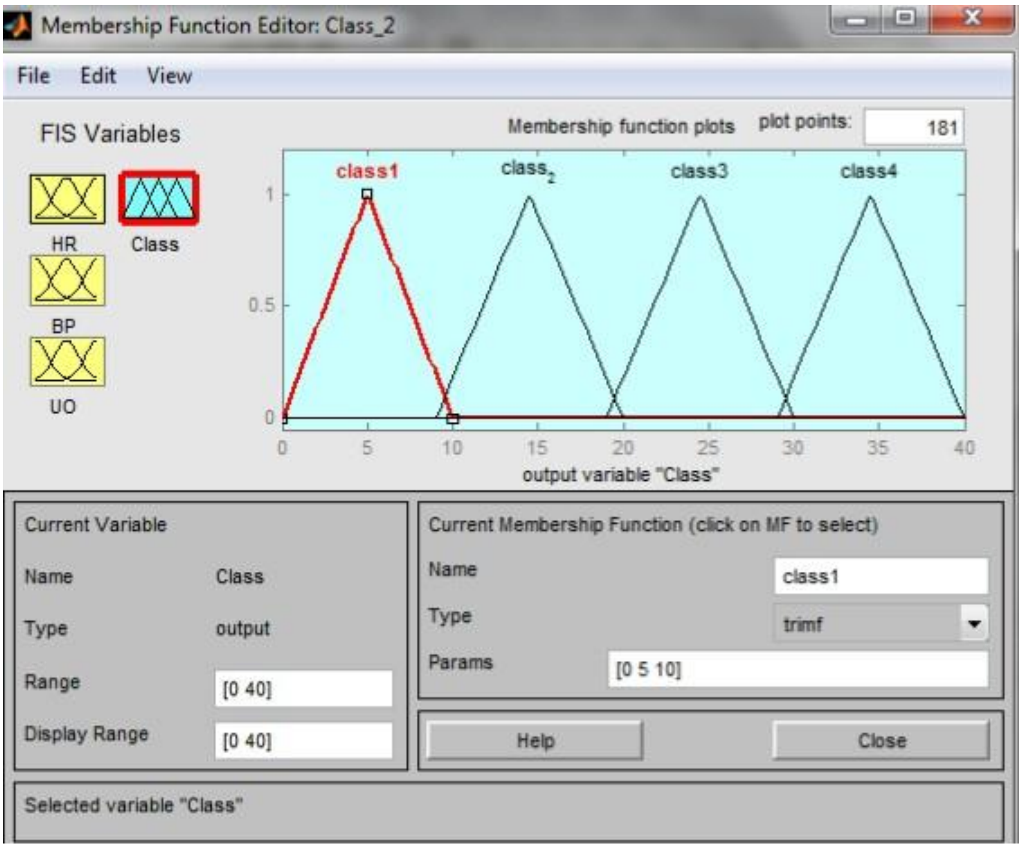


Figure (4.13) plot of total membership functions for the output variable "CLASS"

Table(4.1) show the range of the hypovolemia class level

Hypovolemia class level	Range
No hypo	0—10
Mild	10—20
Moderate	20—30
Severe	30—40

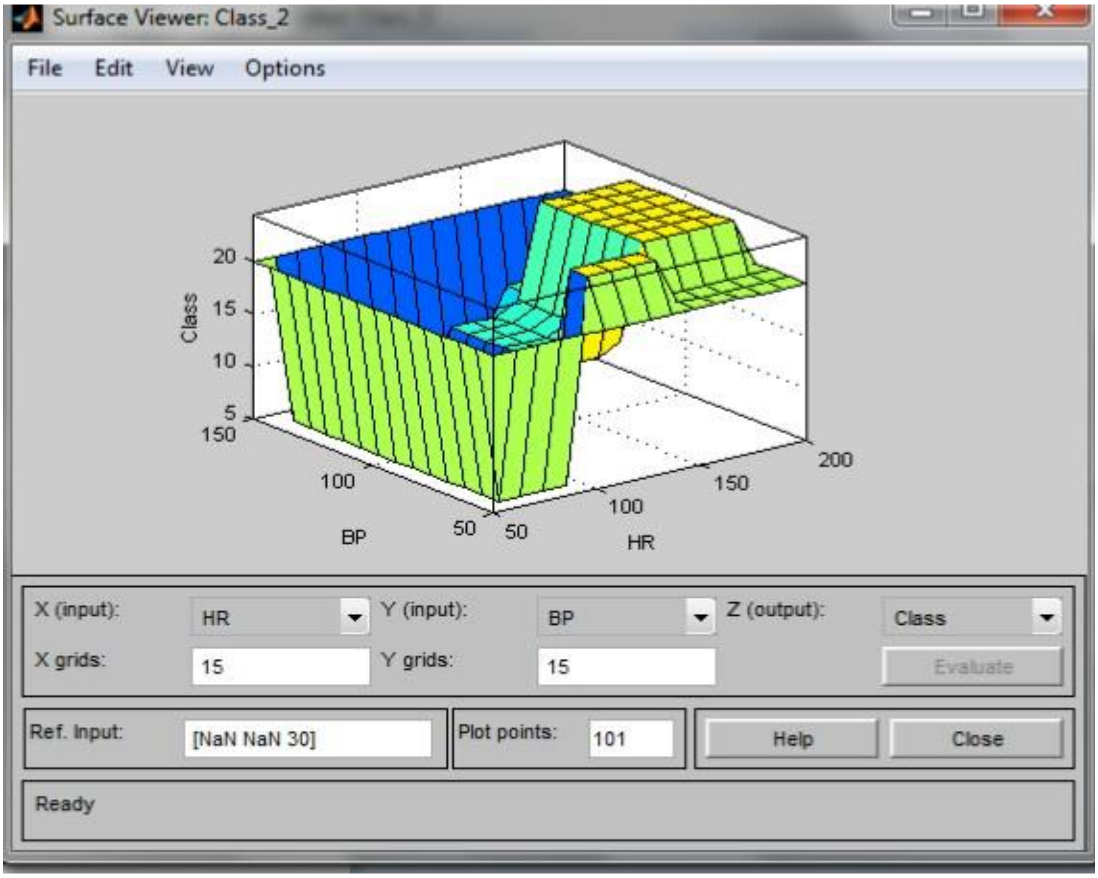
The Rules:

Here there are three input and one output and the total rules number is 64

IF H and B and U then C

Example: If (HR is 45) and (BP is 70) and (UO is 12) then (CLASS is 14.49) and so on for any values.

14.49 refer to mild



Figure(4.14) surface view of hypovolemia class level with BP and HR

4.1.2.3- The FLC system of compensation volume

In this system the output is the compensation volume of hypovolemia class level (no hypo , mild , moderate , severe).

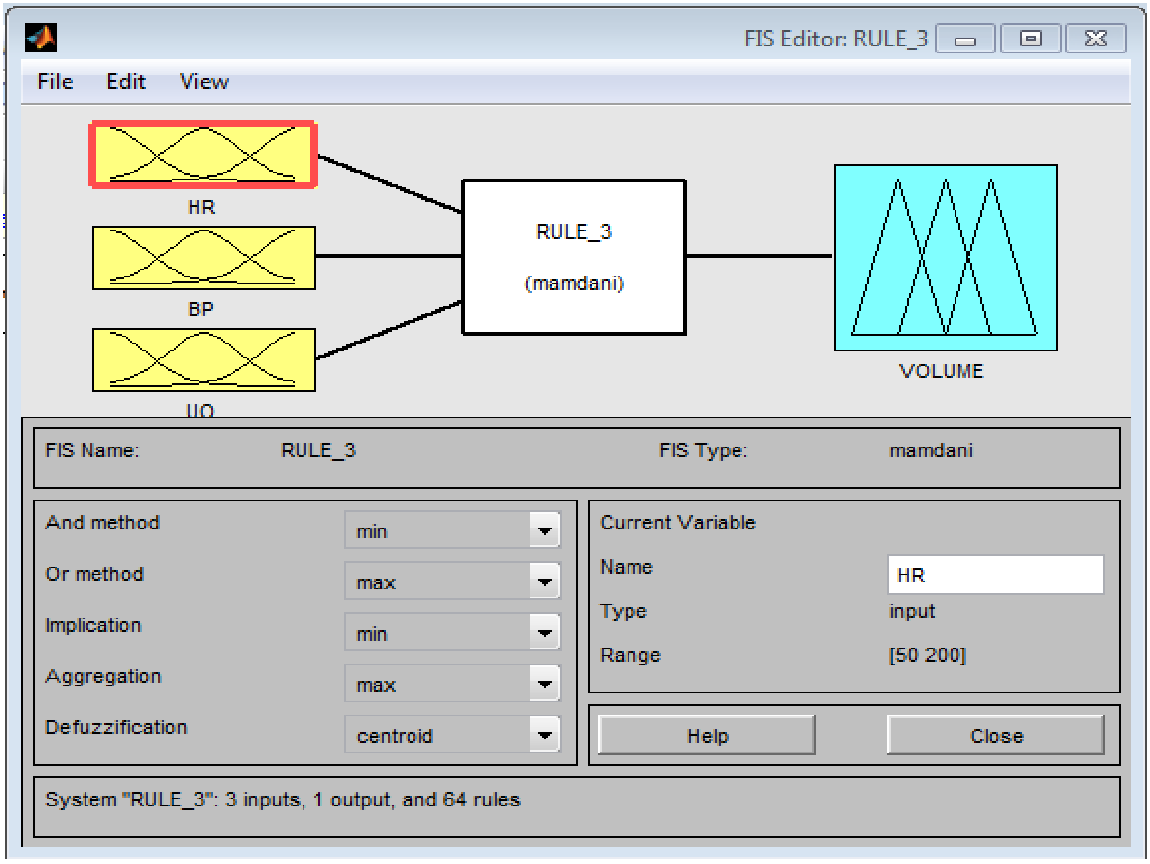


Figure (4.15) The total system input and output

Linguistic variables:

2. Name (HR)

Type (input)

Range [50 —200]

Display range [50—200]

Number of terms (4)

Its membership functions:

-Membership Function1:

Name (no-hypo)

PARAM [50-75-100]

Type of terms (trimf)

-Membership Function 2:

Name (mild)

PARAM [95-107.5-120]

Type of terms (trimf)

-Membership Function 3:

Name (moderate)

PARAM [115-128-140]

Type of terms (trimf)

-Membership Function 4:

Name (severe)

PARAM [135-168-200]

Type of terms (trimf)

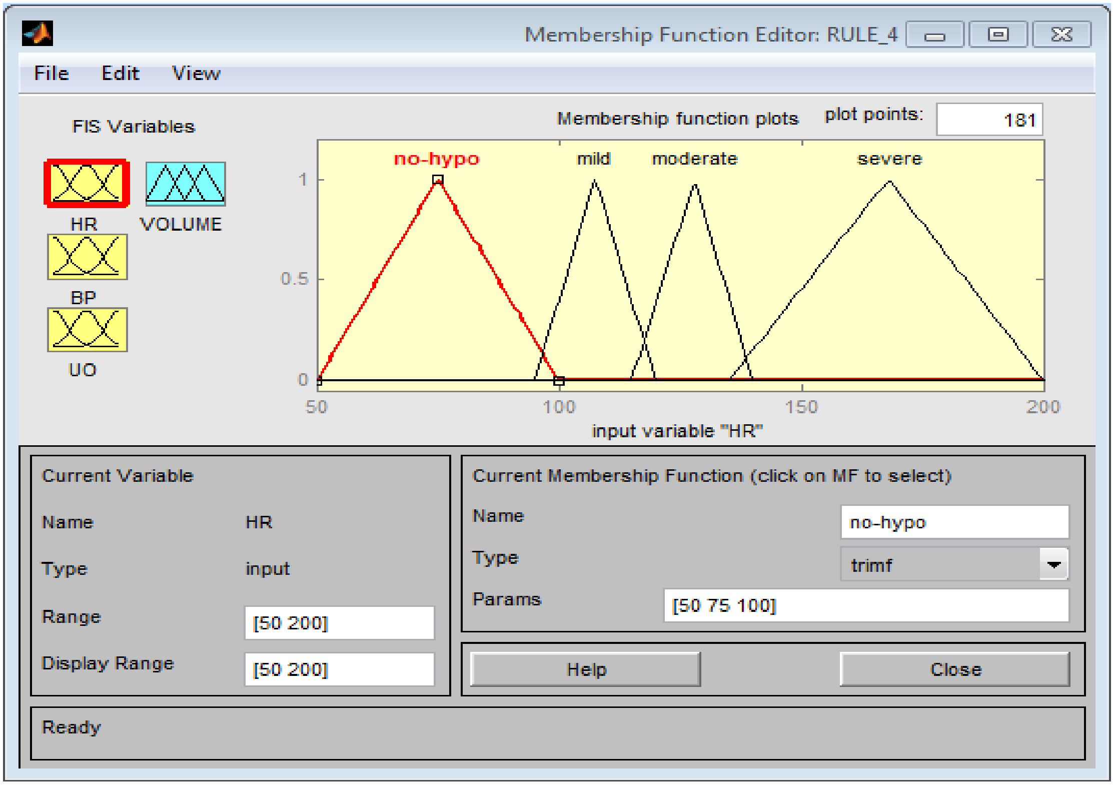


Figure (4.16) plot of total membership functions for the input variable "HR"

2. Name (BP)

Type (input)

Range [50—150]

Display range [50—150]

Number of terms (4)

Its membership function:

-Membership Function 1:

Name (severe)

PARAM [50-60-70]

Type of terms (trimf)

-Membership Function 2:

Name (moderate)

PARAM [65-83-100]

Type of terms (trimf)

-Membership Function 3:

Name (mild)

PARAM [95-115-135]

Type of terms (trimf)

-Membership Function4:

Name (no-hypo)

PARAM [130-140-150]

Type of terms (trimf)

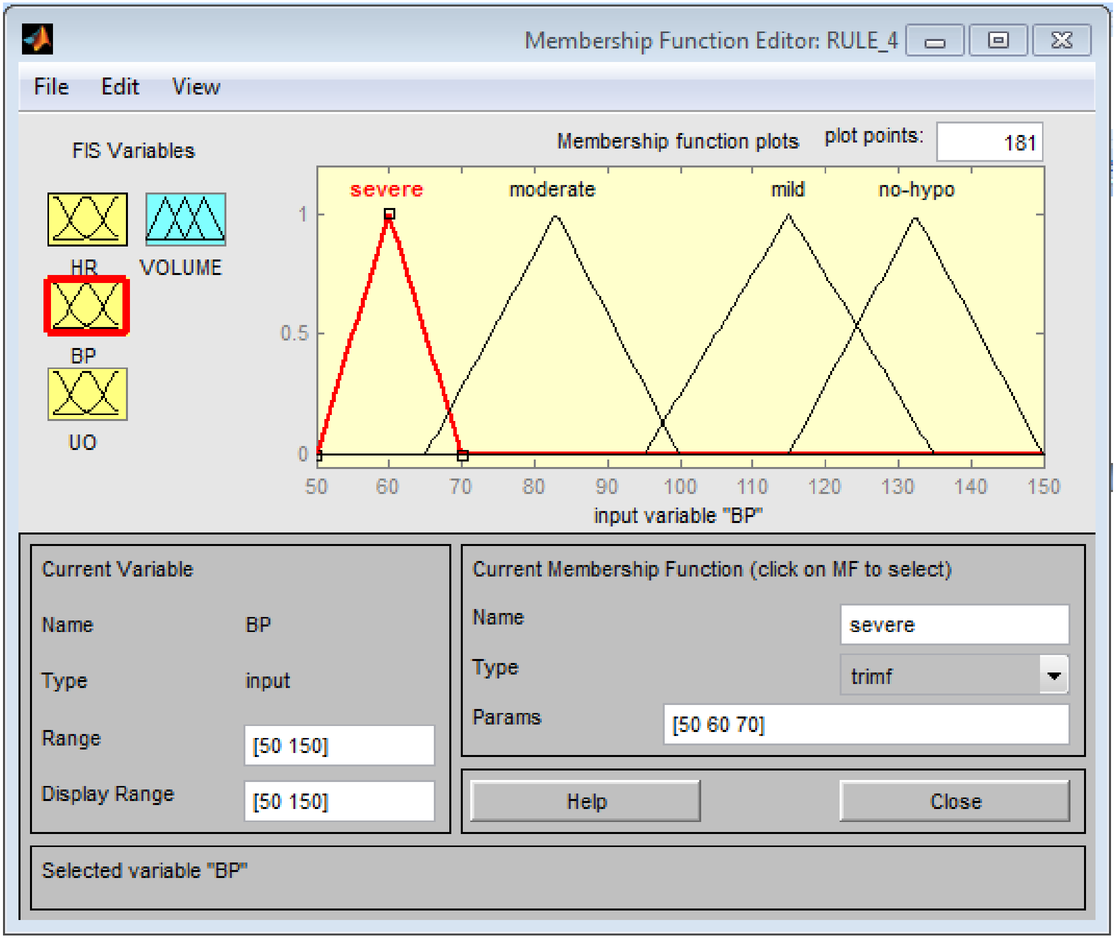


Figure (4.17) plot of total membership functions for the input variable "BP"

3. Name (UO)

Type (input)

Range [0—60]

Display range [0—60]

Number of terms (4)

Its membership function:

-Membership Function1:

Name (severe)

PARAM [0-2.5-5]

Type of terms (trimf)

-Membership Function 2:

Name (moderate)

PARAM [4-9.5-15]

Type of terms (trimf)

-Membership Function 3:

Name (mild)

PARAM [14-22-30]

Type of terms (trimf)

-Membership Function 4:

Name (no-hypo)

PARAM [27-43.5-60]

Type of terms (trimf)

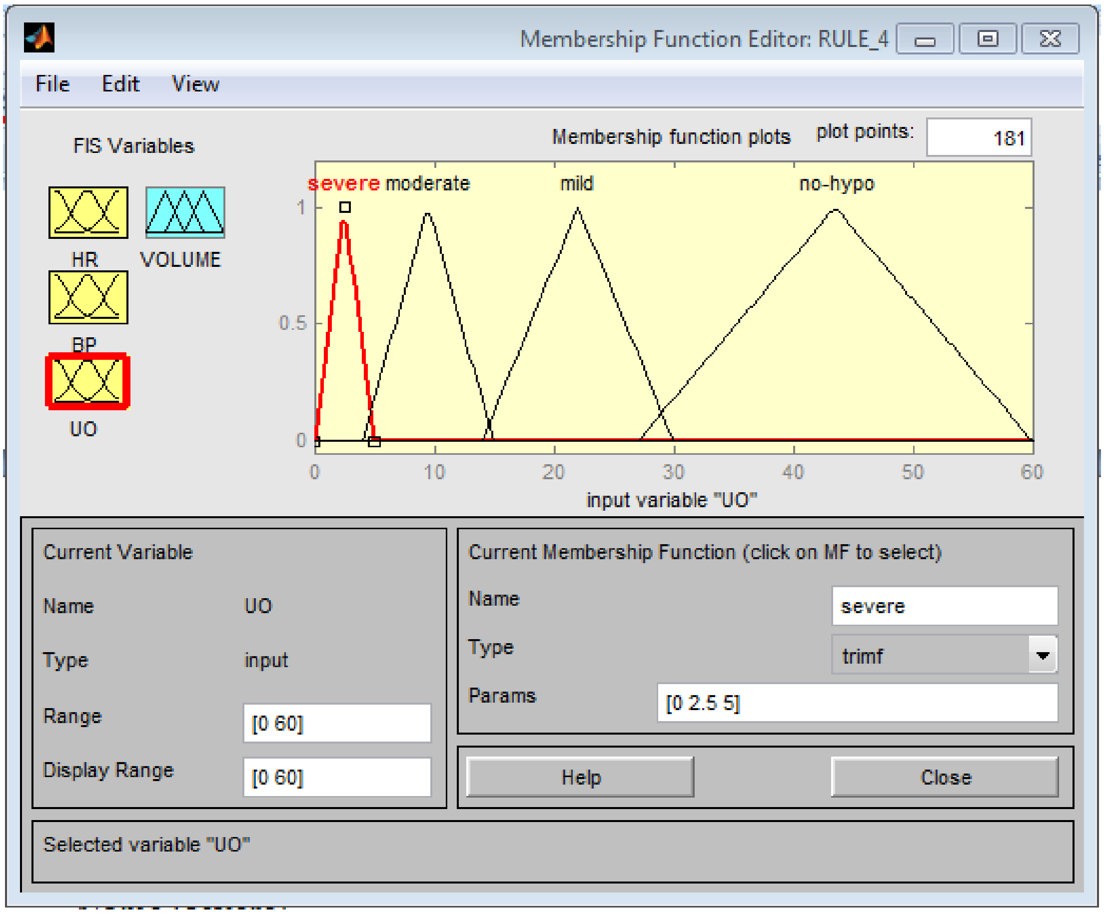


Figure (4.18) Plot of total membership functions for the input variable "UO"

4. Name (VOLUME)

Type (output)

Range [0—3500]

Display range [0—3500]

Number of terms (4)

Its membership function:

-Membership Function 1:

Name (no-hypo)

PARAM [0-375-750]

Type of terms (trimf)

-Membership Function 2:

Name (mild)

PARAM [740-1120-1500]

Type of terms (trimf)

-Membership Function 3:

Name (moderate)

PARAM [1480-1740-2000]

Type of terms (trimf)

-Membership Function 4:

Name (severe)

PARAM [1960-2730-3500]

Type of terms (trimf)

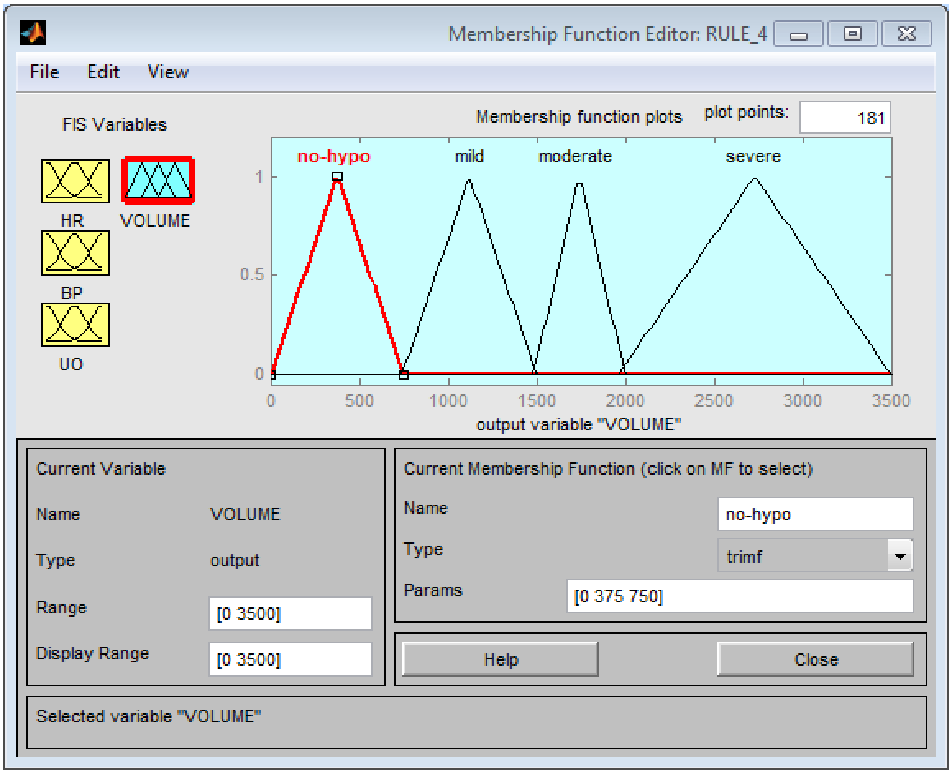


Figure (4.19) Plot of total membership functions for the output variable "VOLUME"

The Rules:

Also here there are three input and one output ,the total rules number is 64

IF H and B and U then C

Example:

If (HR is 130) and (BP is 85) and (UO is 21) then (VOLUME is 1740) and so on for any values.

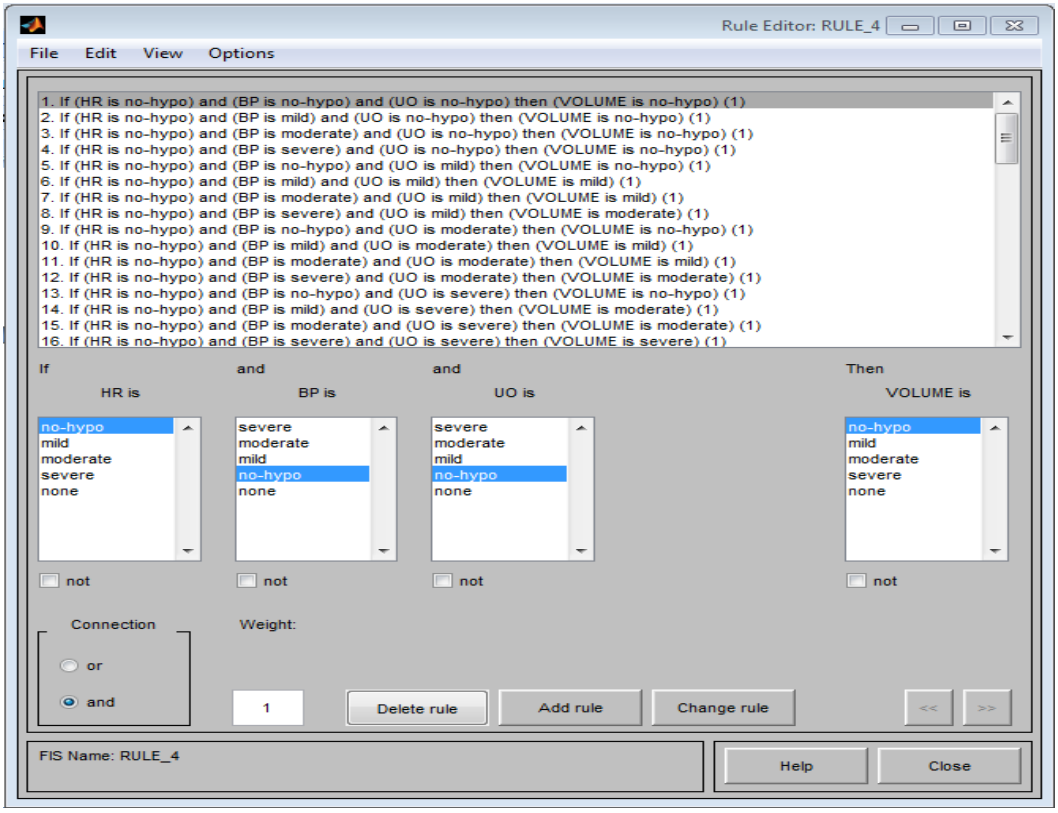


Figure (4.20) The rule base of fuzzy system

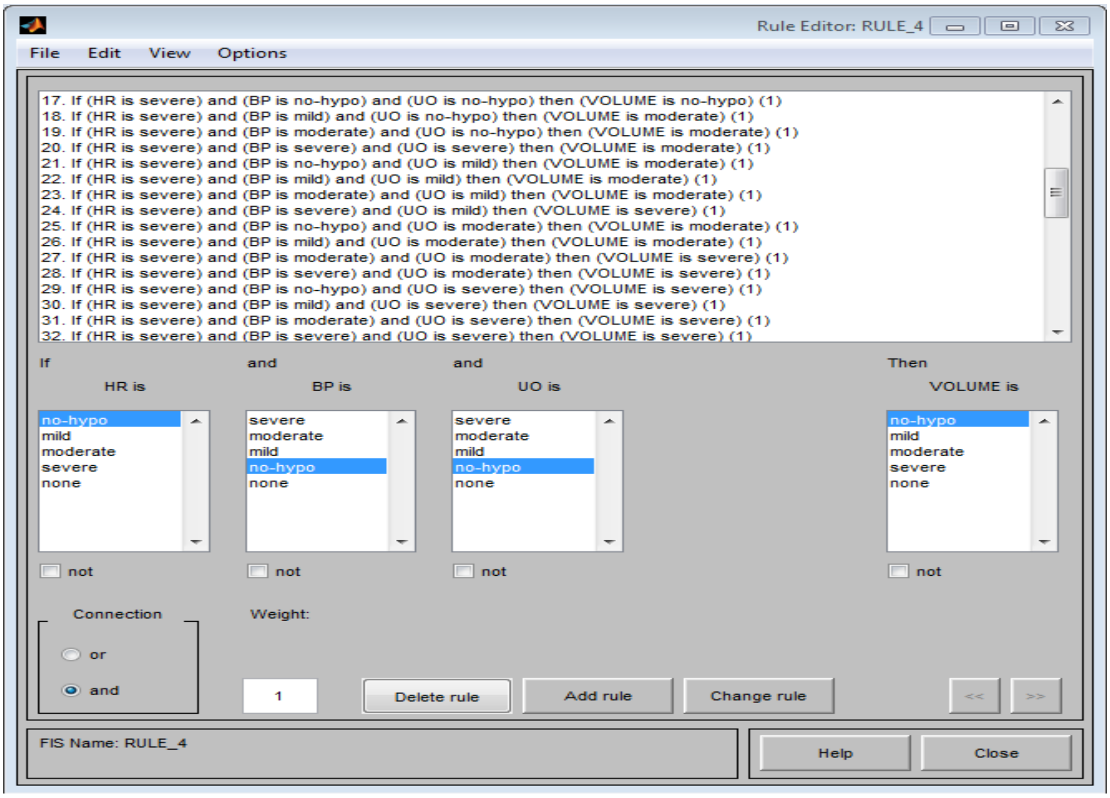


Figure (4.21) The rule base of fuzzy systeM

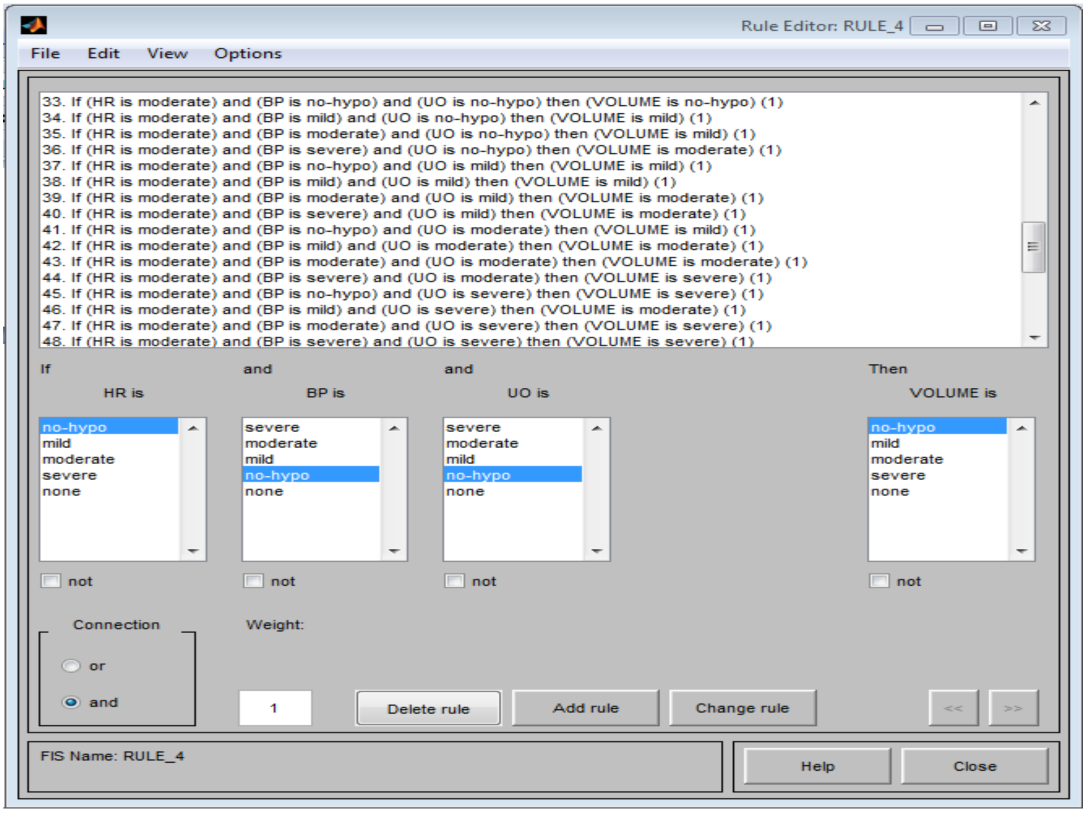


Figure (4.22) The rule base of fuzzy system

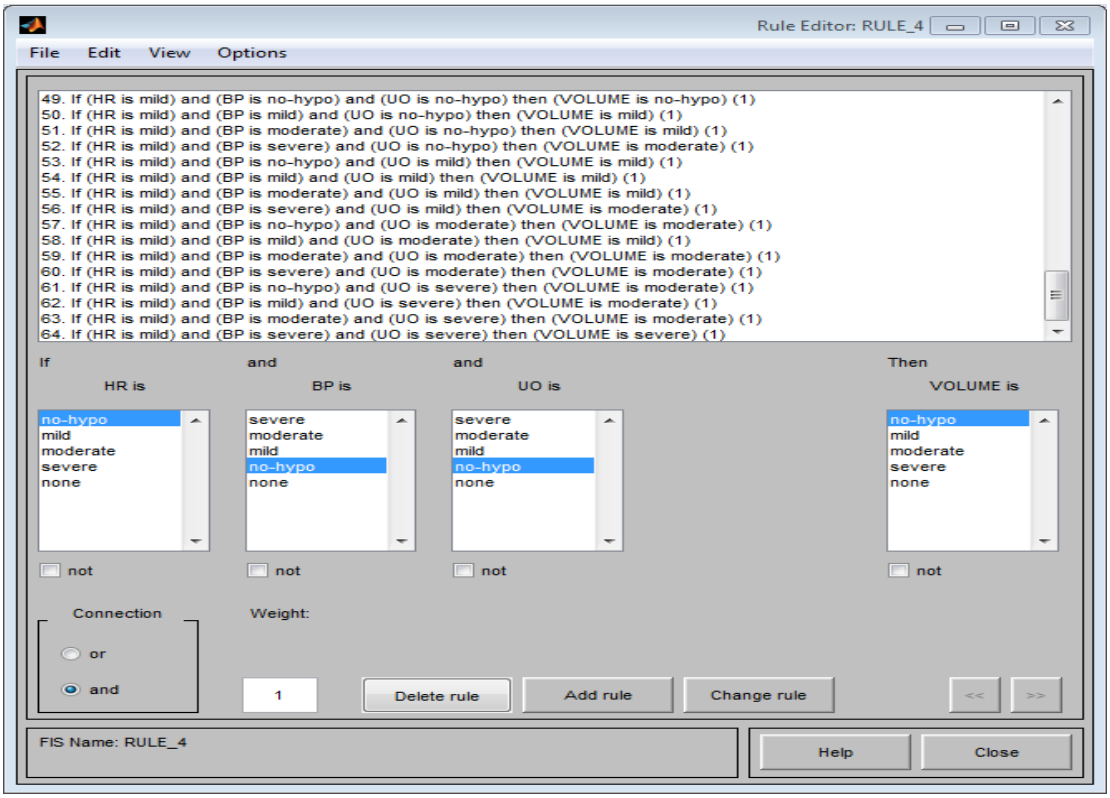


Figure (4.23) The rule base of fuzzy system

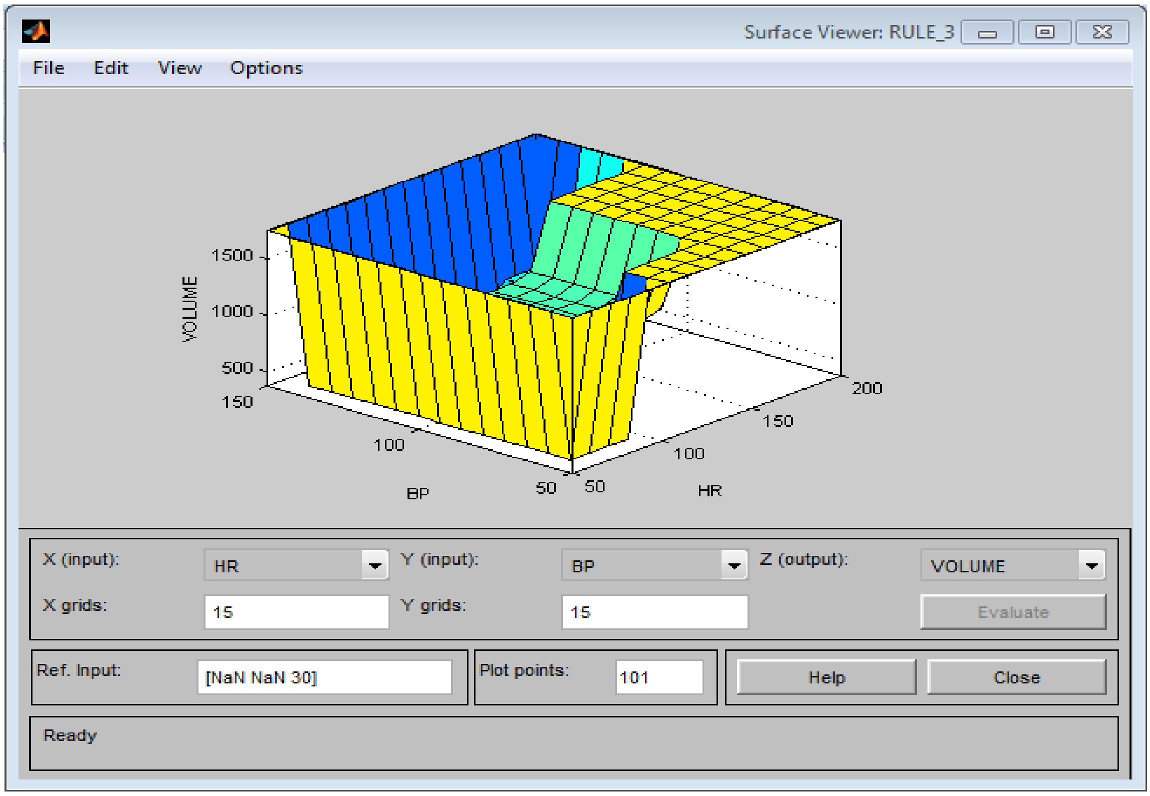


Figure (4.24) Surface view of compensation volume with BP and HR

4.1.2.4- The simulation results

After all this operations FLS will be able to calculate any input value and regulate it by give a degree of output it regulate the given inputs.

Then fuzzy logic was being simulated to give results by using a simulation program (simulink) as shown in figure (4.16).

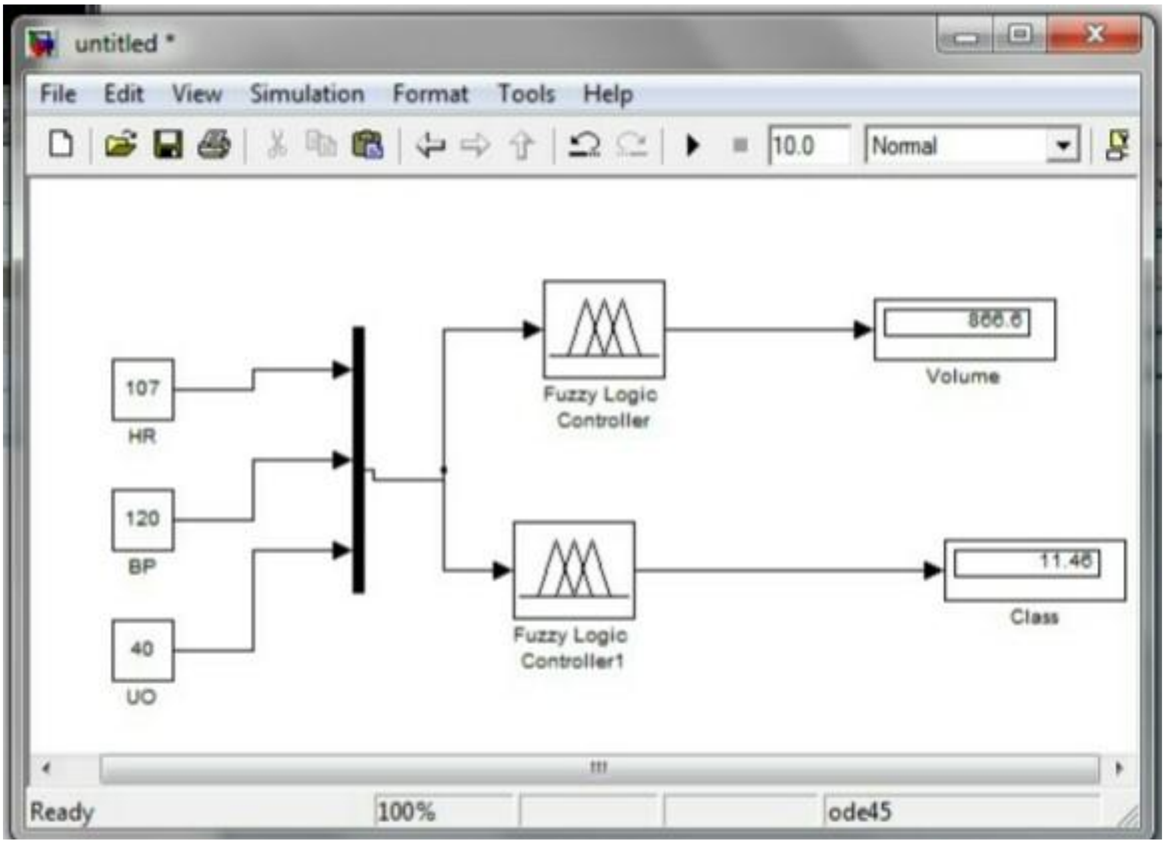


Figure (4.25) Simulation of fuzzy logic system with simulink

The input will be compared to all rules that are saved in FIS, so when all inputs meet it rules the output will be measured to give the final output of the system.

The data (HR, BP, UO, compensation volume) which are used are collected from operations theatre for different surgeries from Omdurman teaching hospital, bahri hospital and police hospital. all these data was entered to the systems and then the systems give the output for each case , the results are shown in tables below:

Table (4.2) Data collection from Omdurman teaching hospital with doctor decision and two systems output (Surgery in the liver)

Case Number	HR (bpm)	BP (mmHg)	UO (ml/h)	Compensation in hospital (ml)	Fuzzy logic output (ml)	Neural network output (ml)
1	50	125	1	500	1750	1120
2	160	70	5	2500	2730	2730
3	160	60	7	1000	2730	2730
4	130	60	19	500	1740	1740
5	130	150	20	1500	1740	375
6	130	85	21	1000	1750	1740
7	110	80	24	500	1120	1120
8	100	120	35	500	799.4	1120
9	107	120	40	No	866.6	1120

Table (4.3) Data collection from Police hospital with doctor decision and two systems output (Caesarean)

Case Number	HR (bpm)	BP (mmHg)	UO (ml/h)	Compensation in hospital (ml)	Fuzzy logic output (ml)	Neural network output (ml)
1	115	70	10	500	1740	175
2	70	80	15	1500	1120	1120
3	160	85	17	1000	1739	1750
4	190	115	24	750	1740	1740
5	137	65	25	500	2178	1740
6	130	100	26	1500	1120	1120

Table (4.4) Data collection from Bahri hospital with doctor decision and two systems output (Caesarean)

Case Number	HR (bpm)	BP (mmHg)	UO (ml/h)	Compensation in hospital (ml)	Fuzzy logic output (ml)	Neural network output (ml)
1	100	105	24	1000	1120	1120
2	105	50	24	1500	1740	1740
3	115	124	27	750	1120	1120
4	80	105	35	500	375.5	175
5	90	109	37	No	375.7	175

Table (4.5) Data collection from Omdurman teaching hospital with doctor decision and two systems output (Surgery for removal gallbladder)

Case number	HR (bpm)	BP (mmHg)	UO (ml/h)	Compensation in hospital (ml)	Fuzzy logic output (ml)	Neural network output (ml)
1	145	90	20	1000	1740	1740
2	140	85	21	500	1741	1740
3	125	69	27	1500	1739	1740
4	90	98	29	750	755.9	1120

5	110	60	30	1000	1740	1740
6	105	105	31	No	1120	1120
7	60	113	35	500	375.7	375
8	85	120	37	250	375.7	375
9	100	135	40	No	375.7	375

Table (4.6) Data collection from Omdurman teaching hospital with doctor decision and two systems output (Surgery for removal spleen)

Case Number	HR (bpm)	BP (mmHg)	UO (ml/h)	Compensation in hospital (ml)	Fuzzy logic output (ml)	Neural network output (ml)
1	160	60	3	500	2480	2730
2	160	60	7	2000	2730	2730
3	135	130	19	1500	1120	1120
4	145	105	19	500	1740	1740
5	172	90	20	1000	1740	1740
6	120	90	21	500	1740	1120
7	130	103	21	1000	1120	1120

Table (4.7) Data collection from Omdurman teaching hospital with doctor decision and system output and the difference between them (Caesarean)

Case number	HR (bpm)	BP (mmHg)	UO (ml/h)	Compensation in hospital (ml)	Fuzzy logic output (ml)	Neural network output (ml)
1	98	80	50	3000	924	1740
2	88	100	No	1500	1750	1740
3	98	60	12	1000	1739	1740
4	94	95	No	1000	1750	1740
5	90	60	No	1000	1750	2730
6	100	80	No	1500	1750	175

in the hospital when hypovolemia occur the doctors do not pay attention to it because they cannot monitor changes which occur in heart rate, blood pressure in patient monitor and the urine catheter and here begin the problem, the bleeding can be internal or external. The external bleeding will be appear to them and they compensate randomly by giving 500 ml as first solution and they continuous give the patient until the bleeding stop, the calculation of lost quantity take a time and does not give the right amount because the bleeding is continuous during the operation of the calculation, if this occur the patient is exposed shock and dangerous complications occur which can lead to death. The real problem occur in internal bleeding which does not appear to doctor and the physiological parameter change but they do not give it attention. so the systems will give output , so the time consumed in the detection of this event is solute ,by this we improve the patient health care in the operation theatre. the compensation volume is not only blood it can be water or plasma as the doctor decide.

neural networks, and fuzzy systems are equivalent in that they are convertible, yet in practice each has its own advantages and disadvantages. For neural networks, the knowledge is automatically acquired by the backpropagation algorithm, but the learning process is relatively slow and analysis of the trained network is difficult , Fuzzy systems are more favorable in that their behavior can be explained based on fuzzy rules and thus their performance can be adjusted by tuning the rules.there are 42 cases inserted to systems ,the fuzzy bases on rules so the result is accurate(64 rules),but the neural network base on training data (60% for train,20% for test,20% for validation from data) ,the percent of network is 90.6% this explain the errors in tables above.

CHAPTER FIVE

Conclusion and Recommendations

5.1- Conclusion

In the previous studies the hypovolemia is only detected and classified but this proposed systems detect and classify hypovolemia in addition to specify the compensation volume for each class level.

This proposed systems is design for detection and classification hypovolemia in the operation theatre by using heart rate, blood pressure and urine output as a parameters, to give the compensation volume and minimize the time of the doctor decision.

In neural network a feed forward back propagation network was used to training the heart rate (HR), blood pressure (BP) and urine output (UO) data with different rate, medians of heart rate (HR), blood pressure (BP) and urine output (UO) taken to represent the input of the network . then training network show in figure (4.2).Then inserted practical data to test that give output show in table (4.2), table (4.3), table (4.4) and table (4.5)

In other system consist of building the fuzzy control system with the standard data for each class of hypovolemia and compensation volume. fuzzy logic system consists of number of membership function and fuzzy sets which indicate to the hypovolemia class level (no-hypo, mild, moderate, severe) . then the rule-base was constructed to make a control to the fuzzy system and it's number is 64 rules .then the overall fuzzy system was simulated by using a simulation program (simulink) as shown in figure (4.16).

the data was collected from different hospitals and it has been applied in the proposed systems , hypovolemia case as shown in table (4.2), table (4.3), table (4.4) and table (4.5).
the systems give an acceptable results compared to hospital decision because it is built with an standard data of hypovolemia stages.

5.2- Recommendations

1- apply in operation theatre.
2- develop a hybrid system combined the fuzzy system and neural network.
3- design a warning alarm or message in this system to indicate the hypovolemia event.

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Appendix

A)

	Class 1	Class 2 (mild)	Class 3 (moderate)	Class 4 (severe)
Blood less	Up to 15% (750 ml)	15-30% (750-1500 ml)	30-40% (1500-2000 ml)	Over 40% (over 2000 ml)
Heart rate	≤100	>100	>120	>140
Blood pressure	Normal	Normal	<100	<70
Urine output	≥30	20-30	5-20	Minimal

[32]

This table show the standard data of Heart rate, Blood pressure, Urine output and the compensate volume for each class based on this parameter values the two systems are built.

B) **Code of network**

```
p=[75 140 44 ;   75 115 44;    75 83 44 ;   75
60 44;   75 140 22 ;    75 60 10 ;  75 140 3;
168 140 44;  83 140 44;  115 140 44;
 75 115 22;    75 83 22 ;    75 115 10;    75 83
10 ;     128 115 44;  128 83 44 ;  128 140 22
;128 115 22;   128 140 10;    108 115 44;    108
83 44;108 140 22;     108 115 22;    108 83 22;
108 115 10;
  75 60 22; 75 60 10;     75 115 3;     75 83 3;
168 115 44;    168 83 44;  168 60 3; 168 140 22;
168 115 22;    168 83 22; 168 140 10;    168 115
```

```
10;      128 60 44;  128 83 22;     128 60 22;
128 115 10;   128 83 10;    128 115 3;   108 60
44;  108 60 22;   108 140 10  ;108 83 10;    108
60 10;108 140 3;108 115 3; 108 83 3 ;
75 60 3 ; 168 60 22; 168 83 10;     168 60 10;
168 140 3;   168 115 3;   168 83 3;    168 60 3;
128 60 10;     128 140 3; 128 83 3; 128 60 3;
108 60 3];
pp=p';
t=[ones(1,10),zeros(1,54);zeros(1,10),ones(1,15)
,zeros(1,39);zeros(1,25),ones(1,26),zeros(1,13);
zeros(1,51),ones(1,13)];
net=newff(pp,t,10);
net=newpr(pp,t,10);
[net,tr]=train(net,pp,t);
save( 'test.mat' , 'net');
```

C) code of GUI

```
function varargout = enas(varargin)
% ENAS MATLAB code for enas.fig
%      ENAS, by itself, creates a new ENAS or
raises the existing
%      singleton*.
%
%      H = ENAS returns the handle to a new ENAS
or the handle to
%      the existing singleton*.
%
%
ENAS('CALLBACK',hObject,eventData,handles,...)
calls the local
%      function named CALLBACK in ENAS.M with
the given input arguments.
%
%      ENAS('Property','Value',...) creates a
```

```
new ENAS or raises the
%      existing singleton*.  Starting from the
left, property value pairs are
%      applied to the GUI before enas_OpeningFcn
gets called.  An
%      unrecognized property name or invalid
value makes property application
%      stop.  All inputs are passed to
enas_OpeningFcn via varargin.
%
%      *See GUI Options on GUIDE's Tools menu.
Choose "GUI allows only one
%      instance to run (singleton)".
%
% See also: GUIDE, GUIDATA, GUIHANDLES

% Edit the above text to modify the response to
help enas

% Last Modified by GUIDE v2.5 20-Oct-2017
20:16:39

% Begin initialization code - DO NOT EDIT
gui_Singleton = 1;
gui_State = struct('gui_Name',       mfilename,
...
                   'gui_Singleton',
gui_Singleton, ...
                   'gui_OpeningFcn',
@enas_OpeningFcn, ...
                   'gui_OutputFcn',
@enas_OutputFcn, ...
                   'gui_LayoutFcn',  [] , ...
                   'gui_Callback',   []);
if nargin && ischar(varargin{1})
    gui_State.gui_Callback =
str2func(varargin{1});
end

if nargout
    [varargout{1:nargout}] =
gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
```

```
end
% End initialization code - DO NOT EDIT


% --- Executes just before enas is made visible.
function enas_OpeningFcn(hObject, eventdata,
handles, varargin)
% This function has no output args, see
OutputFcn.
% hObject    handle to figure
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
data (see GUIDATA)
% varargin   command line arguments to enas (see
VARARGIN)

% Choose default command line output for enas
handles.output = hObject;

% Update handles structure
guidata(hObject, handles);

% UIWAIT makes enas wait for user response (see
UIRESUME)
% uiwait(handles.figure1);


% --- Outputs from this function are returned to
the command line.
function varargout = enas_OutputFcn(hObject,
eventdata, handles)
% varargout  cell array for returning output
args (see VARARGOUT);
% hObject    handle to figure
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
data (see GUIDATA)

% Get default command line output from handles
structure
varargout{1} = handles.output;
```

```
% --- Executes on button press in pushbutton1.
function pushbutton1_Callback(hObject, eventdata, handles)
% hObject    handle to pushbutton1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)


% --- Executes on button press in pushbutton2.
function pushbutton2_Callback(hObject, eventdata, handles)
% hObject    handle to pushbutton2 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
%C:\Users\user\Desktop\sources\Matlab 2011b (32 & 64-Bit) With Crack\archives\doc_ja\bin
%P=handles.P;
TT=zeros(1,3);
TT(1,1)=handles.TT(1,1);
TT(1,2)=handles.TT(1,2);
TT(1,3)=handles.TT(1,3);
disp(TT)
%TT=[50 125 1]
K= TT;
load( 'test.mat' , 'net');

No=[1;0;0;0];
MI=[0;1;0;0];
MO=[0;0;1;0];
S=[0;0;0;1];


simul=sim(net,K');
simul2=round(simul);


if simul2==No;
     set(handles.text3,'String','No Hypo  = 375')
```

```
else

if simul2==MI;
   set(handles.text3,'String','Mild = 1120')
else

if simul2==MO;
   set(handles.text3,'String','Moderate = 1740')
else

if simul2==S;
   set(handles.text3,'String','Severe = 2730')
end
end
end
end

handles.simul2=simul2;


function edit1_Callback(hObject, eventdata,
handles)
% hObject    handle to edit1 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
data (see GUIDATA)

% Hints: get(hObject,'String') returns contents
of edit1 as text
%        str2double(get(hObject,'String'))
returns contents of edit1 as a double


% --- Executes during object creation, after
setting all properties.
function edit1_CreateFcn(hObject, eventdata,
handles)
% hObject    handle to edit1 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    empty - handles not created until
after all CreateFcns called
```

```
% Hint: edit controls usually have a white
background on Windows.
%       See ISPC and COMPUTER.
if ispc &&
isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end



function edit2_Callback(hObject, eventdata,
handles)
% hObject    handle to edit2 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
data (see GUIDATA)

% Hints: get(hObject,'String') returns contents
of edit2 as text
%        str2double(get(hObject,'String'))
returns contents of edit2 as a double


% --- Executes during object creation, after
setting all properties.
function edit2_CreateFcn(hObject, eventdata,
handles)
% hObject    handle to edit2 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    empty - handles not created until
after all CreateFcns called

% Hint: edit controls usually have a white
background on Windows.
%       See ISPC and COMPUTER.
if ispc &&
isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end
```

```
function edit3_Callback(hObject, eventdata,
handles)
% hObject    handle to edit3 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
data (see GUIDATA)

% Hints: get(hObject,'String') returns contents
of edit3 as text
%        str2double(get(hObject,'String'))
returns contents of edit3 as a double


% --- Executes during object creation, after
setting all properties.
function edit3_CreateFcn(hObject, eventdata,
handles)
% hObject    handle to edit3 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    empty - handles not created until
after all CreateFcns called

% Hint: edit controls usually have a white
background on Windows.
%       See ISPC and COMPUTER.
if ispc &&
isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end


% --- Executes on selection change in
popupmenu1.
function popupmenu1_Callback(hObject, eventdata,
handles)
% hObject    handle to popupmenu1 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
```

```
data (see GUIDATA)
 str = get(hObject, 'String');
val = get(hObject,'Value');
 %Set current data to the selected data set.
switch str{val};
    case '50' % User selects peaks.
 TT(1,1)= 50;
case '75' % User selects peaks.
 TT(1,1)= 75;
  case '60' % User selects peaks.
 TT(1,1)= 60;
  case '85' % User selects peaks.
 TT(1,1)= 85;
 case '100' % User selects peaks.
 TT(1,1)= 100;
 case '110' % User selects peaks.
 TT(1,1)= 110;
 case '160' % User selects peaks.
 TT(1,1)= 160;
 case '130' % User selects peaks.
 TT(1,1)= 130;
 case '107' % User selects peaks.
 TT(1,1)= 107;

end
%Save the handles structure.
handles.TT(1,1)=TT(1,1);
guidata(hObject,handles)


% Hints: contents =
cellstr(get(hObject,'String')) returns
popupmenu1 contents as cell array
%        contents{get(hObject,'Value')} returns
selected item from popupmenu1


% --- Executes during object creation, after
setting all properties.
function popupmenu1_CreateFcn(hObject,
eventdata, handles)
% hObject    handle to popupmenu1 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
```

```
% handles    empty - handles not created until
after all CreateFcns called

% Hint: popupmenu controls usually have a white
background on Windows.
%       See ISPC and COMPUTER.
if ispc &&
isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end


% --- Executes on selection change in
popupmenu2.
function popupmenu2_Callback(hObject, eventdata,
handles)
% hObject    handle to popupmenu2 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
data (see GUIDATA)
 str = get(hObject, 'String');
val = get(hObject,'Value');
 %Set current data to the selected data set.
switch str{val};
case '70' % User selects peaks.
 TT(1,2)= 70;
 case '83' % User selects peaks.
 TT(1,2)= 83;
 case '60' % User selects peaks.
 TT(1,2)= 60;
 case '155' % User selects peaks.
 TT(1,2)= 155;
 case '85' % User selects peaks.
 TT(1,2)= 85;
 case '80' % User selects peaks.
 TT(1,2)= 80;
 case '120' % User selects peaks.
 TT(1,2)= 120;
 case '135' % User selects peaks.
 TT(1,2)= 135;
  case '100' % User selects peaks.
 TT(1,2)= 100;
```

```
  case '113' % User selects peaks.
 TT(1,2)= 113;


end
%Save the handles structure.
handles.TT(1,2)=TT(1,2);
guidata(hObject,handles)

% Hints: contents =
cellstr(get(hObject,'String')) returns
popupmenu2 contents as cell array
%        contents{get(hObject,'Value')} returns
selected item from popupmenu2


% --- Executes during object creation, after
setting all properties.
function popupmenu2_CreateFcn(hObject,
eventdata, handles)
% hObject    handle to popupmenu2 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    empty - handles not created until
after all CreateFcns called

% Hint: popupmenu controls usually have a white
background on Windows.
%       See ISPC and COMPUTER.
if ispc &&
isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end


% --- Executes on selection change in
popupmenu3.
function popupmenu3_Callback(hObject, eventdata,
handles)
% hObject    handle to popupmenu3 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
```

```
data (see GUIDATA)
str = get(hObject, 'String');
val = get(hObject,'Value');
% Set current data to the selected data set.
switch str{val};
    case '1' % User selects peaks.
 TT(1,3)= 1;
case '3' % User selects peaks.
 TT(1,3)= 3;
 case '5' % User selects peaks.
 TT(1,3)= 5;
 case '7' % User selects peaks.
 TT(1,3)= 7;
 case '19' % User selects peaks.
 TT(1,3)= 19;
 case '20' % User selects peaks.
 TT(1,3)= 20;
case '21' % User selects peaks.
 TT(1,3)= 21;
 case '24' % User selects peaks.
 TT(1,3)= 24;
 case '35' % User selects peaks.
 TT(1,3)= 35;
  case '37' % User selects peaks.
 TT(1,3)= 37;
 case '40' % User selects peaks.
 TT(1,3)= 40;
end
%Save the handles structure.
handles.TT(1,3)=TT(1,3);
guidata(hObject,handles)


% Hints: contents =
cellstr(get(hObject,'String')) returns
popupmenu3 contents as cell array
%        contents{get(hObject,'Value')} returns
selected item from popupmenu3


% --- Executes during object creation, after
setting all properties.
function popupmenu3_CreateFcn(hObject,
eventdata, handles)
```

```
% hObject    handle to popupmenu3 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    empty - handles not created until
after all CreateFcns called

% Hint: popupmenu controls usually have a white
background on Windows.
%       See ISPC and COMPUTER.
if ispc &&
isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end


function edit4_Callback(hObject, eventdata,
handles)
% hObject    handle to edit4 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
data (see GUIDATA)
simul2=handles.simul2;

handles.simul2=simul2;
guidata(hObject,handles);


% Hints: get(hObject,'String') returns contents
of edit4 as text
%        str2double(get(hObject,'String'))
returns contents of edit4 as a double


% --- Executes during object creation, after
setting all properties.
function edit4_CreateFcn(hObject, eventdata,
handles)
% hObject    handle to edit4 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    empty - handles not created until
after all CreateFcns called
```

```
% Hint: edit controls usually have a white
background on Windows.
%       See ISPC and COMPUTER.
if ispc &&
isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

% --- Executes during object creation, after
setting all properties.
function text3_CreateFcn(hObject, eventdata,
handles)
% hObject    handle to text3 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    empty - handles not created until
after all CreateFcns called
%simul2=handles.simul2;

%handles.simul2=simul2;
%guidata(hObject,handles);

% --- Executes on button press in pushbutton3.
function pushbutton3_Callback(hObject,
eventdata, handles)
% hObject    handle to pushbutton3 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
data (see GUIDATA)
clear

% --- Executes on button press in pushbutton4.
function pushbutton4_Callback(hObject,
eventdata, handles)
% hObject    handle to pushbutton4 (see GCBO)
% eventdata  reserved - to be defined in a
future version of MATLAB
% handles    structure with handles and user
data (see GUIDATA)
close
```