THE UNIVERSITY OF TURKISH AERONAUTICAL ASSOCIATION
INSTITUTE OF SCIENCE AND TECHNOLOGY

SHORT TERM ELECTRICITY LOAD FORECASTING BASED ON THE OPTIMAL ARCHITECTURE OF HYBRID NEURAL NETWORK MODEL

MASTER'S THESIS

FIRAS AHMED

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THE DEPARTMENT OF INFORMATION TECHNOLOGY

MARETER THESIS PROGRAM

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Tez Danışmanı : **Assist. Prof. Dr. Shadi ALSHEHABI**
Türk Hava Kurumu Üniversitesi ....

Jüri Üyeleri : **Assist. Prof. Dr. Tansel Dökeroğlu**
Türk Hava Kurumu Üniversitesi ....

: **Assist. Prof. Dr. Abdül Kadir GÖRÜR**
Çankaya Üniversitesi ....

: **Assist. Prof. Dr. Shadi ALSHEHABI**
Türk Hava Kurumu Üniversitesi ....

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Firas Ahmed

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LIST OF ABBREVIATIONS

AI	ARTIFICAL INTELLIGENCE
NN	NEURAL NETWORK
FL	FUZZY LOGICAL SYSTEM
WT	WAVELET TRANSPORTATION
ANFIS	ADAPTIVE NEURAL NETWORK AND FUZZY LOGICAL SYSTEM
WNN	WAVELET AND NEURAL NETWORK
MAPE	MEAN ABSOLUTE PERCENTAGE ERROR
GA	GENETIC ALGORITHM
MF	MEMBERSHIP FUNCTION

ABSTRACT

SHORT TERM ELECTRICITY LOAD FORECASTING BASED ON THE OPTIMAL ARCHITECTURE OF HYBRID NEURAL NETWORK MODEL

Ahmed, Firas

Master, Department of Information Technology

Supervisor: Assist. Prof. Dr. Shadi ALSHEHABI

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Having the accurate electricity load forecasting truly helps the electric companies to be able to choose the best decision in generating power, planning and maintenance. The electric energy is non-storable unlike the other energy sources which we can be stored, for instance, in tanks and reservoirs. For this reason, most electric generation companies have always sought to know the future demand with great accuracy [1]. This thesis focuses on **short term electricity load forecasting** to predict the future electricity load by making use of the algorithm of artificial **neural network** (ANN) and the **fuzzy logic algorithm (FL)** as a primary aim to improve the performance of electricity consumer organizations through using them as tools in forecasting the load demand in the short term. Here, we propose to improve the neural network (ANN) to predict the electricity load by making use of the data of the previous week in forecasting the electricity load of the following week. Accordingly, we have found the neural network (ANN) as the optimal model, and for the second proposal, we used Adaptive Network based Fuzzy Inference System (ANFIS), the hybrid method of neural network and fuzzy logic system to optimize the results of (ANN).

Keywords: Artificial Neural Network (ANN), Adaptive Network based Fuzzy logic System (ANFIS), Wavelet Transformation Neural Network (WNN)

ÖZET

HIBRID SINIR AGI MODELININ OPTIMAL YAPISINA DAYALI KISA SURELI ELEKTRIK YUKU TAHMINI

Ahmed, Firas

Danışman: Doç. Dr. Shadi ALSHEHABI

May 2017, 81 sayfa

Doğru yük tahmini almak, elektrik enerjisinden zarar gören şirketlerin güç üretme, planlama ve bakım aşamalarında en iyi kararları almasına yardımcı olur. Elektrik enerjisi, tanklarda ve rezervuarlarda stoklanabilen diğer enerji türleri gibi depolanamaz. Bu nedenle, çoğu elektrik üreten firma daima gelecekteki elektrik talebini büyük bir doğrulukla araştırmaya çalışmaktadır [1]. Bu tez, yapay zekalı sinir ağı (ANN) ve bulanık mantıksal (FL) algoritmalarını kullanarak gelecekteki elektrik yükünü tahmin etmek için kısa vadeli yük tahmini üzerine odaklanır. Birincil olarak, kısa vadeli dönem içinde köşebent yük talebini öngörme araçları olarak kullanmak suretiyle, elektrik kullanan bir organizasyonun performansını iyileştirme amacını önermekteyiz. Burada, bir sonraki haftanın verilerini önceden tahmin etmek için içinde bulunulan haftanın elektrik yükünü kullanarak elektrik yük tahminini öngörmek için sinir ağı (ANN) geliştirmeyi öneriyoruz. Bir sonraki haftanın elektrik yükü ve sinir ağı (YSA) için ikinci önerimiz, hibrid yöntemi sinir ağı ve bulanık mantıksal (ANN) sonuçlarının optimizasyonu (ANN) için kullanılan en iyi modeli bulmaktı. Son teklif ise, melez dalgacıktır. Ağdaki veri girdilerini kullanmadan önce verileri analiz edebilmek için sinir ağı ile ulaşım sonunda tüm modellerin nihai sonuçlarını karşılaştırdık ve en iyi modeli seçtik.

Anahtar Kelime: Yapay Sinir Ağı (ANN), Bulanık Sistem Sinir Ağı (ANFS), Dalgacık Dönüşüm Sinir Ağı (WNN)

CHAPTER ONE

INTRODUCTION

1.1 Background

Undoubtedly, load forecasting is one of most significant problems in the industry. The electric companies need innovative predictive models to cut down electricity costs. . The most important criterion in planning or operation of the electric power is the short term load forecasting [1].

Short-term load forecasting is divided into two main categories as artificial intelligent and statistical methods. The statistical method includes methods such as ARIMAX and general exponential smoothing, support vector regression, multiple linear regression and state space model. Our technique is to employ artificial neural network and fuzzy logic algorithm , which we have mentioned above and considered as good methods because they give good results. But, Insuffiency of traditional methods to answer the consistency problem of load forecasting in the context of the relationship between weather variables and electric load forecasting emerged a necessity to employ new techniques like neural network (ANN) [2].

This method enables to predict future load through using the data thanks to the training data input in the network. This thesis aims at explaining the pattern of building and validating a short-term electricity load forecasting This research depends on two multiple sources of information including the data for temperatures and holidays in constructing a day-ahead load forecaster, through using a neural network with a different hybrid method such as fuzzy inference system and wavelet transportation algorithm to predict future electric load. The time period varies from one week to two weeks to measure the quantity of consumption during the day. We selected optimal neural network for our model in terms of a number of layers,and hidden layers. We also detremned number nodes for each layer to learn the rate which gives small sum of errors with less repeat of a network, also we used hybrid algorithm neural network and fuzzy inference system (ANFIS) in order to optimize the results. [3].

What are the differences between artificial Neural network (ANN) and fuzzy inference system (FIS), fuzzy inference system is a form of many-valued logic, in which the truth values of variables may be any real number between 0 and 1 instead of exact and fixed reasoning because in fuzzy logic, truth value may range between 0 and 1 unlike the traditional binary sets which take the truth value true or false for variables.

Artifical Neural network (ANN)has been inspired from the biological neural network of humanbeing Neural network relies on on the information coming from the network containing many layers. Each layer consists of many nodes. After the informatin is training in the network, it can discover the best operating point of the ANN, through the output of the neural network, other Neural network systems enable to get good recognizing patterns but they are unable to explain how they reach their decisions. On the contrary, the fuzzy logic can do those decisions. However, fuzzy logic unable to training the data in a network. This limitation for neural network and fuzzy logic is the main reason to create a hybrid technique (ANFIS) combining ANN and FL in order to overcome the limitation problem of neural network and fuzzy inference system [4].

This thesis used the recorded data of hourly loads and temperature observations(New England ISO) in two successive weeks. The weather consists of dry, cold and humid temperature variables ,where we have used excel program to convert inputs data to values between (0-1) before use it in our models.

1.2 Organization of the thesis

In chapter 2 we give literature review about load forecasting based on artificial intelligent and hybrid adaptive neuro-fuzzy inference system, in chapter 3 methodology we have explained in all algorithms (ANN) and hybrid algorithm (ANFIS) which was used in this thesis In chapter 4 we discuss neural network (ANN) and hybrid algorithm (ANFIS) ,used for the practical part of this thesis, Chapter 5 is focused on the practical aspect of the thesis in the employment of neural network and hybrid algorithm (ANFIS) for short term load forecasting by using recorded data set of hourly loads and temperature observations from the New England ISO for the period of two successive weeks.

CHAPTER 2

LITERATURE REVIEW

Load forecasting can be defined as the system which enables electric to companies to estimate active load depending on actual load quantities previously . Because there is no current implementation of electricity storage, it is very crucial for the companies to have a fuctional forecasting system to make a need and supply balance. For this reason, load forecasting help companies manage to estimate the power quantity which they must product. In the future load forecasting might help the companies to make adjustments for the quantity of consumption, load forecasting of electricity consumption is considered as one of most important techniques to minimize the loss of electric power .

2.1 The Implementation of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to Short Term Load Forecasting of 132/33 Kv .

This research is a study on ANFIS model to find a solution to predict the short load electricity problem and this model includes a three step as short term load forecasting for a week, medium term forecasting for a month and long term forecasting for a year.

According to the research conducted by Idakwo O. Harrison, Dan'isa, A. and Bello Ishaku on short term load forecasting of 132/33KV by using adaptive neuro-fuzzy inference system (ANFIS), an accurate method for the prediction of load forecasting one hour ahead in north eastern region of Nigeria was proven. The data of humidity, and temperatures of one hour ahead, work load of current hour and the day, was provided into the entire system, and with the help of using this input and output with ANFIS technique, and loaded data in the period 2009 to 2012 (4 years) as input and output. All the parameters which involve stochastic process are by nature non-linear. The present study aims to explain the adaptive neuro-fuzzy inference system (ANFIS) through combining tow method neural network with fuzzy logical system and hybrid method predicting the load one hour ahead and select 75% of the data in order to train and select 25% to check.

After analysing this model (ANFIS), the (MAPE) revealed absolute percentage error for days (Monday, Wednesday and Friday) was (12.6%,12.76%and 12.12%), also the total test data was (24.76%) for (MAPE), with the correlation (R) value (84.64%) the analysis presentation of precise with regards for (ANFIS) in order to improve load forecasting one hour ahead [5].

2.2 Nonlinear System Identification model

This thesis explains and analyzes short-term load forecasting from various perspectives. Here, in the initial definition of the load forecasting, the ANFIS model is extrapolated rather than presented using artificial intelligence and statistical methods to load predictions rather than presenting.

According to M. Mordjaoui . B. Boudjema . M. Bouabaz, this research explains the use of the adaptive neuron fuzzy inference system (ANFIS) for short-term load forecasting and ANFIS in the prediction of one week ahead and the use of historical data of the electric load, as well as taking into account the different daily loads used by the Metropolitan of France (2009). According to this study, the forecasting performance was found to be effective.

They also suggest that it is possible to get accurate results for short periodical data by combining two methods fuzzy logical system with neural network and hybrid technique (ANFIS) used in real time. On the basis of this study, it is possible to analyse short-term load forecastingin different days , suggesting that these two methods are able to handle negative aspect of load forecasting model by using temporal record of the data in order to minimising the length of the forecasting time , also reduce the complexity of the neural network. Moreover, this model has accurate results which are not affected by rapid fluctuations in power consumption, one of the drawbacks of artificial neural network (ANN) [6].

2.3 Neural Network and Fuzzy Logical (ANFIS) for Short Term Load Forecasting

The method used in this study takes into consideration of weather variables such as temperature effect and day type for electrical load and using the data from 1st , 2012 to Apr 21, 2012, but without weekends, so it used only weekdays (Monday to Friday) through applying ANFIS model.

Seema Pal and Dr. A. K. Sharma , suggests this research approach as a way of developing adaptive neuro-fuzzy inference system (ANFIS) through applying it in short-term load forecasting model in order to predict the electrical load. It takes into account various types of variables such as temperature, time-related data of the electrical load, Besides, it has taken periodical data from **MPEB Jabalpur** and through website: **www.worldweatheronline.com**. This research explains the basics of the adaptive neuro-fuzzy inference system (ANFIS) using fuzzy system to minimize the limitation of the neural network which fails to take the forecasting process into consideration. On the other hand, using the neural network to minimize limitation of the fuzzy system in forecasting process due to the inefficiency of ruling itself . This study explains the structure of ANFIS by using the method of fuzzy inference system (FIS) through membership function parameters by adjusted through either backpropagation algorithm alone or integrating with least squared type of the technique. After that the fuzzy system is able to process the data. This system proves that (ANFIS) model can help finding relation between the input and output by hybrid method of learning in order to select the optimal distribution of the membership function.In sum, , this study presents short-load forecasting by ANFIS based on the effects of temperature and different type of day on load, andtraining the data set from April 1, 2012 until April21, 2012 and it covers weekdays only. The result of the load forecasting gives the accurate MAPE 5.705%[7].

2.4 Prediction and Interval Estimation by Wavelet with Neural Network.

This employed the spike filtering technique to remove spikes in real time through using the WNN method which enables to capture load components at various frequencies.

Che Guan have used technique of multilevel of the wavelet transportation with neural network (WNN) by data prefultering. The main aim of the thesis is to use a spike filtering method in order to reveal spikes in the load, and correct it without any changes in the load, the goal of the use of wavelet transportation is to decompose the electrical load at many components various frequencies. As for the neural network, it is used to capture the features of the components, where combination results of the neural network in order to supply ultimate forecasting. In order to do ongoing forecast longer than an hour twelve structures based on workout results were used, this proposal works through back propagation without estimating forecasting, this technique is extended to the application of the hybrid (Kalman Filters) in order to improve periodical predictions online, the neural network based on data analysis to train data by low-frequency components in order to find the relationship to be non-linear between the input load and output measurement, but neural network training the data through unscented (Kalman filters) in this case used way low-high and high frequency components to find the nonlinear relationship of them. Shortly this thesis show method of wavelet neural network by applying the hybrid (Kalman filters) and extended Kalman filters neural network (EKFNN) used to find the non-linear relationship between the output measurement and (LL) of the input, as for the unscented Kalman filters neural network (UKFNN) is used to find non-linear (LH, H load) [8].

2.5 Using Optimized ANFIS for Wavelet Based Short Term Load Forecasting

According to Mustafa, Mustapha, Khalid and I. Abubakar, this research is used to optimize adaptive neuro-fuzzy inference system (ANFIS) in order to forecast electric load comsuptaion, also used partical swarm optimization (PSO) to improve (ANFIS), where using wavelet transportation in order to decompose the input components and using Daubechies 2(db2), also this study aims to minimize the outliers as small in the predication data, this research is used data of data of Nova Scotia province (weather and data electric load) and test it by hybrid wavelet –PSO-ANFIS model , this model has proven the best from the other two model Gradient Decent (GD) and Genetic Algorithm (GA) through on lower mean absolute percentage (MAPE), shortly this researcher based on (db2) of wavelet family which used to overcome the outliers and wide different between all the data this load to increase the accuracy of the forecasting (PSO). Furthermore, it can link the (ANFIS) training by changing the Gradient Decent (GD) algorithm in the backward path this help to increase the speed of convergence of the (ANFIS) also improve the accuracy [9].

CHAPTER 3

METHODOLOGY

3.1 introduction

In this chapter, we will expound all the methods used in this thesis, where we explain each method separately. This research based on using this algorithms (Neural network , fuzzy logic system, wavelet transportation) to short term load forecasting from one to two weeks. Firstly, we will expound neural network as a basic method. Then we will select multi layers of the network considered to be the aim of our research in our research and explain it in detail. The second method is fuzzy logic system, where we will use it with neural network as hybrid method.In this chapter, we focus on membership function and rules because the membership function is considered as another aim of our thesis. In order to reduce the error of results neural network to expected electrically load. The third method in this chapter is wavelet transportation also used as hybrid technique in order to improve performance of neural network in prediction processes. These methods used to short-term load forecasting will compare the results between all of them and select the best one with lower prediction error.

3.1 Neural Network Method

3.2.1 Human Nerve Cell

Neuron is the basic unit in the construction of the nervous system in living organisms and spread billions of nerve cells in the body of the organism and subdivided into appendages working to transfer the feeling of sensation and reflexes of the brain, serves to acquire and store knowledge. Of the basic functions of nerve cells next to the collection and processing of the distribution of electrical signals, one of the main difficulties faced by researchers in artificial intelligence is to reach making a machine or device capable of learning and the acquisition of knowledge to solve problems faced in the future. For this reason, scientists are always trying to simulate the nervous system, especially the neurons in living organisms especially through the construction of artificial neural cells have properties similar to living nerve cells as shown in Figure (3.1) [13].

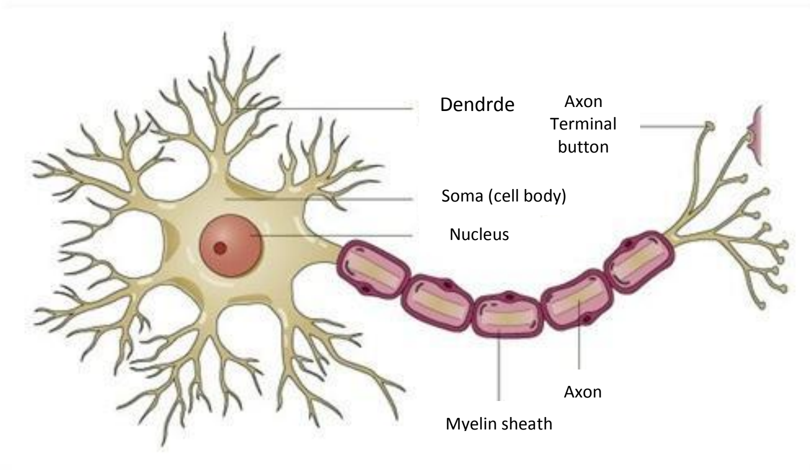


Figure 3.1: Natural neurons [13]

3.2.2 Models of a neuron

As we have seen that the neural networks consist of a set of processing units called one neuron, and as shown in Figure (3.1)

It shows the model is more than a simple artificial neuron:

Just as a person units to interact with the outside world which enriches the five senses, so do neural networks need units of entry. The processing units are the calculations which adjust the weights and get through it on Rose Appropriate action for each entrance of the inputs of the network. Units are called input layer, and units treatment is treatment layer which is coming out the network outputs. And between each layer of these layers there is a layer of Interfaces that connect each layer class that followed and in which they are adjusting the weights of each interface, the network has only one layer of input units, but may contain more than one layer of layers Treatment.

3.2.3 The Mathematical Model for Neuron

The departure point of the scientists to propose a system that simulates the nerve cell in the human brain is the mathematical model for neuron.

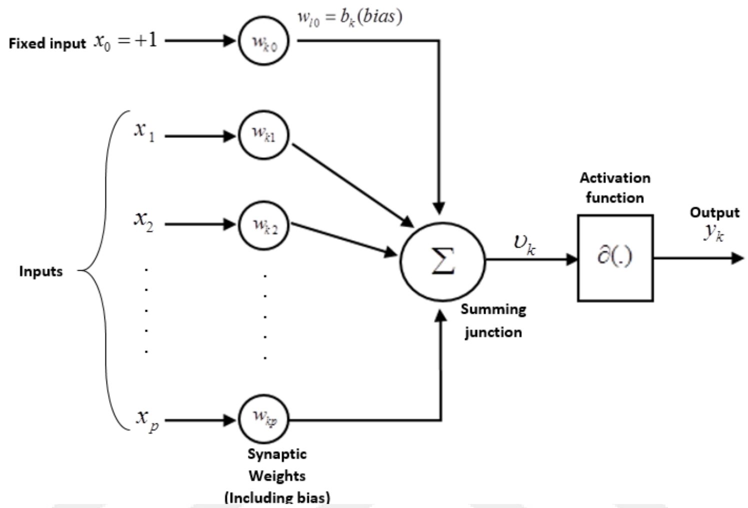


Figure 3.2: The Mathematical Model for Neuron

1. $(x_0, x_1, \ldots\ldots\ldots\ xp)$ represents input signals where either there will be a signal this mean (1), or there is no signal (0) .

2. $(xk_0, wk_1, \ldots\ldots\ wkp)$ represents the degree of the signal input, where the weights represent strong relation between the two vectors

3. Activation function is very important because this function gathers all the singles than compared with (threshold), where if the weights total of the signal more than from (threshold) the output equal (1), but if the signal less than from (threshold) the output equal (0).

   This model of a neuron consists of externally applied bias threshold *wk0= bk* which has the influence of lowering or increasing the net input of the activation function.

As shown in the pair of equations.

$$O_j = f_j \sum_k (w_{jk} x_k) \qquad (1)$$

Where:

o_j : represents the output of a neuron

f_j : represents a transfer function

w_{jk} : represents an adjustable weight

x_k : represents the input of a neuron.

The activation function type (sigmoidal) which makes the output value in the range (0,1) .

3.2.4 The Basic Concepts of the Neural Network

The neural network is one of the most popular ways of artificial intelligence. The basic idea of the neural network is simulation human brain through computer, the development of the neural network increase through many studies in the field of neural network.. The simulation process is done through solving the problem by applying self-learning process which depends on storing information in the network. The idea of neural network has been inspired by biological neural network and proposed by McCulloch and Pitts in 1943. The neural network is also defined as information system similar biological neural network which enables to solve many problems in different fields [12,13] such as:

1. Medicine field, the immediate applications of the principles of medicine which is linked with memory. This help us in pathological sign and diagnosis.
2. Wired-wireless commination filed, using neural network to remove echo which predict from telephone lines, in military radar to identify targets.
3. Banking business, using neural network to open private account in banks through of imprint taches, sound, easy and hoe can identify on baking signatures and headlines and use neural network alternative to traditional models. Moreover, neural network proves to able on predict and solve the problems accurate and easily more than from traditional models. The neural networks are associative system include form neural

process units, where (processing element) able to work as a current memory and action some different treatment processes which are be linked with together to form the network .

3.2.5 Artificial Neural Network

Artificial neural network is defined as mathematical model based on simulation of the humans' neural network , where artificial neuron is considered as foundation for for building the neural network. The mathematical model of the neural network consists of three sets or layers (multiplication, summation and activation), where neural network including three layers (input layer, hidden layer and output layer). There are also weights of the input values, which means each input value will be multiplied by individual weight..After that in second layer of the neural network collect all the weights of input by sum function and bias. In the third layer, there is activation function called transfer function whose jobis to pass the sum previously weights input and bias as shown in Figure 3.3 [10,11].

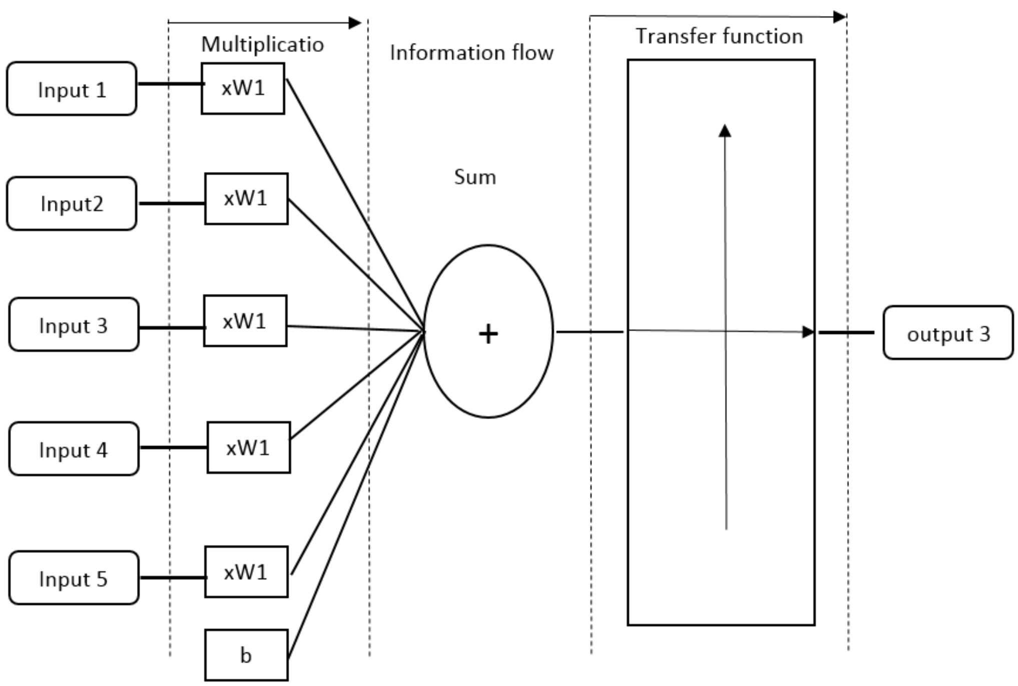


Figure 3.3: Working principle of an artificial neuron [10]

3.2.6 Type of The Activation Function

In the neural network, there are many active functions such as threshold activation function (McCulloch–Pitts model), Piecewise-linear activation function, Sigmoid logistic activation function and Hyperbolic tangent function.

- **Threshold activation function (McCulloch–Pitts model)**

$$\varphi(v) = \begin{Bmatrix} 1, & v \geq 0 \\ 0, & v > 0 \end{Bmatrix} \tag{2}$$

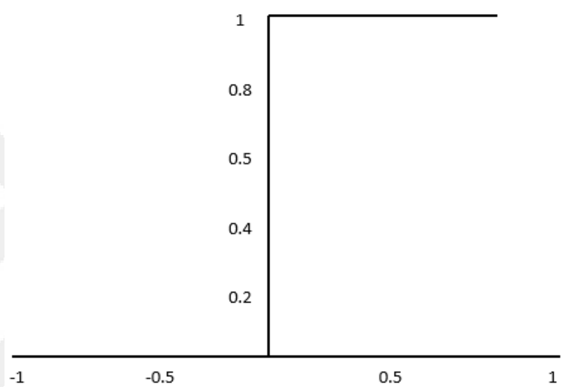


Figure 3.4: Threshold activation function

In this model the outputs are equal (1) if the input is more than (0) or equal (0), while outputs are equal (0) if the inputs are less than (0).

- **Sigmoid (logistic) activation function**

$$\varphi(v) = \frac{1}{1+\exp(-v)} \tag{3}$$

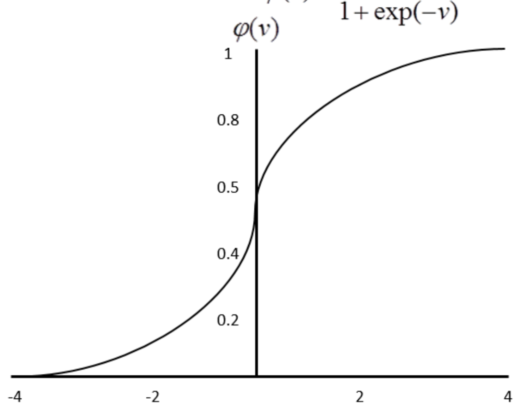


Figure 3.5: Sigmoid (logistic) activation function

In this model the inputs are between (+∞ and -∞), and the outputs are between (0 and 1) this model is used frequently because it has an easy derivation.

- **Piecewise-linear activation function**

$$\varphi(v) = \begin{cases} 1, v \geq \frac{1}{2} \\ v + -\frac{1}{2} < v < \frac{1}{2} \\ 0, v \leq -\frac{1}{2} \end{cases} \qquad (4)$$

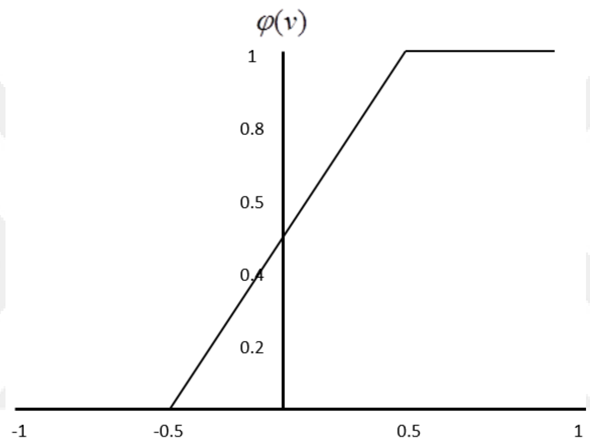


Figure 3.6: Piecewise-linear activation function

The amplification factor inside the linear region is assumed to beunified. The following two situations may be viewed as special forms of the piecewise linear function:

1. A *linear combiner* arises if the linear region of operation is maintained without running into saturation.

2. The piecewise-linear function reduces to a threshold function if the amplification factor of the linear region is made infinitely large.

• **Hyperbolic tangent function**

$$\varphi(v) = \tanh\left(\frac{v}{2}\right) = \frac{1-\exp(-v)}{1+\exp(-v)} \qquad (5)$$

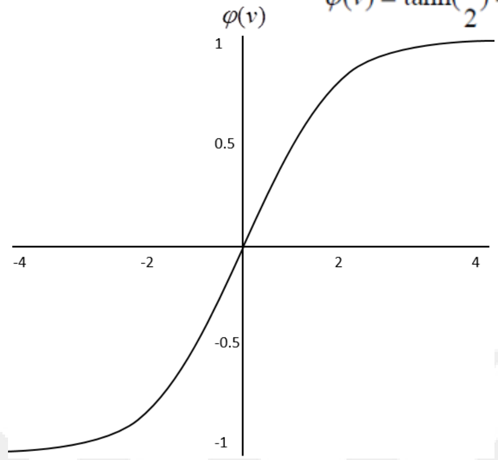


Figure 3.7 Hyperbolic tangent activation function

In this model, it can be easily expressed in terms of the logistic function: (2 ×logistic function – 1).

3.2.7 Type of Neural Network

The neural network is divided into two methods: Feedforward and Feedback.

3.2.7.1 Feedforwards Neural Network

This method is not closed loop from linking between units of the network. This network is considered as one of the most used network, where this network consists of at least two layers. There are also hidden layers between input layers and output layers, where mathematical calculation process starts in one direction to forward from input layers to output through hidden layers, where foreward work on pass output then calculate and compare with required output. Finally, we can compute the error from actual input with desired outputs [16, 17].

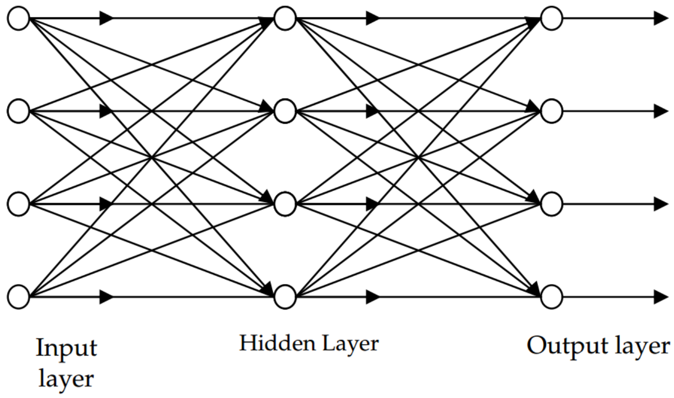


Figure 3.8: Feedforward Neural Network [16]

3.2.7.2 Feedback neural network

This method is used to minimize the errors in modifting weights in the network. The process continues to repeat forward and backward until it gives few errors. Most processes of neural network accept the error value after setting the error value in the network before the process starts.

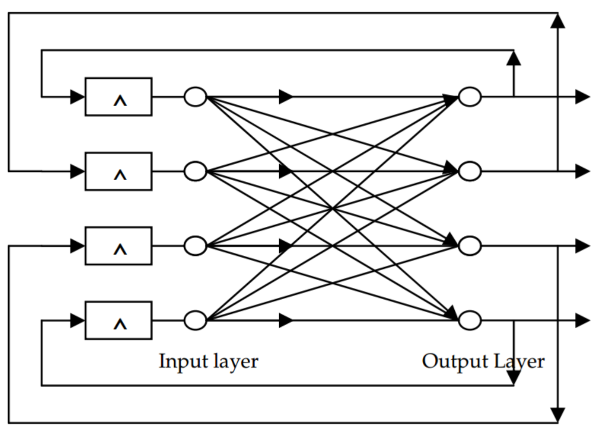


Figure 3.9: Feedback Neural Network [16]

3.2.8 Learning Methods In Neural Network

The target of learning algorithms is determine the value of weights through training the network by one of these methods.

1. **Supervisored Learning.**

   This method works is based on showing the training data for network by pair of patterns (output patterns and input patterns) for each of them .and link by target output vector, The network computes the error function (Delta Function) through calculating the difference between output and real output of the network., This function is used to modify the weights in order to get best results through using weights updating function or learning function [18].

2. **Unsupervised Learning**

   This method is used as self-learning technique in neural network which is based on the discovery of distinctive features for input through group of the data than circulated to the rest of outputs, without any precognition and without give example for the network. What have to do, is contrary to the principal which is followed in supervisor method, This means that unsupervised learning technique is able to self-regulate of weights and follow what is displayed in the patterns for the network [19,20].

3.2.9 Back Propagation Algorithm

This method is considered as one most teachings- ways in neural network of feedforward and it can be implemented through three phases

1. **Forward phase:** In this phase display data on neural network, which specifies for each inlet and outlet predicted value, then computes the error between real value and predict value.
2. **Backward phase:** This phase is different flashback between real value and predicted value in previous phase.
3. **Adaptation of weights phase:** This phase minimizes difference between input and output of the neural network, as shown in Figure 3.10.

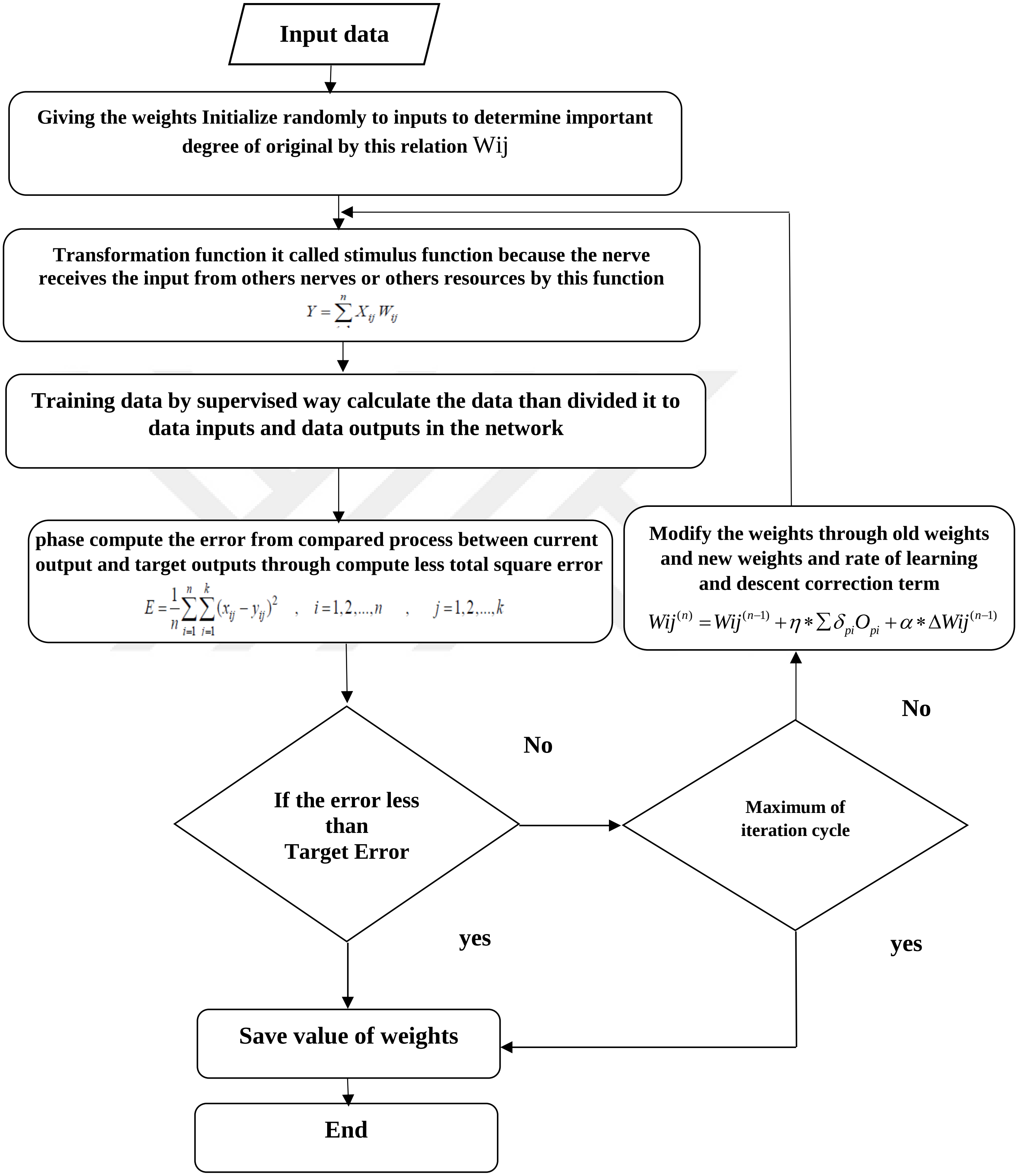


Figure 3.10: Back Propagation Algorithm

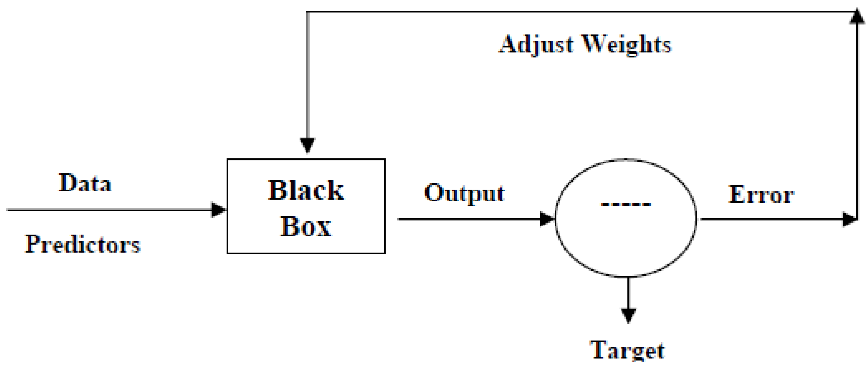


Figure 3.11: Error Back Propagation

Backpropagation

$$Wij^{(n)} = Wij^{(n-1)} + \eta * \sum \delta_{pi} O_{pi} + \alpha * \Delta Wij^{(n-1)} \quad (6)$$

$W^{(n)} \longrightarrow$ new weight factor

$W^{(n-1)} \longrightarrow$ old weight factor

$\eta \longrightarrow$ learning rate

$o \longrightarrow$ input tern

$\alpha \longrightarrow$ momentum coefficient

$\Delta W^{(n-1)} \longrightarrow$ previous weight change

$\delta \longrightarrow$ gradient – descent correction term

3.3 Fuzzy Logic System

3.3.1 Introduction

In 1965 Lotfi Zada discovered fuzzy logic system from expert system and application of Artificial intelligence in University of California, where he developed it in order to using fuzzy logical in data process, but his theory did not receive attention until 1974. Today fuzzy logical is considered as one of the most important techniques used in development systems of the complex control. For this reason the fuzzy logic system has become the most active field of researches because it is charactized by simplicity and flexibility which make it usable in many applications, where fuzzy logic able to solve many problems in different applications, especially after combining neural network with fuzzy logical system [21].

The most important selected suitable algorithm for hybrid design is the system of fuzzy logic and neural network in order to increase learning and adaptation., This leads to a lot of researches to use fuzzy logic and neural network in the recent years.

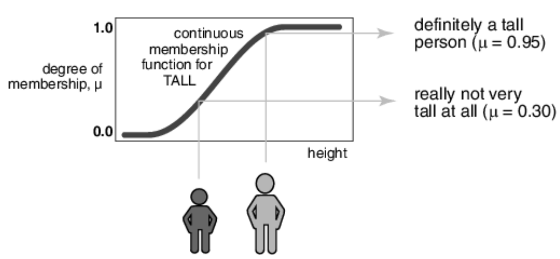


Figure 3.12: fuzzy logic

3.3.2 Why Using Fuzzy Logic System

Actually, in logic, there are equations which we can answer by yes, no, true, false, but there are many cases that the answer should be different such as (maybe, not sure, that depends). For example, in summer we have many types of statement like, the temperature is too high, here we don't know neither true nor false. Reasonably, this statement represents qualitative statement, it doesn't represent objective fact, The basic idea of fuzzy logic is uncertainty engineering through connection of degrees of surety. Here we can ask why using fuzzy is logical? Because fuzzy logic has successes in controlling machines, even with consumer products [22].

3.3.3 Fuzzy Logic System Characteristics.

There many several **characteristics.** of fuzzy logic like.

1. In the fuzzy logic system, everything has the degree of affiliation.
2. Each logic system can be made as a model in fuzzy logic.
3. It can convert knowledge in fuzzy logic as group of variables.
4. Ease of understanding and flexibility and permittivity
5. Mobilizing nonlinear system.
6. Design and reliance on human experience.

3.3.4 Application of Fuzzy Logic

There are many reasons to motivate scientists to develop fuzzy logic. After the developmentof software and computers grew up wanting to discover to system or programming able to deal with information which are not accurate, because the computers can work with accurate information, so this leaded to find expert systems or artificial intelligent, Fuzzy logic is one of those systems Some applications are as follows [23]:

1. Automatic control: Including the most application of control in kinetic variables(Mechanical), which dependson environmental sensors.

2. Video camera: Movement sensor which camera captures it, also any vibrations of the camera.

3. Cars: Providing control of the speed (cruise control), where fuzzy logic computes the acceleration and control the effect of injecting more of fuel or using the brakes.

4. Air conditioner: Fuzzy logic reduces the heat gradually it until reaches to target level of heat.

3.3.5 Concept of the fuzzy logic

Fuzzy groups are considered as one of basics of fuzzy logic which provide studies of fuzzy logic, we will suppose

X represent comprehensive group.

A represent partial set.

3.3.5.1 Membership degree

- Accompanying each element ($x \in X$) where it value is between 0 and 1 This represents the degree of affiliation. This element to group of (A) wherever membership degree is more than the element has been more affiliated.
- The element ($x \in X$) has complete membership in group (A) when the affiliation degree is in group (A) equal (1).
- The element ($x \in X$) it is not element in group (A) when the affiliation degree in group (A)is equal (0).

  The group of (X) which have elements like this called fuzzy logic [24].

3.3.5.2 Function dependent.

It can set affiliation degree thought function dependent are as follows:

$x \in X$ for group (A)

$\mu A: x \longrightarrow [0,1]$ membership dependent

Any group which has membership dependent is fuzzy group

We can write fuzzy groups (the candidate) like binary group, where first number represents element in the group, the second number represents affiliation degree of the group.

Example:

We suppose the comprehensive group

X= {1,2,3,4,5,6,7} so the group (A) is fuzzy logic as follows:

A= {(1,0), (2,0.25), (3,0.5), (4,0.7), (5,0.8), (7,1)}

Here we can see 7 elements have complete membership in group (A), but 1 element is not element in group (A) because the affiliation degreeis equal (0) [25].

3.3.6 Standard Operations of Fuzzy Logic

3.3.6.1 Congregation

The membership is dependent to sum of two groups (A,B) affiliation dependent μA, μB respectively know as a maximum of μA and μB

$$\mu A \cup \mu B = \max(\mu A. \, \mu B) \qquad (7)$$

3.3.6.2 Junction

The membership dependent is junction of two groups (A,B) affiliation dependent μA, m μB respectively know as minimum of μA, mμB

$$\mu A \cup B = \min(\mu A \, , \mu B) \qquad (8)$$

3.3.6.3 Fuzzy Control

There are many stages in fuzzy logic as shown in Figure 3.13 :

- **Fuzzification**
- **Rule Evaluation**
- **Defuzzification**

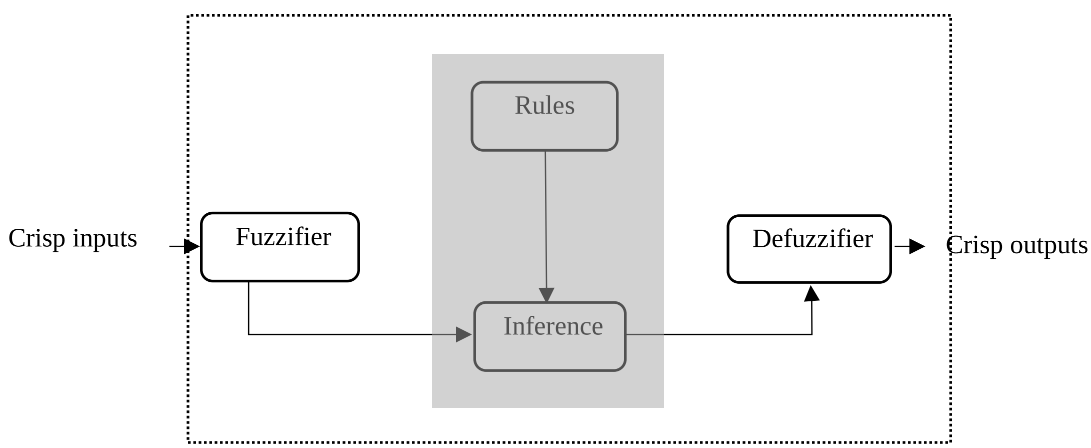


Figure 3.13: Fuzzy logic system

1. **Fuzzification**

   In this phase compline and convert crisp of data fuzzies set through using linguistic variables (membership function and fuzzy linguistic terms) this Phase is called (fuzzification).

2. **Rule evaluation**

   In this phase, the inference will be based on a set of rules.

3. **Defuzzification**

   In this phase, using membership functions to map a crisp output, This is called defuzzification phase.

3.3.6.3.1 Example of fuzzy control

We suppose air conditioner and how can system control by fuzzy logic system Fig (10) This system has to adjust the temperature of the room according to the target value and the current temperature of the room, where the fuzzy system can work periodically in order to make a comparison between the room temperature with target temperature, After that It commands to heat room or cool it [26].

1.The steps of fuzzy logic algorithm

1. Initialization: Define the linguistic variables and terms (Construct the rules base) and (Construct the membership function).

2. Fuzzification: Using the membership function.

3. Inference: Evaluate the rules in the rules base (combine the results of each rule).

4. Defuzzification: Convert the outputs data to non-fuzzy values.

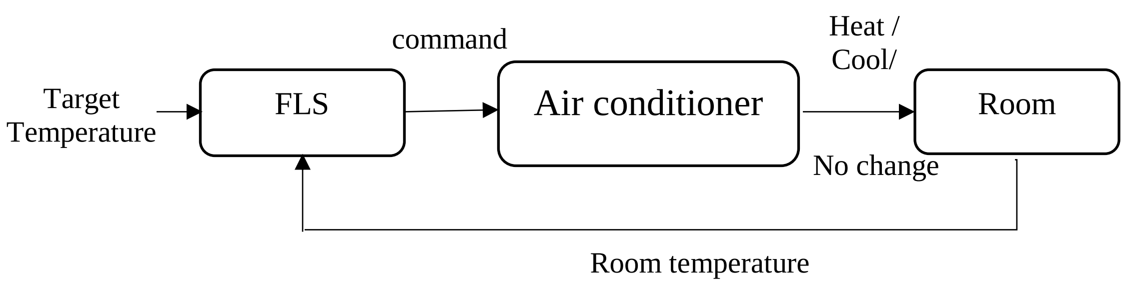


Figure 3.14 Fuzzy logic system

3.3.6.3.2 Linguistic variables

Linguistic variables represent input variables or output variables through sentences or words from mother languageas an instant of numerical value, we can decompose into a set linguistic terms, in air conditioner the temperature (t) which represents temperature in the room in order to determine temperature terms like (Hot, Coll) which is used in our life,

T(t)= {too-cold, cold, warm,hot,too-hot} This represents linguistic term which is a set of decompositions for linguistic variables temperatures

3.3.6.4 Membership Function

In fuzzy logic system we use membership function in order to convert non-fuzzy values to fuzzy linguistic terms, also vice versa. where using membership functions to determine linguistic term Fig (11), Through membership function we can decide the temperatures variables of linguistic terms Also, the numerical value can be in linguistic terms . The numerical value can belong to tow sets iat the same time, For instance, at the same time the temperature value can take case (cold, too-cold) but with different temperatures as shown in Figure 3.15 [26].

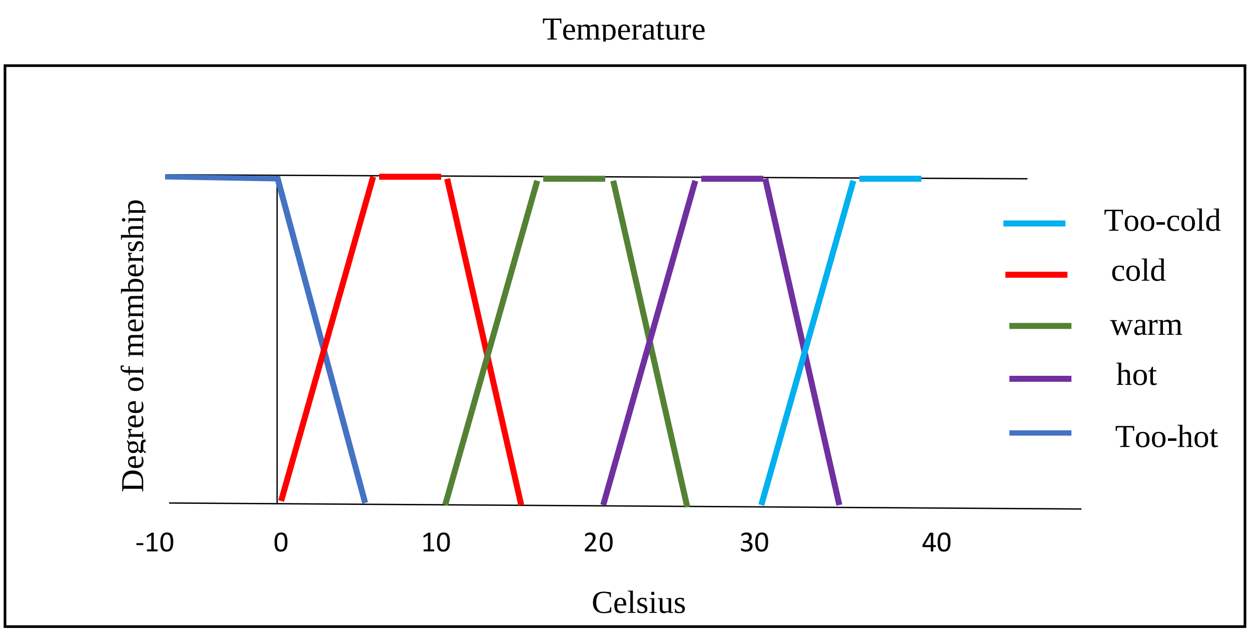


Figure 3.15: Membership Function for T(temperature) = {ftoo-cold, cold, warm,hot, too-hotg.}

3.3.6.5 Fuzzy Rules

In fuzzy logic system to control on output variables, where rules are similar simple (IF-THAN) rule but with condition and conclusion.

3.3.6.6 Defuzzification

After finishing inference phase all results are fuzzy values, so this result has to be convert into defuzzification in order to get final crisp output, where defuzzifiction perfroms according to (membership function) of the output variables as shown in Figure 3.16.

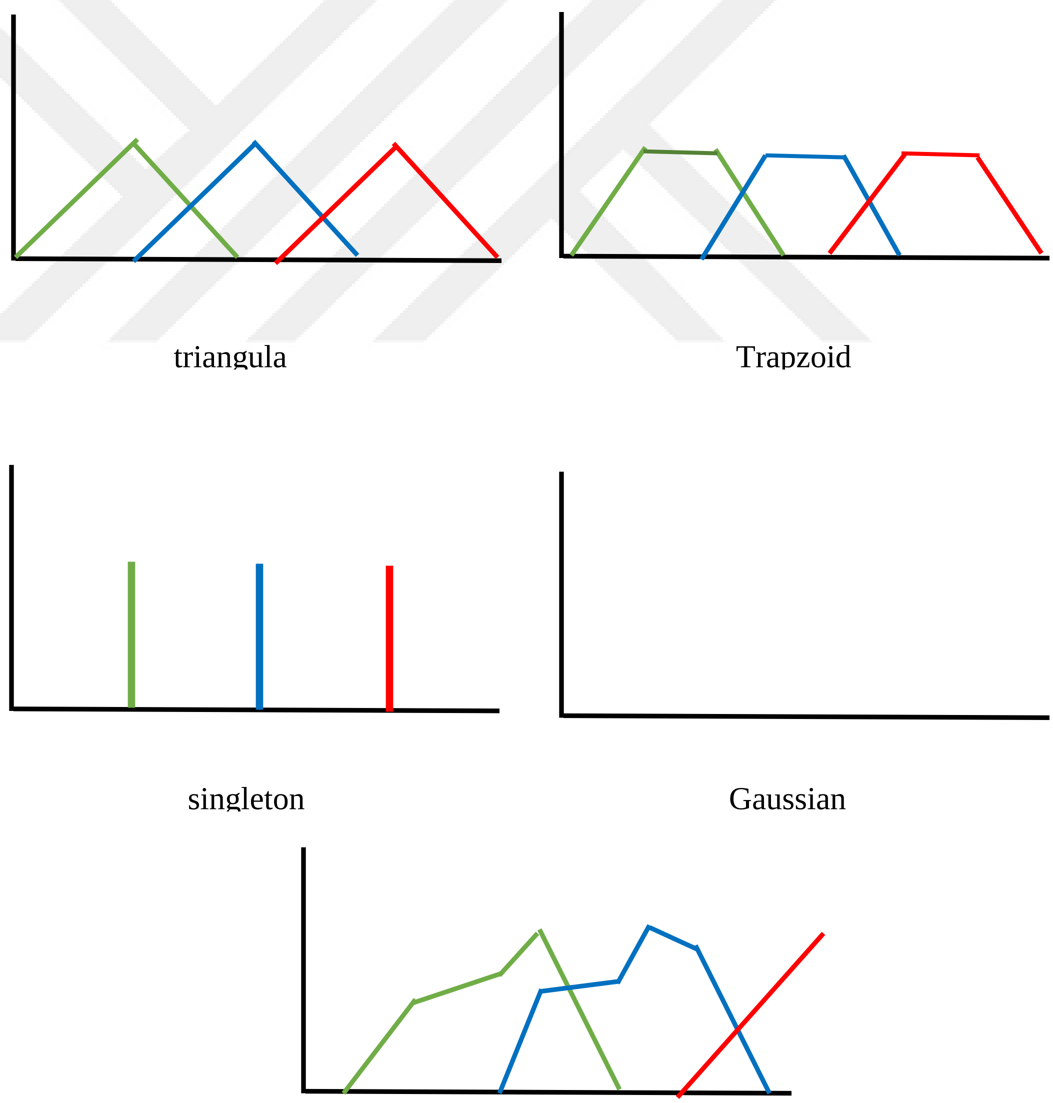


Figure 3.16: different type of membership function

3.4 Wavelet Transformation Algorithm

3.4.1 Introduction

Wavelet transformation (WT)is considered as a type of mathematical technique, through group theory and square integrals in order to detect the signal filed together to space and scale, using the analysis function which is called wavlate by being localized in space in order to obtain on scale decomposition through spreading or contracting before converting it , the signal at infinity is not important and does not play role , So the limited space is important and supports the wavelet. For this reason , we can use wavelet transportation to analyse the signal locally, there are many applications of the (WT) in different fields such as image coding , image processing, prediction, numeral analysis, also the wavelet transportation is still developing [27].

3.4.2 Why Using Wavelet Transformation

Using mathematical model of the wavlate transformation is in order to obtain extra information from the signal which is not easly available in raw signal, We use (WT) in forecasting or prediction which define the process of estimation of all cases which are unknown for us through analysis for elements which effect on future value, or depend on the study of the old data over time,which allows to take accurate decision. The wavelet transformation gives us frequency which allows for effectively diagnosing major frequency component.It also can extract local information from real time [28].

3.4.3 Wavelet Transformation

Wavlate has a number of techniques developed independently of different signals processing, where multi-level of resolution signal, the basic idea in wavlate transportation divides the signals into two parts: high frequency and low frequency through some filters for (high and low frequency) (HH.HL,LH,LL). For example, in image processing wavelet transformation analyse the image in high frequency and low frequency. The components of the edge will recede dramatically in high frequency, the dividing process will replay until the signal decomposes,

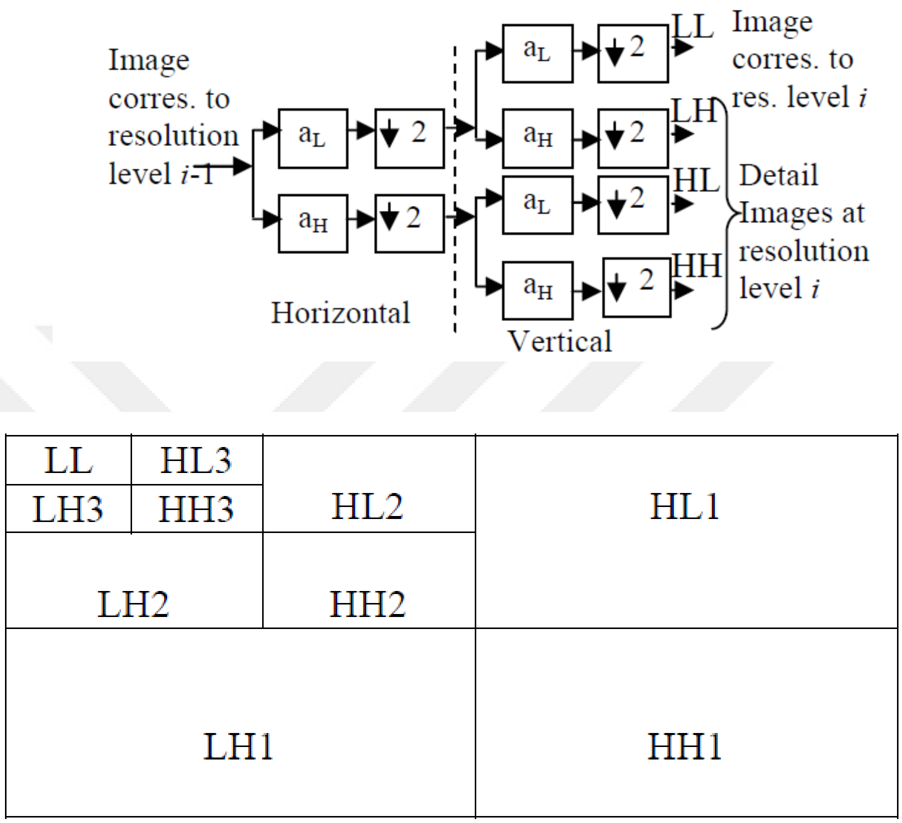


Figure 3.17 Structure of wavelet decomposition [29]

or determine from the user, this for one dimensional, but with multi-dimensional the convert process of the image (m*n) we can define that converting one-dimension wave applied on two dimension wave (m, n) as shown in Figuer (3.17) through wave converting we can use in analysis data to component with limit different dimension that represents the features of the data [29].

3.4.4 Wavelet Decomposition and Reconstruction

The wavelet transformation (WT) is considered as a good technique that decomposes the time series signal to duration or terms of both time and frequency, where Fourier transform is developed to wavelet transformation function. It has been analysed that some wave to analysis a signal than called wavlet by mother wavelet function. It can be considered that the wavelet transform is convolution of the wavelet function and signal, which can be represented by the symbol of mother wavelet **Ψ(t)** [30]

$$\psi(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (9)$$

b $\longrightarrow$ translation parameter

a $\longrightarrow$ dilation parameter

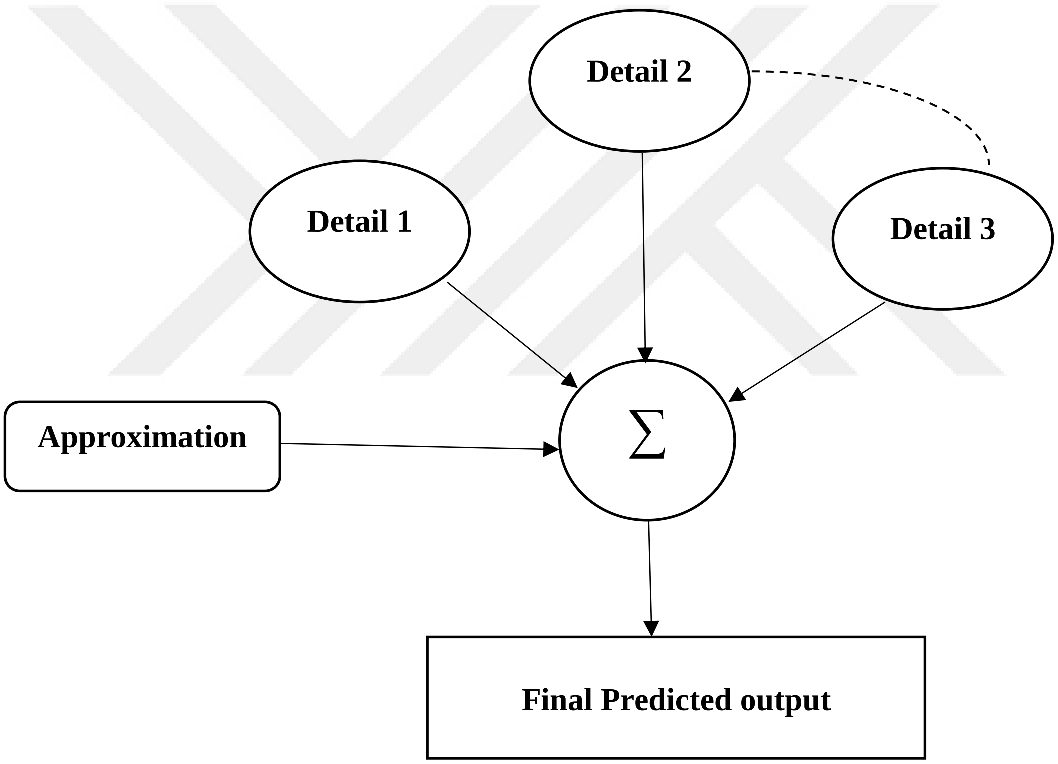


Figure 3.18: A three level decomposition (S=A3+D3+D2+D1)[30].

3.5 Conclusion

In this Chapter, we expounded algorithms which will be used for short term load forecasting and we explained the mathematical model for each method and that the neural network constituted the foundation of this thesis than use other methods such as fuzzy logical system and wavelet transportation to improve results of neural network. In this Chapter, we explained membership function and rules in fuzzy logic system,used with neural network as hybrid technique. We explained wavelet transportation in order to analyse input data to be used as hybrid method with neural network in this Chapter.

CHAPTER FOUR

Neural Network Optimization for Short Term Load Forecasting

4.1 Introduction

In this chapter, we explain our proposal of three hybrid methods: Artificial Neural Network, Fuzzy logic system and Wavelet Transformation. In the first method, we found the optimal model of neural network through selecting optimal node numbers in each layer of network. We aimed to minimize l errors for load electricity. The second is hybrid method is fuzzy logic system which helps to improve neural network and it is able to train neural network able to training but it is unable to take decisions, so through fuzzy logic system the neural network can train and take decisions in order to reduce the errors of load electrical forecasting. The third hybrid method we used is the wavelet transportation which is to analyse the data before using it as a data input for the network where we can reduce the errors inpredicting the electrical load.

4.2 Neural Network Model Short Term Load Forecasting

4.2.1 Input Data

We have used a table of historical hourly loads and temperature observations from the New England ISO, where we have selected the period two weeks of electrical load, the first week have used to train the network those data include five inputs in the neural network as the following:

The first week

1. Temperature Dry.
2. Temperature Dew.
3. Hours: represents hours of each day (1-24) in the first week.
4. Week work: represents the day number in the week (1-7).

5. Weekend: represents the two-type day (1) this day is weekday (0) this day is weekend.
6. Outputs: represents electrical load during the first week.

The data of the second week we have used is for short term load forecasting, where there are five inputs in the neural network without outputs (electrical load) as follows:

The second week

1. Temperature Dry.
2. Temperature Dew.
3. Hours: represent hours of each day (1-24) in the first week.
4. Week work: represents the day number in the week (1-7).
5. Weekend: represent the two-type day (1) this day is work (0) this day is weekend.
6. Outputs: (?).

4.2.2 Learning Methods of Neural Network

As mentioned in Chapter III, there are **Supervised Learning of ANN** and **Unsupervised Learning of ANN** methods, in our research we selected **Supervised Learning of ANN,** the basic idea of which is to display the training data on the network through **input data** and **target.** We selected supervised learning because this technique depends on training the data in the neural network, where we save the input data and opposite output. This fits our data, which represent data training for first one week in order to predict next week though finding similar data and basic learning [31].

4.2.3 Learning Algorithm of Network Learning

The weights are considered to be the most important because they represent preliminary information which helps the network to learn. The weights are modified in training phase, where the weights are important elements as they are responsible for transporting the data from current layer to the next layer. In order to modify the weights, different algorithms were used in back propagation algorithm. This algorithm works with **Feedback-word network** which to be multi layered and nonlinear. The algorithm works on the basis of error correction method. Moreover, we used the mean absolute percentage error (MAPE) in order to compute accuracy of short load forecasting of power. [32]

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|L_{real} - L_{forecasted}\right|}{L_{real}} * 100 \qquad (10)$$

L real ⟶ real value of load electric

L forecasting ⟶ predict value

N ⟶ number of samples

4.2.2 Our Proposed Neural Network model

The aim of this thesis is to find the optimal neural network in order to use this network to load forecasting with less mean absolute percentage (MAPE). For this reason, we use the method of Experimentation and Test for neural network until we reach optimal network for our model, the design of our network consists of three layers' input layers and hidden layers (three hidden layers) and output layer, the input layer includes five inputs (temperature dry, temperature dew, hours, week work , weekend) , the hidden layers consist of three hidden layers, first layer contains 10 nodes, second layer 8 nodes and third layer 8 nodes, finally we used one output layer. . The range of the outputs are collected from all the inputs of signals weights then compared with value of threshold which it will be between (0-1) .

To modify weights, we used Back Propagation Algorithm with Supervised Learning of ANN which deals with training pair that consists of (pattern vector) and (vector target) in order to reach to state which enables the network give the right response of input signal through training process. The training continues until it reaches the error between output and target to less value or reaches to the selection value [37].

<u>The Structure Neural Network</u>

- Numbers of input variables = **5**
- Numbers of output variables = **1**
- Numbers of hidden layers = **3**
- Node of first hidden layer = **10**
- Node of second layer = **8**
- Node of third layer = **8**
- Learning rate = **0.01**
- Momentum coefficient = **0.1**
- Transfer function = **Hyperbolic tangent**
- Target Error = **0.05**
- Initialization method of threshold = **Random**
- Initialization method of weight factor = **Random**
- Analysis update interval (cycles)= **500**
- Sum of error = 0.12319728
- Avg error per output per dataset = 0.000641652
- Processing time (Sec)= **18 Sec**
- Using Feed**-Back Network**

Table (1) The load of electric power for first week (data for 3days)

DryBulb'	'DewPoint'	'Hour'	'Weekday'	'Is Working Day'	'Prev Week Same Hour Load'	Predict load
1	-14	1	1	0	11354	121833.3
1	-13	2	1	0	10710	118936
0	-13	3	1	0	10350	117300.5
0	-13	4	1	0	10175	117999.6
0	-13	5	1	0	10148	120290.9
0	-13	6	1	0	10365	124286.3
-1	-13	7	1	0	10885	131746.8
-1	-12	8	1	0	11406	140657.2
0	-11	9	1	0	12297	148336.2
4	-10	10	1	0	13204	148824
6	-8	11	1	0	13910	155816.2
10	-6	12	1	0	14310	158313.7
14	-5	13	1	0	14559	159253.9
16	-4	14	1	0	14582	163908.1
19	-2	15	1	0	14629	167955.4
20	-2	16	1	0	14856	171163.5
20	-1	17	1	0	16003	175870.4
20	0	18	1	0	17048	178406.6
20	2	19	1	0	16896	179384.1
21	2	20	1	0	16427	177107.7
21	4	21	1	0	15797	174289.1
21	5	22	1	0	14734	169621.3
22	6	23	1	0	13403	164677.6
23	7	24	1	0	12263	159241
22	10	1	2	1	11444	145433.2
22	15	2	2	1	11045	142008.9
22	18	3	2	1	10895	142327.9
22	19	4	2	1	10908	144539.5
22	20	5	2	1	11310	148892.8
22	20	6	2	1	12582	153758.3
23	20	7	2	1	14895	158519.1
23	19	8	2	1	16562	163204.4
23	19	9	2	1	16988	170282.4
24	20	10	2	1	17324	177695.5
25	20	11	2	1	17618	182592.2
26	20	12	2	1	17778	186873.5
27	21	13	2	1	17734	192086.7
28	22	14	2	1	17732	196027.5
29	22	15	2	1	17607	197398.1
29	23	16	2	1	17800	199779.9
30	23	17	2	1	18840	198979.3
29	24	18	2	1	19579	198679.1
29	24	19	2	1	19319	195932.9
28	25	20	2	1	18725	192243.4
28	25	21	2	1	17865	187444.9
28	25	22	2	1	16581	182013.4
28	24	23	2	1	14903	175974
28	24	24	2	1	13429	169647.6

In the Table above, the inputs (6 inputs variables) and output (predict load), where the inputs and outputs are trained in the network in previously week and each day is 24 hours for previously load in order to predict future load.

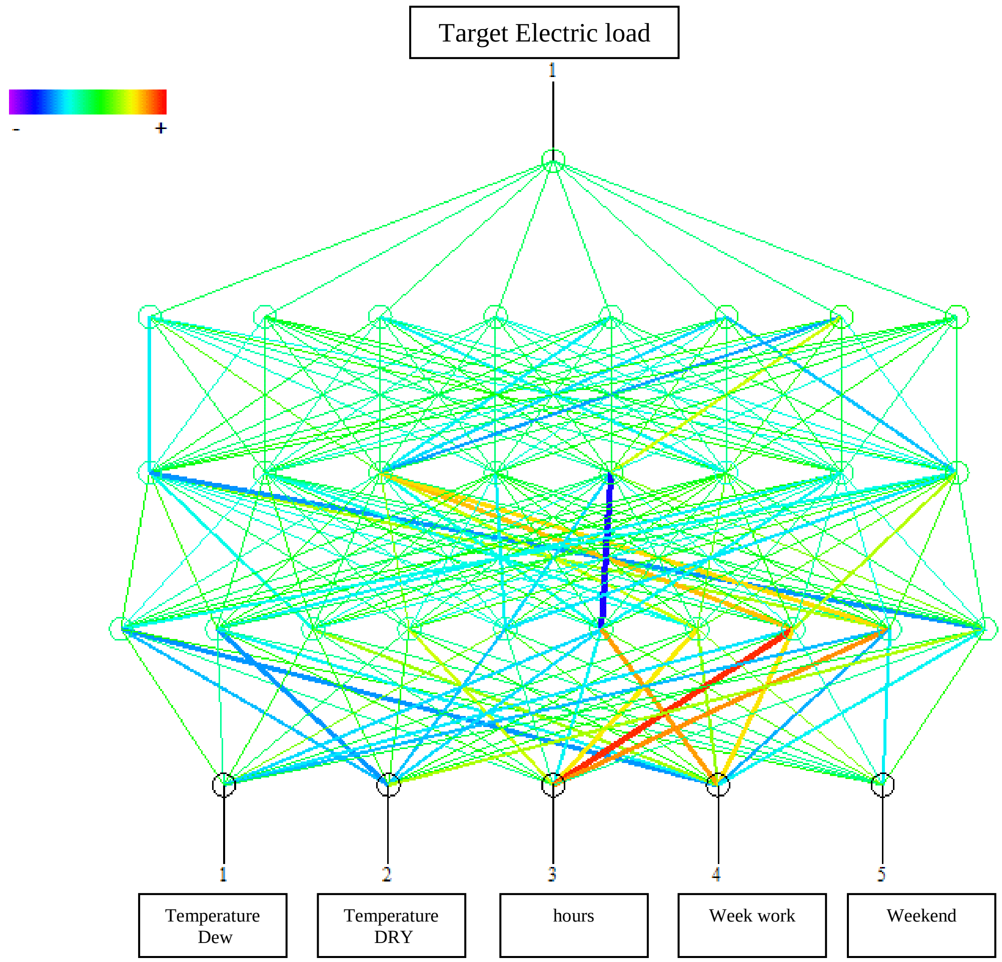


Figure 4.1: The diagram of the Structure Neural Network

In Figure 4.1 , The diagram of the neural network structure which consists on (5 inputs variables), (1 output) and (3 hidden layers), where the red color indicates to high positive number and violet color indicates to high negative number and line width indicates to absolute number of weight factor or threshold value.

Table (2) the electric power predicts of second week (the data 2 days)

'DryBulb'	'DewPoint'	'Hour'	'Weekday'	'IsWorkingDay'	'PrevWeekSameHourLoad'	Load predict(MW)
24	15	2	2	0	13325	144426.5
22	14	3	2	0	13178	141343.5
21	12	4	2	0	13141	140109.9
20	11	5	2	0	13471	140434
20	10	6	2	0	14560	142105.5
20	9	7	2	0	16594	144607.7
19	7	8	2	0	17988	147281.3
19	7	9	2	0	18476	153234.6
19	6	10	2	0	18610	158080.1
21	6	11	2	0	18685	161707.3
21	6	12	2	0	18518	168577.5
23	6	13	2	0	18317	171541.2
22	6	14	2	0	18185	179088.4
23	5	15	2	0	18046	180650.7
22	5	16	2	0	18095	185570.7
21	4	17	2	0	19057	187281.3
19	3	18	2	0	20171	187745
18	3	19	2	0	20071	186049
17	4	20	2	0	19585	182412.5
17	3	21	2	0	18829	177659.7
16	4	22	2	0	17592	171038.3
16	4	23	2	0	15866	164503
15	4	24	2	0	14347	156537.7
15	3	1	3	1	13373	139702.3
15	3	2	3	1	12939	137559.6
15	3	3	3	1	12711	136429.8
15	3	4	3	1	12737	136530.8
14	3	5	3	1	13043	138196.4
14	3	6	3	1	14240	141791.6
14	2	7	3	1	16573	145713.2
13	2	8	3	1	17995	153711
14	2	9	3	1	18234	159480.1
16	2	10	3	1	18241	163318.3
17	2	11	3	1	18258	169062.9
19	2	12	3	1	17997	172420.5
20	2	13	3	1	17729	177451.5
21	3	14	3	1	17606	183359.2
22	3	15	3	1	17546	186754.3
22	3	16	3	1	17772	190619.1
21	3	17	3	1	18814	193876.5
19	3	18	3	1	20339	195174.1
18	3	19	3	1	20609	193311.9
17	3	20	3	1	20347	189525.6
17	3	21	3	1	19799	184700.3
17	1	22	3	1	18702	180044.6
16	1	23	3	1	17179	173153.4
15	1	24	3	1	15859	165495.2

After finishing the training the neural network through previously load and some elements which effect electrical load network such as (temperature, 24 hours of day, weekend numbers) the network is ready for forecasting., We used only effecting elements on the load of electrical network like (temperature, 24 hours of day, weekend numbers) as inputs without a previous load, The neural network can predict the load as shown in the Table above, where in column (previously load) preferment actual load and in column predict load represents the load of next week , we can see the rapprochement between the actual load and forecasting load , because we depend on effect elements on the electrical network.

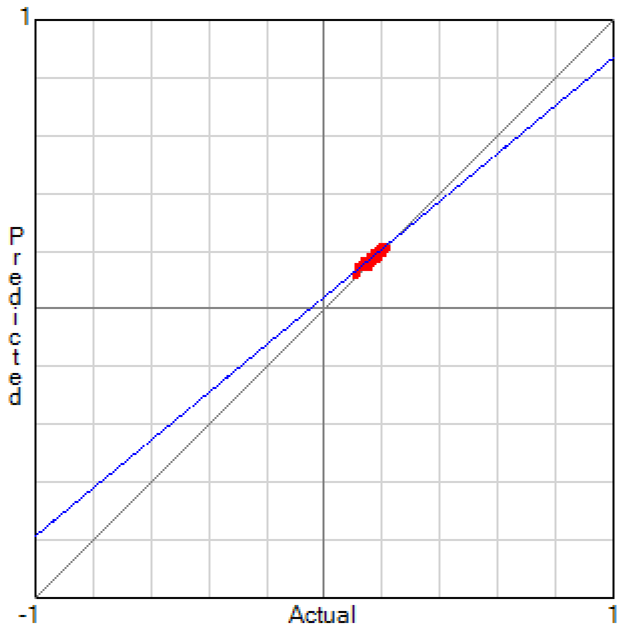


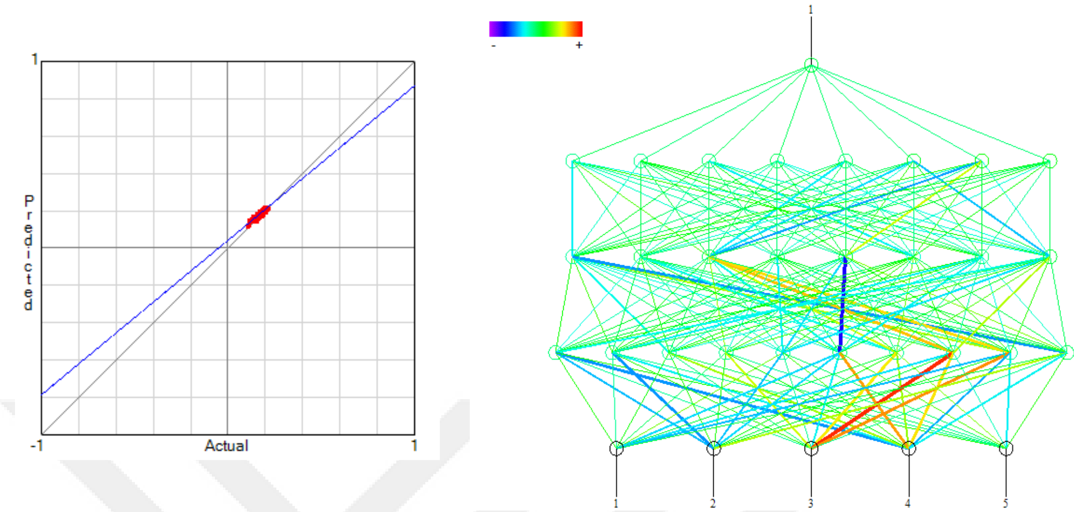
Figure 4.2: The regression

The result is shown in the Figure 4.2, to indicate the regression between actual load and load forecasting. We applied neural network with different model in order to find optimal neural network for our data through using different number layers' nodes of neural network as shown in the table (3) After the tests we found that the optimal network when the nodes of first layers of hidden layers are more than the second and third layers , we get the less sum error with a good time (MAPE = **0.13961**) and(time = 21 min 14 sec) compared with other models We used the 10 nodes in first layer and 8 nodes in second layerand 8 nodes in third layer , so we proved that it is important to increase the number of nodes in first layer of hidden layers because this leads to reduce the sum of errors in neural network . Finally, we used neural network which consists of three hidden layers because this technique makes network training faster, as well as reducing the error of training and testing data.

Table (3) models of neural network

Network	model 1	model2	model3	model 4
Input	5	5	5	5
Output	1	1	1	1
hidden layers	3	**3**	3	3
nodes in first layers	**10**	**5**	**2**	**3**
nodes second layers	**8**	**10**	**15**	**6**
nodes in third layers	**8**	**10**	**15**	**10**
learning rate	0.01	0.01	0.01	0.01
momentum confiscation	0.1	0.1	0.1	0.1
Transfer function	Hyperbolic tangent	Hyperbolic tangent	Hyperbolic tangent	Hyperbolic tangent
Training	200000	200000	200000	200000
target error	0.05	0.05	0.05	0.05
initialization threshold	random	random	random	random
Initialization weight	random	random	random	random
update interval cycles	500	500	500	500
MAPE	**0.13961**	**0.1400**	**0.14012**	**0.1401**
Time	**21min 14 sec**	**20 min 41 sec**	**23 min 13 sec**	**15 min 51 sec**

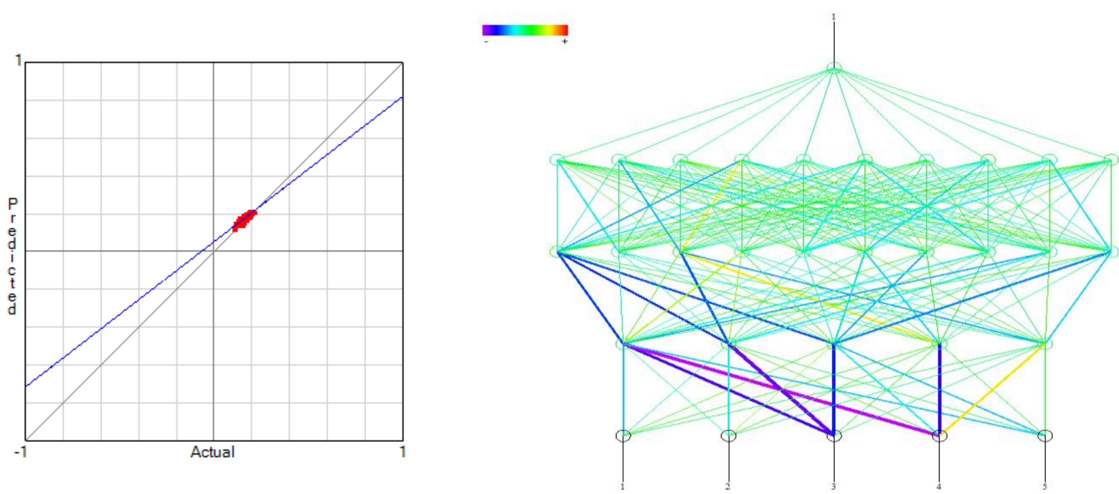
The model 1 of neural network



category	variable	regr coeff	slope	y-intercept
Training	Out 1	0.85544	0.82755	0.04237812
Validation	Out 1	0.01724	-0.06932	0.2192024

Figure 4.4: The model 1 of neural network

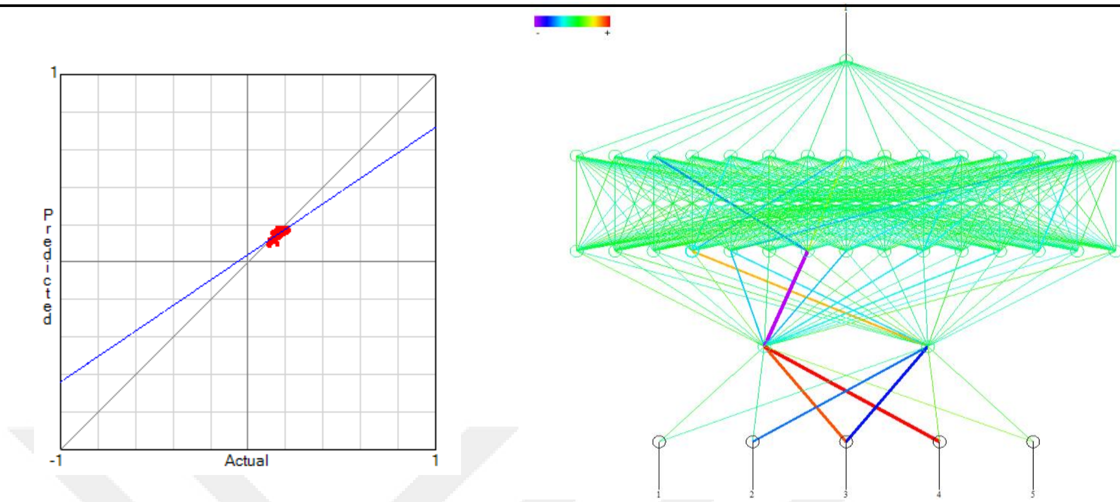
The model 2 of neural network



category	variable	regr coeff	slope	
Training	Out 1	0.801209	0.768336	
Validation	Out 1	0.801209	0.768336	

Figure 4.5: The model 2 of neural network

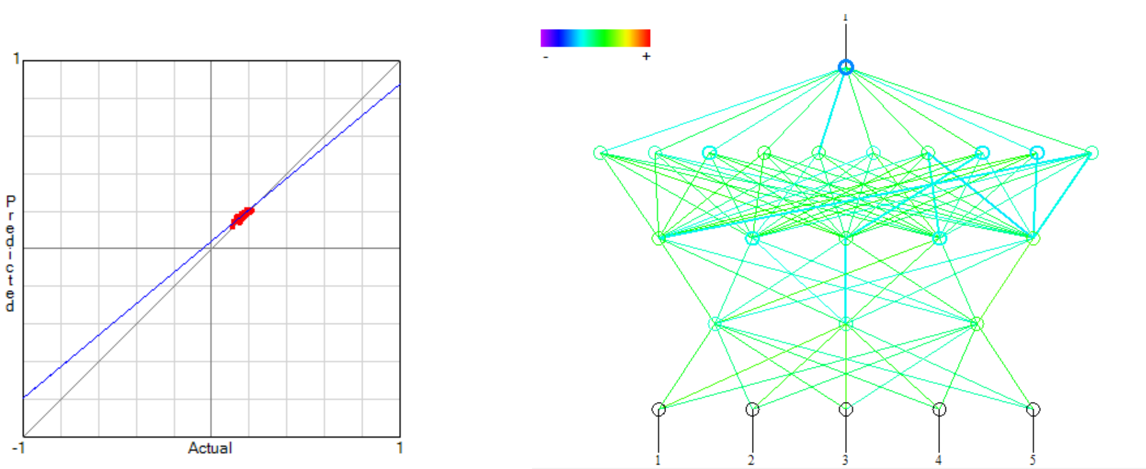
The model 3 of neural network



category	variable	regr coeff	slope	y-intercept
Training	Out 1	0.689934	0.678928	0.04027411
Validation	Out 1	0.689934	0.678928	0.04027411

Figure 4.6: The model 3 of neural network

The model 4 of neural network



category	variable	regr coeff	slope	y-intercept
Training	Out 1	0.833994	0.834543	0.0420929
Validation	Out 1	0.833994	0.834543	0.0420929

Figure 4.7: The model 4 of neural network

4.3 Improving of Adaptive Neural Network with Fuzzy Logic (ANFIS) to Short Term Load Forecasting

ANFIS is defined as a cross between neural network (ANN) and fuzzy inference system (FIS) [33] in our model start used the fussy logic through network which consists of multi layers as neural network, because this hybrid method (ANFIS) enables to sum between training data through neural network and to take the decision through fuzzy inference system like human brain., ANFIS consists of five layers as shown in Figure 4.8. We used only two inputs with tiny or strict? rules because the figure does not fit into all the rules in this thesis where we used 378 rules.

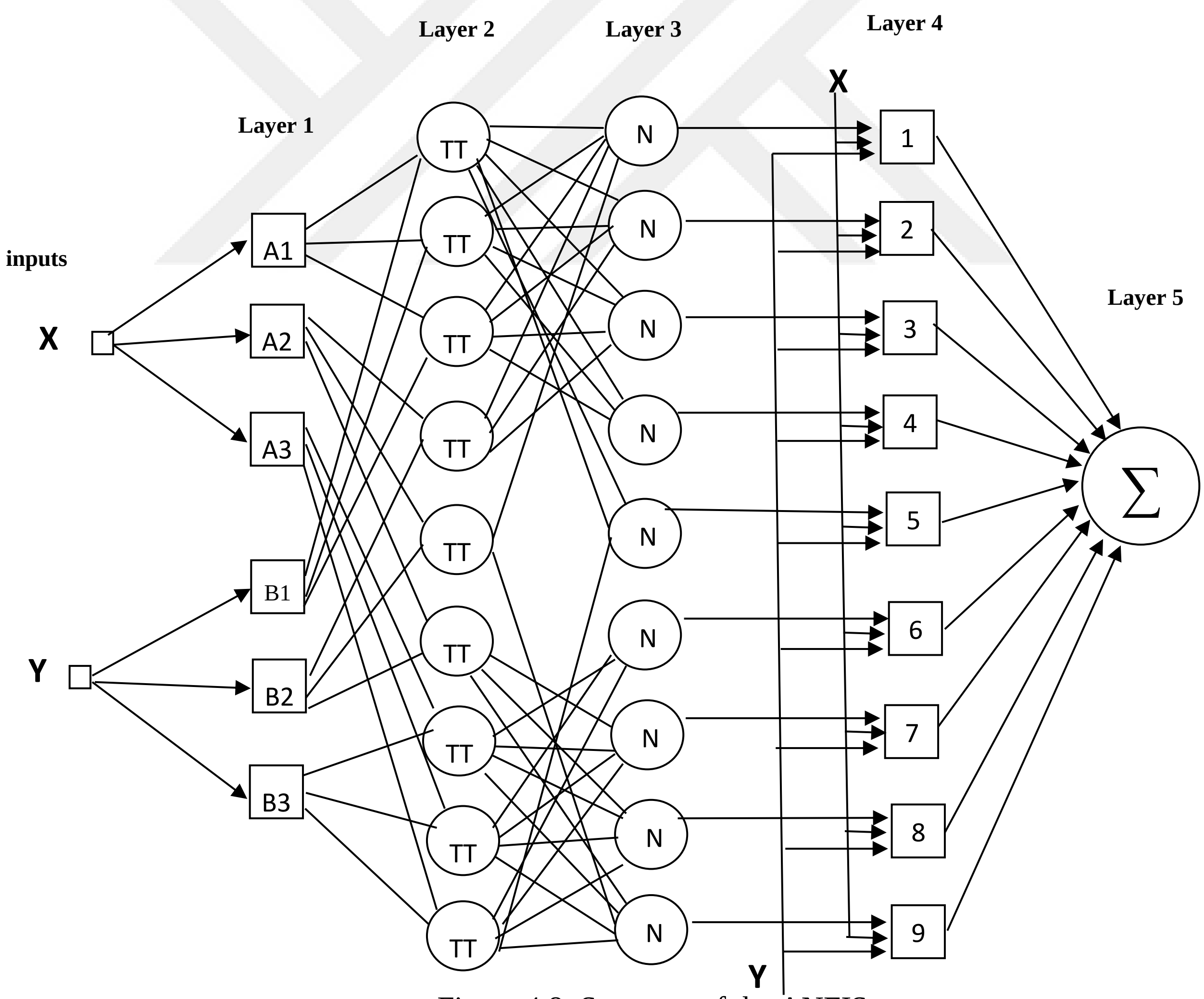


Figure 4.8: Structure of the ANFIS

First layer is executing russification process in this layer using the fazzification in order to convert the data into truth values making all the values between (0-1) , where all the nodes in this layers are adaptive with node function There is also a membership function which plays an important role in this thesis [34] In our model we had one week data in order to foreca next week so we had (186) training data pairs and (168) checked data pairs and used (906) nodes , (378) rules , (68) numbers , nonlinear parameters , (378) linear parameters where we used different number of membership function (MF) in each inputs , We used four membership functions with first input and second input (dry temperatures and dew temperatures) and divided temperatures into four levels by using four membership functions in order to reduce the error in order to present adaptive node function and membership function

Q1,i = μAi(x) , *for i=1,2,3 or*

Q1i = μBi-3(y), *for i=4,5 6*

Q1 is membership function grade of a fuzzy set (Ai or Bi)

$$\mu A(x) = \frac{1}{1 + \left| \frac{x - ci}{ai} \right|^{2b}} \qquad \textit{membership function} \qquad (11)$$

where (ai,bi,ci) is the parameter

- **Second layer is** using the fuzzy rules (if/ and) In this step we used the rules with all input values through (if/and) functionWe combine the inputs which are ambiguous by fuzzy rules in order to find firing strength of rule as nodes outputs. Every nodes in this layer is considered as fixed node labeled ∏, output is the productod the incoming signal, Here we modify these rules in order to reduce the error [34]

Q2, i= Wi = μAi(x) μBi(y), *i=1,2,3* (12)

- **Thread layer** in the previous layer, node is labelled to fix but here (N) this node is labelled in order to calculate the average of firing strength and sum of all these rules.

$$Q3.i = \varpi = \frac{wi}{wi + w2}, i = 1, 2, 3$$ normalized firing strengths output this layer

- **Fourth layer** In this layer we used the firing strength from the third layer with parameters set (*pi, qi, ri)* where all the nodes are adaptive nodes with node function, also in this layer the parameters represent **consequent parameters**

- **Fifth layer** In this layer we computed the overall outputs as summation of all incoming signals ∑

4.3.1 Improving ANFIS Model

In our thesis, we propose a way to determine an best numbers membership function in fuzzy logic system. First of all, we suggested to find correlation between numbers for the hours of day and temperature , where the table (4) represents an effiecient correlation for one week each day (1-24) and hours. Secondly we divided the daily hours into three periods, (Each period is 8 hours))in order to determine low, middle and high temperatures.Through this method, we can use three membership functions with from each input (1) (temperature Dry), input (2) (temperature Dew), so we used and input (3) (Hour), where we found value of (R), R is correlation of coefficiency that statistics quantify the relation between (time with Dry bulb) and (time with Dew point) and (Dry bulb with Dew point), We can consider that the correlation of data (temperature and time) is strong according to results of (R)values in table (4), where the ranges of (R) are (0 < R< 0.3) are considered as weak correlation , (0.3< R <0.7) moderation correlation and (R> 0.7) is strong , Then we computed the (R), Here we got consistent results with previous values (R) This proves that there is a significant relation between temperature and hour of the data , This relation will have positive or negative effects on results of load electrical forecasting We can see the results of correlation in the Table (6), Table (7), Table (8), Table (9) and Table (10), The regressions between (temperatures and hours) , Dew point and hours (R=0.3720) and Dry bulb and hours (R=0.2139) also proves that the hours of day have an effect on temperatures , where we divided time of the day to three periods, each period the size is 8 hours as shown in the figures (4.9) and (4.10) [37].

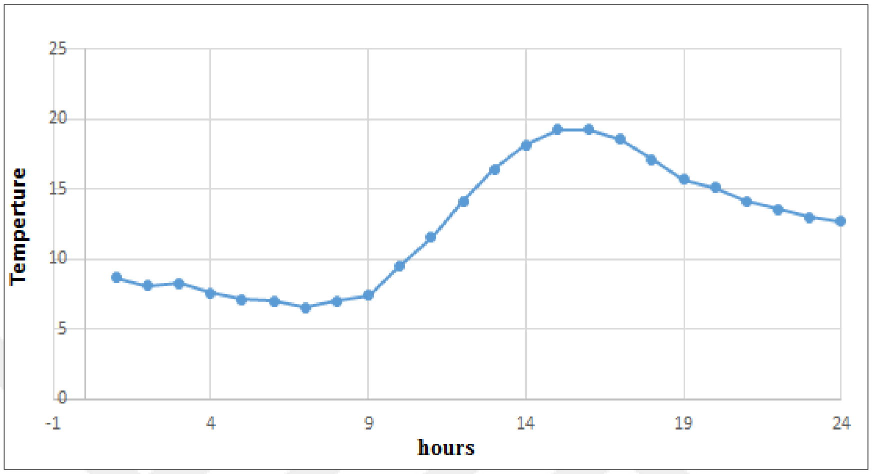


Figure 4.9: the correlation of Dew point and hours

In the figure (4.4) the correlation between the Dew point and time for each day in a week.

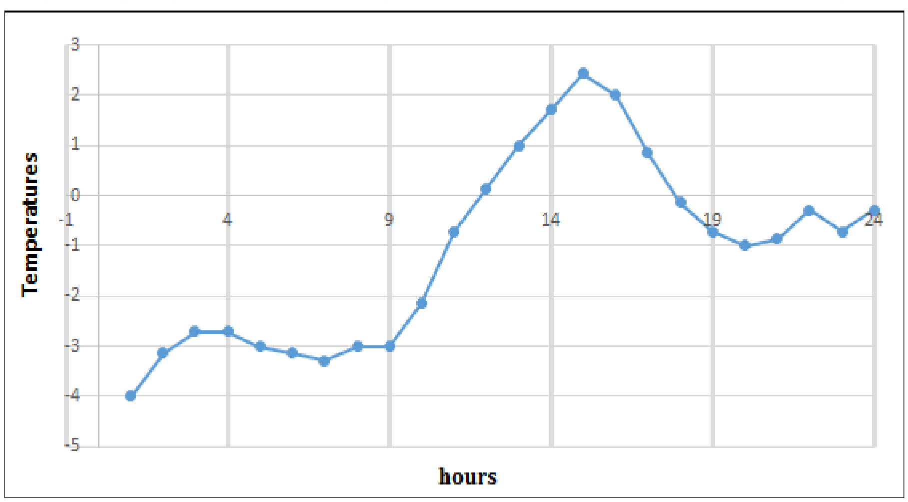


Figure 4.10: the correlation of Dry bulb and hours

In the figure 4.10 the correlation between the Dry bulb and time for each day in week

Table (4) results of coefficiency correlation in (R) 1-24 hours

1	first day (1-24) hour	Dry bulb	Dew point
first day (1-24) hour	1		
Dry bulb	0.936447442	1	
Dew point	0.98045674	0.964577	1
2	second day (1-24) hour	Dry bulb	Dew point
second day (1-24) hour	1		
Dry bulb	0.897298078	1	
Dew point	0.882794158	0.785035	1
3	third day (1-24) hour	Dry bulb	Dew point
third day (1-24) hour	1		
Dry bulb	-0.476986556	1	
Dew point	-0.70601277	0.939147	1
4	four-day (1-24) hour	Dry bulb	Dew point
four-day (1-24) hour	1		
Dry bulb	0.324039838	1	
Dew point	0.46553454	0.589604	1
5	fifth day (1-24) hour	Dry bulb	Dew point
fifth day (1-24) hour	1		
Dry bulb	-0.316296468	1	
Dew point	-0.981964633	0.409985	1
6	sixth day (1-24) hour	Dry bulb	Dew point
sixth day (1-24) hour	1		
Dry bulb	0.912398223	1	
Dew point	0.971327298	0.975921	1
7	seventh day (1-24) hour	Dry bulb	Dew point
seventh day (1-24) hour	1		
Dry bulb	0.831448102	1	
Dew point	0.986062828	0.862342916	1

This table explains the results of coefficiency correlation between temperature and hoursfor all days of the week. Each day we used in the periods of the day (1-24) hours, we we can see the coefficiency correlation has some fluctuations. It is high on the first and second day ,then decreases on the third and fourth day then increases again on sixth and seventh day.

Table (5) Results of coefficiency correlation (R) first day(A), second day(B), third day(C), fourth day(D)

A				B			
1	first day (8) hour	Dry bulb	Dew point	2	first day (1-8) hour	Dry bulb	Dew point
first day (1-8) hour	1			second day (1-8) hour	1		
Dry bulb	-0.9258201	1		Dry bulb	0.755928946	1	
Dew point	0.763762616	-0.707106781	1	Dew point	0.790925521	0.3304093	1
1	first day (9-16) hour	Dry bulb	Dew point	2	second day (9-16) hour	Dry bulb	Dew point
firs day (9-16) hour	1			second day (9-16) hour	1		
Dry bulb	0.992205127	1		Dry bulb	0.991836598	1	
Dew point	0.988317356	0.992428169	1	Dew point	0.967574143	0.948043017	1
1	first day (16-24) hour	Dry bulb	Dew point	2	second day (16-24) hour	Dry bulb	Dew point
first day (16-24) hour	1			second day (16-24) hour	1		
Dry bulb	0.927426034	1		Dry bulb	-0.848668425	1	
Dew point	0.992330611	0.890733739	1	Dew point	0.412393049	- 0.801783726	1

C				D			
3	third (1-8) hour	Dry bulb	Dew point	4	four-day (1-8) hour	Dry bulb	Dew point
third day (1-8) hour	1			four-day (1-8) hour	1		
Dry bulb	-0.66391373	1		Dry bulb	-0.98605527	1	
Dew point	-0.676123404	0.785553319	1	Dew point	-0.972529078	0.988702847	1
3	third day (9-16) hour	Dry bulb	Dew point	4	four-day (9-16) hour	Dry bulb	Dew point
third day (9-16) hour	1			four-day (9-16) hour	1		
Dry bulb	0.831890982	1		Dry bulb	-0.98605527	1	
Dew point	0.65582207	0.947469486	1	Dew point	-0.972529078	0.988702847	1
3	third day (16-24) hour	Dry bulb	Dew point	4	four-day (16-24) hour	Dry bulb	Dew point
Third day (16-24) hour	1			four-day (16-24) hour	1		
Dry bulb	-0.995211574	1		Dry bulb	-0.962250449	1	
Dew point	-0.960834705	0.975617391	1	Dew point	0.897447077	- 0.832423746	1

This table explains the results of coefficiency correlation between (temperature and Hors) for first day(A), second day(B), third day(C), fourth day(D) of week, where we used the period (1-8) hours to three levels for each day of week , We can see the coefficiency correlation is high for all hours of first day, and second day’s coefficiency correlation   is high except (Dry bulb) (9-16) hours is low, the third day(C) and fourth day (D)are considered to have high coefficiency correlation .

Table (6) results of correlation coefficient (R) fifth day(E), sixth day(F), seventh day(I)

E			
5	third (1-8) hour	Dry bulb	Dew point
fifth day (1-8) hour	1		
Dry bulb	-0.906419464	1	
Dew point	-0.864529935	0.816621571	1
5			
fifth day (1-8) hour	1		
Dry bulb	-0.906419464	1	
Dew point	-0.864529935	0.816621571	1
5	third (1-8) hour	Dry bulb	Dew point
fifth day (1-8) hour			
Dry bulb	-0.906419464	1	
Dew point	-0.864529935	0.816621571	1
5	third (1-8) hour	Dry bulb	Dew point
fifth day (1-8) hour	1		

F			
6	four-day (1-8) hour	Dry bulb	Dew point
sixth day (1-8) hour	1		
Dry bulb	0	1	
Dew point	0.810197217	0.194870941	1
Dry bulb	Dew point		
6	four-day (9-16) hour	Dry bulb	Dew point
sixth day (9-16) hour	1		
Dry bulb	0.993524177	1	
Dew point	0.991647659	0.998700454	1
6	four-day (16-24) hour	Dry bulb	Dew point
sixth day (16-24) hour	1		
Dry bulb	-0.577350269	1	
Dew point	0.962713375	-0.504118377	1

I			
7	seventh day (1-8) hour	Dry bulb	Dew point
seventh day (1-8) hour	1		
Dry bulb	0.818923025	1	
Dew point	0.980196059	0.846809798	1
7	seventh day (9-16) hour	Dry bulb	Dew point
seventh day (9-16) hour	1		
Dry bulb	0.984056809	1	
Dew point	0.948504014	0.968247903	1
7	seventh day (16-24) hour	Dry bulb	Dew point
seventh day (16-24) hour	1		
Dry bulb	-0.847721168	1	
Dew point	0.948504014	-0.675882347	1

This table explains the results of coefficiency correlation between (temperature and Hors) for fifth day(E), sixth day(F), seventh day(I) of week, where we used the period (1-8) hours to three levels for each day of week . We can see on the fifth (E)day, the coefficiency correlation of dry with dew point is high Dry bulb with Dew point (1-8) is low in coefficiency correlation , On the sixth day the coefficiency correlation is considered high for all times of the day , On the seventh day the coefficiency correlation is considered high for all the time of day.

4.3.2 Type Membership Function in Our Research

There are many types of membership function in fuzzy inference system In our research we used the best membership function which gives less errors after many trials.. (**0.006**), type membership functions are as follows:

1- triangles membership function (**trimf)**.
This function consists of three parameters (**a, b, c**) type liner linear?

2- trapezoidal membership function **(trampmf**).
this function consists of four parameters (**a, b, c, d**) type liner linear?

3- gaussion membership function (**gaussmf, gauss2mf**)
this function consists of tow parameters (**m, δ**) type noliner nonlinear?

4- bell membership function (**abllmf**)
this function consists of three parameters (**a, b, c**)

5- sigmoidal membership function (**sigmf**)
this function consists of tow parameters (**a, b**)

6- polynomial membership function (**zmf, smf, pimf**).

Actually we have 8 membership functions in adaptive neural network with fuzzy inference system (ANFIS) , In our proposal we have five inputs such as (temperatures Dry, temperatures Dew, hours, week day, work day) and outputs in the network, the data contains on (168) pair , Here our aim is to find optimal numbers of membership function and which type is the best , through finding coefficiency correlation between (temperatures and time of day) for all day week we found the optimal number of membership function for each inputs of the network as follows :

- create three membership function in first input (temperatures Dry)
- create three membership function in second input (temperatures Dew)
- create three membership function in third input (hours)
- create two membership function in forth input (week day)
- create five membership function in fifth input (work day)

We created three membership functions in first input, second input and third input depend on three periods of day. Each period is 8 hours , We created two membership functions in forth input depending on week day work (1) or weekend (0), We created five membership functions in fifth input deepened on work day (5) in the week . The results show that the best membership function is (Pimf) to reduce the error to (0.006) as shown in the table (7)

Table (7) all the results of membership functions when to be (default ,randomly ,our model)

		Number of membership function							
		2,2,2,2,2	3,3,3,3,3	4,2,2,7,2	3,3,3,7,2	2,3,2,4,2	3,2,2,4,2	2,3,4,5,2	2,2,3,2,3
Type membership function	trimf	0.1549	0.0216	0.1407	0.0167	0.0100	0.0104	0.0095	0.0193
	trapmf	0.0114	0.0101	0.0152	0.0270	0.0106	0.0163	0.0100	0.0112
	gbellmf	0.0137	0.0101	0.0383	0.0323	0.0417	0.0372	0.0404	0.0112
	gaussmf	0.0936	0.0131	0.0129	0.0180	0.0185	0.0190	0.0261	0.0128
	gauss2mf	0.0140	0.0233	0.0104	0.0133	0.0113	0.0213	0.0108	0.0104
	pimf	0.0110	0.0072	0.0154	0.0060	0.0105	0.0166	0.0096	0.0079
	dsigmf	0.0209	0.0247	0.0099	0.0072	0.0127	0.0217	0.0107	0.0140
	psigmf	0.0209	0.0246	0.0098	0.0072	0.0125	0.0210	0.0087	0.0140

We have Applicated all membership function the default number of membership function, our proposal of number membership function, also we have employed randomly number of membership function, the Epoch (200), error tolerance (0.001) Optim. method (backprop), through experimental results our proposal is best, also the model which close our proposal it was a good result. This prove that optimization number of membership function lead to reduce error.

4.3.3 The proposed parameters value

1. Number of nodes: 580
2. Number of linear parameters: 270
3. Number of nonlinear parameters: 64
4. Total number of parameters: 334
5. Number of training data pairs: 168

6. Number of checking data pairs: 168
7. Number of fuzzy rules: 378

Table (8) membership functions of fuzzy logic

Inputs	Type inputs	Membership function	Parameters	range
Input 1	Temperatures dry	In1mf1	(0.03652 ,0.1345 0.03652 ,0.0055)	(-0.07- 0.36)
		In2mf2	(0.03652, 0.0805, 0.03652, 0.2095)	
		In3mf3	(0.03652, 0.2955 ,0.03652, 0.4245)	
Input2	Temperatures dew	In2mf1	(0.04501, -0.3195 ,0.04501, -0.1605)	(-0.24 0.29)
		In2mf2	(0.04501, -0.0545 ,0.04501, 0.1045)	
		In2mf3	(0.04501, 0.2105, 0.04501, 0.3695)	
Input3	Hours	In3mf1	(0.01953, -0.0245, 0.01953, 0.0445)	(0.01 0.24)
		In3mf2	(0.01953, -0.0245, 0.01953, 0.0445)	
		In3mf3	(0.01953, 0.2055 ,0.01953, 0.2745)	
Input4	Week day	In4mf1	(0.01019, -0.008, 0.01019 ,0.028)	(0.01 0.07)
		In4mf2	(0.0102, 0.0521 ,0.0102, 0.0881)	
Input5	Work day	In5mf1	(0.0004247, -0.00075, 0.0004247 ,0.00075)	(0 0.01)
		In5mf2	(0.0004247, 0.00175, 0.0004247 ,0.00325)	
		In5mf3	(0.0004247 ,0.00425, 0.0004247 ,0.00575)	
		In5mf4	(0.0004247, 0.00675, 0.0004247 ,0.00825)	
		In5mf5	(0.0004247, 0.00925 ,0.0004247 ,0.01075)`1	

We used (8) different membership functions with same inputs in the network (temperatures Dew, temperatures Dey, hours, week day, work day), we got two groups of figures (Training error) of input data in the network as shown in the figures below

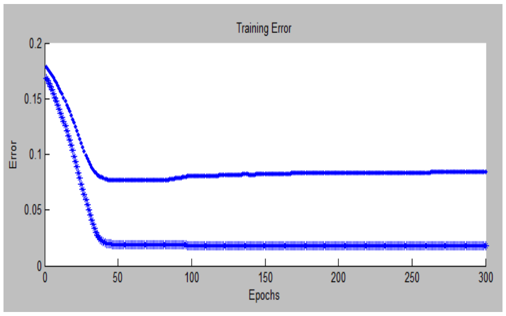


Figure 4.11: Training error of membership function (trimf)

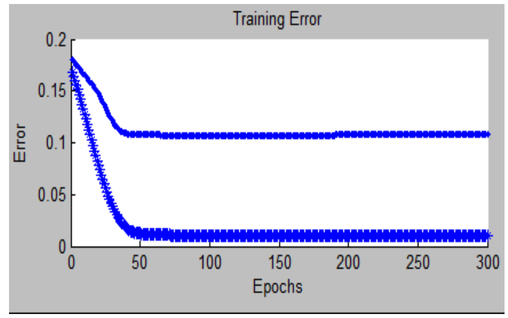


Figure 4.12: Training error of membership function (trapmf)

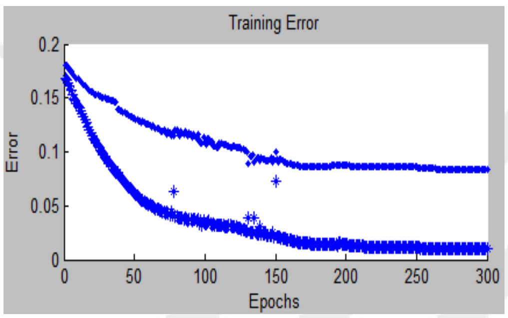


Figure 4.13: Training error of membership function (gaussmf)

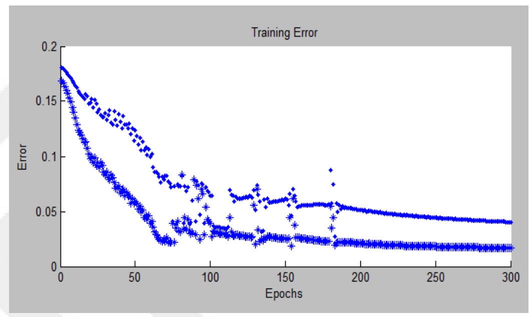


Figure 4.14 : Training error of membership function (gbellmf)

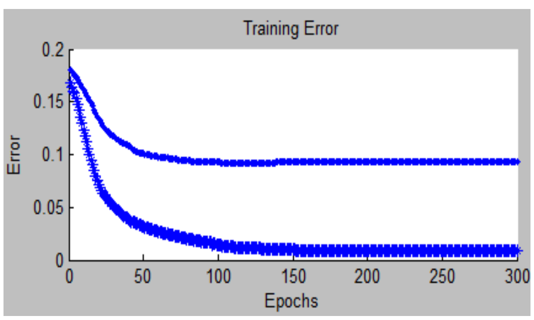


Figure 4.15: Training error of membership function (gauss2mf)

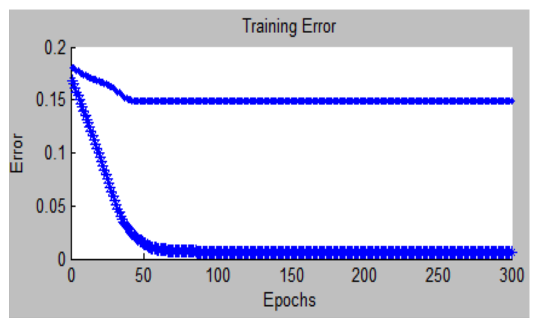


Figure 4.16: sigmoidal membership function Pimf membership

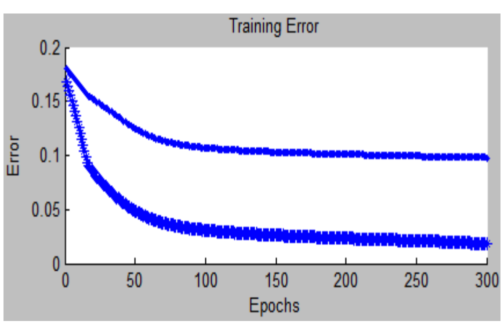


Figure 4.17: Training error of membership function (dsigmf)

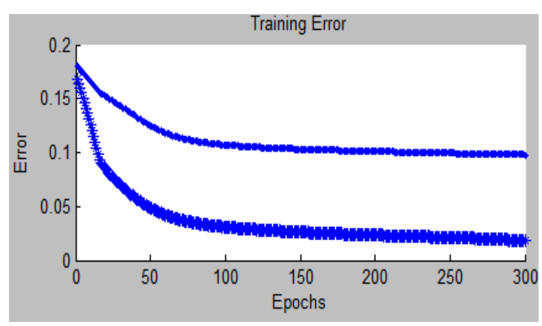


Figure 4.18: Training error of membership function (psigmf)

The second group figures (Test training data) as shown figures below which represent the amount of error in the network training process.Then we selected the best results through less error

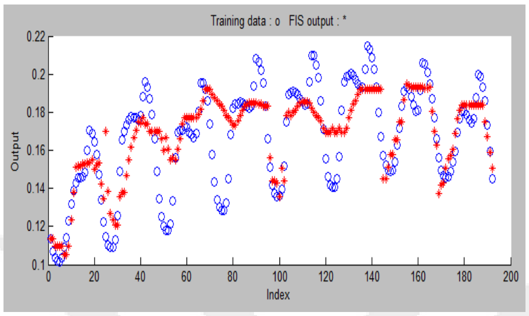


Figure 4.19: Test training data of membership function (trimf)

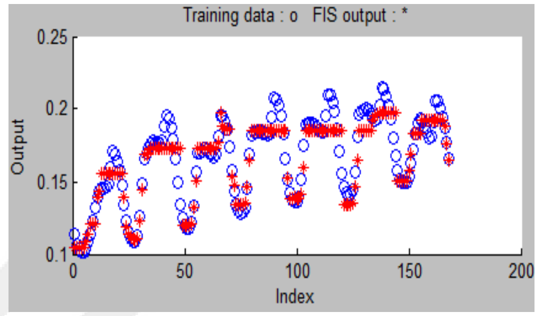


Figure 4.20: Test Training data of membership function (trapmf)

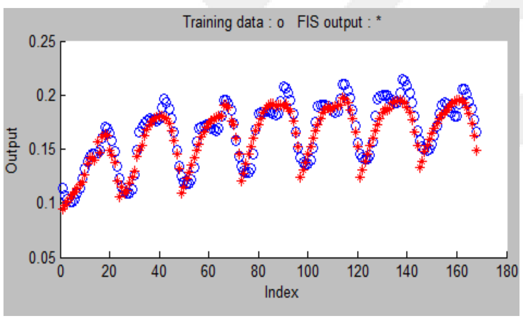


Figure 4.21: Test training data of membership function (gaussmf)

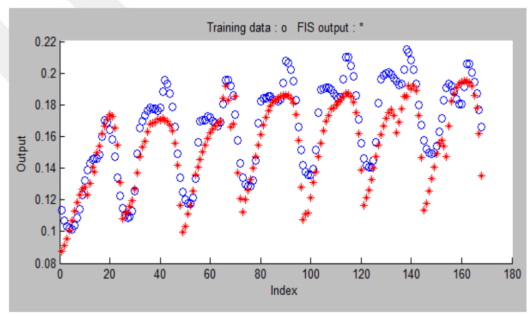


Figure 4.22: Test training data of membership function (gbellmf)

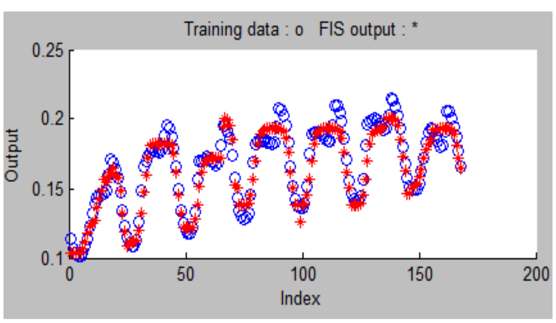


Figure 4.23: Test training data of membership function (gauss2mf)

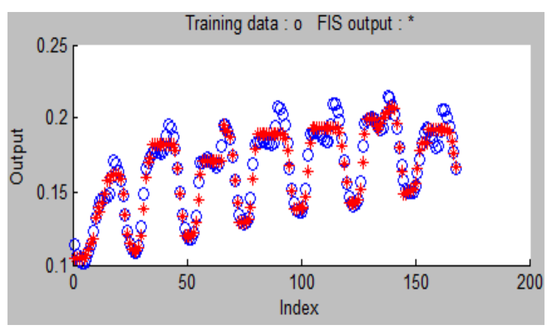


Figure 4.24: Test training data of membership function Pimf

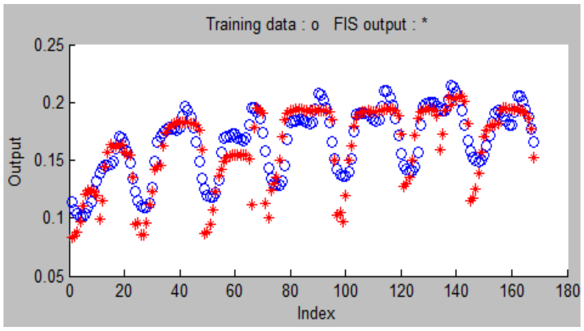


Figure 4.25: Test training data of membership function (dsigmf)

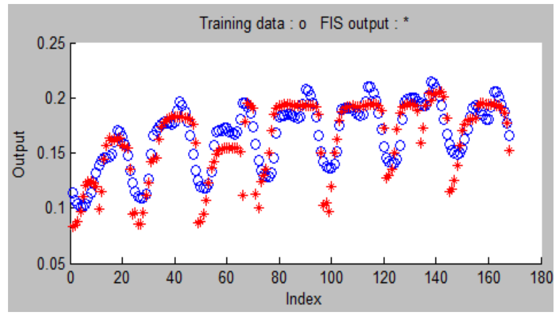


Figure 4.26: Test training data of membership function (psigmf)

According to the results of all the membership function, the membership function (Pimf) is considered as the best, where we can see that in the figure (4.24) the concordance between the previous values and next values of the data in terms of color blue represents the previous values and the red color represent next value of data so was the less of error rate (**0.0060)**

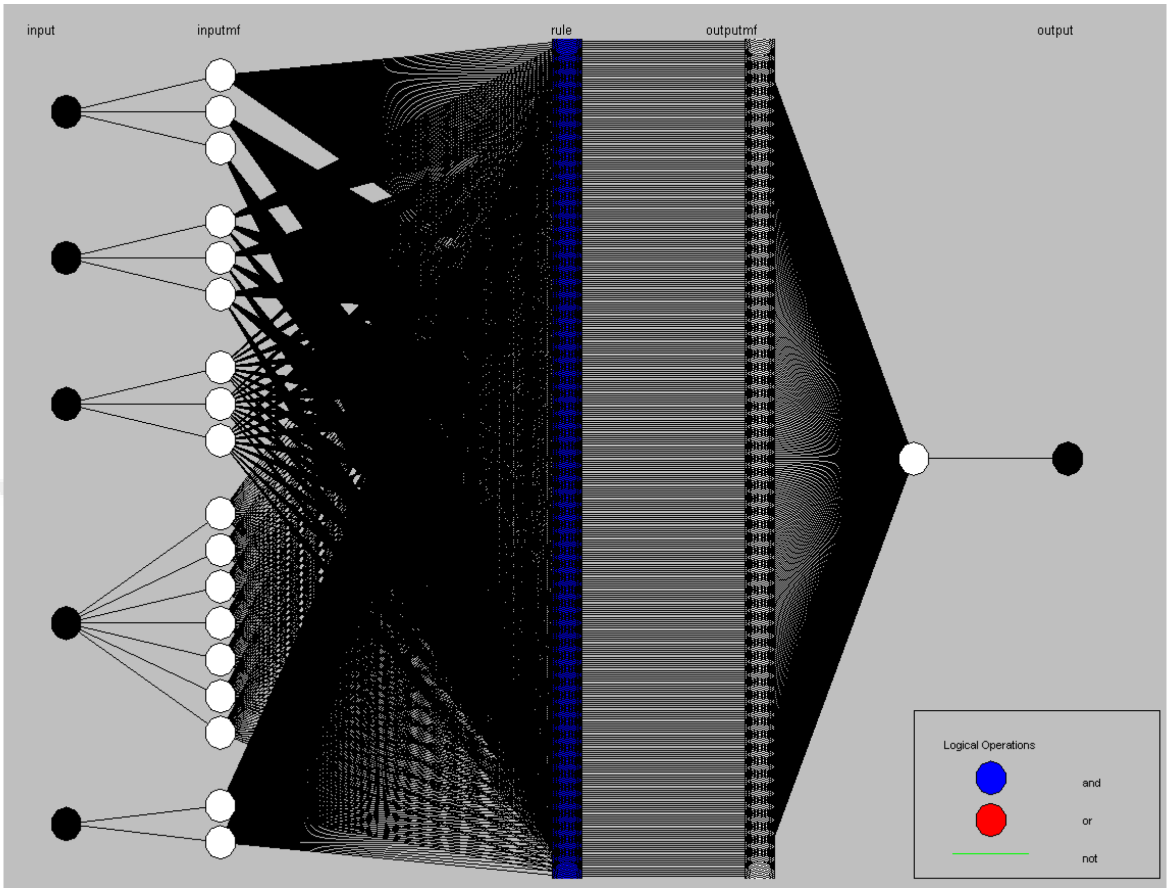


Figure 4.27: Structure of ANFIS [37]

The structure of ANFIS consists of 5 layers, the first layer is inputs; in the second layer is membership function that gives membership degree for every variable; in the third layer are rules where the rule are used in order to compute the membership degree of the variables through using (AND) of the values; in the four-layer normalization of the values than in next layer sum all membership function; and finally the end layer get outputs.

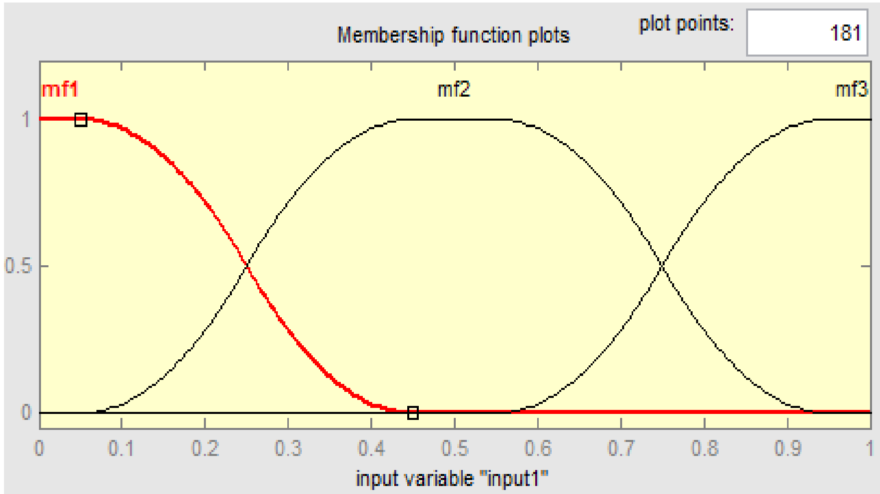


Figure 4.28: The membership function of inputs1

The Figure above explains membership function for input 1 (temperature Dry) where the temperature is divided into three levels (mf1, mf2, mf3) every membership function consists of four petameters, as mentioned in Table 10.

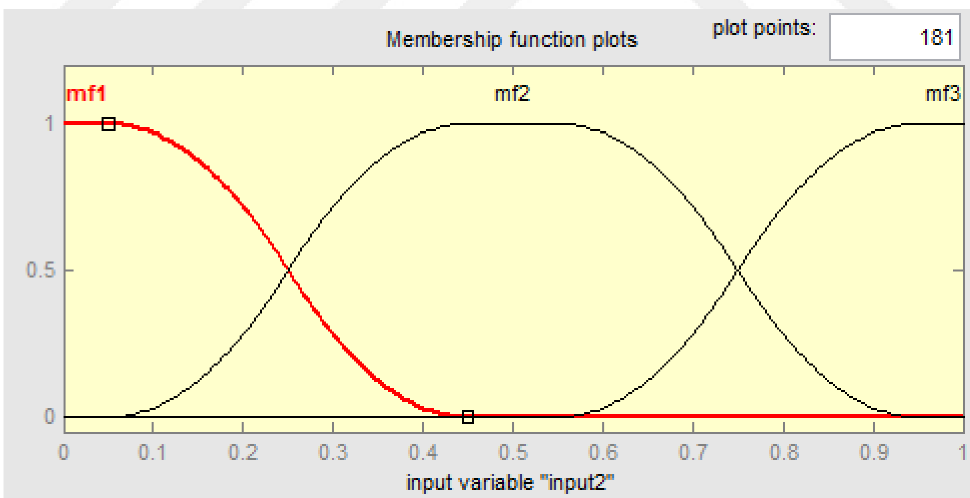


Figure 4.29: The membership function ofnputs2

This figure explains membership function for input 1 (temperature Dew) where the temperature is divided into three levels (mf1, mf2, mf3). Every membership function consist of four petameters as it mentioned in Table 10 .

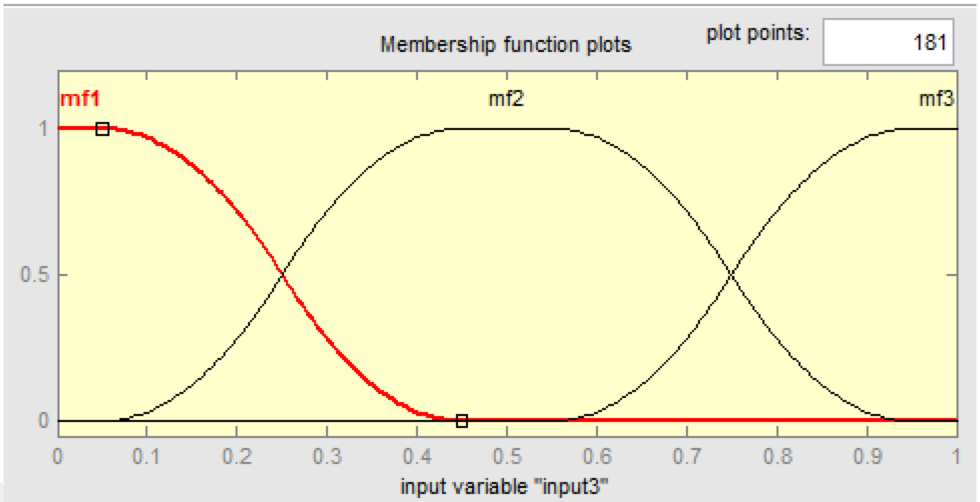


Figure 4.30: the membership function of (inputs3)

This figure explains membership function for input 1 (hours) where the temperature is divided into three levels (mf1, mf2, mf3). Every membership function consist on four petameters as it mentioned in Table 10.

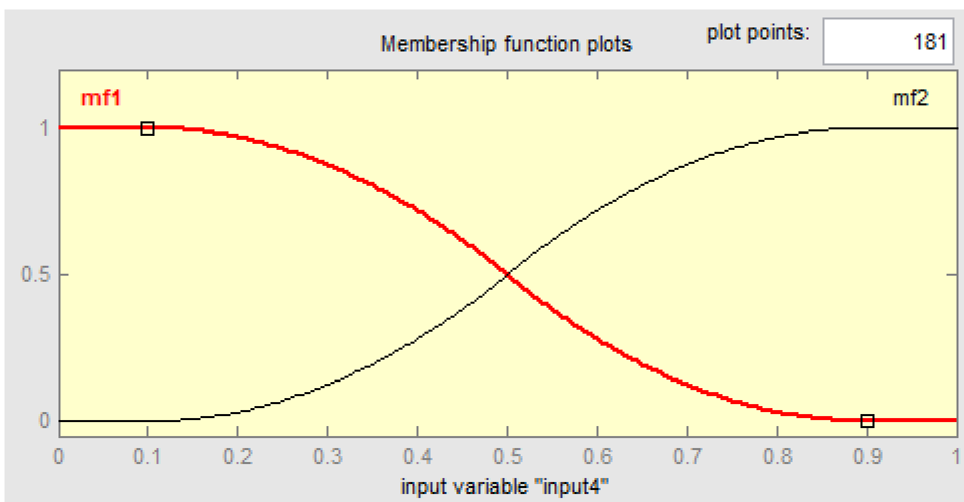


Figure 4.31: The membership function of inputs4

This figure explains membership function for input 1 (work day) where the temperature is divided into two levels (mf1, mf2). Every membership function consists of four petameters, as mentioned in the Table 10.

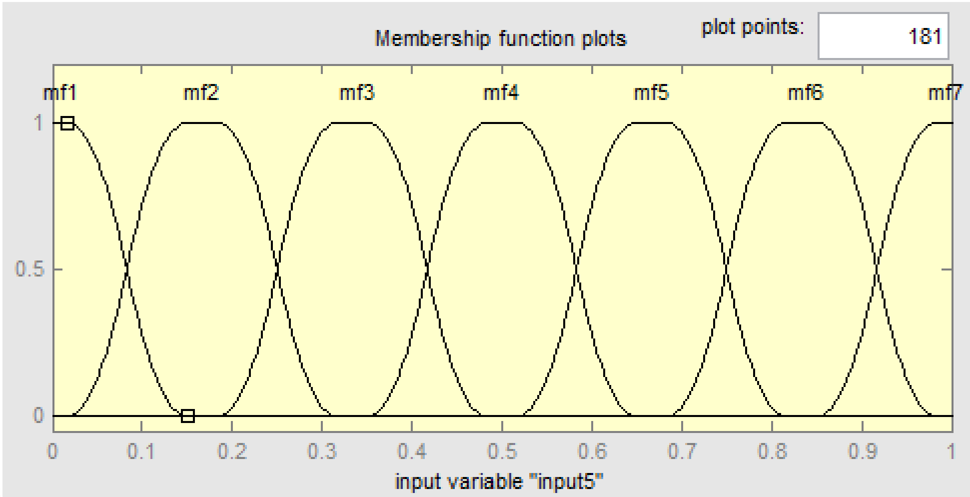


Figure 4.32: The membership function of inputs5

This figure explains membership function for input 1 (number of day in the week) where the temperature is divided into seven level (mf1, mf2, mf3, mf4, mf5, mf6, mf7). Every membership function consists of four pentameters, as mentioned in Table 10.

4.4 Hybrid model Wavlate Transportation and Neural Network to Short Term Load Forecasting

This model we have used wavelet and neural network for short term load forecasting, where we used 5 inputs (Temperature (Dey, Dew), hours, work day, day of week) and we used power load as output of the network, we have benefited from wavelet transportation through using (morlet function) which is considered to be the mother function of wavelet, where this function is used to make the layers active in neural network. The wavelet is analysis of the signal according to a certain measure through mathematical function by limit time period equal zero, it can represent any signal through some change to groups which represent this signal.

Mother function is:

$$\psi_{a,b}(x) = a^{-1/2}\psi(\frac{x-b}{a}) \qquad (13)$$

a : dilation parameter

b : transformation parameter

Ψ : wavelet

The wavelet works on two basic variables (signal and time), where measure the change of the signal with the change of the time. For this reason, when the change is high information the wavelet to be (the low frequency information), when the change is low, the wavelet to be (the high frequency information), so the relation between frequency and time is inverse relationship [35].

4.4.1 Model Network of Wavlate Transformation and Neural Network

The network in our model consist on three layers (input, hidden layer, output) , the input layer include on 5 inputs ('DryBulb', 'DewPoint', 'Hour', 'Weekday', 'IsWorkingDay', 'PrevWeekSameHourLoad'), and use 5 nodes , in the second layer (hidden layers) we used 20 nodes and consist on (morlet function) , the third layer (output) to compute and sum passing by v(n) as shown in Figure 4.33.

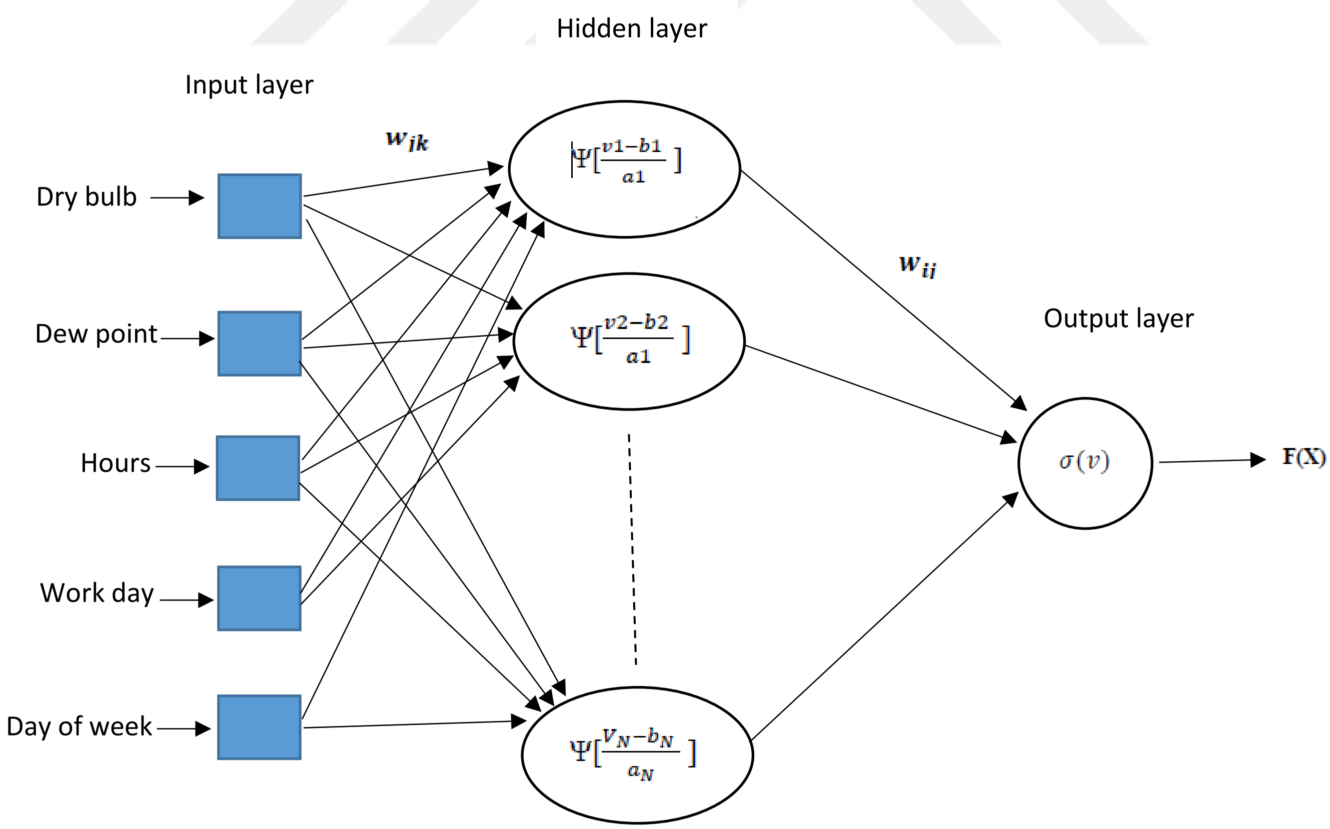


Figure 4.33: Structure of WNN

4.4.2 Implementation of The Model WNN

In this model, the network includes (N) neurons in hidden layers. There is also external input vector involving many variables such as [27]

Wik $\longrightarrow$ the weights between hidden layers and inputs

Wij(n) $\longrightarrow$ the connection weights between outputs and hidden layers

aj(n) and bj(n) $\longrightarrow$ the dilation and translation in hidden layers

Ψ $\longrightarrow$ the morlet function

There are many functions in this model such as:

$Y(n) = \sigma\, [v(n)]$ ………………………………… (14)

This function represents the outputs of the network and consist on *v(n)* is passing and apple through nonlinear function σ

$$v(n) = \sum_{j=0}^{j=N} wij(n) * \Psi_{a,b}[vj(n)] \text{ .... } (15)$$

This function refers to the sum of inputs to the outputs ($\Psi_{a,b}$) refers to morlet function.

$$\Psi_{a,b}[vj(n)] = \Psi[vj(n) - (bj(n)) / (aj(n))] \text{ .... } (16)$$

This is wavelet function and $vj(n)$ refers to internal activity of neuron.

$$vj(n) = \sum_{k=0}^{k=m} wjk(n) * xk(n) \text{ .... } (17)$$

This function refers to net internal activity of neurons at time *(n)*

4.4.3 Learning Algorithm for WNN

In this section, we used many functions in the network such as how to compute the sum error and compute the weights between the hidden layers and inputs, also between the hidden layers and the output which consists of the learning rate. This explains the mother function (mortel function) of wavelet [36]

- We can compute the sum of the error in the time (n) through this function

$E(n) = \frac{1}{2}\, e^2\,(n) = \frac{1}{2}\,[y(n) - d(n)]$……………………………...(18)

Where:

n $\longrightarrow$ represents the time

d(n) $\longrightarrow$represents the outputs

- This function serves to compute the weights between the hidden layers and the unite input.

$$= \eta * e(n) * \sigma[v(n)] * \Psi_{a,b}[vj(n)] + \mu * \Delta wij(n) * \frac{xk(n)}{aj(n)} + \mu * \Delta wjk(n) \dots \text{ (19)}$$

Where:

$\eta \longrightarrow$ learning rate of the network

$\Delta wij(n) \longrightarrow$ the changes in the weights

- This function serves to compute the weights between the hidden layers and the unite output.

$$= \eta * e(n) * \sigma[v(n)] * \Psi_{a,b}[vj(n)] + \mu * \Delta wij(n)$$

- This function represents morlet function

$$\Psi(x) = \cos(1.75x) * \exp^{-x^2} \text{ ……………………………………(20)}$$

In the first section, the neural network and wavelet processing are performed separately, where using wavelet basis to first decomposed of the input signal through neurons in the hidden layers, the outputs off wavelet accordance to one or more summers whose input weights which modified in accordance with some learning algorithm.

The second section combines the two theories: the summer weights with translation and dilation of the wavelet..

4.4.4 Structures of Our Model

In this model, we get the mean absolute percentage error (MAPE) (0.284) with many time of training the network and incense numbers of nodes until (20) node and modify the rate learning until (0.3) they settle these results.

P=168 number of sample

m=5 number of input node

n=20 number of hidden node

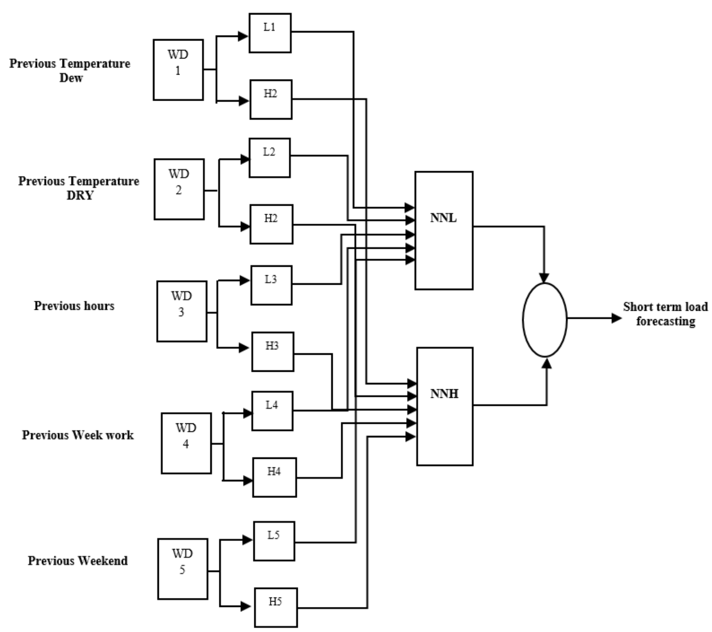


Figure.4.34. Structure of wavelet neural network

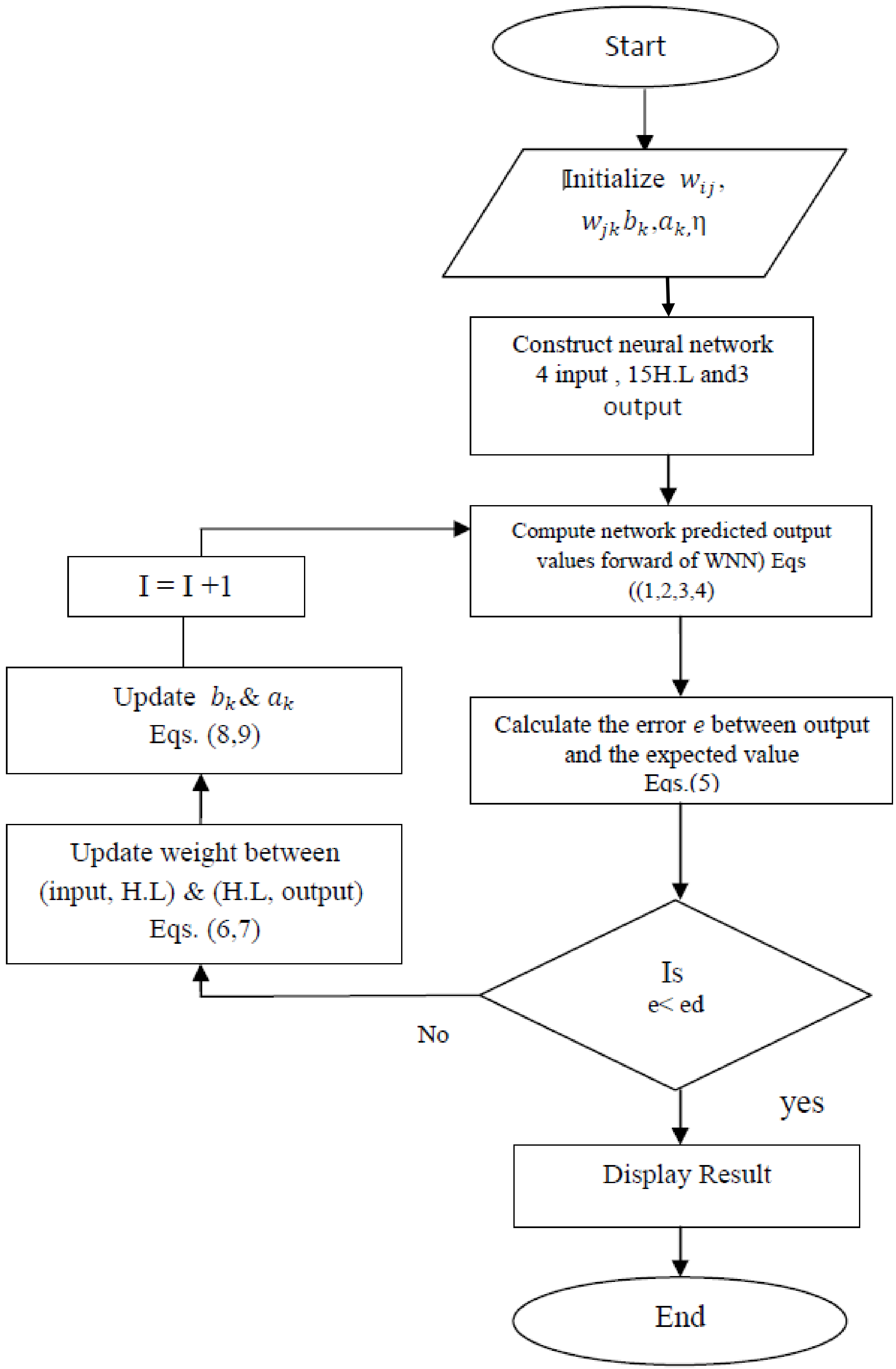


Figure 4.35: flowchart of WNN [36]

N=1 number of output node

epoch=1

epo=3000

error=0.5

err=0.00001

delta =1

lin=0.3 the average leering

a(n) b(n) scale and shifting parameter matrix

x (P,m) input matrix of P sample

net (P,n) output of hidden node

y (P, N) output of network

d (P, N) ideal output of network

phi (P,n) output of hidden node wavelet function

W (N,n) weight value between output and hidden

WW(n,m) weight value between hidden and input node

4.5 Comparing the performance of the forecasting methods

Here we display all the results of all the models (ANN,ANFIS and WNN) where we cumbered between all methods. According to theseresults, the neural network and fuzzy logic are better because this hybrid has less MAPE (0.006). Besides, we can see the results of the neural network (0.139) is best from the results of wavelet and neural network (0.284)

Table (9) all the results of all the models

Methods	epoch	Input	layer	output	Target error	type	MAPE
Neural network	300	5	3	1	0.05	Back Propagation	0.139
Adpative Neural network and fuzzy logic	300	5	3	1	0.05	Back Propagation	0.0060
Wavelet and neural network	300	5	3	1	0.05	Back Propagation	0.284

4.6 Conclusion

In this Chapter, we have used three models in order to predict electrical load in future, where the first model was using just neural network (NN) through use multi layers with Back Propagation algorithm with optimal numbers of nodes in each layer, the second model we have used fuzzy logic system (FLS) with neural network as hybrid method through use different numbers of membership function with each inputs, where the target of the model is improving the performs of the neural network through help the network to take the decisions available in neural network, the third model we have used wavlate transportation with neural network as hybrid method through analysis the input data by the wavlate (WT) to high frequency and low frequency and make the hidden layers more active by using mother function of wavelet transportation. According to the results of all the models throughout the thesis, adaptive neural network and fuzzy logic system are considered to be the best model because the error of short term load forecasting is (0.006), while the error of short term load forecasting of the neural network is (0.139), and last model wavelet transportation with neural network the error is (0.284)

CHAPTER 5

DISCUSSION AND CONCLUSION

5.1 DISCUSSION

It has been our proposal in this thesis is to find best model for short term load forecasting through using artificial intelligent and neural network, and how taring and development the network by using other algorithms such as fuzzy logic system and wavelet transportation to from hybrid method to reduce the error of network prediction for electricity load, where through predict the load electricity we can estimate the perdition of electricity required, where the most important to estimate the electricity because this load to keep the electricity power without waste in this case we can reduce from spent fuel in stations of production of electricity power like (thermal, gas, diesel), also the accuracy of perdition of electricity power reduce to cost of maintenance stations of power electricity. We used the programmes like (Matlab, Visual Gene Developer 1.7, Excel) for simulation, training neural network, feature prediction and compute the relation between the data, and three model were used determine which is better than the other.

First method, we used the neural network only through using (Visual Gene Developer 1.7), where we used data set through table of historical hourly loads and temperature observations from the New England ISO for the years one week to next week , which consists of different type of data such as (temperatures, hours, work day, numbers day of week, electricity load in the week). We used first five inputs in first layer in neural network than using electrify load in the week as output, where we used three layers in the network (input, hidden layers, output) our aim in this model to find best network, we used different nodes three layers of network, (10) node sin first layer, (8) nodes in the second layer, (8) nodes in the third layer.We concluded that increase nodes in first layer lead to reducing the error of the network the best results was (0.006).

The second method we used in this method fuzzy logic system with neural network as hybrid technique. This hybrid is considered to basic aim of the thesis We implement our proposal and get best results and the error was (0.006). The basic aide of the model is to use membership function and rules of the fuzzy to develop the neural network and improve the results first model where we analysed the data inputs in order to determine the numbers of membership function according to data type and time series for each input. We therefore divided temperature into three levels (low , moderate, high) than use three membership function. We also used three function for inputs of (hours), but with inputs of work day we sued tow function because we have two type data (0,1), but with days of week we used seven membership function. The results of this model is considered to the best if we compared with other model .

In the third method, we used wavelet transportation algorithm with neural network, where we used wavelet in order to analyse the data to signal low frequency and high frequency. The aim of using wavelet algorithm is to make hidden layers more active, where we used mother function of wavelet in hidden layers in order to minimize the error of prediction of the future value.

5.2 CONCLUSION

The neural network is considered as one of the most important methods in the prediction because it is nonlinear model, where it is used in different fields such as (industrial, natural and economic. The neural network is able to train different variables to solve the problems which cannot be solved by traditional methods (statistical). In this research, we used hybrid method (neural network with fuzzy logic system) and (neural network with wavelet transportation algorithm) in order to overcome the weaknesses of neural network, where we used fuzzy inference system because neural network is unable to take decisions but through fuzzy logic system the network can take this decisions at the same time the fuzzy logic system unable to training data but with neural network it can The model is able to train and take the decisions. For this reason, this model is considered to be the best with error (0.006). The third model which used neural network with wavelet transformation , where wan the result (0.284) because we think that the change in the value data and time series were bigger this lead to information has low frequency for signal for this reason error percentage was (0.284). Future studies may develop the third model through using genetic algorithm with the third hybrid to improve the results.

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Appendix (1)

The load of electric power for the first week

'Dry Bulb'	'Dew Point'	'Hour'	'Weekday'	'WorkingDay'	'Prev. Week Same Hour Load'	Predict load
6	-14	1	4	1	13415	174190.2
27	22	1	3	1	12496	147781.5
26	22	2	3	1	12000	146118
27	21	3	3	1	11781	146666.4
26	21	4	3	1	11788	147501.5
25	20	5	3	1	12145	149543.6
25	19	6	3	1	13354	152405.1
25	20	7	3	1	15630	159095.2
26	21	8	3	1	16950	165755.5
27	22	9	3	1	17031	172801.7
29	24	10	3	1	17043	179777.5
31	26	11	3	1	17261	186105.9
33	27	12	3	1	17223	189878
35	28	13	3	1	16957	192883.8
36	28	14	3	1	16846	195292.4
36	29	15	3	1	16675	199311.7
33	25	16	3	1	16888	200349.6
30	18	17	3	1	18068	197765.8
27	10	18	3	1	19548	194173.7
22	3	19	3	1	19527	192551.4
16	-3	21	3	1	18572	190497.1
13	-3	22	3	1	17371	186916.1
10	-9	23	3	1	15754	180340.9
8	-11	24	3	1	14315	178741.5
3	-16	2	4	1	12990	146551.4
2	-18	3	4	1	12832	143246.3
0	-19	4	4	1	12866	143038.1
-2	-20	5	4	1	13233	144303.4
-3	-21	6	4	1	14495	148827.9
-4	-22	7	4	1	16855	154826
-5	-22	8	4	1	18233	162557.6
-5	-23	9	4	1	18421	172694.5
-4	-23	10	4	1	18417	179806.8
-2	-21	11	4	1	18532	185690.6
0	-20	12	4	1	18503	191493.2
2	-20	13	4	1	18356	195617.5
3	-19	14	4	1	18302	198161.7
4	-18	15	4	1	18205	202893.1
4	-18	16	4	1	18326	206286.8
4	-19	17	4	1	19397	208855.2
4	-18	18	4	1	20786	209763.1
3	-18	19	4	1	20668	209380.8
3	-18	20	4	1	20206	207650.1
2	-17	21	4	1	19522	204701.6
2	-15	22	4	1	18295	199721.5
2	-11	23	4	1	16598	192961.1
1	-8	24	4	1	15138	182523.2
1	-7	1	5	1	14186	171509.5
1	-7	2	5	1	13757	145582.4
1	-6	3	5	1	13593	147363.2
0	-7	4	5	1	13612	151049.3
0	-8	5	5	1	13963	157553.2
-1	-8	6	5	1	15158	163756.9
-2	-9	7	5	1	17498	174133.3
-1	-10	8	5	1	18924	184141.6
-2	-11	9	5	1	19042	189193
-1	-12	10	5	1	19072	198409.5
0	-12	11	5	1	19063	202486.9
2	-13	12	5	1	18934	207107.8
4	-12	13	5	1	18694	208372.6
5	-13	14	5	1	18543	211050.7
5	-14	15	5	1	18381	212814.5
5	-15	16	5	1	18447	214855.6
4	-17	17	5	1	19587	215759
1	-19	18	5	1	20991	215835
-1	-20	19	5	1	20978	214689
-2	-19	20	5	1	20458	211856.9

‘Dry Bulb'	'Dew Point'	'Hour'	'Weekday'	'Working Day'	'Prev. Week Same Hour Load'	Predict load
-3	-20	21	5	1	19800	207359
-4	-21	22	5	1	18602	203309.6
-6	-23	23	5	1	17094	199016.5
-7	-23	24	5	1	15565	194943.8
-7	-24	1	6	1	14592	189739
-7	-22	2	6	1	14199	159647.2
-6	-21	3	6	1	14064	161045.5
-7	-21	4	6	1	14088	163536.3
-7	-21	5	6	1	14488	169032.9
-6	-21	6	6	1	15661	174909.4
-7	-21	7	6	1	18103	179919.2
-7	-20	8	6	1	19616	189220.7
-6	-20	9	6	1	19871	198114.4
-3	-18	10	6	1	19953	203396.5
0	-15	11	6	1	20015	207504.6
3	-13	12	6	1	19922	212338.2
6	-11	13	6	1	19678	215272.7
9	-8	14	6	1	19467	217428.4
11	-7	15	6	1	19239	219262.7
12	-6	16	6	1	19297	219953.4
11	-5	17	6	1	20238	220364.7
10	-5	18	6	1	21471	219791.7
10	-4	19	6	1	21334	217176.2
10	-4	20	6	1	20846	212825.1
10	-3	21	6	1	20232	208077.9
10	-2	22	6	1	19316	201724.4
10	-2	23	6	1	18006	194596.4
10	-2	24	6	1	16735	187989.5
11	-1	1	7	0	15746	181091.1
11	-1	2	7	0	15199	155688.4
12	0	3	7	0	14965	156453.3
12	1	4	7	0	14898	157765.1
12	1	5	7	0	14975	161712.2
12	2	6	7	0	15399	167495.2
12	2	7	7	0	16278	175599.5
14	3	8	7	0	17153	184122.6
15	3	9	7	0	18304	189035.6
18	4	10	7	0	19070	195245.6
21	5	11	7	0	19340	197110.1
25	6	12	7	0	19218	198621.2
27	6	13	7	0	18843	197321.4
30	6	14	7	0	18373	199502.1
31	7	15	7	0	18057	199014.3
32	7	16	7	0	18074	203135.4
31	7	17	7	0	19129	205526.2
29	7	18	7	0	20588	209894.4
27	8	19	7	0	20555	212884.1
27	8	20	7	0	20068	212344.8
25	8	21	7	0	19458	209382.3
25	9	22	7	0	18692	204912.5
25	10	23	7	0	17688	198905.7
26	11	24	7	0	16623	192172

Appendix (2)

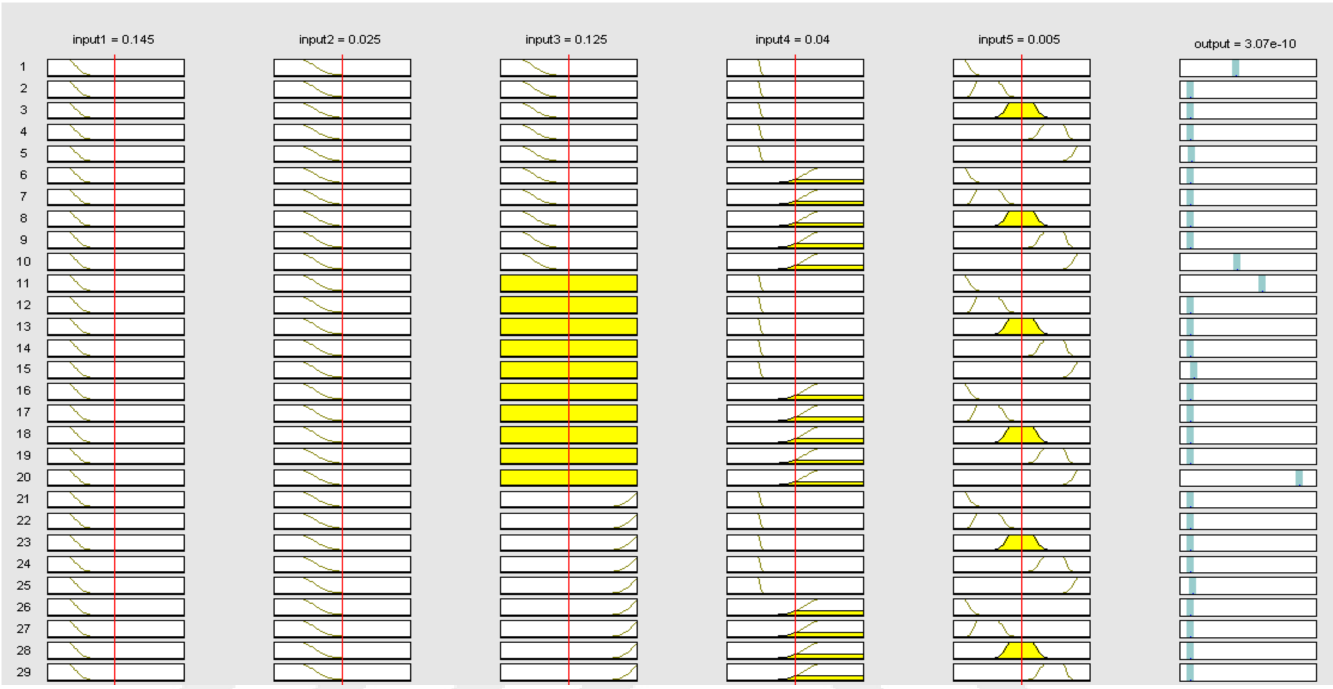
The electric power forecasts of the second week

‘DryBulb'	'DewPoint'	'Hour'	'Weekday'	'WorkingDay'	'Prev.WeekSameHourLoad'	Predict load
14	1	2	4	1	14717	140505.8
14	1	1	4	1	15021	142309.6
13	1	3	4	1	14730	139367.6
13	1	4	4	1	14811	140450.7
13	1	5	4	1	15222	143107.8
12	1	6	4	1	16455	148592.2
12	1	7	4	1	18828	154994
12	1	8	4	1	20231	162664.7
14	2	9	4	1	20367	168122.2
15	2	10	4	1	20480	174205.4
18	2	11	4	1	20493	175432.4
20	3	12	4	1	20407	180224.3
22	4	13	4	1	20206	184478.9
24	5	14	4	1	20063	188044.6
25	5	15	4	1	19857	191402.3
25	5	16	4	1	20011	195353.4
25	5	17	4	1	21101	197739.6
23	5	18	4	1	22477	199936.4
21	4	19	4	1	22419	198978.6
19	4	20	4	1	21837	195481
18	3	21	4	1	21103	190764.3
17	3	22	4	1	19820	184462.4
15	3	23	4	1	18158	176355.3
14	3	24	4	1	16721	168343.6
13	3	1	5	1	15787	143593.1
14	4	2	5	1	15358	143221.4
14	5	3	5	1	15191	144110.4
16	5	4	5	1	15201	145921.9
16	6	5	5	1	15525	149932.1
17	7	6	5	1	16639	154888.5
18	8	7	5	1	18777	161029.6
19	8	8	5	1	20176	166582.6
19	9	9	5	1	20549	176228.5
21	10	10	5	1	20616	181384.3
23	11	11	5	1	20651	186116.9
25	13	12	5	1	20466	191720.8
28	15	13	5	1	20180	194327.4
30	17	14	5	1	20014	197955.5
32	19	15	5	1	19854	200358.6
33	20	16	5	1	20004	202058.5
32	20	17	5	1	21152	203861.7
31	22	18	5	1	22682	204122.2
29	20	19	5	1	22818	201993.3
27	15	20	5	1	22440	198968.5
26	10	21	5	1	21786	195921.2
24	7	22	5	1	20686	191580.3
22	6	23	5	1	19159	185096.6
20	2	24	5	1	17822	180159.4
18	0	1	6	1	16926	154240.5
16	-1	2	6	1	16516	151884.5
15	-2	3	6	1	16275	151741.1
14	-2	4	6	1	16304	152943.2
13	-2	5	6	1	16550	156790.2
12	-2	6	6	1	17510	163420.8
11	-3	7	6	1	19243	171602.8
10	-3	8	6	1	20577	182200.9
11	-3	9	6	1	21239	188423
13	-3	10	6	1	21534	191959.3
14	-3	11	6	1	21665	197681.7
15	-3	12	6	1	21475	202830.2
16	-3	13	6	1	21082	207211.9
17	-4	14	6	1	20716	209951.3
17	-5	15	6	1	20333	213636.2
17	-5	16	6	1	20188	216394.9
15	-5	17	6	1	20746	218648.9
13	-5	18	6	1	21931	217580.1
13	-6	19	6	1	21806	215068.5
11	-6	20	6	1	21136	210169.6
10	-6	21	6	1	20432	204422.5
9	-7	22	6	1	19408	198865.2

'DryBulb'	'DewPoint'	'Hour'	'Weekday'	'WorkingDay'	Previous load	Predict Load
9	-6	23	6	1	18071	191609.7
8	-6	24	6	1	16778	184182.1
7	-6	1	7	0	15819	159712.7
6	-6	2	7	0	15254	161046.3
6	-7	3	7	0	14884	164018.7
5	-6	4	7	0	14733	169925
5	-5	5	7	0	14787	177133.2
5	-4	6	7	0	15161	186095.2
5	-4	7	7	0	15916	194797.3
5	-4	8	7	0	16730	203412.8
6	-4	9	7	0	17552	209181.2
8	-4	10	7	0	18140	212258.1
10	-4	11	7	0	18212	214895.1
12	-6	12	7	0	17933	215287.6
13	-8	13	7	0	17336	217299.4
15	-10	14	7	0	16824	217326.9
15	-11	15	7	0	16474	220763.1
15	-13	16	7	0	16478	222501
13	-14	17	7	0	17421	224713.1
11	-14	18	7	0	18769	224191.8
9	-14	19	7	0	18662	221087.7
8	-14	20	7	0	18091	216813.3
6	-13	21	7	0	17499	210113.9
6	-13	22	7	0	16762	204868.7
4	-12	23	7	0	15680	196608.8
3	-14	24	7	0	14636	191892.4
2	-15	1	1	0	13592	123914.2
1	-15	2	1	0	13062	119915.1
0	-15	3	1	0	12734	117794.6
-1	-16	4	1	0	12586	118082.4
-1	-16	5	1	0	12578	120087.7
-1	-16	6	1	0	12789	123776
-2	-17	7	1	0	13316	130186
-2	-18	8	1	0	14053	136473.3
-2	-18	9	1	0	15150	144709.6
0	-17	10	1	0	16027	149399.4
3	-17	11	1	0	16620	150274.8
6	-16	12	1	0	16900	152357
9	-15	13	1	0	16974	154438.7
11	-15	14	1	0	16803	157452.7
13	-15	15	1	0	16583	160147.7
14	-14	16	1	0	16493	165699.1
14	-15	17	1	0	17145	170178.1
11	-14	18	1	0	17969	178982.5
10	-14	19	1	0	17956	180944.5
9	-13	20	1	0	17673	180076.2
8	-13	21	1	0	17069	177523.4
7	-12	22	1	0	16172	172388.5
6	-11	23	1	0	15064	165770.8
6	-11	24	1	0	14013	159886.9
5	-11	1	2	1	13281	131473.8
5	-11	2	2	1	12926	128756.9
5	-11	3	2	1	12772	127082.1
4	-12	4	2	1	12818	126506.7
4	-12	5	2	1	13158	127772
4	-12	6	2	1	14123	130687.1
4	-11	7	2	1	15610	136131.3
4	-12	8	2	1	16776	141562.2
3	-13	9	2	1	17504	150188.9
5	-13	10	2	1	18045	153821.2
8	-12	11	2	1	18445	156391.9
11	-11	12	2	1	18452	158969.7
13	-11	13	2	1	18366	162264.2
14	-11	14	2	1	18060	167531.3
16	-10	15	2	1	17940	171429.3
16	-9	16	2	1	17972	178390.7
16	-9	17	2	1	18922	182552.1
16	-8	18	2	1	20596	185487.4
16	-8	19	2	1	20698	185962.2
15	-7	20	2	1	20372	184947.4
15	-9	21	2	1	19598	182854.2
14	-8	22	2	1	18346	178188.1
14	-8	23	2	1	16820	173108.6
13	-8	24	2	1	15393	166801.3
13	-8	1	3	1	14429	145187

Appendix (3)

Figure : The Rules Viewer



Appendix (4)

Table ( ): The load and predicted load for one week. numbers of the peris are (168)

current load	predict load
0.1135	0.0007
0.1071	0.0008
0.1035	0.0007
0.1017	0.0007
0.1015	0.0008
0.1037	0.0008
0.1089	0.0007
0.1141	0.0008
0.123	0.0009
0.132	0.0012
0.1391	0.0015
0.1431	0.0019
0.1456	0.0024
0.1458	0.0026
0.1463	0.0028
0.1486	0.0028
0.16	0.0028
0.1705	0.0028
0.169	0.0026
0.1643	0.0024
0.158	0.002
0.1473	0.0018
0.134	0.001
0.1226	0.0001
0.1144	0.0011
0.1105	0.0018
0.109	0.0047
0.1091	0.0061
0.1131	0.0078
0.1258	0.0081
0.149	0.0102
0.1656	0.009
0.1699	0.0093
0.1732	0.0136
0.1762	0.0166
0.1778	0.02
0.1135	0.0007
0.1071	0.0008
0.1035	0.0007

current load	predict load
0.1017	0.0007
0.1015	0.0008
0.1037	0.0008
0.1089	0.0007
0.1141	0.0008
0.123	0.0009
0.132	0.0012
0.1391	0.0015
0.1431	0.0019
0.1456	0.0024
0.1458	0.0026
0.1463	0.0028
0.1486	0.0028
0.16	0.0028
0.1705	0.0028
0.169	0.0026
0.1643	0.0024
0.158	0.002
0.1473	0.0018
0.134	0.001
0.1226	0.0001
0.1144	0.0011
0.1105	0.0018
0.109	0.0047
0.1091	0.0061
0.1131	0.0078
0.1258	0.0081
0.149	0.0102
0.1656	0.009
0.1699	0.0093
0.1732	0.0136
0.1762	0.0166
0.1778	0.02
0.1773	0.0271
0.1773	0.0361
0.1761	0.0422
0.178	0.0483
0.1884	0.056
0.1958	0.0564

current load	predict load
0.1932	0.0577
0.1873	0.0582
0.1787	0.0595
0.1658	0.0609
0.149	0.0561
0.1343	0.0574
0.125	0.0228
0.12	0.0202
0.1178	0.0212
0.1179	0.0187
0.1215	0.0142
0.1335	0.0127
0.1563	0.0152
0.1695	0.021
0.1703	0.0284
0.1704	0.0479
0.1726	0.0771
0.1722	0.1091
0.1696	0.1521
0.1685	0.1724
0.1668	0.1925
0.1689	0.0979
0.1807	0.0328
0.1955	0.0062
0.1953	0.0019
0.1918	0.0028
0.1857	0.0028
0.1737	0.0026
0.1575	0.002
0.1432	0.0017
0.1341	0.001
0.1299	0.0008
0.1283	0.0007
0.1287	0.0006
0.1323	0.0005
0.145	0.0004
0.1686	0.0004
0.1823	0.0004
0.1842	0.0003

cruent load	perdict load
0.1842	0.0004
0.1853	0.0005
0.185	0.0006
0.1836	0.0007
0.183	0.0008
0.182	0.0009
0.1833	0.0009
0.194	0.0009
0.2079	0.0009
0.2067	0.0009
0.2021	0.0009
0.1952	0.0009
0.183	0.001
0.166	0.0012
0.1514	0.0013
0.1419	0.0011
0.1376	0.0011
0.1359	0.0012
0.1361	0.0011
0.1396	0.001
0.1516	0.001
0.175	0.0009
0.1892	0.0009
0.1904	0.0008
0.1907	0.0009
0.1906	0.0016
0.1893	0.001
0.1869	0.0012
0.1854	0.0012
0.1838	0.0012
0.1845	0.0011
0.1959	0.001
0.2099	0.0007
0.2098	0.0006
0.2046	0.0006
0.198	0.0005
0.186	0.0005
0.1709	0.0004
0.1557	0.0004

cruent load	perdict load
0.1459	0.0003
0.142	0.0003
0.1406	0.0003
0.1409	0.0003
0.1449	0.0003
0.1566	0.0004
0.181	0.0003
0.1962	0.0004
0.1987	0.0004
0.1995	0.0005
0.2001	0.0008
0.1992	0.0011
0.1968	0.0014
0.1947	0.0019
0.1924	0.0021
0.193	0.0023
0.2024	0.0023
0.2147	0.0022
0.2133	0.0023
0.2085	0.0023
0.2023	0.0024
0.1932	0.0025
0.1801	0.0025
0.1674	0.0025
0.1575	0.0023
0.152	0.0024
0.1497	0.0025
0.149	0.0026
0.1497	0.0026
0.154	0.0027
0.1628	0.0027
0.1715	0.0028
0.183	0.0028
0.1907	0.0027
0.1934	0.002
0.1922	0.0002
0.1884	0.0018
0.1837	0.0053
0.1806	0.0085

cruent load	perdict load
0.1807	0.0107
0.1913	0.0091
0.2059	0.0062
0.2056	0.0049
0.2007	0.0052
0.1946	0.003
0.1869	0.0042
0.1769	0.0056
0.1662	0.0088

Appendix (5)

Table (10) represents the weight value between hidden and input nodes (WW(n,m)) , and table (11) represents the weight value between output and hidden nodes W(N,n)

Table (10)

Input 1	Input 2	Input 3	Input 4	Input 5
0.953539973	0.830559739	0.182192247	0.208905742	0.260548082
0.162795659	0.818359882	0.065436183	0.116332096	0.08482246
0.970455087	0.938169404	0.610350262	0.646220068	0.298132851
0.597006665	0.000326096	0.701552809	0.10841109	0.917129359
0.240227119	0.640389225	0.111617713	0.983496924	0.470518193
0.070295161	0.007355693	0.095823732	0.248344038	0.269467553
0.300041215	0.106421107	0.597833772	0.60635572	0.762970477
0.813544824	0.106794413	0.81223261	0.816695273	0.772172105
0.076709874	0.367109044	0.814578174	0.830054213	0.021299624
0.354473095	0.239607701	0.089436965	0.489039332	0.879986192
0.132010874	0.346140202	0.731278705	0.760728256	0.798170184
0.15817963	0.249619835	0.903856576	0.915107935	0.324165239
0.062147052	0.387064314	0.452231787	0.900974956	0.669044417
0.701843479	0.42103837	0.070687676	0.21423751	0.296293863
0.086481697	0.640077289	0.241278155	0.547061106	0.929952044
0.61678724	0.787552973	0.73186506	0.784709481	0.281960435
0.173771583	0.269994424	0.040491616	0.194441094	0.168879971
0.651401065	0.843982361	0.424522763	0.746889152	0.745166604
0.498696406	0.74046838	0.540215087	0.475558224	0.477134352
0.284510689	0.826101949	0.953827838	0.583258581	0.653444541

Table (11)

Output
0.535081
0.39844
0.670458
0.440534
0.132874
0.439204
0.547643
0.395136
0.398272
0.751349
0.52235
0.490433
0.088679
0.250852
0.447559
0.637961
0.709445
0.99262
0.932195
0.092229