ADDIS ABABA UNIVERSITY

ADDIS ABABA INSTITUTE OF TECHNOLOGY

SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

POWER ENGINEERING STREAM

LONG TERM LOAD FORECASTING AND TRANSMISSION SYSTEM EXPANSION PLANNING

(CASE STUDY: CENTRAL AND SOUTHERN REGION OF ETHIOPIAN ELECTRIC POWER)

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DECLARATION

I, Girma Zeleke, declare that this thesis has been composed solely by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or processional qualification except as specified.

Signature: ___________________________

Date : ___________________________

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ABSTRACT

A sustainable supply of electric power is a prerequisite to foster all sorts of development in any country. Development of electricity infrastructure is undoubtedly a capital intensive project that needs a careful planning especially when future expansion of Generation and Transmission systems is taken into consideration. To keep Ethiopia abreast with other developing countries, the existing gap between the electric power demand and supply scenario of the country must be bridged. Till now, the country is still deeply entrenched in constructing opportunity for development due to frequent power outages resulting from an insufficient transmission lines even if there is enough generation capacity for existing demand. Furthermore, inefficient transmission and distribution facilities have been another recounted setback in the electric power sector of the country. Moreover, within the ambient of socio economic development and increase in human population, electric load demand will tend to increase from time to time over the year to come. Thus, the performance of the existing transmission system facilities must be investigated and appropriate expansion planning may be carried out to supply the future load demand of the country

Load demand forecasting is an essential process in electric power system operation and planning. It involves the accurate prediction of both magnitude and geographical location of electric load over the different period of the planning horizon. The electric power transmission system has the prominent role of connecting the generation system with distribution system and large industrial consumers. The design and configuration of transmission network should assure the much needed equipoise of electrical load demand and supply for a foreseen future period.

In this thesis, long term load forecasting for the whole country is carried out using Artificial Neural Network (ANN) and transmission system expansion planning to supply the future load demand of the country is investigated using highly interactive MATLAB and ETAP 16 software. The performance of the existing transmission system for central and southern regions of the Ethiopian Electric Power (EEP) is investigated through load flow analysis to identify and find the overloading problems in the system. A method for choosing the best possible expansion plan for the transmission system is presented. Furthermore, contingency analysis (CA) is carried out to investigate the performance of the expanded transmission system by simulating the contingencies such as unexpected opening of the power transmission lines, generators tripping condition, sudden changes in power generation and unexpected changes in loads.

The long term load forecasting used by Ethiopian Electric power (EEP) and EEP master plan (PB) engineers for next 26 year was Econometric method while the Artificial Neural Network (ANN) does it for 22 years. Both forecasts have the same load profile. The estimated demand in year of 2037 is 137752.09GWh. Comparing the ANN forecast with the earlier EEP master Plane (PB) as well as the updated EEP forecast, total demand is significantly lower, during 2022-2027 period; the single large impact is lower the increased anticipated demand and the export are lower with several belated anticipations beyond 2030.

In the Central and Southern region of EEP, there are twenty nine 132/15kV substations. From this, 25 (almost 90%) substations are congested and load shading is imminently looming and frequent power interruption is going during peak hours (morning from 09:30 AM- 12PM and night 06:00PM- 09:00PM.

Key words: Long Term load forecasting, electric load, Power, Ethiopia, sustainable development, ANN, Mat lab, ETAP Software, Transmission System Expansion Planning.

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LIST OF NOMENCLATURE

EEP	Ethiopia Electric Power
EEU	Ethiopia Electric Utility
MOFEC	Ministry of finance Economic and Corporation
GW	Giga Watt
KWh	Kilo Watt Hour
GTP I	The first Growth and Transformation Program
GTP II	The second Growth and Transformation Program
MW	Mega Watt
SVR	Support Vector Regression
TEP	Transmission Expansion Planning
LSR	Linear Least Square
ETAP	Electrical Power System Analysis
GDP	Growth Domestic Product
LTLF	Long Term Load Forecasting
PB	Parsons Brinkerhoff
GERD	Great Ethiopian Renaissance Dam
PPA	Power Purchase Agreement
CSA	Central Statics Agency
MSE	Mean square Error
MAPE	Mean Absolut Percentage Error
TSO	Transmission System Operation
TL	Transmission Line

CHAPTER 1

INTRODUCTION

This graduate thesis is about solving an old problem, load forecasting and its load flow analysis, by using state of the art technologies—Artificial Neural Network (ANN) and using a fully comprehensive and integrated computer program as well as a power system analysis software package. It is about trying to step in with a solution to the old problem and to help the new participants in the game of electricity markets.

1.1- Overview

For any nation, it is very difficult to make a living without the presence of electric power. Its demand of usage is soaring day by day, because it is the cheapest and reliable way of transportable form of energy. As the demand of electricity keeps on increasing every day, a good strategic planning for the growth of the power system is critical for the future of this dynamic society.

According to the international energy agency (IEA) [1] report, the global electricity demand will be rocketed to 85% in 2040. Owing to the rise of living standards, the thriving of economies and the perennial demand of electric energy, electricity demand forecasting plays an important role on load allocation and planning for future generation facilities and for the beefing up of transmission line. Load demand in a given season is subject to a range of uncertainties including underlying population growth, adverse climate change and diversified economic conditions. Moreover, historical data have a substantive importance in demand forecasting.

Pursuant to Messrs., M.G Mengiste, B.Simegn, G.Eshete report in 2015[2], Ethiopia has multifarious renewable energy resources, viz. the estimated potential for hydropower is 45GW, wind is 10GW, geothermal is 5 GW, and solar irradiation potential ranges from 4.5kWh/m2/day to 7.5kWh/m2/day [2]. Based on the availability of energy resources, the government of Ethiopia through National Development Plan GTP [3] was planned to increase the power generation capacity from 2000MW in 2009/10 to 8000MW and to increase the construction of transmission lines from 11,440 km to 17000 km by the end of 2014-2015, and also in GTP – II [4] the plan was to increase the capacity of generation and transmission lines from 8000MW to 17000MW and from 1700km to 21728km respectively. Based on the actual fact to minimize the gap between supply and demand, the generation and transmission line expansion plan should rely on appropriate demand forecast which considers the growth of all possible scenarios.

In nutshell, accurate models for electric power load forecasting are essential to the operation and planning of any power and utility company. Load forecasting helps an electric power and utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development.

1.2- Statement of the Problem

In the past decade Ethiopia has been experienced average GTP I growth of 10.1% and the projected growth in GTP II is 11 percent per annum under the best case scenario and needs extra 13817 MW generation (to fulfill GDP I and II deficit), the target of GTP II for generation capacity is 17,208MW.The target of transmission line construction at the end of GTP II is 21728km and needs to construct additional length of 4578km from GTP –II[4].

In order to have reliable and sustainable energy to fulfill the planned economy, it requires a huge amount of investment in different sources of energy along with transmission line expansions. Otherwise, there would be high power interruption and loss of investment especially for planned energy export, for constructed and under construction of industrial parks. This initiated the researcher to make case study on the Ethiopia Electric Power functional performance.

Therefore, the purpose of this project is to include the government growth and transformation plan in the demand forecasting and transmission system expansion plan to obtain most accurate and reliable planning which will help to bridge the supply scenario and demand Power.

1.3- Objectives of the project

General objective is to make long – term load forecasting (up to 2037) and carry out transmission system expansion planning for central and southern region of Ethiopia under the organization of Ethiopian Electric Power.

The specific objectives of this thesis are:

- To carry out load forecasting using Artificial Neural Network (ANN)
- To collect and analyze past load data and un-served energy
- To develop an appropriate load model and test it with the model used by EEP
- To make recommendation and possible suggestion to EEP

This thesis makes an estimate of the electric needs of Ethiopia by the year 2037.

The data generated as a result will be useful in future generation planning for the country either from hydroelectricity or alternative sources of power. Therefore, load forecasting applications are of great importance. This information can be provided only by electric load forecasting. Nowadays the load forecasting is, by and large, done using the state-of-the-art deep learning technology.

1.4- Methodology

The necessary data for this study will be collected from Ethiopia Electric Power (EEP), Ethiopia Electricity Utility (EEU), reports from the Ministry of Water, Irrigation and Energy, and Ministry of Finance and Economic Corporation (GTP growth, and GDP projection) MOFEC.

Based on the collected data, the long–term load forecast will be done using artificial neural network method for the year of 2037 of Ethiopian Electric power. In this method the effect of uncertainty like Growth Domestic Product, population number of Ethiopia, Un- served –served electricity demand, the historical data of the driving parameter will be compared with existing EEP load forecasting Model.

Using a Computer Program Software “ETAP” the forecasted load found from Artificial Neural Network (ANN) will be analyzed to handle the complex electrical transmission system expansion plan for central and Southern Region of Ethiopian Electric power.

Additionally ,a review of literature will be conducted on the area of long term Load forecasting and Transmission system expansion planning is penetrating into system from available books, journals, case studies, and previous research are retrieved in order to have a clear understanding of the subject matter and adopting different concepts and methodologies as required.

Finally modeling and simulation studies will be conducted with appropriate software like ANN using MATLAB R2015a and ETAP 16 to analyze the forecast and Transmission system expansion.

1.5- Scope and Limitation of the Thesis

Albeit best of efforts to minimize all limitations that might creep in course of this thesis, there were certain constraints within which the research was completed. These are discussed below:

One of the constraints was the difficulty of collecting historical row data in time from the designed institutions (from Ethiopian Statistics Agency, Ethiopian Electric Utility, Ethiopian Electric Power, National Meteorology agency alike) due to their poor quality record management and documentations. Because of this the mentioned input historical data to feed the Artificial Neural Network (ANN) for thesis was garnered from the designed institutions has been took almost three months and needed to connect the highly scrambled information thoroughly and meticulously to give a pertinent meaning.

Given its abstract nature and the unprecedented complexity of the machine learning concept of artificial intelligence, collecting material and references and studying its behavior of how to get the maximum accuracy of electricity load forecasting for this particular paper was arduous task and time consuming.

The other predicament was fixing the technical glitch of MatlabR2015a and ETAP 16.0 software to run ANN toolbox and Load Flow Analysis respectively. Since the mentioned computer program are vastly advanced and comprehensive, making them working in tandem with the current Microsoft windows environment needed a painstaking technical effort.

To cap it all, the scope of the thesis resets solely on predicting of future long term load forecasting with possible error minimizing so as to use it for the load analysis of future transmission expansion and its limitation might be the reservation of assuring the near perfect accuracy of the electricity load forecasting for the given time with the given input.

1.6 - Thesis Structure

This thesis has five sections and summarized as follows.

Chapter 2: Discuss about literature review of the thesis, load forecasting techniques, theoretical back ground of Artificial Neural Network (ANN), benefits of ANN and Load forecasting using ANN.

Chapter 3: Discuss data collection, developing the model, training, validation of ANN simulation result, and compering the forecasted of ANN with data with EEP model (forecasted by consultant of EEP (Parsons Brinkerhoff) and updated EEP forecast).

Chapter 4: This Chapter represents the Transmission System Expansion Planning on the forecasted data for central and Southern part of Ethiopian Electric (EEP) network.

Chapter 5: The research work of these theses is concluded in this chapter, together with recommendation and further research work.

CHAPTER 2

LONG TERM LOAD FORCASTING AND TRANSMISSION LINE EXPANSION PLANNING

2.1 Literature review of Electric Load Forecasting

Long term Load Forecasting is the first and primary step in planning the future requirements of generation, transmission and distribution facilities in an electric grid. It is very essential for future network planning and expansion of the power system. In general, long term forecasts span from one year ahead up to ten years and they are often complex in nature due to future uncertainties such as creation of new village and towns, urbanization, etc.. With the recent growing advancements in technologies and smart grid developments, forecasting these values accurately, has become much more complex. An overestimated forecasted value will lead to unnecessary investments in power generation, whereas an underestimated value will result in customer discontentment. A relatively accurate prediction helps electric utilities in planning their existing networks properly which can provide more reliable and quality power to their customers. There are a large number of influential factors that affect directly or indirectly the underlying long term load forecasting process which are discussed in the next section.

Load forecasting is vital for fostering an electric utility to make important decisions on power market, load switching, voltage control, network reconfiguration, and infrastructure development. Load forecasting can be categorized into three types, viz***. Long term, Medium term and Short term.***

Long-term electric load forecasting used to supply electric utility company management with prediction of future needs for expansion, equipment purchases or staff hiring. This is longer than a year. *Medium-term* electric forecasting used for the purpose of scheduling fuel supplies and unit maintenance. This is usually from a week to a year. Short-term electric forecasting, it is used to supply necessary information for the system management of day-to-day operations and unit commitment [5][6]. Since this thesis uses long term load forecasting, its main focus remains mainly on it. Forecasting methods can generally classified into two major categories: Parametric (conventional) methods and non-parametric (Artificial Intelligence based) methods.

During the last few decades, many technics have been developed for long term electricity load forecasting in parametric methods, some of them Multiple Regression [7], Auto regression (AR) [8,9] Moving average [8,9], and Auto regression Moving (ARMA) ,etc.[9].

In [10] authors had presented extended the Artificial, Neural Network (ANN) technique to forecast electricity load for long term and was published in 2002.

Al-Saba and El –Amain [10] used artificial neural network for long term electricity load forecasting using Saudi Arabian Utility data. The utility provides service to large industry, commercial and residential load. They compered the result of ANN with Parametric method (AR) and the obtained result showed that ANNs provides relatively accurate result over Auto Regression (AR). This due to ANNs methods are able to automatically map the relationship between input and output by learning this relationship and store this learning into their parameter. And also ANNs has the ability to handle the non –liner relationship between the load and the factors affecting it. Whereas, “Parametric methods cannot properly present the complex non liner relationship that exist between the load and the factor affecting it”[11].

2.1.1 Long-Term Electric Load Forecasting

The end-use modeling, econometric modeling, and their combinations are the most often used methods for and long-term load forecasting. Descriptions of appliances used by customers, the sizes of the houses, the age of equipment, technology changes, customer behavior, and population dynamics are usually included in the statistical and simulation models based on the so-called end-use approach. In addition, economic factors such as per capita incomes, employment levels, and electricity prices are included in econometric models. These models are often used in combination with the end-use approach. Long-term forecasts include the forecasts on the population changes, economic development, industrial construction, and technology development. Long-term load forecasting methods are:

Econometric Analysis*:* The combination of economics theory and statistical techniques for forecasting of electricity demand is called Econometric methods. It uses historical data to forecast. It hypothesizes explicitly the causal relationship between energy or power (dependent variable) and independent variables such us Gross Domestic Product (GDP), technological utensils such us a number and type of appliance, industrial process and demography such us population [12]

i) **Artificial Neural Networks*:*** "Uses parallel distribution models that are capable of performance nonlinear modeling and adaptation without any assumption about the model" [17]. It does require assumption of functional relationship between load and weather variables in advance. We can adapt the ANN by exposing it to historical as well as new data to train and test the network with the large data and forecast the load for the required years.[13]

ii) **Multiple Linear Regressions*:*** Regression is one of the most widely used statistical techniques. Since, the load is totally dependent on the temperature, humidity, wind speed and day type parameters hence regression is used to obtain the relationship between load and these parameters. [14]

2.1.2.. Factors Affecting Long Term Electric Forecasting

i) **Economic Factor***:* The standard of living of people's living style will also affect the energy consumption. Apart from the increase in population, the increase in the standard of living of the people also does affect electricity consumption and is independent from the population increase as well as growth in country's economy. It is a process of natural evolution of mankind and the inherent urge for a better and comfortable life. The various indicators of standard of living are discussed.[15]

ii) **Weather Factor** Weather conditions do affect the electrical energy consumption as well as peak load. While the role of weather variables for short term forecasting is obvious, when it comes to long term load forecasting, the instantaneous variations in the weather variables may not have any effect on the forecast due to various reasons e.g. climate change etc., but the overall weather pattern change does affect the overall energy demand and annual peak load, as discussed below.

- **Temperature**: Day to day temperature variation might not be exactly needed, but the mean value of temperature round the year, or seasonal average temperatures as well as seasonal maximum temperatures might be better indicators as to estimate the temperature dependent trend in the energy consumption. The average of daily range of temperatures over the year might be another indicator. [15]

- **Humidity:** Humidity in the weather causes the weather to be cool, thus decreasing the electricity consumption. But in summer, humid weather causes sultriness in the weather and thus might cause increase in the energy consumption. [15]

- **Rainfall***:* Rainfall does effect the energy consumption. While the rainfall might cause the decrease in electrical energy consumption because of cooling effects, on the other hand, longer durations of rainfall might cause increased energy consumption because of increased usage of driers and heaters. Also, rainfall in off seasons (winter in most of our case) might reduce the usage of cooling equipment used in winter, but rainfall in summer and rainy seasons might hint increased energy consumption. Average rainfall in a year might better indicate the dependence of energy consumption. [15]

Even if the weather factor has a rare influence in the current Ethiopian climate condition, the above process has added as a theoretical background for the thesis.

iii) **GDP**: The market value of all final goods and services produced within a country in a given period of time is represented by GDP. It indicates the country's standard of living. GDP shows the size of economic activities that occur within a country[15]

iv) **Population:** Increase in population obviously hints the increased demand for electricity. In addition to this, various other related indicators exist that convey the increased demand with the increase in the population.

v) Economic factors such as per capita incomes and Electricity prices
Even if the weather factor has a rare influence in the current Ethiopia climate condition the above process has added as a theoretical background for the thesis.

2.2- How Load Forecasting Is Critical In Ethiopia

Ethiopia, being a developing country, electrical load forecasting is one of the most concerned tasks in the power market. Apart from the conventional factor that affects the load forecasting, there are some more factor that play an important role in the load forecasting in the country's power companies. Some of those can be listed as Energy Deficit Market, Significant Growth, Incessantly perennial growth of GDP (but from the bottom level) of the last decade, Technical and Commercial Losses, Shambolic Distribution Infrastructure, Inadequate Metering Infrastructure, Nascent Market Mechanism Regulatory Policies and alike.[15]

2.3- Load Forecast Technique

The only certainty about load forecasting is that it will not match the desired upshot. Developing a suitable demand forecasting technique is essential to tackle this variance of unmatched outcome. No technique would be considered incorrect for load forecasting.

The techniques used for load forecasting are classified into two categories: **parametric** and **artificial intelligence** based methods.

Parametric methods construct a statistical model of load by mining the qualitative relationships between load and factors affecting load. These methods include multiple linear regression, autoregressive and moving average, needed assumed parametric estimated from historical data. Usually they cannot deal with nonlinear or random relationships between load and factors affecting load.

Artificial intelligence methods comprise Fuzzy Logic, Artificial Neural Network (ANN), Dynamic theory (DS), Particle Swarm Optimization (PSO). Besides, there are also various hybrid methods [10] that combine the ability of individual methods to improve the accuracy of Long Term Load Forecasting (LTLF).

For this thesis ANN is proposed for a 22 year load forecasting in Ethiopia. ANN is a soft technique used in various optimization processes. These methods are able to perform nonlinear modeling and adaptation. It does not require assumption of any functional relationship between load and weather variables in advance. We can adapt the ANN by exposing it to new data. The ANN is also currently being probed as a tool in other power system problem such as security assessment, harmonic load identification, and alarm processing fault diagnosis and topology observability [16].

2.4- Artificial Neural Network

This chapter expounds a detailed theoretical background of an Artificial Neural network, its components and the know-how of their functionality behind the scene of the machine they operate.

2.4.1 WHAT IS ARTIFICIAL NEURAL NETWORK?

An artificial neural network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron. The processing ability of the network is stored in the inter unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns [17].

To flesh this out a little we first take a quick look at some basic neurobiology. The human brain consists of an estimated 100 billion) nerve cells or neurons, highly stylized example of which is shown in Figure 2.1. Neurons communicate via electrical signals that are short-lived impulses or "spikes" in the voltage of the cell wall or membrane. The interneuron connections are mediated by electrochemical junctions called synapses, which are located on branches of the cell referred to as dendrites. Each neuron typically receives many thousands of connections from other neurons and is therefore constantly receiving a multitude of incoming signals, which eventually reach the cell body. Here, they are integrated or summed together in some way and, roughly speaking, if the resulting signal exceeds some threshold then the neuron will "fire" or generate a voltage impulse in response. This is then transmitted to other neurons via a branching fiber known as the axon [17].

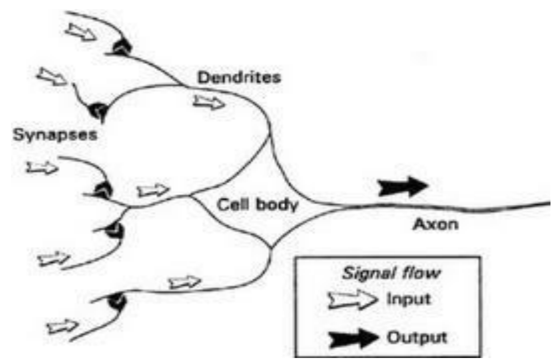

Figure 2.1 Essential components of a neuron shown in stylized form [16]

In determining whether an impulse should be produced or not, some incoming signals produce an inhibitory effect and tend to prevent firing, while others are excitatory and promote impulse generation. The distinctive processing ability of each neuron is then supposed to reside in the type—excitatory or inhibitory—and strength of its synaptic connections with other neurons [17].

It is this architecture and style of processing that we hope to incorporate in neural networks and, because of the emphasis on the importance of the interneuron connections, this type of system is sometimes referred to as being connectionist and the study of this general approach as connectionism. This terminology is often the one encountered for neural networks in the context of psychologically inspired models of human cognitive function. However, we will use it quite generally to refer to neural networks without reference to any particular field of application. The artificial equivalents of biological neurons are the nodes or units in our preliminary definition and a prototypical example is shown in Figure 2.2. Synapses are modeled by a single number or weight so that each input is multiplied by a weight before being sent to the equivalent of the cell body. Here, the weighted signals are summed together by simple arithmetic addition to supply node activation. In the type of node shown in Figure 1.2—the so-called threshold logic unit (TLU)—the activation is then compared with a threshold; if the activation exceeds the threshold, the unit produces a high-valued output (conventionally "1"), otherwise it outputs zero. In the figure, the size of signals is represented by the width of their corresponding arrows, weights are shown by multiplication symbols in circles, and their values are supposed to be proportional to the symbol's size; only positive weights have been used. The TLU is the simplest (and historically the earliest (McCulloch & Pitts 1943)) model of an artificial neuron [17].

The term "network" will be used to refer to any system of artificial neurons. This may range from something as simple as a single node to a large collection of nodes in which each one is connected to every other node in the net. One type of network is shown in Figure 2.3. Each node is now shown by only a circle but weights are implicit on all connections. The nodes are arranged in a layered structure in which each signal emanates from an input and passes via two nodes before reaching an output beyond which it is no longer transformed. This feed forward structure is only one of several available and is typically used to place an input pattern into one of several classes according to the resulting pattern of outputs. For example, if the input consists of an encoding of the patterns of light and dark in an image of handwritten letters, the output layer (topmost in the figure) may contain 26 nodes— one for each letter of the alphabet—to flag which letter class the input character is from. This would be done by allocating one output node per class and requiring that only one such node fires whenever a pattern of the corresponding class is supplied at the input [17].

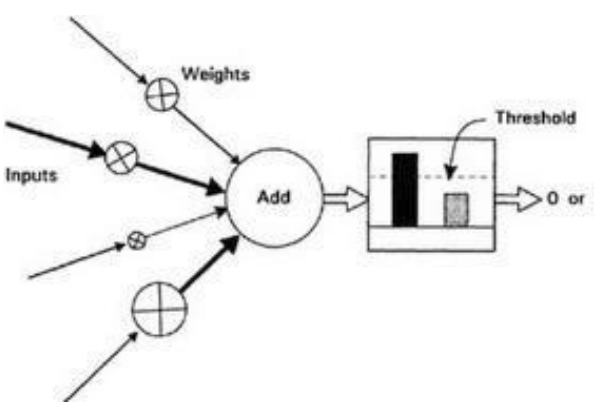

Figure 2.2 Simple artificial neuron [16].

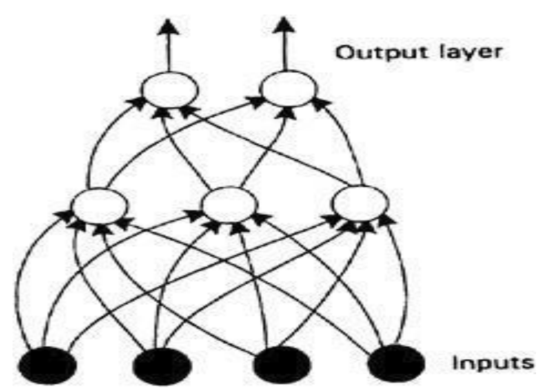

Figure 2.3 Simple example of neural network[16]

Returning to our working definition, and by noticing the emphasis on learning from experience, so much has implemented for the basic structural elements and their operation. In reality, neurons that have a synaptic strength might, under certain circumstances, be modified. Means, the behavior of each neuron can change or adapt to its particular stimulus input. In artificial neurons the equivalent of this is the modification of the weight values. In terms of processing information, there are no computer programs here—the "knowledge" the network has is supposed to be stored in its weights, which evolve by a process of adaptation to stimulus from a set of pattern examples. In one training paradigm called supervised learning, used in conjunction with nets of the type shown in Figure 2.3, an input pattern is presented to the net and its response then compared with a target output. In terms of our previous letter recognition example, an "A", say, may be input and the network output compared with the classification code for A. The difference between the two patterns of output then determines how the weights are altered. Each particular recipe for change constitutes a learning rule, details of which form a substantial part of subsequent chapters. When the required weight updates have been made another pattern is presented, the output compared with the target, and new changes made. This sequence of events is repeated iteratively many times until (hopefully) the network's behavior converges so that its response to each pattern is close to the corresponding target. The process as a whole, including any ordering of pattern presentation, criteria for terminating the process, etc., constitutes the training algorithm. [17]

What happens if, after training, we present the network with a pattern it hasn't seen before? If the net has learned the underlying structure of the problem domain then it should classify the unseen pattern correctly and the net is said to generalize well. If the net does not have this property it is little more than a classification lookup table for the training set and is of little practical use. Good generalization is therefore one of the key properties of neural networks.

2.4.1.1. Benefits of Artificial Neural Network

It is ostensible that a neural network derives its computing power through, first, its massively parallel distributed structure and, second, its ability to learn and therefore generalize. Generalization refers to the neural network’s production of reasonable outputs for inputs not encountered during training (learning).These two information-processing capabilities make it possible for neural networks to find good approximate solutions to complex (large-scale) problems that are intractable. In practice, however, neural networks cannot provide the solution by working individually. Rather, they need to be integrated into a consistent system engineering approach. Specifically, a complex problem of interest is decomposed into a number of relatively simple tasks, and neural networks are assigned a subset of the tasks that match their inherent capabilities. It is important to recognize, however, that we have a long way to go (if ever) before we can build a computer architecture that mimics the human brain. [17] Neural networks offer the following useful properties and capabilities:

- Non-Linearity. An artificial neuron can be linear or nonlinear. A neural network, made up of an interconnection of nonlinear neurons, is itself nonlinear. Moreover, the nonlinearity is of a special kind in the sense that it is distributed throughout the network. Nonlinearity is a highly important property, particularly if the underlying physical mechanism responsible for generation of the input signal (e.g., speech signal) is inherently nonlinear.

- Input-output Mapping. A popular paradigm of learning, called supervised learning, involves modification of the synaptic weights of a neural network by applying a set of labeled training examples, or task examples. Each example consists of a unique input signal and a corresponding desired (target) response. The network is presented with an example picked at random from the set, and the synaptic weights (free parameters) of the network are modified to minimize the difference between the desired response and the actual response of the network produced by the input signal in accordance with an appropriate statistical criterion. The training of the network is repeated for many examples in the set, until the network reaches a steady state where there are no further significant changes in the synaptic weights. The previously applied training examples may be reapplied during the training session, but in a different order. Thus the network learns from the examples by constructing an input-output mapping for the problem at hand.

- Adaptively. Neural networks have a built-in capability to adapt their synaptic weights to changes in the surrounding environment. In particular, a neural network trained to operate in a specific environment can be easily retrained to deal with minor changes in the operating environmental conditions. Moreover, when it is operating in a non-stationary environment (i.e., one where statistics change with time), a neural network may be designed to change its synaptic weights in real time. The natural architecture of a neutral network for pattern classification signal processing, and control application, coupled with the adaptive capability of the network makes it a useful tool in adaptive pattern classification, adaptive signal processing, and adaptive control.

- Evidential Response. In the context of pattern classification, a neural network can be designed to provide information not only about which particular pattern to select, but also about the confidence in the decision made. This latter information may be used to reject ambiguous patterns, should they arise, and thereby improve the classification performance of the network.

- Fault Tolerance. A neural network, implemented in hardware form, has the potential to be inherently fault tolerant, or capable of robust computation, in the sense that its performance degrades gracefully under adverse operating conditions. For example, if a neuron or its connecting links are damaged, recall of a stored pattern is impaired in quality. However, due to the distributed nature of information stored in the network, the damage has to be extensive before the overall response of the network is degraded seriously.

Uniformity of Analysis and Design. Basically, neural networks enjoy universality as information processors. We say this in the sense that the same notation is used in all domains involving the application of neural networks. [17]

Table 2.1 Benefits of Artificial Neural network

Industry	Application
Aerospace	High-performance aircraft autopilot, flight path simulation, aircraft control systems, autopilot enhancements, aircraft component simulation, and aircraft component fault detection

Automotive	Automobile automatic guidance system, and warranty activity analysis
Banking	Check and other document reading and credit application evaluation
Defense	Weapon steering, target tracking, object discrimination, facial recognition, new kinds of sensors, sonar, radar and image signal processing including data compression, feature extraction and noise suppression, and signal/image identification
Electronics	Code sequence prediction, integrated circuit chip layout, process control, chip failure analysis, machine vision, voice synthesis, and nonlinear modeling
Entertainment	Animation, special effects, and market forecasting
Financial	Real estate appraisal, loan advising, mortgage screening, corporate bond rating, credit-line use analysis, credit card activity tracking, portfolio trading program, corporate financial analysis, and currency price prediction
Industrial	Prediction of industrial processes, such as the output gases of furnaces, replacing complex and costly equipment used for this purpose in the past
Insurance	Policy application evaluation and product optimization
Manufacturing	Manufacturing process control, product design and analysis, process and machine diagnosis, real-time particle identification, visual quality inspection systems, beer testing, welding quality analysis, paper quality prediction, computer-chip quality analysis, analysis of grinding operations, chemical product design analysis, machine maintenance analysis, project bidding, planning and management, and dynamic modeling of chemical process system
Medical	Breast cancer cell analysis, EEG and ECG analysis, prosthesis design, optimization of transplant times, hospital expense reduction, hospital quality improvement, and emergency-room test advisement
Oil and gas	Exploration
Robotics	Trajectory control, forklift robot, manipulator controllers, and vision systems
Speech	Speech recognition, speech compression, vowel

	classification, and text-to-speech synthesis
Security	
Telecommunications	Image and data compression, automated information services, real-time translation of spoken language, and customer payment processing systems
transportation	Truck brake diagnosis systems, vehicle scheduling, and routing systems

(Source summarized from Neural Networks and Learning Machines third edition)

2.4.2 Network Architectures

The manner in which the neurons of a neural network are structured is intimately linked with the learning algorithm used to train the network. We may therefore speak of learning algorithms (rules) used in the design of neural networks as being structured. In general, there are three fundamentally different classes of network architectures:

2.4.2.1. Single Layer Feed-Forward Networks

In a layered neural network, the neurons are organized in the form of layers. In the simplest form of a layered network, we have an input layer of source nodes that projects directly onto an output layer of neurons (computation nodes), but not vice versa. In other words, this network is strictly of a feed-forward type. It is illustrated in Figure 2.4 for the case of four nodes in both the input and output layers. Such a network is called a single-layer network; with the designation "single-layer" referring to the output layer of computation nodes (neurons).We do not count the input layer of source nodes because no computation is performed there.

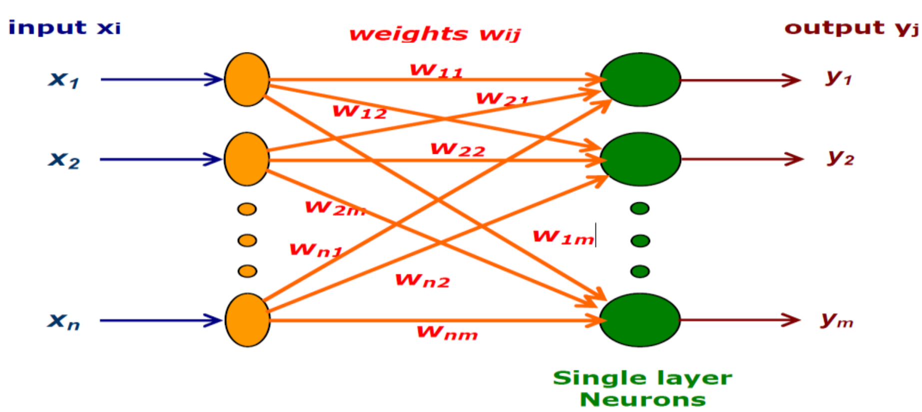

Figure. 2.4- Single layer feed forward network. [17]

2.4.2.2. Multilayer Feed-Forward Networks

The second class of a feed-forward neural network distinguishes itself by the presence of one or more hidden layers, whose computation nodes are correspondingly called hidden neurons or hidden units; the term “hidden” refers to the fact that this part of the neural network is not seen directly from either the input or output of the network. The function of hidden neurons is to intervene between the external input and the network output in some useful manner. By adding one or more hidden layers, the network is enabled to extract higher-order statistics from its input. In a rather loose sense, the network acquires a global perspective despite its local connectivity, due to the extra set of synaptic connections and the extra dimension of neural interactions.

The source nodes in the input layer of the network supply respective elements of the activation pattern (input vector), which constitute the input signals applied to the neurons (computation nodes) in the second layer (i.e., the first hidden layer).The output signals of the second layer are used as inputs to the third layer, and so on for the rest of the network. Typically, the neurons in each layer of the network have as their inputs the output signals of the preceding layer only. The set of output signals of the neurons in the output (final) layer of the network constitutes the overall response of the network to the activation pattern supplied by the source nodes in the input (first) layer. The architectural graph in Figure.2.5 illustrates the layout of a multilayer feed-forward neural network for the case of a single hidden layer. For the sake of brevity, the network in Figure 2.5 is referred to as a x_e–y_m–y_n network because it has x_e source nodes, y_m hidden neurons, and y_n output neurons.

2.4.2.3. Recurrent Networks

A recurrent neural network distinguishes itself from a feed forward neural network in that it has at least one feedback loop. For example, a recurrent network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons, as illustrated in the architectural graph in Figure.2.6. In the structure depicted in this figure, there are no self-feedback loops in the network; self-feedback refers to a situation where the output of a neuron is fed back into its own input. The recurrent network illustrated in Figure.2.7 also has hidden neurons.

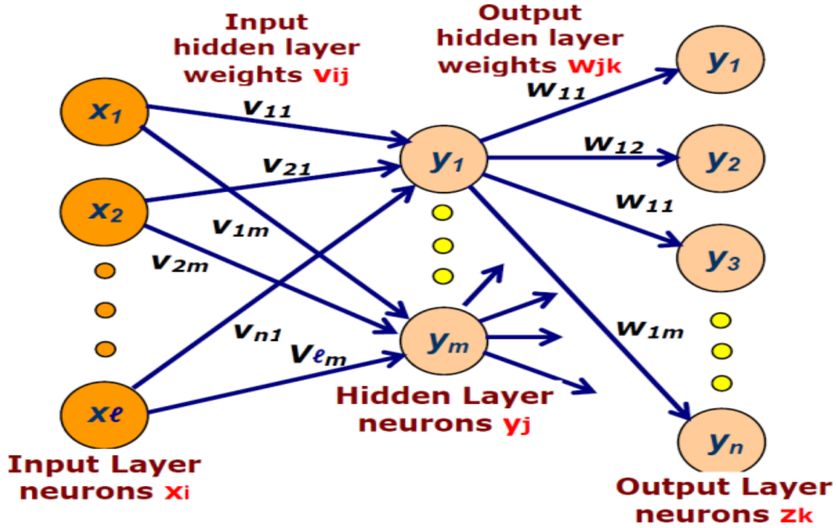

Figure 2.5- Multiple layer feed forward network [17]

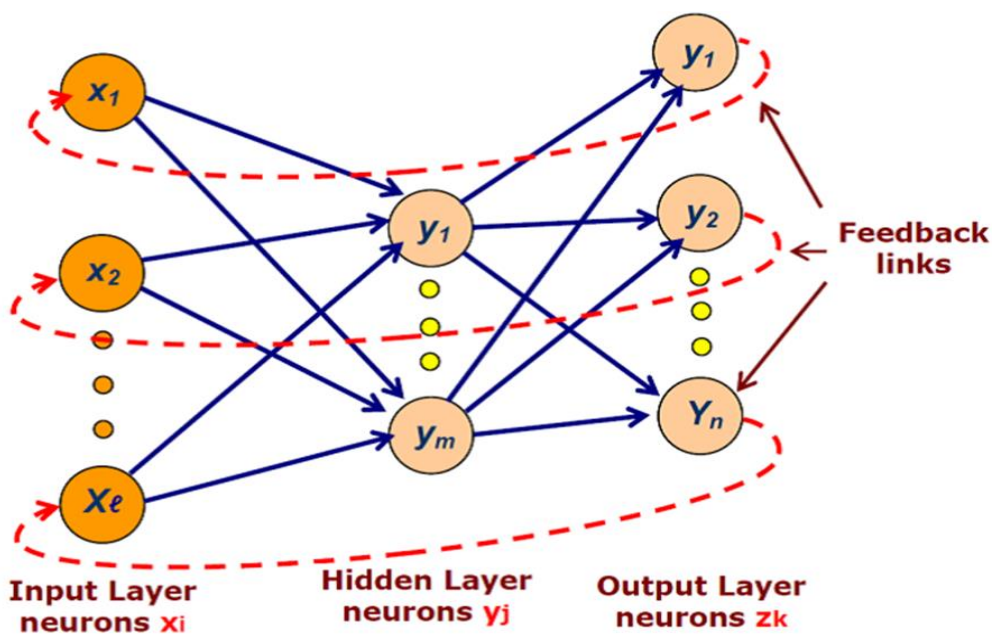

Figure 2.6- Recurrent Neural Network [17]

2.4.3 Learning Processes

Just as there are different ways in which we ourselves learn from our own surrounding environments, so it is with neural networks. In a broad sense, we may categorize the learning processes through which neural networks function as follows: Supervised learning and unsupervised learning. Figure 2.7 portrays learning process in neural network.

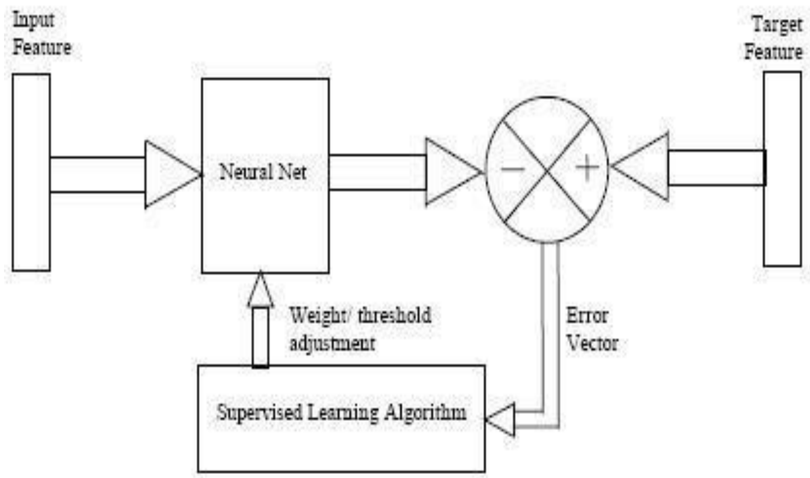

Figure 2.7 - Learning processes in neural network [17].

2.4.3.1. Supervised learning Process

In order for supervised learning to occur a teacher is need to give the neural network a target response. Using the training vector and the error signal, the network parameters adjust under the combined influence of the training vector and the error signal. Error correction learning (a step-by-step adjustment process) is used to get the neural network to copy the teacher. Figure 2.8 depicts the supervised learning process.

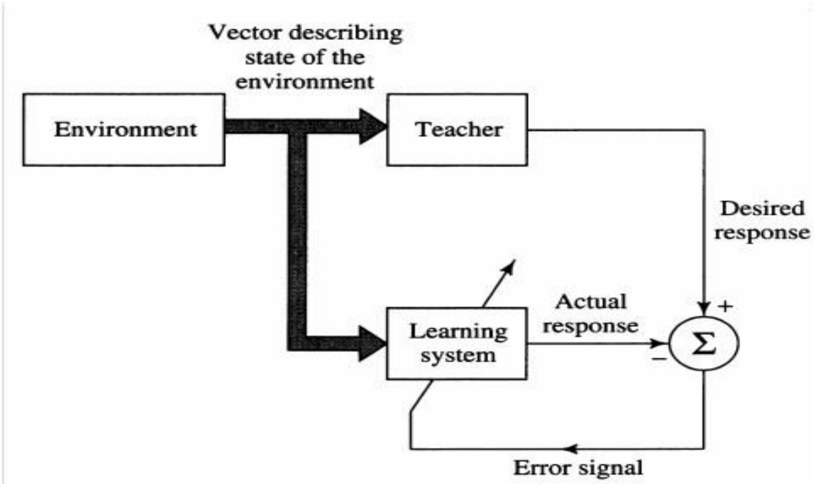

Figure 2.8 – Supervised learning process [17]

In supervised learning the training set consists of input patterns as well as their correct results in the form of the precise activation of all output neurons. Thus, for each training set that is fed into the network the output, for instance, can directly be compared with the correct solution and the network weights can be changed according to their difference. The objective is to change the weights to the effect that the network cannot only associate input and output patterns independently after the training, but can provide plausible results to unknown, similar input patterns.

2.4.3.2. Unsupervised learning Process

Unsupervised or self-organized learning process occurs without the use of a teacher. In other words, there are no specific samples of the function that the network needs to learn. Once the network understands the statistical regularities of the input data, it can automatically create internal representations for encoding features of the input data Figure 2.9 shows the unsupervised learning

Figure 2.9 – Unsupervised learning process [17]

Unsupervised learning is the biologically most plausible method, but is not suitable for all problems. Only the input patterns are given; the network tries to identify similar patterns and to classify them into similar categories [17].

2.4.4 MULTI-LAYER NEURAL NETWORK ARCHITECTURE

2.4.4.1. Neuron Model (logsig, tansig, purelin)

An elementary neuron with *R* inputs is shown below (in Figure 2.10). Each input is weighted with an appropriate *w*. The sum of the weighted inputs and the bias forms the input to the transfer function *f*. Neurons can use any differentiable transfer function *f* to generate their output.

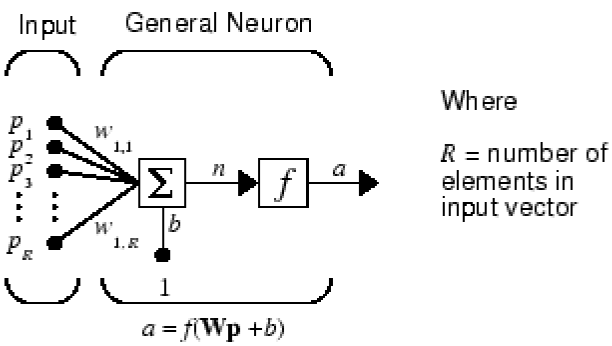

Figure 2.10 – Neuron model [10]

As Figure 2.11 below, multilayer networks often use the log-sigmoid transfer function logsig.

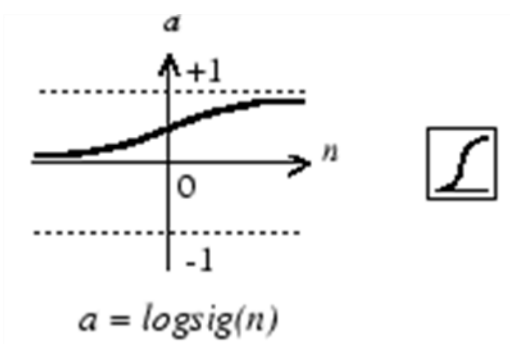

Figure 2.11 – log-sigmoid transfer function curve [10]

The function logsig generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity.

Alternatively, multilayer networks can use the tan-sigmoid (shown in Figure. 2.12) transfer function tansig.

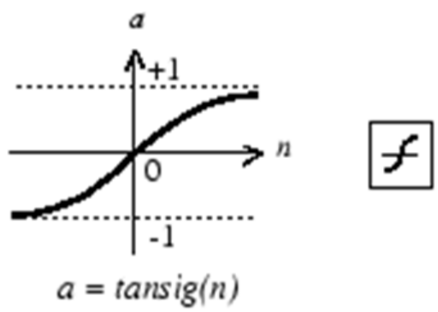

Figure 2.12– tan-sigmoid transfer function curve [10]

Sigmoid output neurons are often used for pattern recognition problems, while linear output neurons are used for function fitting problems. The linear transfer function purelin is shown below in Figure 2-11.

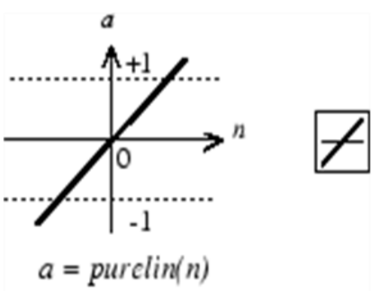

Figure 2.13 – Linear transfer function curve [10]

The three transfer functions described here are the most commonly used transfer functions for multilayer networks, but other differentiable transfer functions can be created and used if desired.

2.5.4.2. Feed-forward Neural Network

A single-layer network of *S* logsig neurons having *R* inputs is shown below (in Figure. 2-14) in full detail on the left and with a layer diagram on the right.

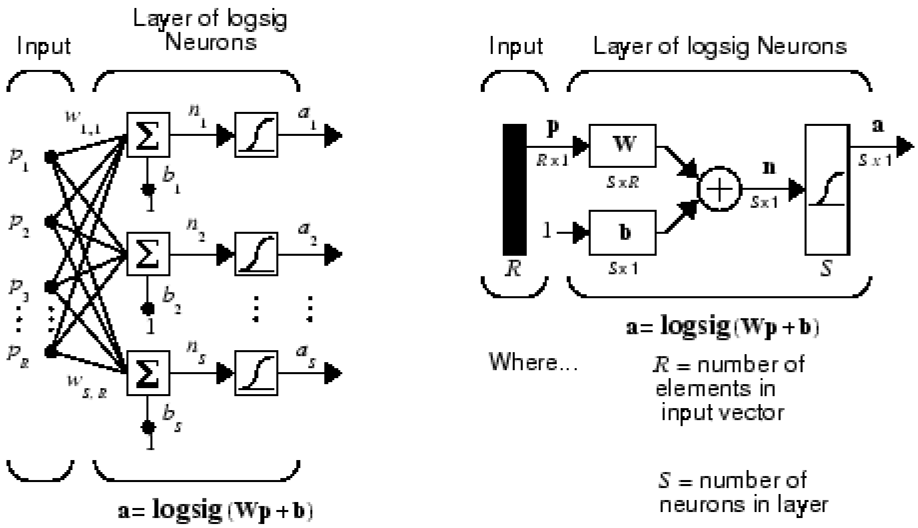

Figure 2.14 – A single-layer feed-forward network of *S* logsig neurons [10]

Feed-forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear relationships between input and output vectors. The linear output layer is most often used for function fitting (or nonlinear regression) problems.

On the other hand, if you want to constrain the outputs of a network (such as between 0 and 1), then the output layer should use a sigmoid transfer function (such as logsig). This is the case when the network is used for pattern recognition problems (in which a decision is being made by the network).

For multiple-layer networks the layer number determines the superscript on the weight matrix. The appropriate notation is used in the two-layer tansig/purelin network shown next.

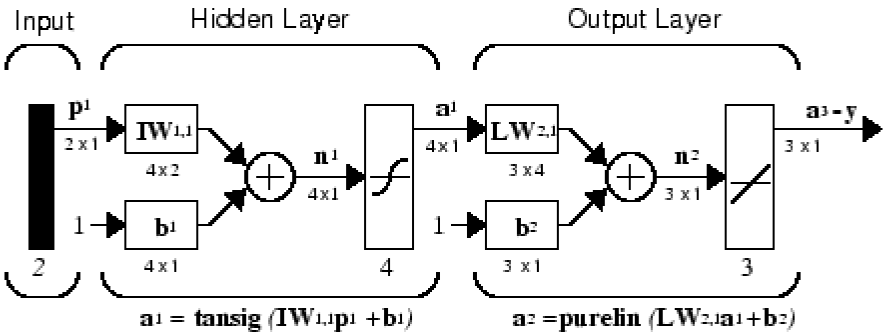

Figure 2.15 – A Multi-layer feed-forward network of tansig/purelin network [10]

This network can be used as a general function approximator. It can approximate any function with a finite number of discontinuities arbitrarily well, given sufficient neurons in the hidden layer.

2.4.5 LOAD FORECASTING USING ANN

The work flow for the general neural network design process has the following steps:

i) **Data Collection**: Before beginning the network design process, first collect and prepare sample data. It is generally difficult to incorporate prior knowledge into a neural network; therefore the network can only be as accurate as the data that are used to train the network. It is important that the data cover the range of inputs for which the network will be used. Multilayer networks can be trained to generalize well within the range of inputs for which they have been trained. However, they do not have the ability to accurately extrapolate beyond this range, so it is important that the training data span the full range of the input space. After the data have been collected, the pre and post processes are conducted. It is easiest to think of the neural network as having a preprocessing block that appears between the input and the first layer of the network and a post processing block that appears between the last layer of the network and the output.

ii) **Create, Configure and Initialize the Network**: After the data has been collected and divided in to two, as a predefined set of input and target vectors, they are ready to create the network by the ANN Toolbox in MATLAB program (the weights and biases of the network are initiated in the Ann toolbox).

iii) **Train, Validating and Testing the Network**: Once the weights and biases of the network are initialized, the network is ready for training, validating and testing. All these are also done by clicking the subsequent wizards created by ANN Toolbox in MATLAB program.

Then use the network for the intended load forecasting purpose.

2.6- Literature review of Transmission System expansion Planning (TEP)

The transmission line network expansion planning (TEP) is defined as the problem of determining where to locate the new transmission line, where and how much additional new capacity must be installed. The transmission line network expansion planning can meet increasing load demand and generation capacity over a given time horizon based on the national plan.

In Ethiopia both Transmission and generation assets are belonging to Ethiopian Electric power, (Government). In this setting, transmission Expansion planning should ideally be performed jointly with generation expansion. However, since the resulting optimization problem would be too complex to handle, electrical transmission and energy generation expansion plans are often determined separately, at least for large power system.

When the transmission line owner (mostly government) is under a regulated environment, the objective of the planning are to minimize the total revenue which required to implement a resource plan, as referenced in [18] and thus it is mostly a least cost planning approach has indicated, by Stoll, H.G. [19]. Because of in the regulated system, all data like demand forecasts, existing generators, are available for the planner with allocated financial resource and the required financial return investment plan.

Most of time the traditionally, the deterministic N-1/N-2 contingency planning methodology has been used for TEP. The system security is one of the challenge and important accept of Transmission System Operation (TSO). Because one of the most important factors in operation of power system is the desire to maintaining the system security.

Pursuant to a number of different literatures the expansion planning horizon is divided into short-, medium- and long-term periods, in accordance with type of decisions to be made, and with quality of the availability data information involved in the planning process, referenced in literature [19].

Proposing a method for linear flow estimation as an effective guide in the development of preliminary network design can be used for expansion planning referenced [20].

In recent years, a wide-ranging studies and researches have been conducted to crack on with the Transmission Expansion Planning (TEP) in order to simplify the problem and assuaging the onerous computational burden.

To desist from intricate integer variables, TEP is formulated using nonlinear or linear programing respectively. The rudimentary idea behind is that from the simulation result, an overloaded route indicates where new lines could be constructed. A number of papers formulate TEP as a mixed integer liner problem [21, 22], where nonlinear constraints are supplanted by equivalent lines ones. Albeit AC model describes power system most accurately, it can always lead to a large and convoluted nonlinear programing. As result, on basic of certain assumption, DC model ignoring reactive components is widely adopted to reduce the size of TEP [23, 24, and 25].

Myriads of methods have been applied and adapted to decipher the number-crunching computational algorithms. Branch and bound algorithm is proposed to directly deal with mixed integer non-linear problem in [26], where relaxation and separation strategies are utilized specifically, with the property of integer variable relaxed, the original problem is amended as a linear programming and solved directly. If the solution is integer, the global optimum can be obtained. Otherwise, the integer will separate the relaxed problem into two sub- problem based on the value of non- integer. Then the two sub problems are calculated independently and the same procedure is repeated until a global optimum is found [27].

The nonlinear and non-convex property of TEP has a focus area now days. Artificial methods like particle swarm optimization [28, 29], genetic algorithm [30], and chaos optimal algorithm [31] are implementing to solve heuristic methods of TEP problem. The primary advantage of these heuristic methods is interactive planning that is the system planner can observe the expansion process and direct its directions as it is, we cannot get optimal solution .Because the heuristic can be considered to be custom- made , contrary of model to mathematics [31].

Albeit it’s still a daunting task to crack the TEP conundrum when it comes to a gargantuan-scale power system and when multitude aspects have to be amounted, some simplification and computational techniques have been applied. Many studies and researches on TEP barely focus on applying a certain computational technique to the problem with taking a modicum of specific technical, economical or society based issues into considerations. Attention has not given to solve or simplify the challenges TEP problems [32]

CHAPTER 3

LONG-TERM LOAD FORECASTING

3.1- Demand Forecasting

In this chapter the data collected from different firms and the long term load forecast result obtained by following the procedure given in section 2.4.4 the comparison between the updated Ethiopian electric power (EEP) and the master plan (PB) load forecast against Artificial Neural Network performed.

3.1.1 Data Collection

The historical data of new demand requests (industrial sector, transport demand (rail way) and export sector) waiting customers (demand for waiting customers) ,the historical and forecasted data of the Gross Domestic Product (GDP) and population number of Ethiopia are collected from different firms and are given in section 3.2.2, to, 3.2.7, economic factor (the increase the standard of living of the people and the growth in the country economy) are also included .Maximum & Minimum temperatures, humidity and wind speed provided in Appendix A.

3.1.2 Industrial Sector Demand

There is a specific program being driven by government to establish industrial zone and specific information provided by EEP from Industrial Park development Corporation. The strategic plans of the Government is to build these premises, to provides the sufficient power supply and rent or sell it to the export oriented industries like: Leather processing, Textile manufacturing and Pharmaceutical appliances

Table 3.1 Industrial zone power requirement from 2019 on wards

#	Name of Industrial Park (IP)	Location	Demand(MW)	Project to be completed to utilize the required demand (G.C)
1	HAWASSA IP	HAWASSA	200	2023
2	MEKELE IP	MEKELE	117	2023
3	KOMBOLCHA IP	KOMBOLCHA	60	2022
4	BOLE LEMI 1IP	ADDIS ABABA	60	2020
5	BOLE LEMI 2IP	ADDIS ABABA	104	2021
6	KILINTO IP	ADDIS ABABA	160	2021
7	ADAMA IP	ADAMA	183	2024
8	JIMMA IP	JIMMA	50	2025
9	DIRE DAWA IP	DIREDAWA	200	2024
10	BAHIRDAR IP	BAHRDAR	50	2027
11	ARERTI IP	ARERTI	60	2021
12	DEBREBREHAN IP	DEBREBREHAN	200	2024
13	BEAKER Agro IP	HUMERA	50	2021
14	BURE Agro IP	BURE (DEBREMARKOS)	50	2021
15	GENDE ARBA Agro IP	BULBULA	50	2021
16	YIRGALEM Agro IP	YIRGALEM	50	2021
17	ISHA (AYSHA)	SOMALE Region	60	2025

(Source: Industrial Park Development Corporation (IPDC, 2018)

In addition to Industrial Park demand, both Ethiopian Electric Utility (EEU) and Ethiopian Electric Power (EEP) have received request applications for the supply of power from variety of industries which are not considered as Export Industries. The List of new Low Voltage (LV) and High Voltage (HV) industrials demand is provided in Appendix B

3.1.3 Historical Demand Data

The historical demand for the last 18 years (2001-1017) is presented on Table 3.2 below. All historical data calendar are adjusted from Ethiopian's to Gregorian's.

Table 3.2 Historic Electricity demand and Export demand from 2001 up to 2018 years

Year	Domestic (GWh)	Commercial (GWh)	Low Volage Industrial (Gwh)	High Volatge Industrial (Gwh)	Street Lighting (GWh)	Aux +own consumption (GWh)	Total sale (GWh)	Export (GWh)
2001	507.6	331.8	276.3	262.0	10.2	3	1388	0
2002	568.7	383.8	301.0	330.9	12.6	3	1597	0
2003	583.9	394.1	369.7	314.0	16.6	3	1678	0
2004	638	446.8	346.9	364.4	21.2	5	1817	0
2005	704.6	511.7	401.5	386.8	28.3	5	2033	0
2006	759.8	562	494.1	468.1	32.1	6	2316	0
2007	973.1	646	489.2	404.8	44.8	7	2558	0
2008	971.4	701.1	575.6	507.0	39.6	7	2795	0
2009	1192.7	632.5	519.5	543.0	18.8	7	2906	0
2010	1350.3	724.6	562.9	588.7	20.4	6	3247	0
2011	1541.7	1000.8	738.9	772.7	26.8	15	4081	17
2012	2140.3	881.1	1057.3	560.4	20.3	34	4659	332
2013	2056.7	1313.2	1263.1	876.2	27.5	42	5537	563
2014	2356.1	1504.4	1447.0	1003.7	31.5	49	6343	730
2015	2548.8	1627.5	1565.4	1085.9	34.1	54	6862	762
2016	3050.7	1947.9	1873.6	1299.7	40.8	61	8210	564
2017	3508.8	2240.4	2154.7	1494.6	46.9	70	9445	1305
2018	3818.8	2498.4	2754.7	2079.3	51	82	11284.2	2205

(Source: Ethiopian Electric utility 2018)

The Welfare Monitoring Survey reports on 2011 by Central Statics Agency (CSA) indicates that the total number of households was 16.14 million. Therefore, the number of people per household was 4.77 for the country as a whole.

Table 3.3 Historic Population, Household, and Customers from 2001 up to 2017 years

Year	Population	Number of house hold	Number of people per household	Number of Domestic Customers	Number of Commercial Customers	Low voltage Customers	Number of High voltage Customers	Straight Light Customers
2001	60	12.3	4.87804878	511788	75793	7916	91	917
2002	61.5	12.7	4.842519685	535254	79731	7957	96	987
2003	63.1	13.0	4.853846154	571975	83806	8204	93	1139
2004	64.7	13.4	4.828358209	637016	91863	8871	101	1267
2005	66.3	13.8	4.804347826	739009	104331	10036	122	1546
2006	68.0	14.1	4.822695035	820514	114281	11422	131	1782
2007	69.7	14.5	4.806896552	923390	125853	12083	154	2105
2008	71.5	14.9	4.798657718	1158640	164810	18432	200	2455
2009	73.3	15.3	4.790849673	1216270	162165	18104	169	2635
2010	75.2	15.7	4.789808917	1236869	165028	17476	158	2638
2011	77.1	16.1	4.788819876	1346439	189543	18796	266	2988
2012	79	16.6	4.759036145	1450252	209241	21682	142	3036
2013	81.0	17.0	4.764705882	1536390	230051	24133	220	3263
2014	83.1	17.5	4.748571429	1634052	248541	25322	134	3153
2015	85.2	18.0	4.733333333	1648532	258869	25083	94	3307
2016	87.3	18.4	4.744565217	1900908	287287	30698	286	3529
2017	90	18.9	4.761904762	2093159	317205	34503	315	3600

(source: Ethiopian Electric Power and Ethiopian Electric Utility 2018)

All the data: domestic customers, straight light, low voltage industrial and high voltage industrials customers were collected from Ethiopian Electric Power and Electric Power utility. For the domestic Customers, the number of customers doesn’t represent the actual number of customers household. Because some customers uses as shared connection form others who has energy meter.

3.1.4 Waiting list Customers

In the long term load forecast, the suppressed demand from 2016 to 2019, mostly urban customers and new connections of Urban and rural (lower consumers) are included.

Table 3.4 Waiting Costumer List

ETHIOPIAN ELECTRIC UTILITY CONNECTION WAITING CUSTOMERS LIST								
No.	**Region**	**Previous years backlog in numbers**			**Current year backlog in numbers**			**Total**
		Single Phase	**Three Phase**	**Total**	**Single Phase**	**Three Phase**	**Total**	
1	Northern AAR	5,550	896	6,446	1,380		1,380	7,826
2	Southern AAR	838	108	946	522	221	743	1,689
3	Eastern AAR	1,283	105	1,388	1,535	246	1,781	3,169
4	Western AAR	5,572	231	5,803	5,572	231	5,803	11,606
5	North Region	10,133	159	10,292			-	10,292
6	South Region	8,869	585	9,454	3,232	99	3,331	12,785
7	North west Region	14,810	878	15,688	10,166	27	10,193	25,881
8	West Region	8,317	473	8,790			-	8,790
9	North East Region	4,759	401	5,160			-	5,160
10	South East Region	10,133	159	10,292	2,082	60	2,142	12,434
11	East Region			4,133				4,133
12	Gambela Region	471	33	504	93	73	166	670
13	Giggiga Region			-			-	-
14	Assosa Region	318	43	361			-	361
15	Semera Region	-	-	-	-	-	-	-
	Total	71,053	4,071	79,257	24,489	884	25,373	104,796

(Source: The Ethiopian Electric Utility (EEU, 2018

Note:

The data source is head of Retail Business Office (EEU)

Almost all of the single phase applications are residential customers

The three phase customers could fall in all categories but the data providers unit has not sort out data in the form you are looking for currently.

3.1.5 New Railway Consumers

Apart from the currently main modern railway in the country –Addis Ababa- Djibouti (Sebeta –Mieso- Denwanle) Ethiopia has already planned the infrastructure of another ten main lines across the country which inevitable will demanded a significant amount of electricity demand. The inputs of rail way presented in Table 3.5

Table 3.5 Rail way demand input

Name of the project	Length (Km)	No of Traction Station	Power Demand in MW	Project to be compited
AWASH- WELDEYA/ HARA GEBEYA	403	10	380	2020
WELDIYA -MEKELE	260	6	240	2020
MOJO -XZEWAYE-AWASSA	197	5	165	2020
SEBETA- IJAJI- JIMMA -BEDELE	491	12	430	2022
WELDEYA/HARA GEBEYA -ASAYTA	229	5	200	2022
ASAYTA- ETHIO DIJUBUTEE BORDER	58	1	40	2021
SHASHEMENE -SODO-AREBAMINCH	246	6	200	2023
LJAJI- NEKEMT	96	2	80	2023
WELDEYA/HARA GEBEYA -WERETA	245	6	200	2024
FENOTE SELAME -BAHIRDAR -WERETA	216	5	170	2027
Total demand			2105	

(Source: Rail way Corporation 2018)

3.1.6 Export Demand

The current electricity export agreement with the neighbor Countries: Sudan (100MW), Djibouti (100MW), to Egypt through Sudan, to Kenya and to Tanzania are retained into the long term load forecast. The Ethio –Kenya first phase export agreement is based on the Power Purchase Agreement (PPA) [33], is the first 400mW Dc transmission line has signed for the next 25years. The second phase (1000MW) will follow suit based on the available of energy for export, the performance implementation of the existing agreement and Kenyan power system need. Note that all PPA is firm capacity and EEP should avail 95% the firm contractual capacity throughout the agreement period

The additional export to Sudan via Egypt and Tanzania are aligned with expected commission date for new large hydro power project (Great Ethiopian Renaissance Dam (GERD)).Exporting the additional energy in addition agreed one is based on the availability of energy and the price on the time. The price for all the export demand listed on the table 3.4 is fixed and agreed. The total demand export to neighboring countries is presented in Table 3.6

Table 3.6 Demand from export

	Peak Demand (MW)						
Year	Djibouti	Sudan	Sudan or Egypt	Kenya	Kenya II	Tanzania	Total
2012	100	100					200
2013	100	100					200
2014	100	100					200
2015	100	100					200
2016	100	100					200
2017	100	100					200
2018	100	100					200
2019	100	100					200
2020	100	100		400			600
2021	100	100		400			600
2022	100	100		400			600
2023	100	100		400			600
2024	100	100	1000	400		412	2012
2025	100	100	1000	400		412	2012
2026	100	100	1000	400		412	2012
2027	100	100	1000	400		412	2012
2028	100	100	1000	400		412	2012
2029	100	100	1000	400		412	2012
2030	100	100	1000	400		412	2012
2031	100	100	1000	400		412	2012
2032	100	100	1000	400		412	2012
2033	100	100	1000	400		412	2012
2034	100	100	1000	400		412	2012
2035	100	100	1000	400		412	2012
2036	100	100	1000	400		412	2012
2037	100	100	1000	400		412	2012

3.1.7 Population Data

The historical population data adopted in the forecast is based on the data obtained from the Federal Bureau of Central Statistics Agency of Ethiopia. The historical and projected population data used for the purpose is presented in Table 3.7 below.

Table 3.7 Population data

YEAR	POPULATION (millions)	Percentage growth (%)	YEAR	POPULATION (millions)	Percentage growth (%)
2002	61		2021	99.6	2.59%
2003	62.6	2.67%	2022	102.2	2.60%
2004	64.4	2.79%	2023	104.8	2.60%
2005	66.1	2.72%	2024	107.5	2.60%
2006	67.9	2.64%	2025	110.3	2.60%
2007	69.6	2.58%	2026	113.2	2.59%
2008	71.4	2.51%	2027	116.1	2.59%
2009	73.4	2.76%	2028	119.1	2.59%
2010	75.2	2.57%	2029	121.9	2.59%
2011	77.2	2.57%	2030	125.1	2.36%
2012	79.2	2.57%	2031	128.3	2.59%
2013	81.2	2.57%	2032	132.6	2.58%
2014	83.3	2.57%	2033	135	2.57%
2015	85.4	2.58%	2034	138.5	2.57%
2016	87.6	2.58%	2035	142	2.57%
2017	90.1	2.81%	2036	145.7	2.57%
2018	92.2	2.36%	2037	149.4	2.57%
2019	94.6	2.59%	2038		
2020	97.1	2.59%	2039		

*(*Source: Central Statics Agency (CSA, 2007)

According Central Statics Agency of Ethiopia, the country has not made projection of the number of population after 2007. The projected populations of Ethiopian were collected from website of Population Pyramids of the World Forum 1950 to 2100 and tabulated on table 3.8

Table 3.8 Projected population of Ethiopian by Population Pyramid of the world form

YEAR	POPULATION (millions)	YEAR	POPULATION (millions)
2002	61	2021	114.6
2003	62.6	2022	117.2
2004	64.4	2023	119.8
2005	66.1	2024	122.4
2006	67.9	2025	125
2007	69.6	2026	127.7
2008	71.4	2027	130.3
2009	73.4	2028	133
2010	75.2	2029	135.6
2011	77.2	2030	138.3
2012	79.2	2031	140.9
2013	81.2	2032	143.6
2014	83.3	2033	146.2
2015	85.4	2034	148.8
2016	87.6	2035	151.4
2017	90.1	2036	154
2018	92.2	2037	148.8
2019	109.4	2038	
2020	111.97	2039	

(Source; populationpyramid.net)

According to Population Pyramids in the World from 1950 to 2100, the number of population of Ethiopian is around 109Million in 2019. This result is slightly higher than the estimation done by the Central Statically Agency in 2017 that projected the total Ethiopian population in 2019 to be around 94.6 million.

3.1.8 GDP data

The historical Gross Domestic Product (GDP) from 2015-2018 and forecasted of GDP from 2019-2022 are obtained from International Money Fund (IMF) and World Bank websites and presented below in Table 3.9

Table 3.9 Historic GDP data

	2015	2016	2017	2018	2019	2020	2021	2022
International Monetary Fund (IMF) portal http://www.imf.org/external/datamapper/NGDP_RPCH@WEO/ETH?year=2017	10.40%	8%	10.36%	8.55%	8.34%	8.05%	7.80%	8.04%
Statistics portal. https://www.statista.com/statistics/455074/gross-domestic-product-gdp-growth-rate-in-ethiopia/	9.60%	8.40%	8.46%	8.45%	8.08%	7.80%	7.47%	7.47%
World Bank portal. http://www.worldbank.org/en/publication/global-economic-prospects#data	9.60%	7.50%	8.50%	8.20%	7.80%	7.80%		

3.2 Sugar Factory

The demand for sugar industries is used to be curtailed during the crop season (May to October) of the year in which the factories are cogenerated using their own plant using bagasse to cover their own power demand. During the off- crop season (June to September), through, their power demand is tapped to EEP grid. Means, only during the off- crop season demand is to be included in the demand forecast. The required Demand is tabulated in Table 3.10

Table 3.10 Maximum power request for housing, irrigation and factory for new sugar factories.

Year	2020				2021			
Site Neme	Tana Beles	Welkait	Omo	Kesem	Tana Beles	Welekiyte	Omo	Kesem
No. factories	4	1	6	1	4	1	6	1
Residential (MW)	12.22	4.9	26.72	5.4	1.14	1.78	13.36	1.2
Non-residential (MW)	4.46	1.42	7.21	2.9	0.414	0.52	3.6	0.7
Compound Light (MW)	0.51	0.41	1.12	0.2	0.05	0.15	0.56	0.1
Power for irrigation (MW)	2	57.38	82.88			19.13	27.63	
Power for factories (MW)	20	5	30	5			15	5
Total (MW)	43.19	70.11	153.93	10.2	5.604	22.58	66.15	6.9

3.3 New Irrigation Demand

There is an extensive program for developing of new agricultural irrigation around the country. The information from each region was collected from EEP and EEP and also the estimated required consumption rate for each irrigable land as well. It is 0.34 - 5.4 kW per hectare. The required power for agriculturally irrigable schemes is enclosed in Appendix C.

3.4- Forecast Model

This section portrays an ANN-based model that was developed as a solution to specification, based on the literature that was reviewed. For comparative purposes, data from EEP (forecasted data) was obtained. The first two sections describe the procedures used in to develop the models starting with ANN. Results from two models are then analyzed and compared.

The data used in the model to train the Neural Networks are:

- Previous year load demand
- Maximum and Minimum temperatures
- Humidity
- Wind velocity

3.5- Development of the ANN model

The standard steps of the Neural Network model design steps are as follows: [10]

- Collect data
- Create data
- Configure the Network
- Train the Network
- Validate the network

Following these steps using the Graphic User Interface (GUI) in MATLAB2015a program The model uses the Neural network Fitting Function (one of the functions in the GUI)

1. Open the Neural Network Start GUI with this command: nn start

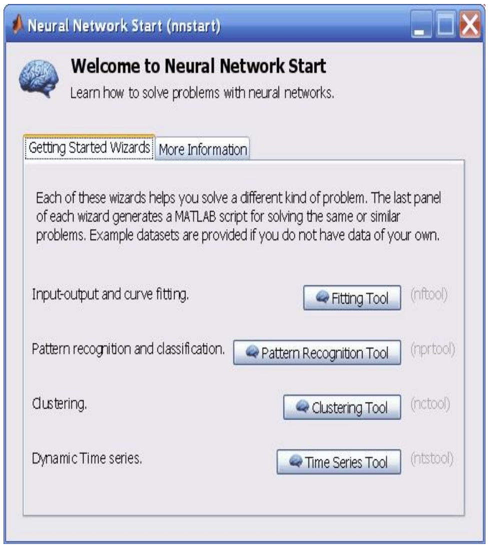

Figure 3.1: The wizard that shows the neural network start

2. Click Fitting Tool to open the Neural Network Fitting Tool.

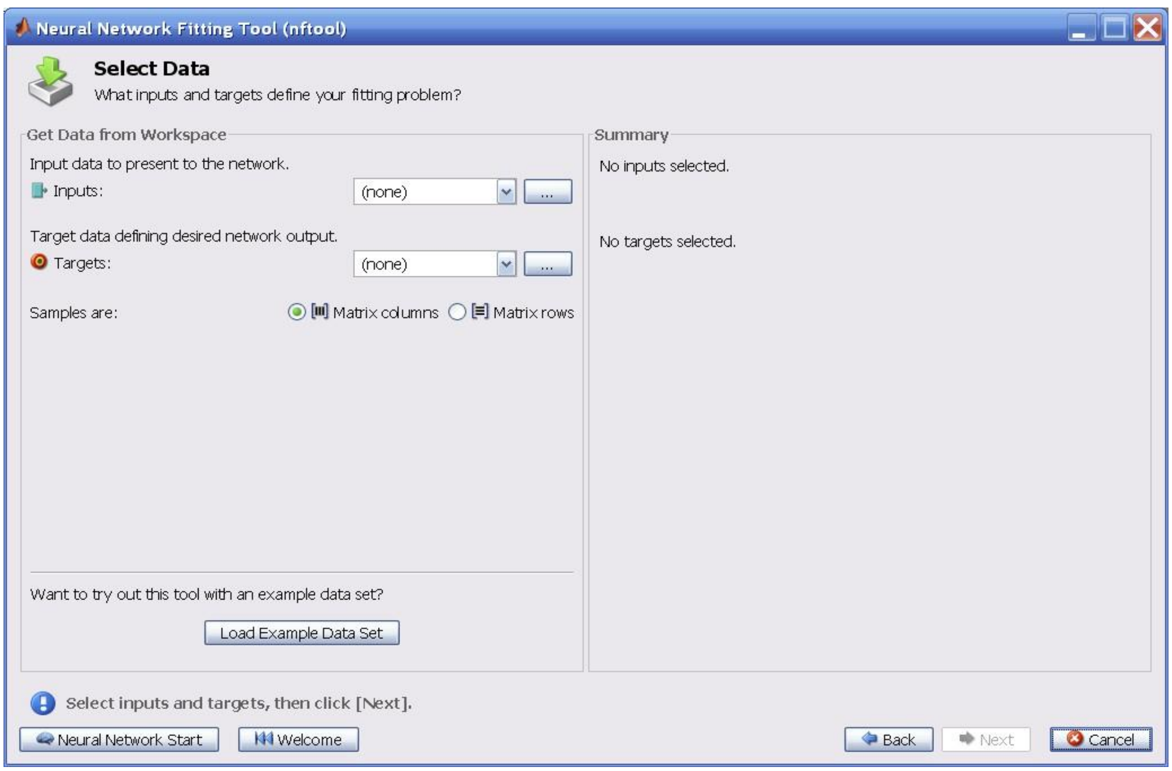

Figure 3.2: The wizard that shows the neural Fitting tool

Select data to proceed (data is selected from the gathered)

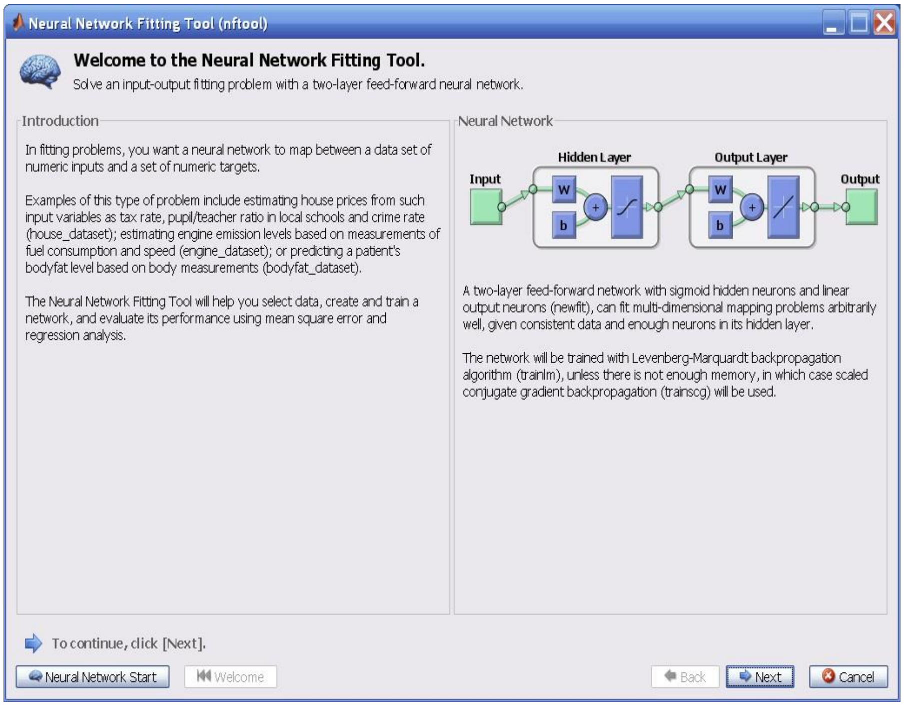

Figure 3.3 the wizard that shows the gathered data selection

At this point, the Inputs and Targets options lead to load data from the MATLAB workspace.

Click Next to display the Validation and Test Data window, shown in the following figure The validation and test data sets are each set to 15% of the original data. With these settings, the input vectors and target vectors will be randomly divided into three sets as follows:

- 70% will be used for training.
- 15% will be used to validate that the network is generalizing and to stop training before fitting
- The last 15% will be used as a completely independent test of network generalization

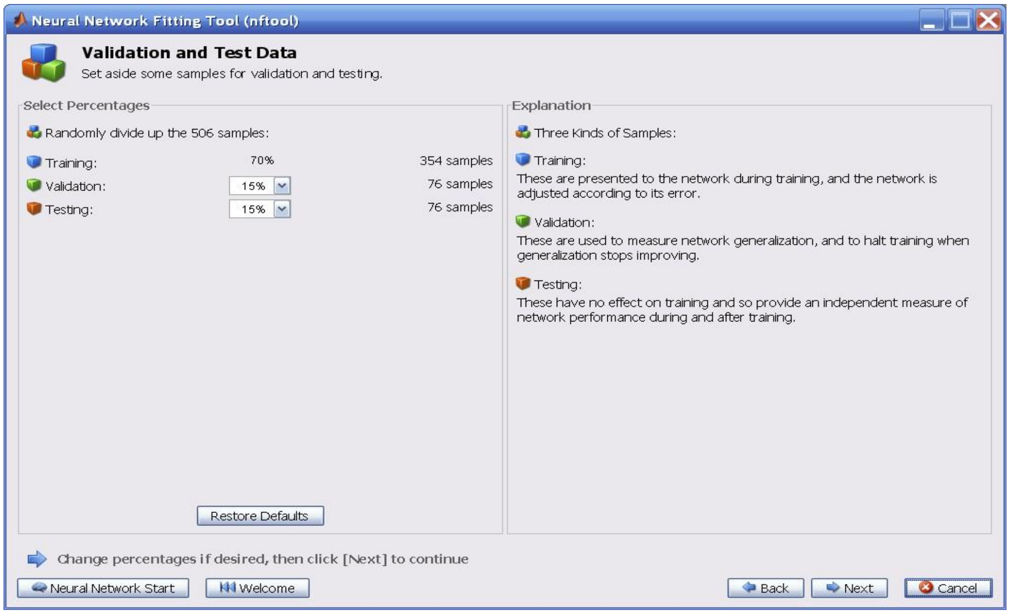

Figure 3.4 the wizard that shows the validation and test data

Click next

The standard network that is used for function fitting is a two-layer feed forward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The default number of hidden neurons is set to 10. It can be increase this number later, if the network training performance is poor.

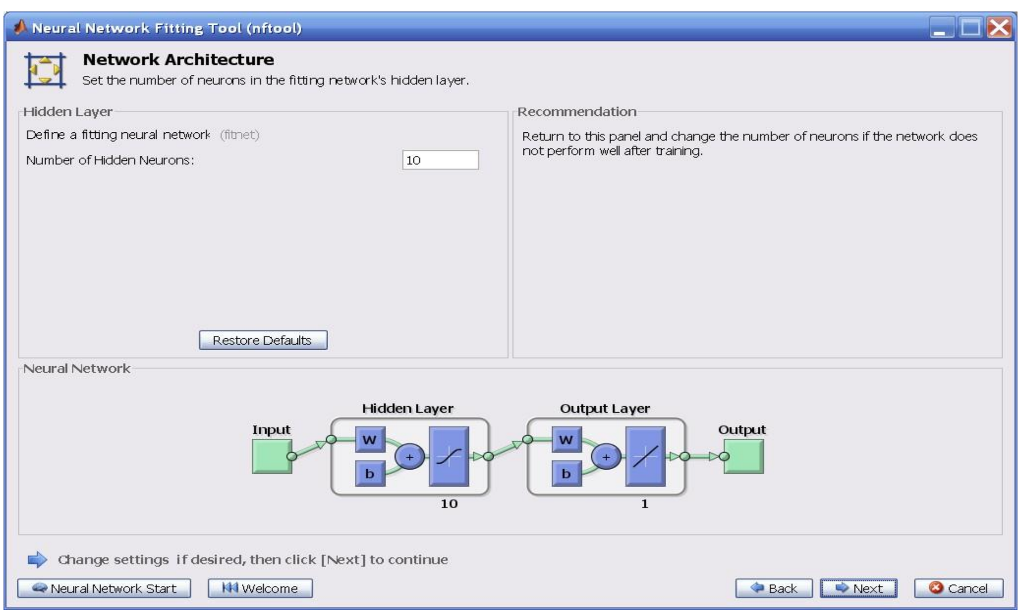

Figure 3.5 the wizard that shows Network structure

3. Click next

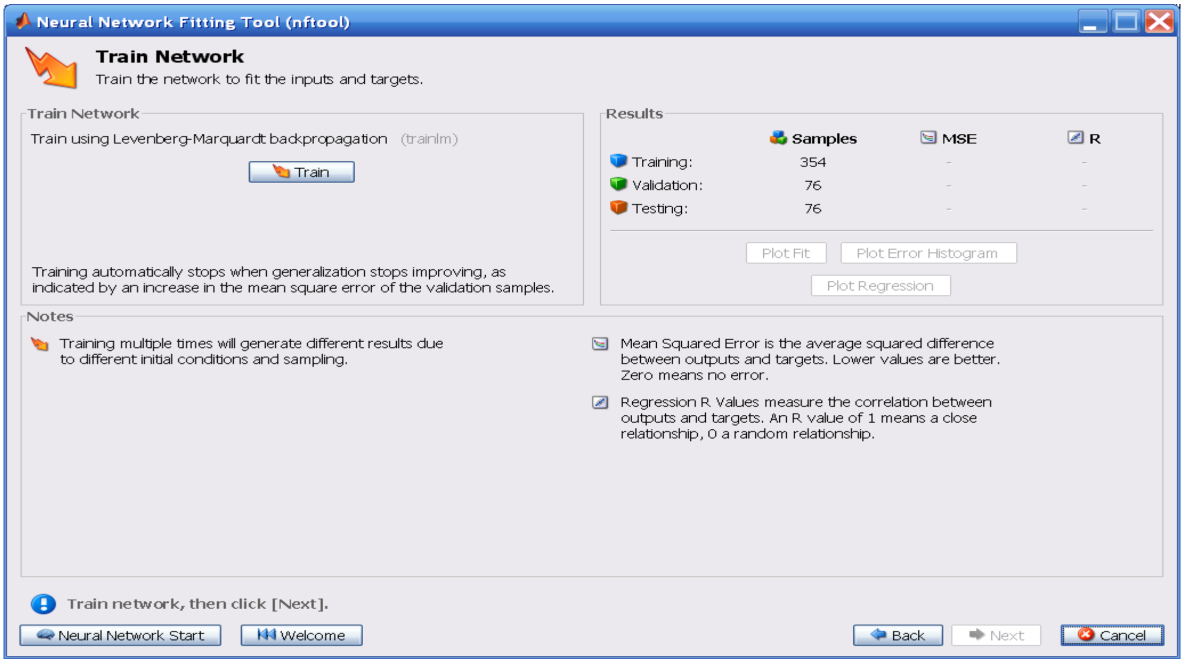

Figure 3.6 the wizard that shows the train network page

So far has generally been the standard procedure of modeling the general neural network on the Neural Network Toolbox. For this particular project (with specific input and target data), the steps are implementing in the next section.

3.6- Long Term Load Forecasting Using ANN

3.6.1 Data collection and implementation of ANN for long term load Forecasting (from 2002-2009)

The historical data can be divided into two categories which are actual load and the monthly weather parameters such as temperature, humidity, wind speed, rainfall. The actual load and the weather data were garnered from the Ethiopian Electric Utility and Ethiopian Electric Power Companies, and it covers a period of 96 months from January 2002 to December 2009.

3.6.2 Implementation of ANN using MATLAB R2015a

- By in putting the data saved in the excel spreadsheet, the historical seven year data has fed into the neural network fitting tool found in the Neural Network toolbox in MatlabR2015a software. The neural Network has two layer feed forward network with sigmoid hidden neurons and linear output neurons and used a Lavender Marquardt back –propagation algorithm for the training as shown in figure 3.2. Next, the data chosen is divided into two parts as input of weather variables and previous year load , and the other is actual load as an output as shown in figure 3.3.

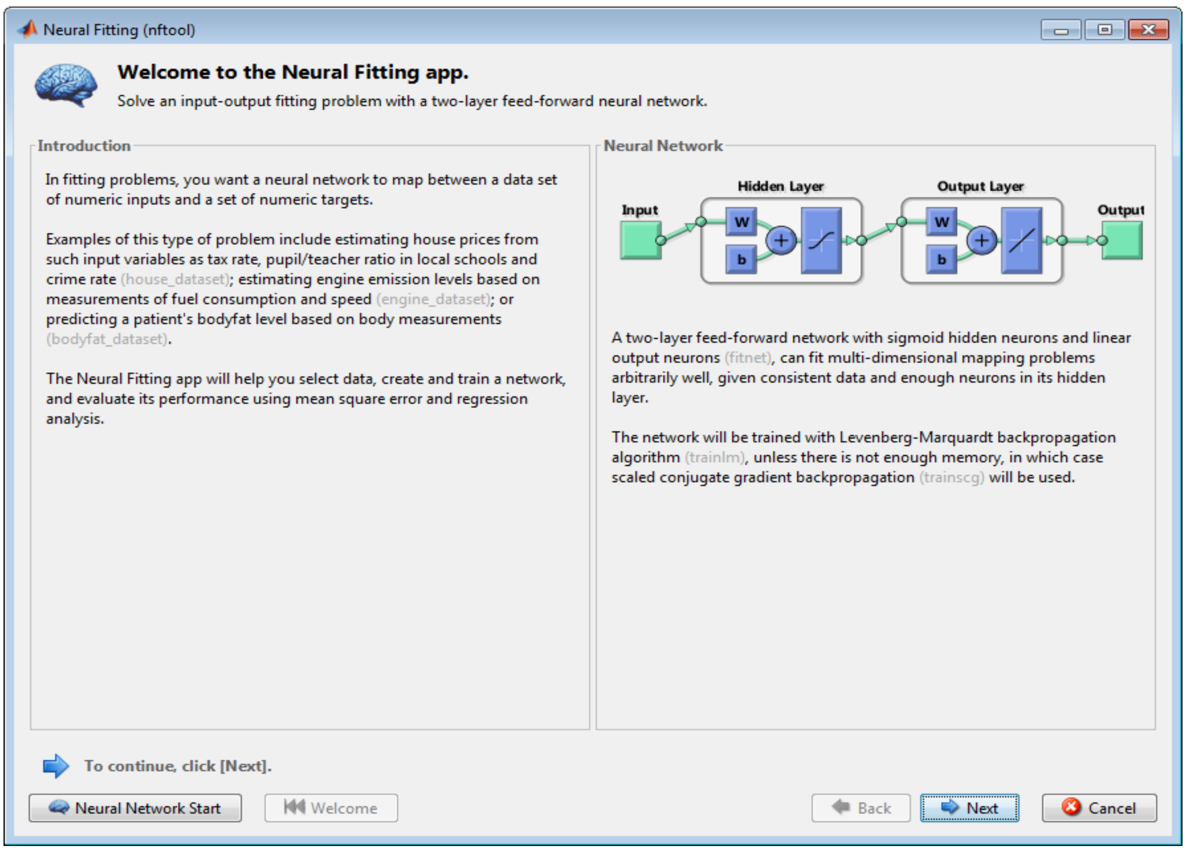

Figure 3.7- Neural fitting tool in MATLAB R2015a

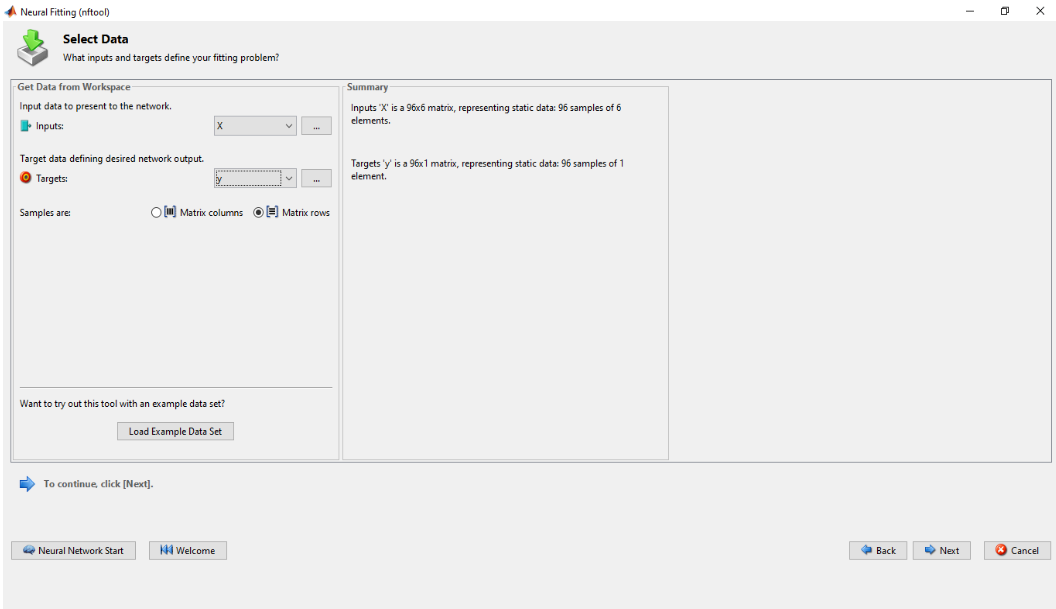

Figure 3.8- ANN input and output data preparation

- Next step was Training, validation and testing settings, on which, the training was set to 70% of samples, validation and testing was both share equally 15% of the remaining samples as depicted in figure 3.4

- Number of hidden neurons was 10 but could be increased if the error got high and retrain would be done in order to obtain the plots of the implement. The hitherto optimization of the ANN implementation in this project is depicted in figure3.5.

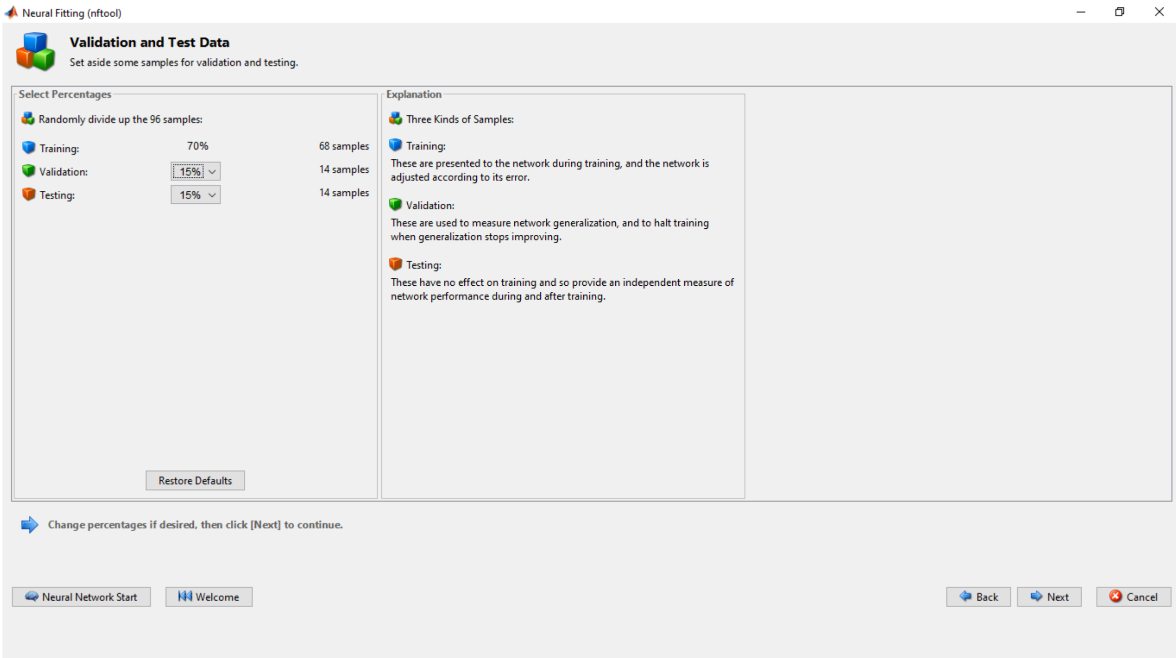

Figure 3.9 Training, Validation and testing setting

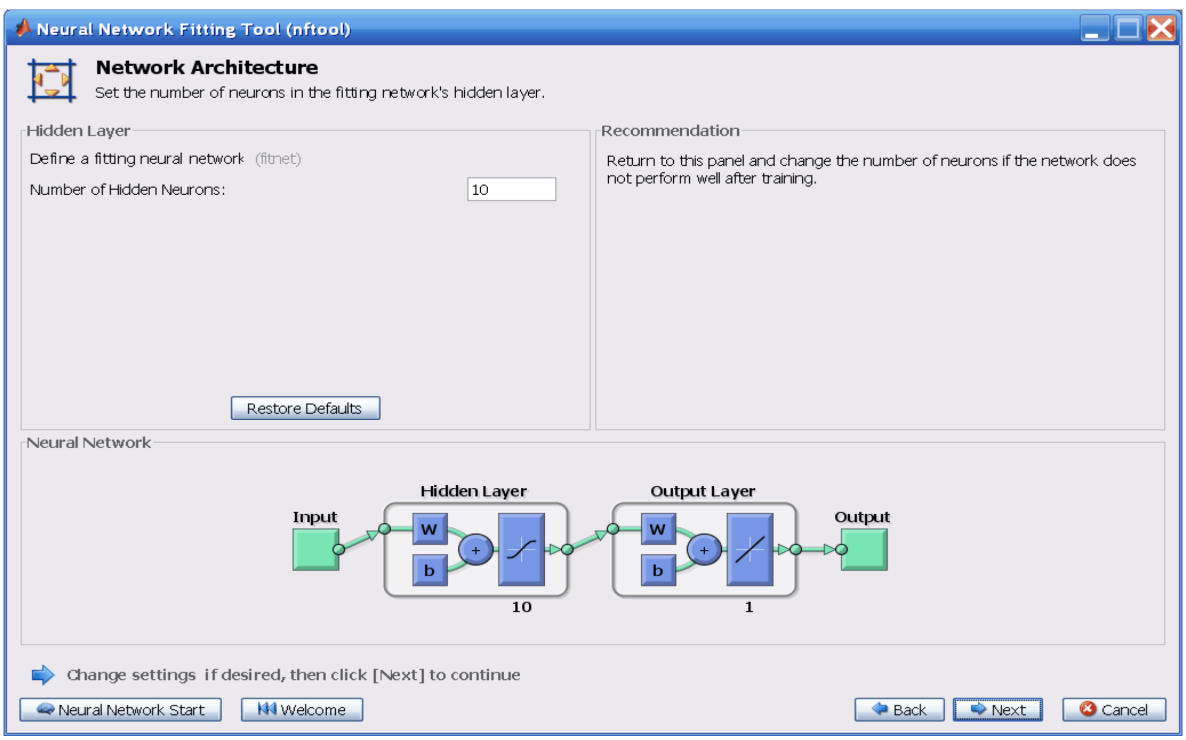

Figure 3.10 – Optimized Network Architecture

- The training was done in supervised manner that is for every input vector, the desired outputs is given and weights are adapted to minimize an error function that measures the discrepancy between the desired output and the output computed by the network. Given the input historical data and number of neurons in hidden layers (10) for this specific network the training tool in the neural network toolbox delivered twenty four iterations has processed as shown in figure 3.6.

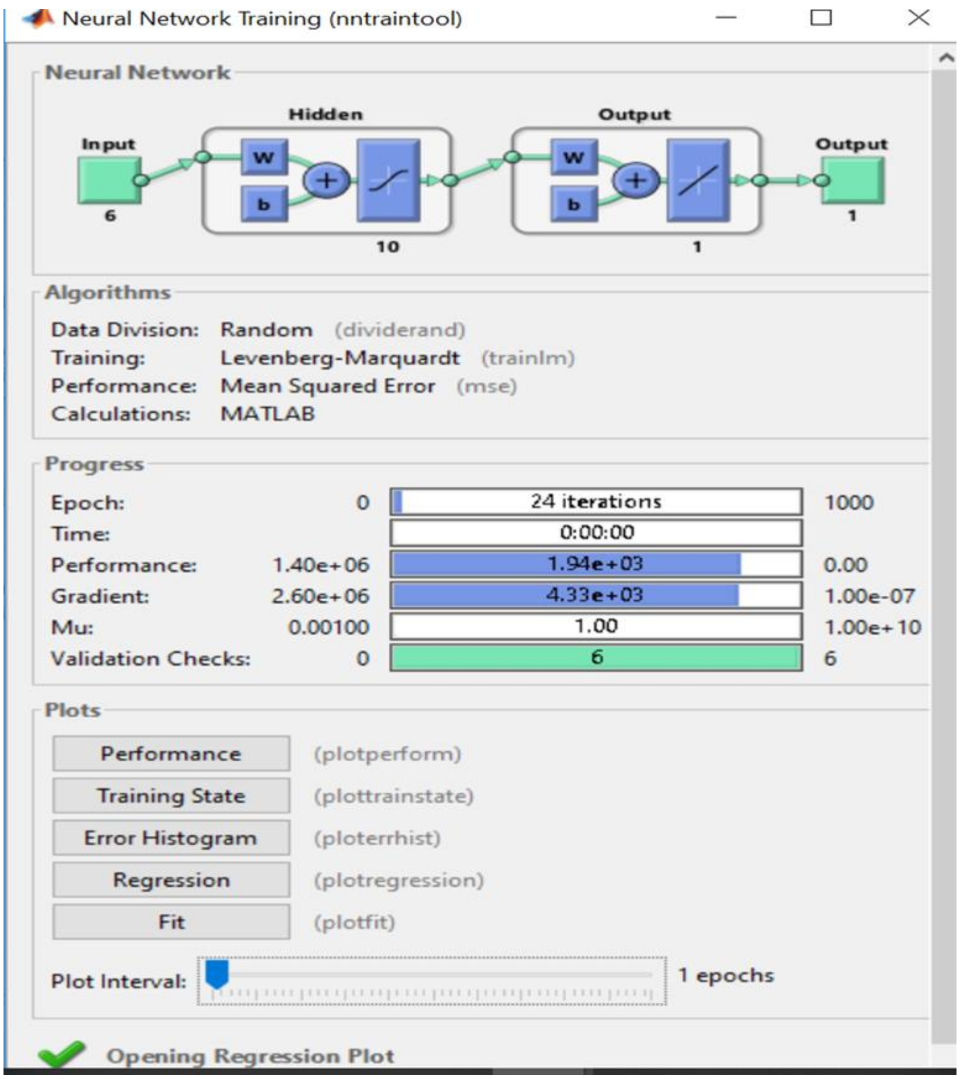

Figure 3.11 – Results of ANN for the mentioned particular entries

- After the training phase has processed all epochs (an entire data set is passed forward and backward only once through NN [10]), its performance could be judge in terms of the globally calculated MSE. After all epochs of the training phase were processed the network was ready for predication and generalization. The foregoing ANN performance plot is portrayed in figure 3.12.

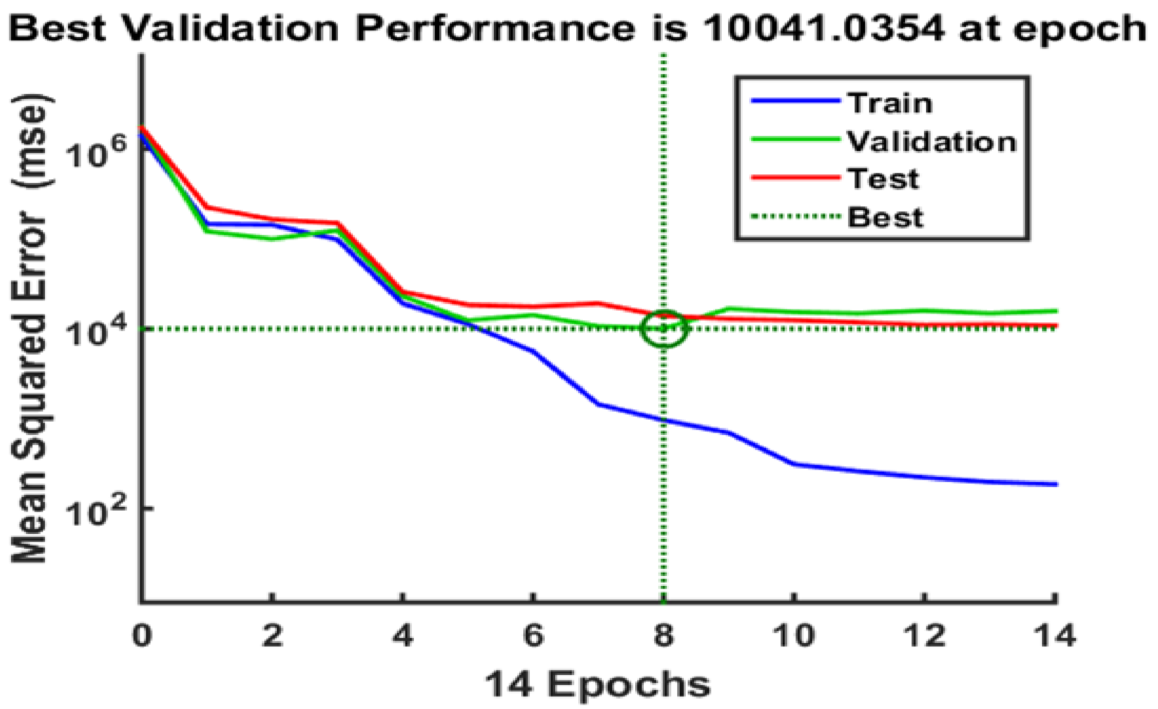

Figure 3.12 – ANN performance plot

An epoch is when an entire dataset is passed forward and backward only once through the Neural Network [15]. From figure 3.12 the total number of each epoch produced is 14. It also can be seen that the best validation performance is 10041.0354 at epoch 8.

As depicted in figure 3.13 below, there are three juxtaposed plots that expound the training, test and validation regression. The aggregate plot shows the fair closeness between the outputs and the target. The regression plot value of one (R = 1). The regression plot for training is R = 0.9828. Also, for testing is R = 0.96097. By the same token, for validation is R = 0.98337. This indicates that the neural network predicted the output satisfactorily.

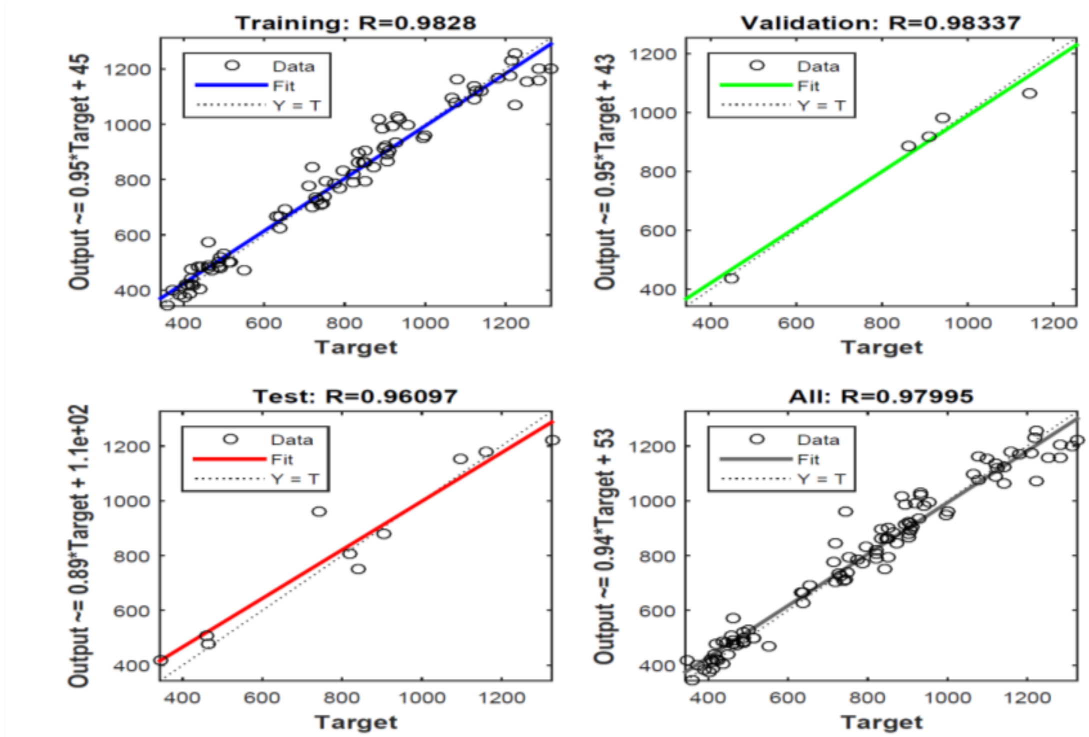

Figure 3.13 – ANN regression plot

3.7 Simulation Results

The plot below portrays the simulation outcome of the ANN

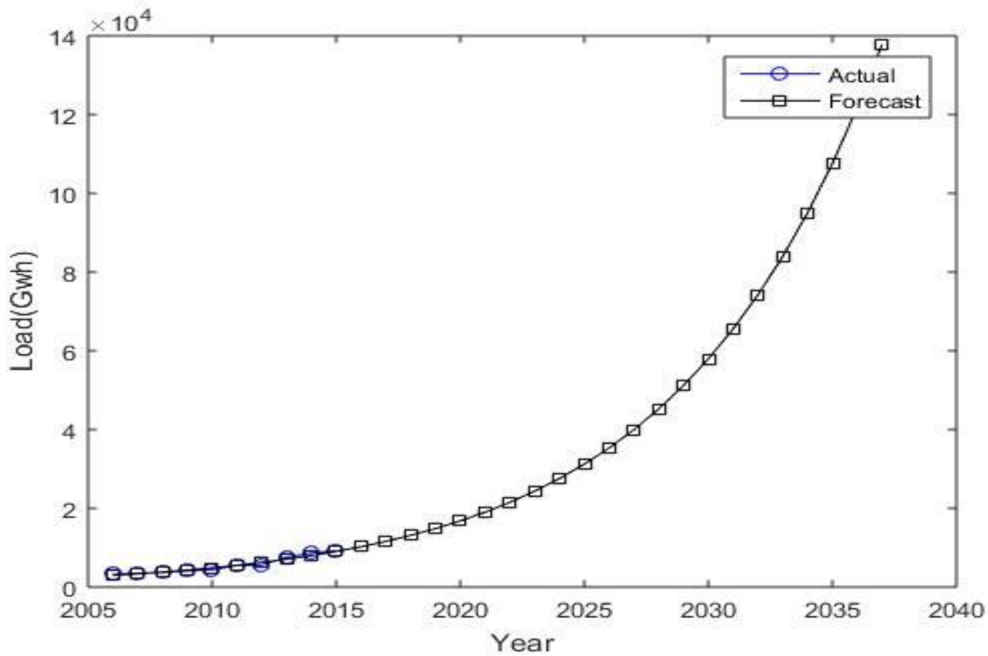

Figure 3.14: ANN output results (forecasted load for 2016-2037)

The observed simulation result is used to compare with the conventional method implemented by EEP model.

3.7.1 Simulation Result of Long Term Load Forecasting using ANN and comparison with EEP Model

Table 3.11 below presents, the future 22 years forecasts by updated EEP, Parrson Brinkerhoff (master plan of EEP) and ANN by using identical load profile.

Table 3.11: ANN, PB (EEP master plan) and updated EEP forecasted results (GWh)

Year	Ann Forecast	PB Forecast (EEP master Plan	EEP Normalized Forecast
2016	10245.21	18090	14167.60
2017	11594.78	23350	17472.39
2018	13122.13	28291	20706.56
2019	14850.67	32716	23783.33
2020	16806.91	36810	26808.45
2021	19020.84	41106	30063.42
2022	21526.40	46848	34187.20
2023	24362.01	50830	37596.01
2024	27571.15	54984	41277.58
2025	31203.03	59511	45357.01
2026	35313.32	64554	49933.66
2027	39965.05	70082	55023.52
2028	45229.53	76124	60676.77
2029	51187.50	82713	66950.25
2030	57930.29	89756	73843.14
2031	65561.29	97415	81488.14
2032	74197.50	105660	89928.75
2033	83971.33	114486	99228.67
2034	95032.65	123881	109456.82
2035	107551.04	133884	120717.52
2036	121718.45	144532	133125.22
2037	137752.09	155786	146769.04

The comparison curves among ANN, updated EEP and PB (EEP, master plan) forecast are portrayed in the plot below. Since human manipulation (which could be error-prone) of the data is rare in the artificial intelligence based ANN Toolbox, it's more effective method than the other two

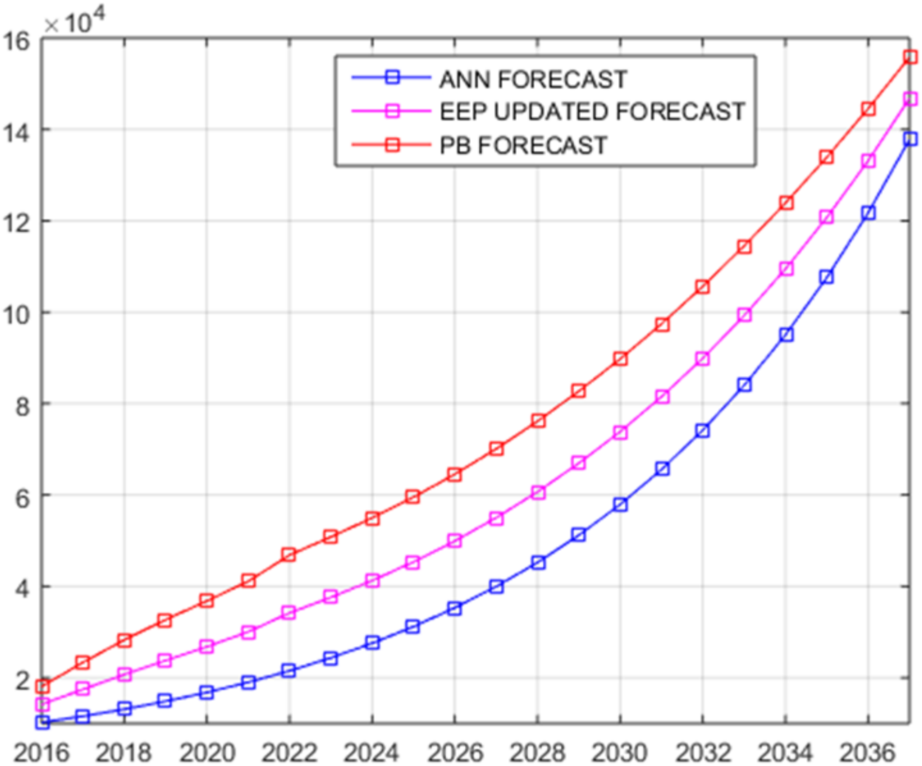

Figure 3.15: ANN, PB (EEP master) and updated EEP forecast results (Load vs Years)

Figure 3.15 shows the comparisons PB (EEP master plan), updated EEP and ANN forecasted curves. As shown on the plot, compared with the EEP master plan forecast , total demand forecast is significantly lower, during the 2022- 2027 period. The single largest impact is lower than the increased anticipated demand. And also the forecast assumes that Ethiopian will be East Africans electricity hub and will be the main exporter in the region as well. Compared with EEP master plan, exports are lower with several anticipations delayed beyond 2022.

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CHAPTER 4

TRANSMISION SYSTEM EXPANSION PLANNING FOR CENTRAL AND SOUTHER PART OF ETHIOPNA ELECTRIC POWER

4.1- Introductions

The existing transmission system in the Central and Southern reign of EEP in 2018GC were approximately 600km for 500kV lines, around 587km for 400kV lines, around 1530km for 230kV lines and around 2028km for 132kV lines. By then, the 500kV line only supplied one substation, the 400kV fed around 5 substations, and 230kV fed little more than 5 substation of 230/132kV rating with a combined capacity more than 723MVA which translated to 615MVA at utilization factor of 85%. Furthermore, the 132kV lines fed around 24 substations of 132/15kV rating with combined capacity around 956MVA which also translate to 813MVA at utilization factor of 85%. The specific voltage variation limit is bounded at ±5% for transmission 500KV, 400kV, 230kV, and 132kV [29]. In addition to these, two wind farms namely Adma I and II that generates 51MW and 102MW respectively. There are also five hydro power plants; Gelge Gibe III, Melka Wakena, Koka, Awsha I and II that generate 1800MW, 153MW, 42MW and 32MW respectively. Finally, Genale Dawa III hydro power plant that generates 250MW capacity is under commission stage.

The existing transmission and substation in Central and southern region of EEP tabulated on Table 4.1 and 4.2.

Table 4.1.Existing Transmission line in Central and Southern region of EEP

Voltage Level	Single Circuit	Double Circuit	Total (km)
500kV Transmission Line	—	2	600
400 kV Transmission Line	3	1	587.75
230kV Transmission Line	7	4	1530.22
132kV Transmission Line	34	3	2028.627

Table 4.2. Existing subsations in Central and Southeren region of EEP

Name of Substation	Voltage Level	Remarks	Name of Substation	Voltage Level	Remarks
Holta	500kV		Debrebrehan I	132kV	
Gebreguracha	400kV		Derba	132kV	Cement factory Substation
Yirgalem II	400kV	Under Commissioning	Debre Zeit II	132kV	
Alaba	230kV		Elala Geda	132kV	
Awash 7Kilo	230kV		Guder	132kV	
Chancho	230kV		Hawasa I	132kV	
Debre Brehan	230kV		Hageremariyam	132kV	
Hossina	230kV		Key Afere	132kV	
Hawsa II	230kV	Under commissioning	Muger	132kV	Cement factory Substation
Koka	230kV	Switching station	Metehara	132kV	
Melkawakena	230kV	Power Plant Substation	Melkawakena Yugo	132kV	
Ramo	230kV		Nazareth II	132kV	
Welikite	230kV		Sawla	132kV	
Assela	132kV		Shashemene	132kV	
Alba I	132kV		Shakiso	132kV	
Arba Minch	132kV		Wonji	132kV	
Admitulu	132kV		Wonji II	132kV	Shuger factory
Butajira	132kV		Yirgalem I	132kV	
Bukuluguma	132kV		Welito sodao I	132kV	

Table 4.3 Transmission line Characteristics of the central and Southern region

	Transmission line characteristics in the Central and Southern region			
No.	ITEM NOMBER	Welayta Sodo – Gelan 400kV	Melka Wakena – Koka-Gelan -Kaliti I 230kV	Melka Wakena –Yugo Sha-Shemene 132kV
1	Tower Configuration (Single or Double)	Single Circuit on double tower	Double circuit	Single circuit
2	Length (kM)	267	221	119
3	Conductor Type	AAAC	ACSR	ACSR
4	Conductor Cross section	851	445	173
5	Conductor Code	Twin Aster		
6	Rating (A)			
7	Maximum Load (A)	1600	890	89
8	Active Power P(MW) m	815		
9	Reactive Power Q(MVar	138		
10	Resistance R (ohm/km)		0.029689	0.153691
11	Reactance X (ohm/km)		0.1278	0.1278
12	Impedance Z (ohm/km)	32.2		
13	Status (in service or not)	In Service	In service	In Service

4.2 Transmission System Expansion Planning

The transmission System Expansion Planning has been developed for central and Southern region of EEP's Transmission Network for the period spanned between 2017- 2037. And it has performed based on the forecasted load. Using the Electrical Transient Analysis program software (ETAP), the model represents the network at different stage of development over planning period of (2017-2037). The transmission system expansion planning was divided into two terms; Short term and long term. The short term planning covers the period spanned in 2017-2021 while the long term planning traverses the period from 2022-2037. The transmission system expansion planning includes the transmission project required to meet the forecasted demand.

4.2.1 Short term Transmission Expansion Planning

By and large, the short term planning is based largely on the project identified by Ethiopian Electric power. Year 2017, 2019 and 2021 are considered as key year for short term planning and the proposed development to construct (Transmission Line and Substation is tabulated on Table 4.6 and 4.7

In terms of expansion planning, the already saturated transmission lines and the one those being planned are portrayed in the following consecutive tables respectively.

Table 4.4 Over-loaded Transmission lines

From	To	Bus kV	Loading	Rating	Percentage
Koka Power plant	Nazert II	132kV	123.4	82	50.48%
Adami Tulu	Shashemene	132kV	117.6	82	43.42%
MelkaWakena	Shashemene	132kV	121	82	43.41%
Alaba	Welaita Sodo	132kV	124	82	47.56%
Derezite II	Gelan	132kV	117.8	82	43.65%
Awsah Power Plant	Assela	132kV	119	82	45.12%
Cotebe	Debrebrehan	132kV	120.4	82	46.82%
Koka Power plant	Mojo	132kV	126	82	53.66%

Table 4.5 Planned transmission line to alleviate overload transmission line

Overloaded transmission line	Transmission Line to be constructed
Koka PP - Nazareth 132kV TL	From Awash 7kilo - Hurso line Lillo to Nazareth III 230 kV substation
Debrezite - Gelan 132kV TL	400kV transmission line from Gelane - Dukem - Debrezite III
Koka PP - Mojo 132kV TL	230kV transmission line from Debrezite III to Mojo 230kV substation
Legetafo - Debrebrehan 132kV TL	Legetfo - Combolch II lilo to Debrebrehan II 230kV new substation
Melka Wakena Sheshemene 132kV TL	Melkawakena PP to Hawasa II 230 kV substation
Awsh 7kilo - Asela 132kVTL	Koka -Dire Dawa III Lillo to Asela Bokoji 230kV substation
Alaba - Welita Sodo 132kVTL	Striging of the second 400kV circuit from Welayta to Gelan 400/230/132kV subsation and constrcting Welikete -Alaba 230kV transmission line

The expansion planning accomplished in central and southern part of the country, presented in the table 4.5, will definitely be alleviated the current congestion (listed in the table 4.4) that is being experienced in these days.

Construction of the new transmission line will help to transfer additional power and to ease the overburden of the mentioned saturated transmission lines (TL). Also, it will improve the reliability of the grids in the whole EEP because, for instance, due to a single outage of 132kV transmission line will affect power system (it may create overloaded to others transmission lines and transformers), and in vice versa, the addition of newly minted transmission lines will improve it significantly. These days, the challenge for Transmission Operation System (TSO) mangers during peak hours is the deficit of reliable energy to satisfy all customers which inevitably leads to load shading. As seen from the expansion planning in this thesis, the mentioned problems just discussed will be addressed at least in the central and south part of the country plus values will be added substantially to improve EEPs grid.

Table 4.6. Planned Transmission Line list in the short term

Planned year	Name of Transmission Line	Voltage Level	Length of Transmission in km	Remark
2014	Akaki II – DebreZiet IIII	400kV double circuit quad Dove	30	Under construction
2014	Debre –Ziet III - Mojo	230kV single circuit twin Ash	8	Under construction
2015	Yirgalem –Awasa II	230kV single circuit ,twin Ash	35	Constructed
2015	Yirgalem II- Genale Dawa III	400kV double circuit ,quad	274	Constructed
2015	Gobesa- Balerobe	132kV single circuit Ash	32	Not constructed
2015	Melkawakena power plant - Yugoslavia	132kV single circuit Ash	5	Not constructed
2015	Yirgalem I - Yirgalem II	230kV double circuit, Twin Ash	12	
2017	Debre ziet III- Modojo II	230kV single circuit ,Twin Ash	8	Under construction
2017	Wolyta – sodo – Arbaminch	230kV Double circuit Twin Ash	109	Not constructed
2017	Wolyta – Sodo –Omo Kuraz sugar Factory 1	230kV double circuit Twin Ash	245	Not constructed
2017	Yirgalem Shakiso	230kV double circuit Twin Ash	133.21	Not constructed
2017	Yirgalem -Dilla	230kV double circuit Twin Ash	40	Not constructed
2019	Wolayta Sodo- Akaki II	the second circuit 400kV quad Dove	133.5	committed
2020	Adami Tulu- Butajira	132kV single circuit Ash	78	
2020	Awassa – Sha Shamene	230kV double circuit Twin Ash	30	
2020	Debre zeit III - shashemene	400kV double circuit quad Dove	83	
2020	Debre zeit III - Awash 7Kilo	400kV double circuit quad Dove	166.5	
2020	Sha Shamene - Yirgalem	400kV double circuit quad Dove	60	
2025	Nazreth –Methara	230kV single circuit Twin Asah	90	
2030	Dilla- Hagere Mariyam	230kV double circuit Twin Ash	90	
2030	Hagere Mariyam - Bocolugma	230kV double circuit Twin Ash	199	

Table 4.7 Planned Subsations in the short term

Planned year	Name of Substation	Capacity of Transformer	Remark
2014	Debre Ziet III	400/230/KV, 500MVA	Under construction
2015	Dukem II	230/15kV, 2*63 MVA	Under construction
2015	Naziret II substation	230/132kV,125MVA	Under construction
2015	Yirgalem I	230/132/15, 125/125/37.5 MVA	Constructed not energized
2015	Yirgalem II	400/230kV ,500MVA	Constructed not energized
2015	Shasheme	132/15kV, 63MVA Upgrading of Existing transformer	Not Constructed
2015	Yirgalem Agro Industrial Park	230/33kV, 120/150MVA	Not Constructed
2017	Arbaminch	230/132/15kV , 2* 63/4023MVA	Not Constructed
2017	Omo Kuraz Sugar Factory -1	230/132kV,125MVA	Not Constructed
2017	Omo Kuraz Sugar Factory -2	132/15kV,40MVA,	Not Constructed
2017	Omo Kuraz Sugar Factory -3	132/15kV,40MVA,	Not Constructed
2017	Omo Kuraz Sugar Factory -4	132/15kV,40MVA,	Not Constructed
2017	Omo Kuraz Sugar Factory -5	132/15kV,40MVA,	Not Constructed
2020	Sha Shamene II	400/230, 250MVA	Proposed
2025	Butajira	132/33/15kV ,63/4023MVA	Proposed
2025	Methara	230/132kV, 2*63MVA	Proposed
2025	Shakiso	230/132/15kV,2*125/125/37.5	Proposed

4.2.2 Long Term Transmission System Expansion Planning

The long term Transmission System Expansion Planning on the other hand covers the period from 2022 - 2037. The required transmission line and associated substation tabulated on table 4.8 and 4.9

Table 4.8 Planned Transmission Line for long term

Planned year	Name of Transmission Line	Voltage Level	The lengthe of transmission line (km)	Remark
2022	Melkawakena Bokoji	230kV double circuit Twin Ash	1.5	Commited
2025	Nazreth –Methara	230kV single circuit Twin Asah	90	Proposed
2030	Dilla- Hagere Mariyam	230kV double circuit Twin Ash	90	Proposed
2030	Hagere Mariyam - Bocolugma	230kV double circuit Twin Ash	199	Proposed

Table 4.9 Planned Substations for long term

Planned year	Name of Substation	Capacity of Transformer	Remark
2022	Bokoji	230/33kV	Commited
2025	Butajira	132/33/15kV ,63/4023MVA	Proposed
2025	Methara	230/132kV, 2*63MVA	Proposed
2025	Shakiso	230/132/15kV,2*125/125/37.5	Proposed

From Table 4.6 the planned, transmission system expansion planning from 2014- 2019 (EEP short term plane) is around 1057km. From this; 321km has constructed, 46km is under construction and around 705km has not yet constructed. From table 4.7the planned associated subsections are two 400kV, six 230kV, four 132kV and one Upgrading of existing substation. From the planned only one 400kV, and two 230kV substation are under construction. Only one 400kV and 230kV substations are under commissioning stage. However, for 132kV, and two 230kV substations are not constructed. From this we understand that, it is very difficult to accommodate the forecasted and ~~to serve~~ the existing demand unless, all planed transmission and substations constructed. That is why, currently, there is a frequent load shading in central and southern region of EEP.

4.3- Performance analysis of the existing system of central and southern Region EEP network

4.3.1 Transmission Line Over loading

The existing transmission line voltage level for Central and a southern region of the current electricity network comprises 500kV, 400kV, 230kV, and 132kV. The corresponding medium voltage distribution network consists of 15kV distribution line gained from stepping down of transformers rate at 132kV/15kV. Almost most of 132kV transmissions lines and the medium voltage switch gear are aged (25-35 years) from commissioning time.

Pursuant to load demand forecasts, there are number of load demands on the networked system on both industrial and agricultural infrastructures at the region like ADAMA Industrial Park which needs 200MW, Arerti industrial Park 60MW, Yergalem Agro

Industry which demands around 50MW and Gendearba Agro industry that requires 50MW.

The maximum thermal capacity of 132kV of existing transmission line is 70MW and it is difficult to accommodate the forecasted and the existing demand (during peak hours Morning 09:00AM – 12:00PM and evening from 6:00-9:00PM).

To catch up with this demand soaring in the whole country, the following are core investments in power sector: Great Ethiopian Renaissance Dam (GERD), Genale Dawa III, Koysha Hydro power plant, Aisha wind farm and expansion of Aluto Langanno geothermal (from 7MW to 70MW) power plant . The investment for all hydro power plants, wind farm and the geothermal power plant is from the Government of Ethiopia. There is also Independent Power Producer (IPP) such as Corboriti Geothermal power plant, Asela wind farm, and solar (Mekele, Metehara, Humerea and Welenchti) power plant.. As an upshot of such investment, a lot of newly minted power plants have started operation and are being constructed. As a result, the power generation capacity is considered commensurate to the demand in question.

On the other hand, in response of rapid industrial demand growth as mentioned above, the development of transmission and distribution network including substations are insufficient. There are several industrial (Adama, Arereti Industrial Park and Bulbula and Weyanta Agro Industry park), household and small scale industrial customers that are waiting electricity connection owing to the power supply cannot cope with an increase of power demand. To cope up with further economic growth in the region, amelioration of distribution and transmission network is a vital issue of the power sector in the country.

The methods of the transmission line overload is embedded and synchronously programmed in ETAP software load flow analysis. The over loading problems are collected from alert view button of ETAP which contains a list of overloading of transformers, transmission and all equipment in the system. The result of transmission line loading provided in table 4.9

4.3.2 Transformer Loading

One of the most indispensable and intensive components a power system network is the power transformer. The efficacy of transmission and distribution system of electricity network among different voltage levels is made possible by using power transformer. Any outage of power transformer may affect the reliability of the entire network and has considerable economic impact on the system.

Good planning and accurate controlling have to be taken into account in order to use power transformer efficiently. Normally, transformers are designed to operate with in its name plate ratings. However, power transformer are occasionally loaded beyond nameplate rating because of existing possible contingencies on the transmission lines, any failure or fault in power system or economic considerations. The method of transmission line overload is programmed with ETAP load flow analysis. The result of transformer over loading given in table 4.8

4.3.3 Contingency Analysis

Contingency analysis (CA) — also known as security analysis— in the power system is to evaluate the power systems and find the overloads and problems that might happen in electrical network. Contingency analysis in power system may be needed in abnormal condition due to contingency condition an entire system or some part of the systems coming under congestion. Contingency analysis may also needed for unexpected opening of the power transmission lines, generators tripping condition, Sudden changes in power generation, unexpected changes in loads.

4.3.3.1. N-1 Contingency Analysis

Congestion might occur in the power system due to line outage, generator outage, change in energy demands and uncoordinated transaction. In those Objective, N-1 contingency analyze is to identify that mostly severed transmission lines and that lines are considered for analysis. In the loss of any power system portion that has only one transmission apparatus or power plant tripped but not includes the bus bar and radial line.

N-1 Contingency is characterized by one of the following:

- Loss of a single – circuit overhead interconnection or internal line with an exception of those radial circuits which connected to loads using a single overhead line or cable;
- Loss of one circuit within a double - circuit overhead interconnection or internal line;
- Loss of a single transformer excluding those which connects loads using a single radial transformer;
- Loss of shunt devices Capacitor/ Reactor/ SVC
- The results of contingency analysis are given in ANNEX

4.4- Performance analysis of the expanded system of central and Southern region EEP network

Given the network of EEP power system used as a reference case system, it is assumed to be operational under balanced condition and is prepared by single line diagram. The system contains 50 buses.

The input data (of March 2019) for power flow program represents the load and generation based on the power flow analysis. The slack bus voltage at 1.05 p.u, is taking as the corresponding slack bus.

By analysis load flow, it can be found the system has weak points such as, Nazaret II, Asela, Adamitulu, Awassa, Shashemene, etc. (as indicated in table 4.10) and also the over voltage on Shakiso and Arbaminch, Key Afer, Sawla132kV substation. In load flow program, the voltage magnitude is set to 1.0 per unit and the specified voltage variation limits are bounded at ±5%. So, the voltage magnitude must be in the range of 0.95 per unit to 1.05 per unit. The Table 4.10 Shows the weakest points in the system that has the voltage magnitude under 0.95 per unit, not least when the demand is bumping up from year to year. The overloaded transmission line and transformer indicated on the table 4.9 and 4.10

4.5- Analysis of the result

4.5.1 Load Flow modeling Data

The “Electrical Transient analysis Program” ETAP 16.0 software performs load flow analysis in two methods: the Gauss –Seidel and Newton – Raphson method. The Gauss-Seidel method is more effective when there is less number of busses involved, whereas the Newton – Raphson method prevails where more number of busses involved. Therefore, in this thesis the Newton Raphson method was used for simulation on the ETAP. The convergence tolerance is met for the first 23 Iteration.

4.5.2 Load flow analysis

Load flow analysis of the system has done for peak loading condition of the system and the result of bus voltage profile; overloaded transmission line and transformer are tabulated on table 4.10, 4.11 and 4.12.

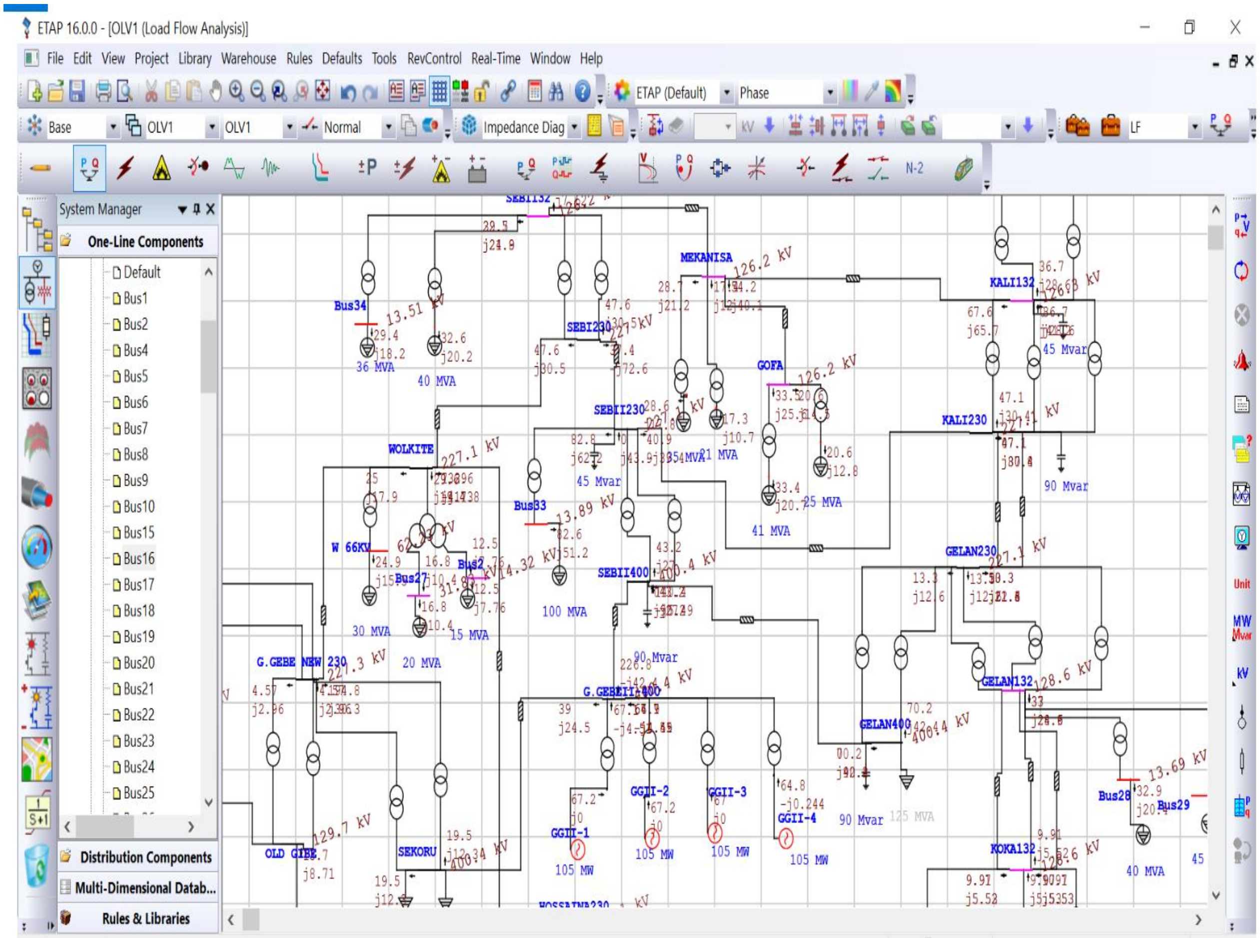

Figure 4.1 Load flow analysis

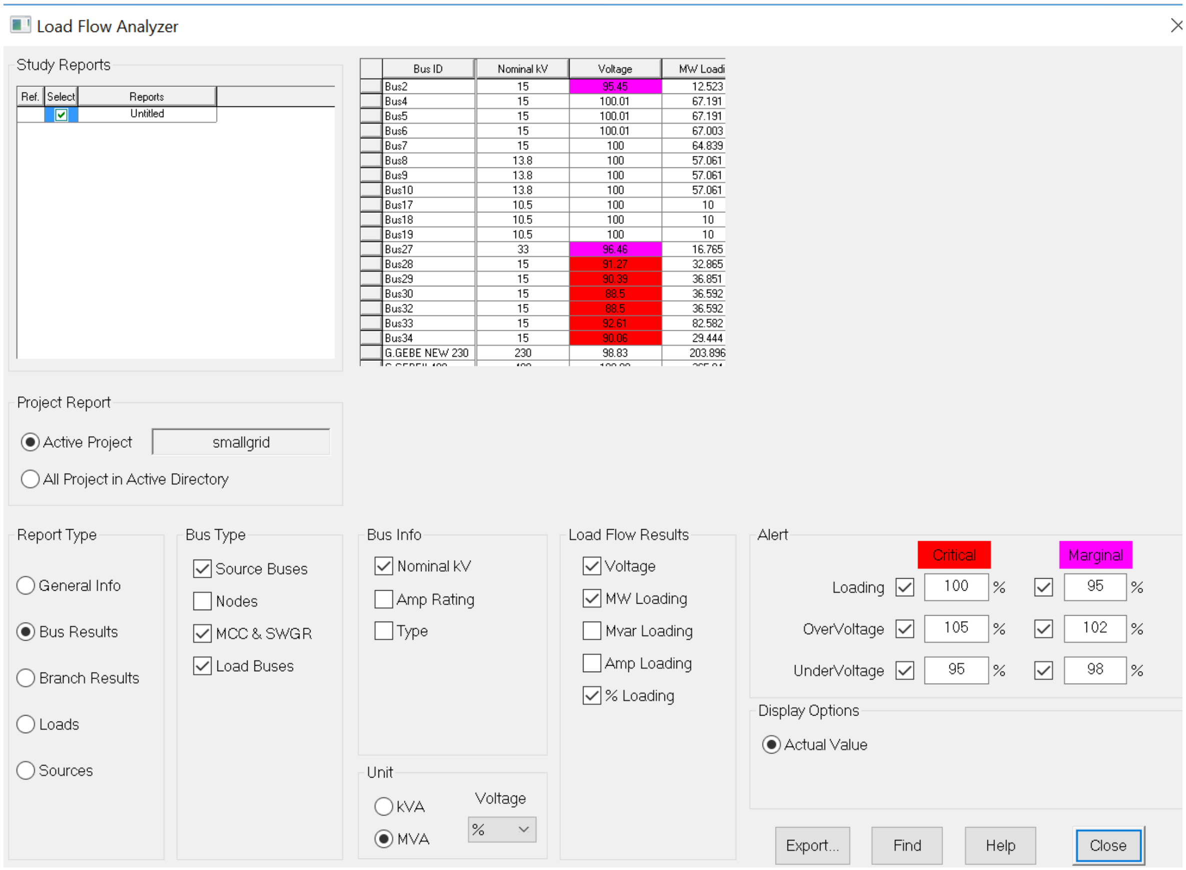

Figure 4.2 Load flow result analyzer

After carrying out load flow analysis using ETAP an alert summary report is generated which tells us which part of the system needs immediate attention. The summarized voltage magnitude collected from load flow result analyzer are clearly seen from table 4.8

Table 4.10 Bus voltage magnitude

BUS ID	NOMINAL KV	2019 LF Analysis	2024LF Analysis	2029LF Analysis	2034 LF Analysis	2037LF Analysis
Awash 7K	132	0.9674	0.951	0.943	0.912	0.901
Asela	132	0.944	0.94	0.9372	0.935	
Adamitulu	132	0.933	0.9311	0.9301	0.9201	0.9179
Hawasa	132	0.9475	0.936	0.9321	0.9301	0.92986
Modjo	45	0.9487	0.9435	0.9407	0.94	0.9382
Nazaerth II	132	0.9656	0.9492	0.9467	0.9443	0.9403
DB-Zeit II	132	0.9641	0.9571	0.9486	0.9475	0.9436
Koka	132	0.9662	0.9571	0.9492	0.9487	0.9457
Elala Geda	132	0.9706	0.9612	0.9586	0.9543	0.9471
Shashemene	132	0.9494	0.9464	0.941	0.94011	0.9397
Yergalem	132	0.9421	0.9402	0.9401	0.9386	0.9365
Shakiso	132					
Key Afere	132	1.0625	1.0575	1.0547	1.0544	1.05
Sawla	132	1.0709	1.0637	1.0577	1.0569	1.0544
Arbamnich	132					
Koka	230	0.968	0.9311	0.93	0.9281	0.9261
Awash 7K	230	1.0846	1.0841	1.0713	1.0711	1.0709

4.5.3 Transmission Line overloading of Central and southern Part of EEP Network

Base on the forecasted data (on table 3.1) the overloading transmission collected from load flow result analyzer (figure 4.5), and has shown in the table 4.9

Table 4.11 Transmission Line loading

ID	Allowable	LF Analysis 2019	LF Analysis 2024	LF Analysis 2029	LF Analysis 2034	LF Analysis 2037
Awash-7kL<>Methara 132kV	359	40	65	84	100	100
AdamiTulu <> Assela 132kV	359	167	230	370	397	447
Adami Tulu <> Shashemene 132kV	359	300	361	380	400	450
Assla <> Wonji Shuger TP 132kV	359	166	200	235	257	300
Awash II PP <> Wonji Shuger 132kV	359	194	210	300	358	445
Koka PP <> Nazereth II 132kV	359	330	659	676	833	891
Methra <> Nazerth 132kV	359	50	88	100	158	200
M. Wakena -Yugo <> Shashemene 132kV	389	341	366	400	452	497
DB-Zeit II<> Gelan 132kV	359	247	301	359	400	427
Arba Minch <> Welayta 132kV	359	93	115	170	200	253
Alaba <> W.Sodo 132kV	359	359	461	500	556	600
Awasa <> Yirgalem 132kV	359	244	334	371	397	425

From table 4.11 the transmission lines of Koka Nazreth II, Alaba - W.Sodo are overloaded starting the year of 2019. Both Adma and Arerity industrial park are waiting for the required power and also Yrgalem and GendArba Agro Industrial parks waiting for the required power.

4.5.4 Transformer over loading

Base on the forecasted load the overloaded transformers are collected from load flow result analyzer (figure 4.5), and tabulated in table 4.12

Table 4.12Transformer overloading

ID	Allowable	LF Analysis 2019	LF Analysis 2024	LF Analysis 2029	LF Analysis 2034	LF Analysis 2037
ADM TR1	25MVA	115.7	119.8	126	128.7	131.7
ADM TR2	12MVA	14.6	15.8	17	18	
ASS TR1	25MVA	114.3	119.8	129.3	134.1	139.4
ASS TR2	12MVA	60.1	71.4	76.6	78.8	81.5
BUT TR1	12MVA	68.1	71.4	76.6	78.8	81.5
DB-ZET II-TR1	31.5 MVA	137.2	139.8	149.3	154.1	169.4
DB-ZET II-TR2	31.5 MVA	137.2	139.8	149.3	154.1	169.4
DB-ZET II-TR3	25MVA	106.7	109.9	115.1	116.8	117.8
ELA-GD	12MVA	52	58.1	68.4	71.6	78
MET	20MVA	77	88.8	99.1	101.8	105.1
NAZ -II TR1	25MVA	112.5	112.9	113.6	116.8	122.4
NAZ -II TR2	25MVA	112.5	112.9	113.6	116.8	122.4
WON	25MVA	100	107	112.5	118.7	120
AWS-7KL	12MVA	50	71.4	76.6	80	82.5
AWS-7KL	125MVA	43.6	47	54	57.8	62.1
AWS-7KL	125MVA	43.6	47	54	57.8	62.1
Modjo (MOBIL)	16 MVA	68.1	71.4	76.6	78.8	81.5
AWS TR1	25MVA	104.7	119.8	126	128.7	131.7
AWS TR2	25 MVA	104.7	119.8	126	128.7	131.7
AWS TR3	16MVA	65	68.2	70.4	71.6	76.5
SHS TR1	25MVA	115.7	119.8	126	128.7	131.7
SHS TR2	25MVA	67.2	72.4	75.7	78.9	81.5
YRG	25MVA	14.8	20.4	61.4	63.1	65.2
SKS TR1	12.5MVA	14.7	15.6	17.2	18	19
SKS TR2	12.5MVA	14.7	15.6	17.2	18	19
SKS TR3	25MVA	15	18	22	61.3	63.3
ALB TR1	12MVA	68.1	71.4	76.6	78.8	81.5
ALB TR2	60MVA	33.6	46	59.8	61.3	63.3
ALB TR3	60MVA	33.6	46	59.8	61.3	63.3
HOSS TR1	25MVA	53.6	56	59.8	61.3	63.3
HOSS TR2	63MVA	32.7	37.4	41.7	44	44.8
ARB TR1	20MVA	13	36	85.2	88	95
ARB TR2	20MVA	13	36	65.9	76.5	80.1
WOL-SD- TR1	31.5MVA	18	21	46	47.8	50
WOL-SD- TR2	31.5MVA	18	21	46	47.8	50
KEY-AF TR1	25MVA	12	18	22	32	44.7
SAW TR1	25MVA	15.2	16.2	17.3	27.8	35.2
DIL TR1	25MVA	21.5	33.8	40.4	41.3	45.6
HG-MAR	25MVA	12	17.8	22	48	57

From the above table most of the transformers will inevitably be overloaded starting from 2019. EEP has started to construct ADAMA II 230/132 kV substation and Debreziet III 400/230/132 and is now under commissioning stage to satiate the soared demand of Adama and Debrezeit small scale and household customers.

According to the result of load flow simulation, the voltage level as indicated on table 4.8 in central and southern region is lower than the specified lower voltage level 0.95p.u. So, the voltage levels on both substations are required to improve for proper system operation. Aging infrastructure, week and radial configuration , and over loaded transformer and transmission lines result in frequent system collapse , with high transmission and distribution losses and poor voltage profile.

In the Central and Southern region of EEP, there are twenty nine 132/15kV substations. From this, 25 (almost 90%) substations are congested and load shading is imminently looming and frequent power interruption is going during peak hours (morning from 09:30 AM- 12PM and night 06:00PM- 09:00PM).

4.5.5 Contingency analysis

Under normal loading condition, the system is stable. Bumping up of the demand ensues the augmentation of the corresponding load. The system will inevitably get congested given the overloading condition. In this case, the congestion of the system owing to the overloading the connected excess loads on the buses Nazirt, Debreziet, Alaba, and Wolita Sodo. In this Congested overloaded power system, N-1 Contingency analysis is done and the results are presented on Appendix E. While running the N-1 Contingency analysis for the line loading condition of central and Southern region has presented in Appendix E.

CHAPTER FIVE

CONCLUSIONS, RECOMMENDATIONS AND FUTURE WORK

5.1- Conclusion

The findings of this study portrays a model that forecasts for many future years and analyze the load flow analysis of future transmission system expansion planning for power or utility company using one of the modern artificial intelligence astonishing feats—Artificial Neural Network(ANN). In this particular project, the model forecasted the load for the next 22 years ahead using the mentioned machine learning technic pursuant to the detailed specification enunciated in the paper. The model uses the ANN Toolbox that is imbedded in Matlab 2015a software and ETAP 16 for the corresponding load flow analysis. A historical load data, Gross Domestic Data, number of Population , new industrial park, agro Industrial Park, Economic growth and weather condition has taken into account in the model. For comparative purposes as well as to investigate and deduce whether ANN produces effective results, EEP master plan and updated EEP forecasted results were used as well. This investigation revealed that the proposed model of ANN stand out as being more is both by nuancing the characteristics of load demand parameters and its corresponding factors than the Econometric Model (the combination of economic theory and statistical techniques for forecasting of electricity demand) that was implemented by Ethiopian Electric Power (EEP) company. Moreover, the ANN model gives the analyzer the privilege of watching the input data on the toolbox's wizard while training, validating and testing even retraining the data right on the software during the process so as could minimize the errors.

Further assessment of comparison between the two models divulges that the more the periodical years marched on to be predicted, the better is the ANN model in precision than EEP and the Normalized forecast as well as the load growth rate of ANN forecast is more plausible than that of EEP Master plan and the updated EEP forecast. It has seen that for the year of 2037, the estimated demand is 137752.09GWh. Compared with the EEP master plane forecast, total demand forecast is significantly lower during the 2022-2027. The single largest impact is lower than the increased anticipated demands as well as export is lower with several anticipation delayed beyond 2022.

The transmission System Expansion Planning is done for the year 2037 based on forecasted load. From the analysis EEP should construct the planned transmission line and associated substations and also should construct the proposed transmission line and substation to alleviate frequent power interruption due to congested substations and overloaded transmission line.

5.2- Recommendations

The following recommendations could elicited from stated conclusion

- Artificial Intelligence-based techniques, ANN concept in particular, is highly effective and a cutting-edge tool for implementing of long-term electric load forecast for the Ethiopia Electric Power and utility Companies.
- A state-of-the-art comprehensive and high processing computer program, such as Matlab, is a suitable tool for the development of the ANN model.

5.3- Suggestion for further work

In order to develop the model to more versatile use (to accommodate the growing electricity demand in the country so as fit to the forecasted high demands and implementation of transmission and substations proper allocation), future research into this subject should also include like the appliance in the area including age and the appliance sales data etc. for such expansion of load demands, using the new techniques like “Knowledge-Based Export Systems” that have emerged as a result of advanced technology in Artificial Intelligence is recommended..

Another avenue of research could be to institute a case study of several successful artificial intelligence and machine learning for load forecasting of high voltage electricity for transmission expansion and planning to discover their unique allocation of automated generation plants and substations around the whole regions of the country. The information from the case studies could be combined to ascertain if there are common practices successful energy management implementations are using. This type of research could also be used to study successful training programs or strategies for the power sector employees. The researchers could study successful programs that create structures allowing the researchers to report the amount of power system analysis gain for each unit of the country's power and utility companies.

The relatively accurate long term forecasted loads corresponding load flow analysis from these forecasted loads are used as in put to plan and design for building of new substations and transmission lines across the proper place of the central and Southern region of EEP in future could take as an achievement from the study.

As shown in Section 4.1 on table 4.4, from planned (2014-2020) six 230kV and two 132kV transmission lines and four 132kV and three 230kV substations has not constructed until now and the industrial demand in the Central and southern region of EEP is around 350MW (Adama and Arereti Industrial Park are waiting supply of electricity to start production, and Genederba and Yirgalem agro Industrial Park are under construction). In addition to these, the substations in Adama, Shashemene, Asela and others are congested.

To supply the industrial parks, to satisfy a new customers demands and to overcome saturation of the existing substation the following transmission lines and Rehabilitation and Upgrading of the existing substation has proposed and tabulated on table 5.1 and 5.2

Table 5.1 Proposed Transmission line

Transmission Lines	Rate	Capacity	Year to implement	Remarks
Gilgel Gibe III <> Gelan	400kV	1936A	2020	Based on Load Flow
Debrezite III <> Hurso <> Direda Dawa VI	400kV	1936A	2028	
Koka -Hurso Lilo <> Arerti Industrial park	230kV	1009A	2020	
Koka <> Adama II Lilo	230kV	1009A	2020	
Yrgalem II <> Weyanata agro industry	132kV	503A	2020	
Koka <> Adma II <> Adama industrial Park	230kV	1009A	2021	

Table 5.2 Proposed new substation and Rehabilitation and upgrading existing substations

Name of station	Capacity	Remarks
Arerti Industrial Park	230/33/33kV, 2*125 MVA	Based on the load flow
Adama Industrial Park	230/33/33kV, 4*125 MVA	
Yergalem Agro Industrial Park	132/33kV, 2*50/40MVA	
Genda Arba agro Industrial Park	132/33kV, 2*50/40MVA	
Nazirete (ADAMA II) III	230/33 kV, 2*125MVA	
Shasemene	Rehabilitating the existing substation to 230/15kV ,2*63MVA	
Adamitu 132kV	Rehabilitating the existing substation 2*50MVA	
Asela 132kV	Rehabilitating the existing substation 2*50MVA	
Nazirete II 132kV	Rehabilitating the existing substation 2*50MVA	
AWASAA 132kV	Rehabilitating the existing substation 2*50MVA	
ARBA MINCH 132kV	Rehabilitating the existing substation 2*31.5MVA	
Methara 132kV	Rehabilitating the existing substation 2*31.5MVA	

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