JIMMA UNIVERSITY

JIMMA INSTITUTE OF TECHNOLOGY

SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

MSC. THESIS

ON

SHORT TERM LOAD FORECAST IN JIMMA CITY BY USING ARTIFICIAL NEURAL NETWORK

BY

ERMIAS SHIFERAW

THESIS SUBMITTED TO SCHOOL OF GRADUATE STUDIES OF JIMMA INSTITUTE OF TECHNOLOGY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

IN

ELECTRICAL POWER ENGINEERING

OCTOBER, 2016

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Declaration

I, The undersigned, declare that this MSc thesis entitled "Short Term Load Forecast in Jimma City by using ANN "is my original work, has not been presented for fulfillment of a degree in this or any other university, and all sources and materials used for the thesis have been acknowledged .

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Contents

Declaration......i
Acknowledgements......iv
List of Abbreviations......vii
Abstract......viii
Chapter 1......1
1. Introduction......1
1.1Background......1
1.2 Factor affects power demand......6
1.3 Statement of the problem......7
1.4 Objectives......7
1.4.1 General Objectives......7
1.4.2 Specific Objectives......7
1.6 Scope of the study......8
1.6 Methodology......8
1.7 Contribution of the Thesis......8
1.8 Limitations......9
1.9 Thesis Outline......9
Chapter 2......10
2.1. Literature Review......10
2.2. Summary of literature review......12
Chapter 3......14
3. Materials and Methods......14
3.1 Input Data......14
3.2 Pre-processing......14
3.2.1 Date......14
3.2.2 Time......22
3.2.3 Calendar Designations......22
3.3. Load forecasting methods......23

3.3.1 Similar-day approach 23

3.3.2 Regression methods 24

3.3.3 Time Series 24

3.3.4 Fuzzy logic 24

3.3.5 Neural Network 24

3.3.5.1. Benefits of Artificial Neural Network 25

3.3.5.2. Mathematical Model of a Neuron 25

3.3.5.3. Training the Forecast 26

3.3.5.4. Network Structure 27

3.3.5.5. Performance Metrics 28

3.4. Network topologies artificial neural networks (ANN). 29

3.4.1. Feed forward neural network 29

3.4.2. Radial basis function (RBF) network 30

3.4.2. Recurrent neural network (RNN). 30

Chapter 4 31

Results and Discussion 31

4.1. Load Forecast Results 31

4.1.1 Selection of Network Architecture and Parametric Values 31

4.1.2 Selection of Epoch and Performance ratio 32

4.2. Load Forecast Discussion 45

Chapter 5 48

Conclusions and Recommendations (Future Research) 48

5.1 Thesis Conclusions 48

5.2 Recommendations (Future Research) 49

List of References 50

Appendix 52

Appendix A – Matlab Code 52

Acknowledgements

First of all I would like to offer our deepest gratitude to JIMMA UNIVERSITY INSTITUTE OF TECHNOLOGY (JIT), for providing this opportunity in my field of study.

I would like to give our endless heart full thanks for My Advisor Dr Dereje shiferaw (ph.d) and K.Saravanan (Ass. Prof.) for their endless help me without boring at all-time starting from research begins till knows and gives appreciation and hints to do and analysis this research.

I would like to thank administrator the substation ATO Mehammed ,Demebelash and ATO Fikadu for obtaining some of the data required for this research. I also want to thank all of my family and friends whose encouragement and confidence in me helped me see my studies through to the end and graduate.

List of figure

Figure 1-1 location of jimma city from Google map ……………………………………………………1

Figure 1.2 View of Jimma substation…………………………………………………………..…..4

Figure 1.3 One line diagram of Jimma substation…………………………………………………5

Figure 3-1 Comparison of hourly Monday 22/09/07and Monday 25/12/07 measured power load…12

Figure 3.2 Comparison of hourly Tuesday 23/09/07, 26/12/07 and 6/13/07 measured power load..12

Figure 3.3 Comparison of hourly Wednesday 24/09/07, Wednesday 27/12/07 and Wednesday 1/1/08 measured power demand..14

Figure 3.4 Comparison of hourly Thursday 25/09/07 and 28/12/07 measured power load………...14

Figure 3.5 Comparison of hourly Friday 26/09/07and 29/12/07measured power demand................16

Figure 3.6 Comparison of hourly Saturday 27/10/07 and 30/12/07 measured power demand….…16

Figure 3.7 Comparison of hourly Sunday 28/09/07 and Sunday 1/13/07 measured power demand...17

Figure 3.8 Model of an ANN……………………………………………………………………...22

Figure 3.9 Architecture of ANN applied to Jimma City electrical load profile…………………......24

Figure 4.1 Comparison of actual and forecasted (feed forward, radial basis and recurrent) ANN power demand..36

Figure 4.2 Comparison of actual and forecasted (feed forward, radial basis and recurrent) ANN power demand..38

Figure 4.3 Comparison of actual and forecasted (feed forward, radial basis and recurrent) ANN power demand…………………………………………………………………………...40

Figure 4.4 Comparison of actual and forecasted (feed forward, radial basis and recurrent) ANN power demand…………………………………………………………………………...42

Figure 4.5 Comparison of actual and forecasted (feed forward, radial basis and recurrent) ANN power demand…………………………………………………………………………...44

Figure 4.6 Effect of the number of hidden unit on the network performance...................................47

List of table

Table 1.1 jimma climate classification......................…………..2

Table2.1. Short Term Load Forecasting Classified By Type Of Models………………………..…..13

Table 3.1 Comparison of hourly Monday 22/09/07,25/12/07 and Tuesday 23/09/07, 26/12/07, 6/13/07 measured power load……………………………………………………….….…15

Table 3.2 Comparison of hourly Wednesday 24/09/07, 27/12/07, 1/1/08 and Thursday 25/09/07, 28/12/07 measured power load………………………………………………………....13

Table 3.3 Comparison of hourly Friday 26/09/07, 29/12/07 and Saturday 27/09/07,30/12/07 and Sunday 28/09/07, 1/13/07 measured power load……………..…………………..……...15

Table 3.4 Winter, summer and holiday peak load Measured Data from typical electrical load profile of Jimma City....................……………..………...18

Table 4.1 Tested network architectures and their performances in terms of MAPE..........................32

Table 4.2 Variation in performance ratio parameter with model accuracy …………………………33

Table 4.3 Optimal values of our model parameters...34

Table 4.4 Actual and Forecasted load (Tuesday 23/09/2007 E.C)……………………………......35

Table 4.5 Actual and Forecasted load (Wednesday 24/09/2007 E.C)…………………….............37

Table 4.6 Actual and Forecasted load (Tuesday 26/12/2007 E.C) ………………..........................39

Table 4.7 Actual and Forecasted load (Wednesday 27/12/2007 E.C) ………………..…………... 41

Table 4.8 Actual and Forecasted load (Wednesday 01/01/2008 E.C)……………………….…...43

Table 4.9: MAPE for the model on the test set……………………..………………….……………45

Table 4.10: Winter, summer and holiday peak load forecasted Data from typical electrical load profile of Jimma City…………..……………………..…………………….……………46

List of Abbreviations

JC	Jimma City
EEU	Ethiopia Electric Utility
ANN	Artificial Neural Network
STLF	Short Term Load Forecast
JIT	Jimma University Institute of Technology
kW	kilowatts
hrs	hours
FFN	Feed Forward Network
FFBP	Feed Forward Back propagation
RBF	Radial Basis Function
RBFN	Radial Basis Function Network
RNN	Recurrent Neural Network
HVAC	High Voltage Alternating Current
MAPE	Mean Absolute Percentage Error
A	Actual Value
F	Forecast Value
N	Number of points being forecast
t	time

Abstract

For optimal power system operation, electrical generation must follow electrical load demand. The generation, transmission, and distribution utilities require forecasting the electrical load so they can utilize their electrical infrastructure efficiently, securely, and economically. The short-term load forecast (STLF) represents the electric load forecast for a time interval of a few hours to a few days. This thesis is a study of short-term electric power forecasting in the jimma power system using artificial neural network model. The model is created in the form of a simulation program written with MATLAB tool. The model, a feed forward neural network, for radial basis neural network and recurrent current artificial neural network trained with error, was made to study the pre-historical load pattern of a typical jimma power system in a supervised training manner. After presenting the model with a reasonable number of training samples, the model could forecast correctly electric power supply in the jimma power system 24 hours in advance. An absolute mean error was obtained and compares three neural networks feed forward neural network 0.5180 to 6.3868, for radial basis neural network 0.0861 to 2.8703 and recurrent current 0.2811 to 13.8851 from this choose the least absolute mean error radial basis neural network 0.0861 to 2.8703. The trained neural network model was tested on one week, daily hourly load data of a typical jimma power station. This result demonstrates that ANN is a powerful tool for load forecasting.

One week (winter **Monday 22/9/07** – **Sunday 28/9/07**) , One week (Summer **Monday 25/12/07** – **Sunday 1/13/07**) and One day (Holiday **Wednesday 1/1/08**) of electrical load. Load data was recorded for JIMMA CITY, so there are 15 days of data collected.

Keywords: - artificial neural network (ANN), Short Term Load Forecasting (STLF), feed forward Back Propagation, Radial Basis Function Neural Network (RBFNN), recurrent network (RC), Mean Absolute Percentage Error (MAPE).

Chapter 1

1. Introduction

1.1Background

This study was conducted at Jimma city, Southwestern Ethiopia, in October 2016.Jimma is one of the biggest and dominant political, Economic, cultural and historical citys in the southern part of the country, which has been, founded the late 1830s. Since then it has been the center of most of the regimes administration and commercial activities. Jimma is locally known as the town of Aba Jiffar. It is situated 365kms from Addis Ababa on the high way of Mettu - Gambella at an altitude of 1620 m.a.s.l. Geographically, the town is located 70 40’N latitude and 360 60’E longitudes.

Figure 1.1 location of jimma city from Google map

Jimma city population increases are necessary for economic growth raise and power load demand increases. The main economic activities in the town are commerce (trading & catering services) and small scale manufacturing enterprises. The industries in the town are small- scale and cottage industries like grain mills, oil mills, wood & metal workshops, coffee hullers, hollow block manufacturing, bakeries and pastries. The dominant manufacturing activities that account 70% of the total number of manufacturing enterprise in the town are grain mills and wood works.

Jimma has a tropical climate classification. It features a long annual wet season from Sep to Aug. Temperatures at Jimma are in a comfortable range, with the daily mean staying between 19°C and 26°C year-round.

Table 1.1 jimma climate classification Feb

Month	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Average high °C (°F)	27 (81)	27 (81)	28 (82)	28 (82)	28 (82)	29 (84)	28 (82)	27 (81)	26 (79)	24 (75)	24 (75)	25 (77)
Daily mean °C (°F)	23 (73)	23 (73)	23 (73)	22.5 (72.5)	23 (73)	24 (75)	24 (75)	23.5 (74.3)	23 (73)	21.5 (70.7)	21.5 (70.7)	22 (72)
Average low °C (°F)	19 (66)	19 (66)	18 (64)	17 (63)	18 (64)	19 (66)	20 (68)	20 (68)	20 (68)	19 (66)	19 (66)	19 (66)

About Jimma substation

The substation was established in 1979 within one year later in the establishment of Gilgel Gibe hydro power. This substation obtain its input from Gilgel Gibe means the generation feeds 132kv to the substation then was divide by step down around Jimma city and online to different Wereda. The oldest substation has only one Trafo (132/15kv) that have only four lines. Those are: Line 1-kochi Line 2- Jimma university Line 3-city line 4-agri line 5- kitto campus line

Currently the substation has fulfilled with many control equipment, switching and protection. It receives power from Gilgel Gibe hydro power plant and from transmission lines and it transforms high to low voltage. It distributes electricity to customers and supervises and protects the distribution network to keep it working safely and efficiently. Now days the substation has 6 bays (incoming and outgoing terminals).

Those are; Bay1- abba line (132kv,40kA),Bay2-bonga line(132KV,40KA) ,Bay3-trafo 132/15kv,Bay4-gilgelgibe(132incoming),Bay5-agaro(132kv,1okA).

Trafo132/15kv has the following lines:- Kochi line ,Jimma university line ,City line, Kitto campus line ,Agri-line

Trafo132/33kv has the following lines:-Limu genet line, Line 2-hydro

As we stated earlier Jimma electric substation has different lines. Those lines have many customers in Jimma town and other towns around Jimma town.

Trafo 132/15kv has the following customers;

Kochi line; customers- Deppo,Jiren, Era, water treatment, Kato, Bulbul, Serbo

Capacity- 4.8MW

C.T ratio- 300/600/5/5A

Jimma university line; customer-Jimma university

Capacity- 3.3MW

C.T ratio -75/150/5/5A

City line; customers-Beno, Kera, Dedo town, Bus station.

Capacity-4.2MW

C.T ratio -100/200/5/5A

Kitto campus line; customer- kitto campus

Capacity-1MW

C.T ratio -25/50/5/5A

Agri line; customers-Agri college, Gebrier church, Frenj areda, airport, Melko, Seka, alma.

Capacity-4MW

C.T ratio-50/100/5/5A

Trafo 132/33kv has the following customers;

Limu genet line1; customers- Sombo, Bilida , Kentere, Babu, Kosa, Anbuwye, Limu town

Capacity-3.5MW

C.T ratio -75-150/5/5A

Line2; customers- Atnago and Bage

Capacity-3.2MW

C.T ratio -50/100/5/5A

Atnago line; customers- Limu seka,gejib and Atnago town

Bage line; customers-Mecha, chalelaki and Bage town **Agaro**, **Abba** and **Bonga** lines have also many customers.

Figure 1.2 View of Jimma substation

One line diagram of Jimma substation

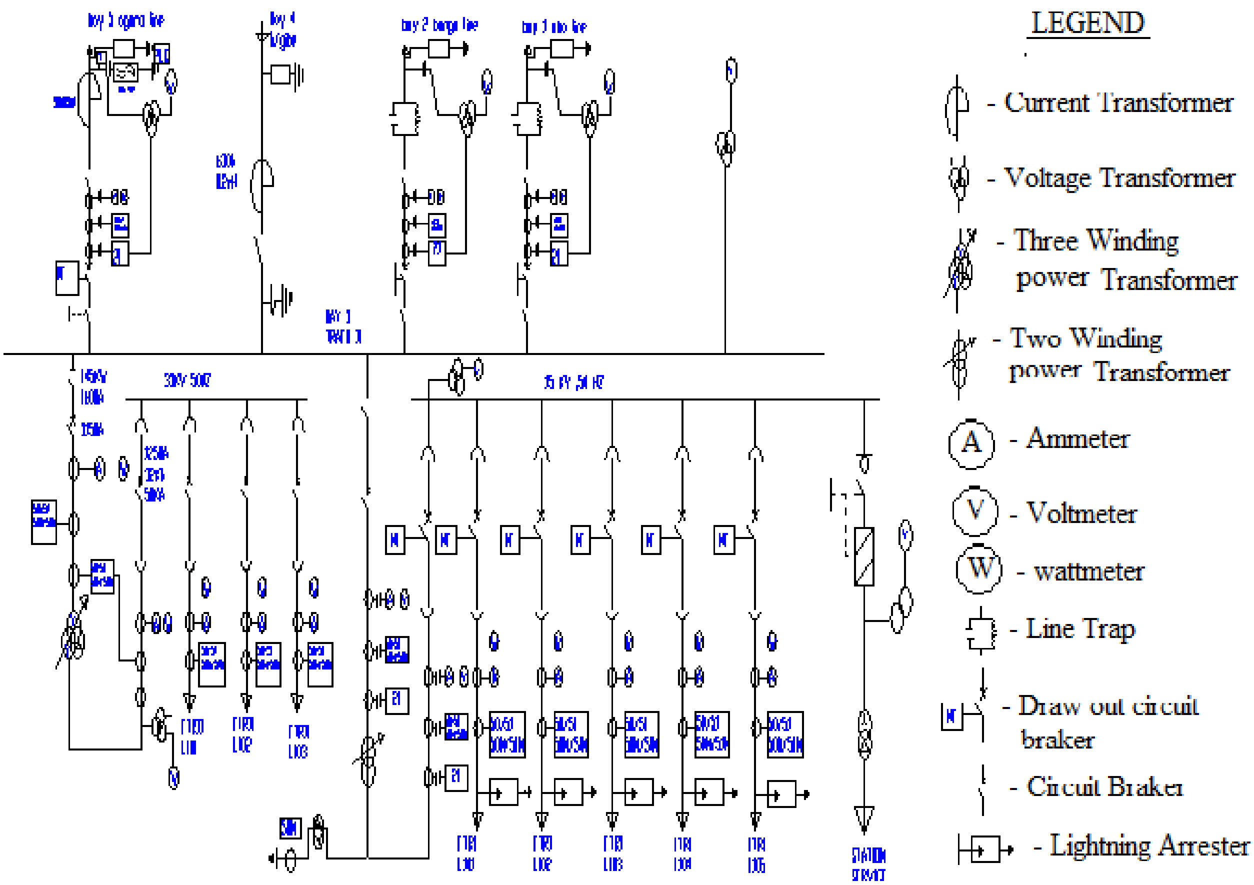


Figure 1.3 One line diagram of Jimma substation

I have selected Jimma city for the short term load forecasting study using neural network because of the following main reasons. (1) The proposed problems are clearly visible, and (2) Being one of the coffee and business centers of south west Ethiopia, the solution of the problem will have significant impact on the economy of the area. Since there is no existing short term load forecasting by using artificial neural network Jimma city, to solve this problems has been proposed a solution.

However, short-term load forecasting is more accurate than medium and long term load forecasting due to the several factors. For short-term load forecasting several factors should be considered, such as time factors, seasonal data, and possible customers' classes.

This thesis would define short-term electric load forecast (STLF) as a 24-hour-ahead load forecast whose results would provide an hourly electric load forecast in Kilowatts (KW) for the future 24 hours (a 24-hour load profile).

The intent of this research is to perform short-term electric load forecasting for a specific facility, whereas most other STLF studies are for utility transmission and distribution systems. The facility to be studied is the Jimma City (J.C).

1.2 Factor affects power demand

The system load behavior is affected by a number of factors. These factors are economic, time, weather and random effects. Economic factors such as the service area demographics, levels of industrial activity, the nature and level of saturation of the appliance population, developments in the regulatory climate and more generally, economic trends have significant impacts on the system load growth/decline trend. In addition utility-initiated programs, such as changes in rate design and demand management programs also influence the load. It is important to account for these factors in the updating of forecasting models from one day to the next or possibly from one season to another. The economic factors are not, however, explicitly represented in the short term load forecasting models because of the longer time scales associated with them. Time factors such as seasonal effects, weekly-daily cycle and legal and religious holidays play an important role in influencing load patterns. Certain changes in the load pattern occur gradually in response to seasonal variations such as the number of day-light hours and the changes in seasonal events, which bring about quick but important structural modifications in the electricity consumption pattern. The activities during vacation periods (Christmas-New Year period). The existence of statutory and religious holidays has the general effect of significantly large the load values to levels well large ‘normal’. Meteorological conditions are responsible for significant variations in the load pattern. This is because most utilities have large components of weather-sensitive load, such as those due to space heating, air conditioning. In many systems temperature is the most important weather variable in terms of its effects on the load. Past temperatures also affect the load profile. Humidity is a factor that may affect the system load in a manner similar to temperature particularly in hot and humid areas. Finally a power system is continuously subject to random disturbances reflecting the fact that the system load is composed of a large number of very small disturbances. There are also certain events such as widespread strikes, shut-down of industrial facilities. [21].

1.3 Statement of the problem

Electricity cannot be stored (directly) for future use. however, Electricity consumption Varies Load Forecasting every day with time, season and other factors which are not insignificant Power generation is not equal to power demand .therefore, the production of power is over can be a loss/wastes and the production of power is insufficient the result can be low power quality. Predict the future electric demand based on historical load, climate factors, seasonal factors, social activities, and other possible factors.

This approach has been implemented in this paper to data obtained from the jimma substation along with traditional ANN based forecaster. This approach allows us to achieve one major improvements as compared to the traditional ANN based forecaster. It ensures a better accuracy. There is a good chance that some values of input variables out of this domain will produce incorrect forecasts. The sensitivity of this phenomenon depends greatly on the neural network design. Network with too many input variables or too many hidden neurons, providing a good accuracy. This means that the forecast accuracy represented in the training data.
To develop Artificial Neural Network-based models for Short-Term Load Forecasting and apply these models to a real life case study to evaluate the performance of the proposed approach and provide one day ahead forecast for the Jimma City (JC) power system network.

1.4 Objectives

1.4.1 General Objectives

The general objective of this thesis work is to study the power load of the Jimma city (JC). Therefore, to observe the existing power are studied. Then, the appropriate forecasted power loads are also provided by studying the short term load forecasting Neural Network method.

1.4.2 Specific Objectives

- To identify the electrical load demand of 24 hrs Jimma city.
- To identify the specific hourly load demand that is used to get maximum power with specific hour.
- To design and simulate load forecast using Matlab, Neural Network toolbox.
- To compare the types of neural networks.
- To compare the results of the Actual and forecasted load.

1.6 Scope of the study

This thesis work focuses on a specific area of load forecasting, short-term load forecasting. The forecasts are achieved by using artificial neural network model using feed forward neural network, radial basis neural network and recurrent current developed in MatLab and Simulink environment. The model are applied to the actual load data of jimma city different areas to forecast what is often referred to as consumer own forecast. The scope of this study focuses only on short-term load forecasting.

1.6 Methodology

This research work concludes and analyze with the implementation of following methodologies:

- In the first phase, using measured (historical) load data
- Construction an ANN architecture having two neurons in input layer, five neurons in hidden layer and one neuron in output layer.
- Training of the network using feed forward neural network, for radial basis neural network and recurrent current artificial neural network with different learning rates.
- Finding the forecasted values using the best ANN using feed forward, radial basis and recurrent current.
- The load curve for the next day (daily module) and find the peak lade curve.
- Find the least (minimal) producing errors for training MAPE forecasted values.

1.7 Contribution of the Thesis

Work in this thesis has contributions in the area of electric short-term load forecasting (STLF) using Artificial Neural Network (ANN). The contributions are the following:

• Classical ANN-based STLF models use Back Propagation (BP) Algorithm for training, which does not ensure convergence and hangs in local minima more often because BP requires much longer training time, which makes it difficult for real-time application. To overcome this problem, Modern ANN-based STLF models use Feed forward (FF) Algorithm has been used to develop directly ANN by considering it as an optimization problem, with Feed forward Back Propagation responsible for training; we can adapt ANN in any way to suit the problem or class of problems.

• To accommodate the size and complexity of patterns involved in the training of ANN, I have decomposed the STLF problem to its discrete level and try to build small ANN models based on hourly load in the historical time varying window. The small models act as building blocks for making twenty-four hours ahead hourly load forecasting model. The resultant small models get trained faster due to simple network structure and perform efficiently due to Feed forward (FF) based training strategy.

1.8 Limitations

The research face difficulty to access all relevant data and few respondents are not willingness to provide the required information and may hide the real facts. The major limitation in this study is lack of relevant socioeconomic data on population of the city. Time and budget are always in scarce which also view come upon this study.

1.9 Thesis Outline

Chapter 1 discusses the background, purpose of the work and breakdown structure of the work.

Chapter 2 covers literature review i.e. methods used for load forecasting, comparisons of various papers, findings and remarks. In this chapter, drawbacks of different forecasting methods are also highlighted.

Chapter 3 presents the analysis techniques used to implement a STLF for J.C. The methods and Matlab® functions used to create an ANN are discussed in detail.

Chapter 4 presents the STLF simulation results and compares the forecasted results with the actual 24-hour load.

Chapter 5 summarizes the research and results presented in this thesis. This chapter also proposes future work in electrical STLF for Jimma City.

Chapter 2

2.1. Literature Review

Ethiopian Power System Expansion Master Plan Study Prepared for EEU. The Ethiopia Electric Utility says to study load forecast methodologies that we have employed are founded on well-established principles of Economic/econometric modeling of key economic drivers to produce a demand forecast. Developing the demand forecast for Ethiopia required that traditional widely used forecasting methods [19].

Feinberg and Genethliou 2005 Variations in weather are largely regarded as important factors in modeling electricity demand of the exogenous variables models, weather time interval or a few hours related variables (e.g., temperature) have by far been the most popular and at times, the most complex to account for (Ramanathan et al. 1997) [20].

David Palchak [5]**.** This paper describes the techniques of predictions for proving useful in the growing of consumer, or end-user, participation in electrical energy consumption. These predictions are based on exogenous variables, such as weather, time and population variables, such as day of week and time of day as well as prior energy consumption patterns. An Artificial neural network technique is accepts weather condition and time variables as an input signal [1].

Deloitte Consulting. This paper helps to work short term load forecast uses a defined methodology to analyze the inputs into the country's electricity usage and, as an output, predicts future growth in the energy sector across technologies and different customer groups (i.e. residential, industrial, and commercial). This paper helps to work short term load forecast [6].

L. Ghods and M. Kalantar . Describes the artificial intelligence methods parametric load forecasting methods can be generally categorized under three approaches: regression methods, time series prediction methods and Similar-day approach. Traditional statistical load demand forecasting techniques or parametric methods have been used in practice for a short time [15].

Tai Hein Fong [HYPERLINK \l "TAI09" 7].This paper describes main stages of the types of inputs how artificial network is process depends on the natural effect temperature, time and data. Also learning of the pre-processing of the data sets, network training, and forecasting [14].

Isaac Gautham P. Das, Chandrasekar S., Piyush Chandra Ojha. Researchers Describes the methods are mainly classified into two categories: Classical approaches and Modern approaches based techniques. Classical approaches are based on various statistical modeling methods such as time- series, regression and Similar-day approach. However, these classical methods cannot properly represent the complex non-linear relationships that exist between the load and series of factors that influence it [15].

As from 1990s, researchers began to use different approaches for STLF other than classical approach. The emphasis shifted to the implementation of various AI techniques for STLF. AI techniques such as neural network, fuzzy logic and expert systems have been applied to deal with the non-linearity, large data sets requirement in implementing the STLF system and other difficulties in modeling of classical methods used for the application of STLF [15]. Among the AI techniques available, different models of neural network have received a great deal of attention by researchers in area of STLF due to its flexibility in data modeling.

Eric Lynn Taylor. Used an ANN based on back propagation for forecasting and analyzed and discussed a comprehensive approach for STLF using ANN. Their proposed architectures were trained and tested using previous one day actual load data obtained from Institutional/Industrial power. In their study, four ANN models were implemented and validated with reasonable accuracy on real electric load generation output data [17].

Mohammed and Sanusi. developed a multilayer feed forward ANN model for 132/33KV substation, Kano, Nigeria using Levenberg- Marquardt optimization technique to train the network , presented a method for STLF, based on ANN targeted for used in large-scale system as distribution management system (DSM). Functionality of the proposed method was tested. ANNs have been integrated with several other techniques to improve their accuracy, presented a hybridization of a neural network with a novel stochastic search technique for STLF and used adaptive neural-fuzzy inference system (ANFIS) to study the design of STLF systems [4].

Pituk Bunnoon, Kusumal Chalermyanont, and Chusak Limsakul. In this literature we can find a wide range of methods for electric load forecasting. The classification is based on certain characteristics, such as the type of load model, the type of data to provide the model, the computational time required, the prediction algorithm and the availability of experimental results. Various methods and ideas have been tried for load forecasting, with varying degrees of success. They may be classified into two categories, statistical (classical) and Modern or artificial intelligence [3].

2.2. Summary of literature review

The importances of load forecasting have been proposed several reviews in the past. These reviews can generally be classified in to two categories. These are **classical methods of load forecast and Modern methods of load forecast** Methods of classical methods of load forecast use statistical means to arrive at a forecast solution and Linear equation expressed in terms of previous load values and Popularity for STLF is low [14]. Method of Modern methods of load forecast uses an algorithm that combines previous system load and time data and predicts a future load pattern. The type and description of artificial network training and selection of ANN type by error minimization techniques and simplest method [21]; ANN is trained with an input data set to approximate a target data set. Load forecasting is an inherent nonlinear problem and the structure of an ANN is suited for multivariate, nonlinear, and non parametric computer program. Must be trained on historical data and Popularity for STLF is high. MLF neural networks, trained with a back-propagation learning algorithm, are the most popular and easy to predict the demand load neural networks [1], [15]. These reviews also are use the effect of temperature, time, weather and load data for Short Term Load Forecasting. The above document to select this thesis work time, weather and load data are uses Short Term Load Forecasting on jimma city but the temperature is almost constant (very small variation) in jimma city .This city used only ventilator for hot air but did not use heater because of air is hot at any season [5], [14].

Table 2.1. Short Term Load Forecasting Classified By Type Of Models.

Author name	Title	Types of model	Drawback
Eric Lynn Taylor	Short-term Electrical Load Forecasting for an Institutional/Industrial Power System Using an Artificial Neural Network	FFNN (feed-forward neural networks)	Only focused on FFNN MAPE(1% - 3%)
Manoj Kumar	SHORT-TERM LOAD FORECASTING USING ARTIFICIAL NEURAL NETWORK TECHNIQUES	FFNN (feed-forward neural networks)	Only focused on FFNN MAPE(2.64%)
A.Indira1, M. Prakash2, S.	Short-term Load Forecasting of an Interconnected Grid by using Neural Network	RBFNN (radial basis function neural network)	Only focused on RBFNN MAPE(0.8895%)
Mahrufat D. Olagoke	Short Term Electric Load Forecasting using Neural Network	FFNN (feed-forward neural networks)	Only focused on FFNN MAPE(4.705%)
Simaneka Amakali	Development of models for short-term load forecasting using artificial neural networks	**RNN** (recurrent neural networks) FFNN (feed-forward neural networks)	**RNN** MAPE(6.09 %) FFNN MAPE(0.367077%)

Chapter 3

3. Materials and Methods

This chapter describes the material and methods used to create ANNs that Perform 24-hour load forecasts. MATLAB is the computer software used to create and implement the 24-hour load forecast for JIMMA TOWN. The Neural Network Toolbox in MATLAB provides built-in functions and applications to assist in modeling nonlinear systems. It supports ANN training, testing, and simulation. Appendix A contains the 24-hour load forecast MATLAB m-file code.

3.1 Input Data

One week (winter **Monday 22/9/07** – **Sunday 28/9/07**) , One week (Summer **Monday 25/12/07** – **Sunday 1/13/07**) and One day (Holiday **Wednesday 1/1/08**) of electrical load. Load data was recorded for JIMMA CITY, so there are 15 days of data collected. This data was used for training and testing of the 24-hour load forecasting ANN. The load data was collected from a database containing data recorded from power meters located at the JIMMA CITY substation. The load data contains the electrical load for JIMMA CITY recorded for the previous hourly, however, the 24-hour forecast ANN only requires hourly metered load data as inputs, so the half-hour values were not used.

3.2 Pre-processing

3.2.1 Date

The metered/recorded load and weather data parameters were imported into MATLAB® as individual column vectors.

Winter, summer and holiday Measured Data from typical electrical load profile of Jimma City

Table 3.1

hrs	Monday 22/09/07 (KW)	Monday 25/12/07 (KW)	Tuesday 23/09/07 (KW)	Tuesday 26/12/07 (KW)	Tuesday 6/13/07 (KW)
1	9300	10400	7800	10600	9300
2	9600	11700	9300	11400	11200
3	9300	11700	10100	10900	11700
4	9600	11100	10500	10600	12200
5	10100	11500	11900	11200	12800
6	10600	12200	12000	12000	13300
7	11100	12200	11700	11100	11100
8	9300	10400	11700	10100	10600
9	7900	9100	6900	10100	10300
10	10300	9000	11700	10000	10600
11	11200	10600	11600	10000	10600
12	12000	10600	11700	9300	12000
13	12500	11100	12500	13300	14900
14	12500	13300	12700	11100	14400
15	12200	11100	12500	11900	14100
16	10900	10600	11700	10600	12200
17	10100	7900	10500	5300	10600
18	5800	5300	9000	5200	5800
19	3400	4500	5300	5300	7500
20	9200	4300	5300	5300	6200
21	8700	4000	5300	5300	5800
22	5300	4800	5300	5300	5600
23	5800	5900	5300	5300	7700
24	7700	6700	6400	6300	8500

Measured Data from typical electrical load profile of Jimma City.

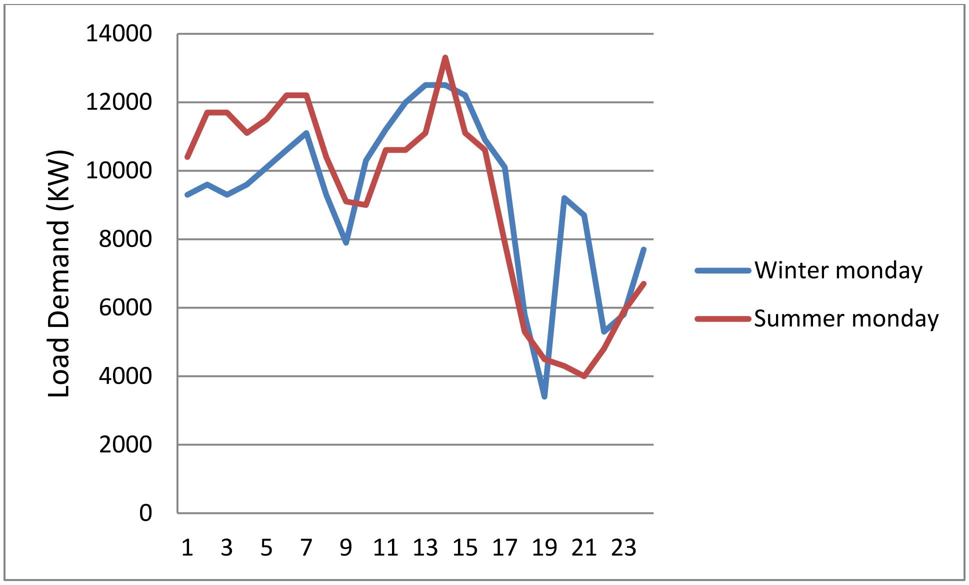


Figure 3-1 Comparison of hourly Monday 22/09/07and Monday 25/12/07 measured power demand

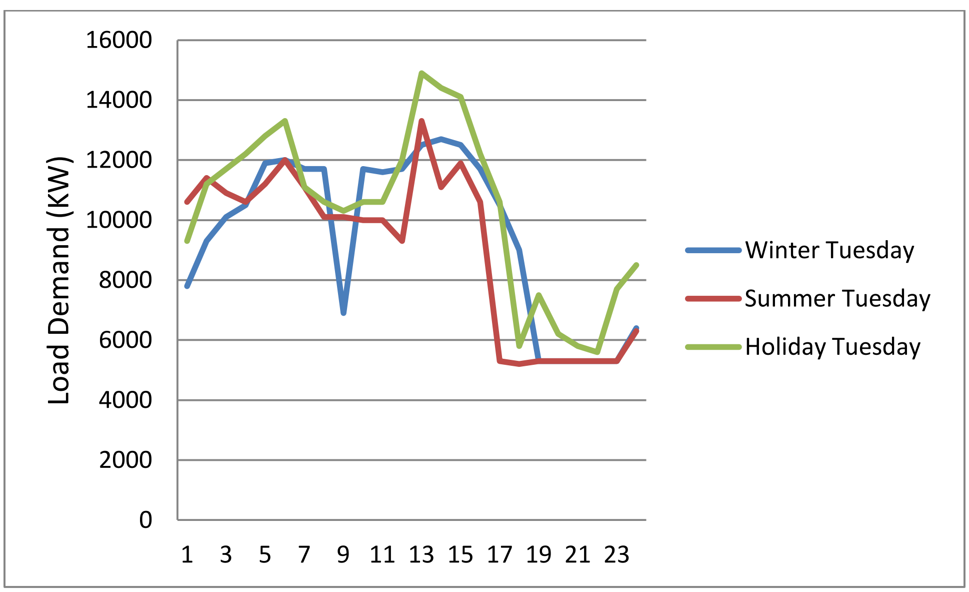


Figure 3-2 Comparison of hourly Tuesday 23/09/07, Tuesday 26/12/07 and Tuesday 6/13/07 measured power demand

Winter, summer and holiday Measured Data from typical electrical load profile of Jimma City

Table 3.2

hrs	Wednesday 24/09/07 (KW)	Wednesday 27/12/07 (KW)	Wednesday 1/1/08 (KW)	Thursday 25/09/07 (KW)	Thursday 28/12/07 (KW)
1	9000	10600	9000	5300	11700
2	4600	10600	10600	5900	10700
3	10100	10600	10100	5800	10600
4	4600	10600	9800	6100	10600
5	10500	11200	10300	10900	11100
6	10600	12700	10600	10900	12800
7	10700	11700	10600	7500	9500
8	10500	9100	9300	5900	9000
9	9500	8500	7900	9000	9500
10	7100	9500	8400	12000	9600
11	7200	9300	8200	11900	9300
12	10400	6700	8400	11000	9400
13	10600	11700	11700	11700	11100
14	12200	13300	11700	13000	13000
15	12000	11900	10600	7900	12000
16	10600	10500	7900	6800	9600
17	5300	6600	5800	6300	7200
18	4300	5300	5300	6200	5900
19	5300	5000	4800	4000	5300
20	5300	4800	4800	3700	5200
21	5300	4600	4800	3500	4900
22	5300	4800	5300	3800	4900
23	5400	5300	5600	4200	4900
24	7900	5400	6300	4800	6700

Measured Data from typical electrical load profile of Jimma City.

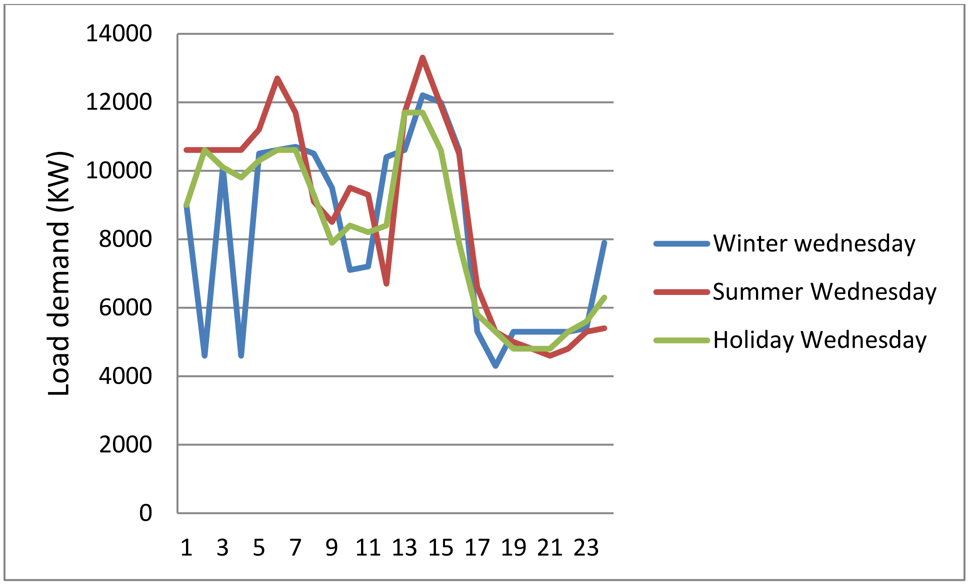


Figure 3-3 Comparison of hourly Wednesday 24/09/07, Wednesday 27/12/07 and Wednesday 1/1/08 measured power demand

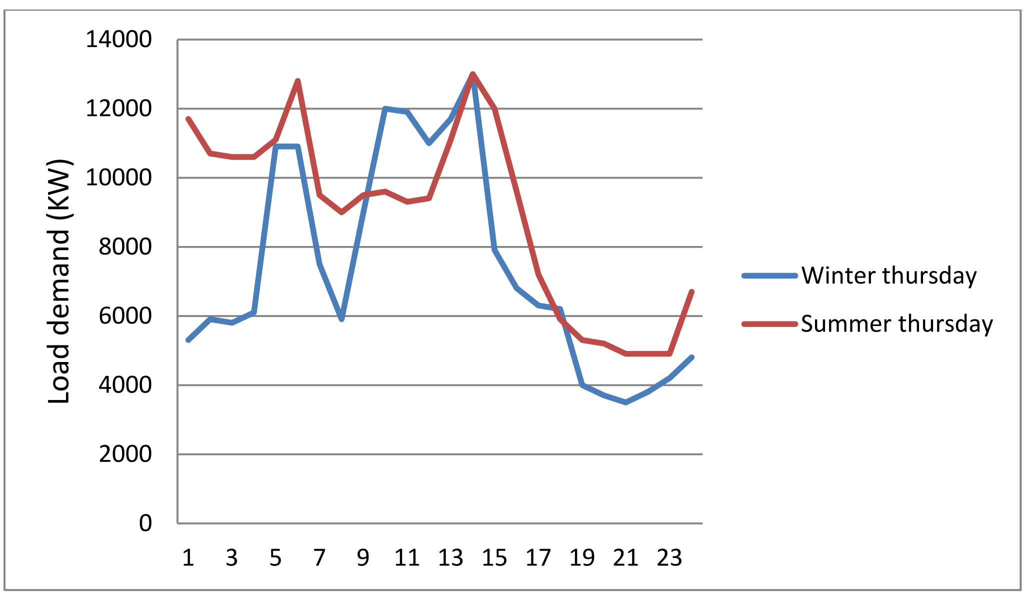


Figure 3-4 Comparison of hourly Thursday 25/09/07and Thursday 28/12/07 measured power demand

Winter and summer Measured Data from typical electrical load profile of Jimma City

Table 3.3

hrs	Friday 26/09/07 (KW)	Friday 29/12/07 (KW)	Saturday 27/09/07 (KW)	Saturday 30/12/07 (KW)	Sunday 28/09/07 (KW)	Sunday 1/13/07 (KW)
1	8500	9800	9000	10100	7900	6700
2	9100	11200	9800	10900	9300	11100
3	9800	11200	10000	10400	6900	6900
4	9800	10900	10600	10100	6900	6300
5	10600	10800	9800	11200	9600	6300
6	11400	10900	12200	11200	10600	7400
7	11300	11700	11700	10600	10600	10600
8	10300	9600	11400	10100	10400	10600
9	6600	9400	10900	8500	10500	10100
10	6200	9000	10600	7900	9800	7400
11	6800	9000	10400	8500	10100	8300
12	11700	10600	10600	9300	10400	9700
13	11900	11400	10900	11700	10400	12800
14	13300	12700	12300	12700	12000	12800
15	12700	11100	11700	7900	11700	12600
16	10600	5800	8700	7800	10600	10600
17	10200	6300	6300	6800	8500	7000
18	7900	5300	6100	5300	6900	4600
19	6000	5100	5800	5300	6000	5000
20	5800	4800	5800	5000	5800	7500
21	5600	4500	5200	5000	5400	7200
22	5300	4500	5200	5000	5300	7500
23	5200	5800	5300	5300	6600	5800
24	5800	6100	6900	5300	6700	6300

Measured Data from typical electrical load profile of Jimma City.

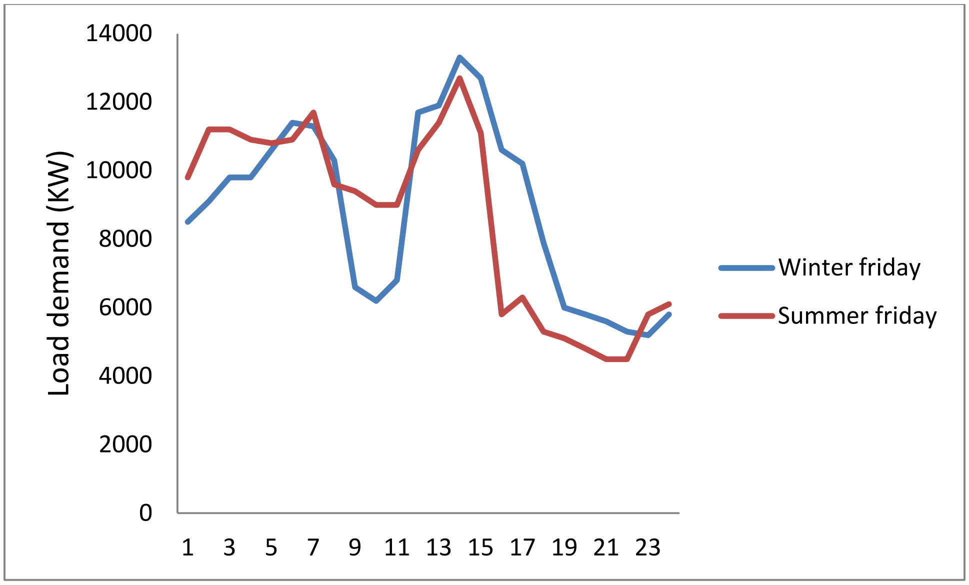


Figure 3-5 Comparison of hourly Friday 26/09/07and Friday 29/12/07measured power demand.

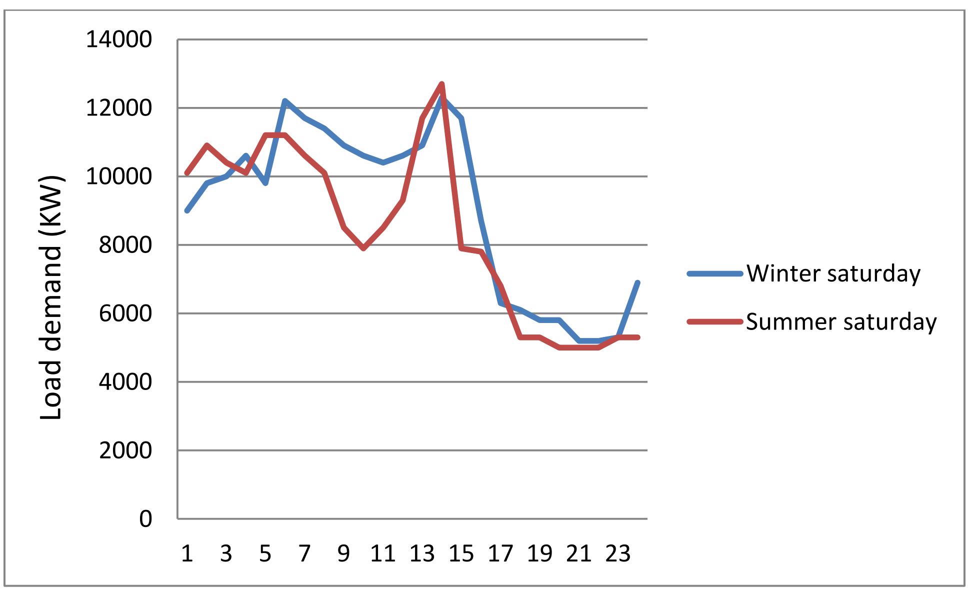


Figure 3-6 Comparison of hourly Saturday 27/10/07 and Saturday 30/12/07 measured power demand

Measured Data from typical electrical load profile of Jimma City.

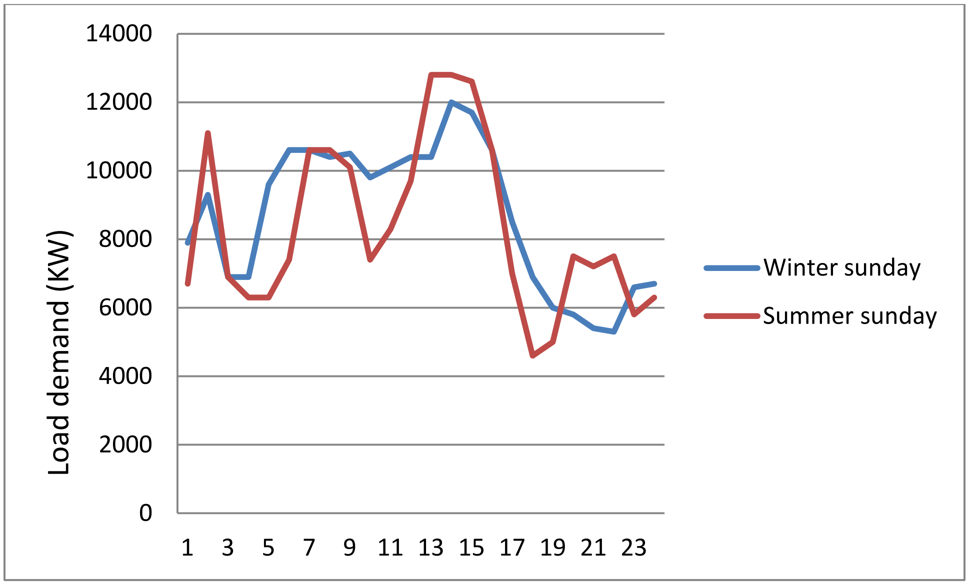


Figure 3-7 Comparison of hourly Sunday 28/09/07 and Sunday 1/13/07 measured power demand

Winter, summer and holiday peak load Measured Data from typical electrical load profile of Jimma City

Table 3.4

Time	Days	Peak load	Peak load
14	Monday 22/09/07	12500 KW	12.500 MW
14	Monday 25/12/07	13300 KW	13.300 MW
14	Tuesday 23/09/07	12700 KW	12.700 MW
14	Tuesday 26/12/07	14900 KW	13.300 MW
14	Tuesday 6/13/07	13300 KW	14.900 MW
14	Wednesday 24/09/07	12200 KW	12.200 MW
14	Wednesday 27/12/07	13300 KW	13.300 MW
14	Wednesday 1/1/08	11700 KW	11.700 MW
14	Thursday 25/09/07	13000 KW	13.000 MW
14	Thursday 28/12/07	13000 KW	13.000 MW
14	Friday 26/09/07	13300 KW	13.300 MW
14	Friday 29/12/07	12700 KW	12.700 MW
14	Saturday 27/09/07	12300 KW	12.300 MW
14	Saturday 30/12/07	12700 KW	12.700 MW
14	Sunday 28/09/07(KW)	12000 KW	12.000 MW
14	Sunday 1/13/07(KW)	12800 KW	12.800 MW

3.2.2 Time

The future electrical load is greatly influenced by previous load values. As a result, it was imperative that previous load values were used as inputs to the ANN. Time is not vary used 1-24hrs but the date is vary due to winter, summer and holiday

3.2.3 Calendar Designations

The date-stamps for each input load data were further processed to create daily, weekend, and holiday records. The daily record contained a numerical representation of the daily (22/10/07 through 28/10/07, 25/12/07 through 1/13/07 and 1/1/08) each load data value was recorded.

3.3. Load forecasting methods

Generally, there are two different categories of forecasting models which are the traditional models and the modern technique [4] [8] [15].

Traditional models

Traditional forecast model employ time series and regression analysis through the use of statistical models such as peak load models and load shape models.

Modern technique

Techniques such as neural networks, fuzzy logic, and expert systems, it is known that these technique can be use to operate the load forecast model more effectively and accurately. Since load forecasts can be divided into three categories: short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year, therefore this means that for each of the categories, there will be the most appropriate methods to operate the forecast models. First for the medium- and long-term forecasting, the so-called end-use and econometric approach are broadly used. Whereas, a variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, and expert systems, have been developed for short-term forecasting.

For the research, I develop short-term load forecasting using artificial neural networks data in MATLAB.

Some of the techniques that have been proposed and implemented to create STLF are [14]:

1. Similar-day approach
2. Regression methods
3. Time Series
4. Neural Network
5. Fuzzy logic

3.3.1 Similar-day approach

This approach is based on searching historical data for days with in one, two, or three years with similar characteristics to the forecast day. Similar characteristics include weather, day of the week, and the date. The load of a similar day is considered as a forecast. Instead of a single similar day load, the forecast can be a linear combination or regression procedure that can include several similar days. The trend coefficients can be used for similar days in the previous year's [4].

3.3.2 Regression methods

Regression is the one of most widely used statistical techniques. For electric load forecasting regression methods are usually used to model the relationship of load consumption and other factors such as weather, day type, and customer class. Their models incorporate deterministic influences such as holidays, stochastic influences such as average loads, and exogenous influences such as weather [8].

3.3.3 Time Series

Time series can be defined as a sequential set of data measured over time, such as the hourly, daily or weekly peak load. The basic idea of forecasting is to first build a pattern matching available data as accurate as possible, then obtains the forecasted value with respect to time using established model [15].

3.3.4 Fuzzy logic

Fuzzy logic is a generalization of Boolean logic; it allows deduction of output system from fuzzy imprecise inputs. However, model based on fuzzy logic are robust in forecasting because there are no need to mathematical formulation between system inputs and outputs. Electrical load forecasting using fuzzy logic controller can use several factors as inputs like temperature and time. A defuzzification process is used to produce the desired output after processing logic inputs 2],[10].

3.3.5 Neural Network

The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. Artificial Neural Networks are mathematical tools originally inspired by the way human brain process information. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. Based on learning strategies, neural network methods for load forecasting can be classified into two groups. The first one is a supervised neural network that adjusts its weights according to the error between pre-tested and desired output. The second are methods based on unsupervised learning algorithm. Generally, methods based on supervised learning algorithm like a multilayer perceptron are used [1], [15].

3.3.5.1. Benefits of Artificial Neural Network

1. They are extremely powerful computational devices.
2. Massive parallelism makes them very efficient.
3. They can learn and generalize from training data – so there is no need for enormous feats of programming.
3. They are particularly fault tolerant – this is equivalent to the "graceful degradation" found in biological systems.
4. They are very noise tolerant – so they can cope with situations where normal symbolic systems would have difficulty.
5. In principle, they can do anything a symbolic/logic system can do, and more

3.3.5.2. Mathematical Model of a Neuron

A neuron is an information processing unit that is fundamental to the operation of a neural network. The three basic elements of the neuron model are:

1. A set of weights, each of which is characterized by a strength of its own. A signal xj connected to neuron k is multiplied by the weight wkj. The weight of an artificial neuron may lie in a range that includes negative as well as positive values.
2. An adder for summing the input signals, weighted by the respective weights of the neuron.
3. An activation function for limiting the amplitude of the output of a neuron. It is also referred to as squashing function which squashes the amplitude range of the output signal to some finite value.

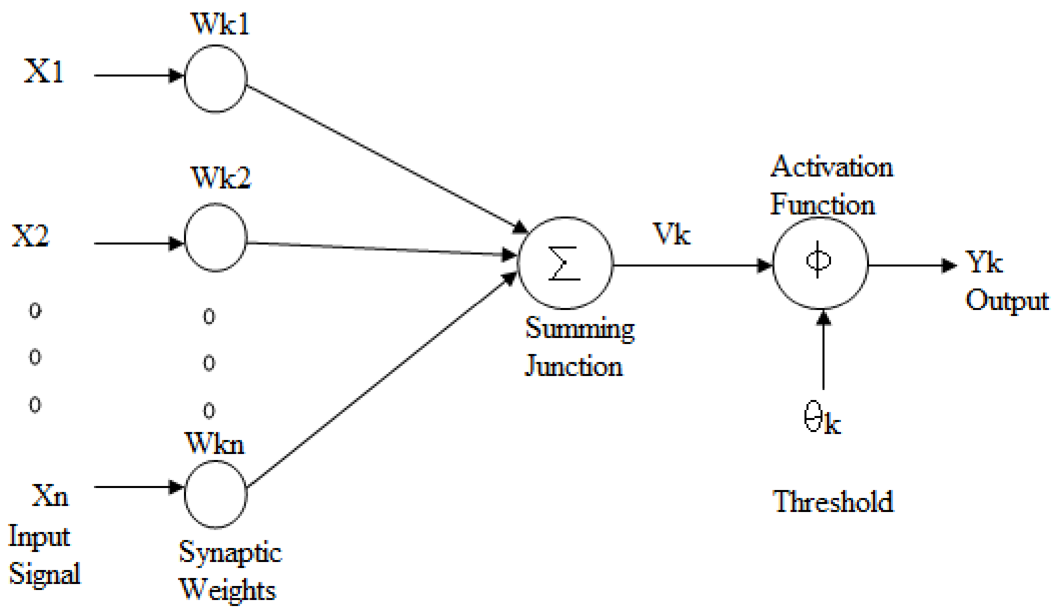


Fig 3.6 Model of an ANN

3.3.5.3. Training the Forecast

After the Matlab code analysis was performed on the training and forecast predictor datasets, the number of hidden layers, or neurons, in the ANN was defined and the ANN was created for the user-defined forecast day. The built-in Matlab training function was used to perform the feed forward, radial basis and recurrent training of the ANN. This process iteratively updated the internal weight and bias values of the ANN to obtain a low error output when utilizing the training predictor dataset and a target dataset. The target dataset consists of the actual load values for a given predictor dataset. After training, the ANN was tested using only the training predictor dataset. This step allows the user to verify the trained ANN can produce low error forecasts on in sample data. After testing, the ANN performed a 24-hour forecast using only the forecast predictor dataset. The results of this forecast were stored, and the entire ANN training, testing, and forecasting process was repeated a set number of times with the intention of reducing the forecast error. Two methods were concurrently used to minimize the forecast error.

Method 1 assumes the 24-hour forecast's MAPE will be minimized if the trained ANN's testing step MAPE was minimized. After each training iteration, if the ANN's training MAPE was reduced, the newff, newrb and newelm trained ANN would replace the previously stored ANN.

Method 2 assumes the 24-hour forecast's MAPE will be minimized if the MAPE of the previous day's 24-hour forecast is minimized. This requires a STLF to be performed for the day prior to the forecast day. Since the previous day's load is known, an accurate MAPE can be calculated. The prior day's MAPE was iteratively minimized in a similar manner as Method 1 above. When a new minimum MAPE for the previous day was stored, the trained ANN associated with that minimum MAPE was stored. Once the training error was minimized, the 24-hour forecast associated with Method 1 was stored. Method 2 created a new 24-hour forecast for the forecast day using the stored ANN obtained in Method 2. This entire error minimization and forecast storage process would repeat a fixed number of iterations. At the end of each iteration, the stored 24-hour forecasts were added to the previously stored 24-hour forecast so that at the completion of the forecasting algorithm, the 24-hour forecast values were averaged. 24-hour load forecasts for the same forecast day. The intent of the STLF is to forecast the next day's 24-hour load; the actual load values would not be known. Therefore, it was assumed the day prior to the forecast day had a similar load profile as the forecast day, so its load values would be used to calculate an approximate MAPE for both minimization methods' forecasts. The method that had the lower approximated MAPE was defined as the final 24-hour load forecast.

The reasoning behind the error minimization and repeating forecasting steps is that the Matlab® Neural Network Toolbox assumes random initial values when it begins the ANN training algorithm. Sometimes the initial values lead to an ANN that outputs very low error; other times, they lead to an ANN with low error, but not minimum error. Averaging the multiple runs of the 24-hour forecasted loads created a more consistent forecast MAPE. The absolute percent errors for each hour forecast and mean absolute percent error for each 24-hour forecast were calculated.

3.3.5.4. Network Structure

The ANN for STLF for the Jimma City forecaster that utilizes the sequence of inputs as formative to the prediction. Figure 3.4 shows the basic structure of the network. This is representative of non-linear external inputs of ANN, which is a dynamically-driven feed forward network that consists of an input layer, a hidden layer, and an output layer. The choice of one hidden layer is a combination of historical success with acceptable predictions. The output power at time t is informed by inputs presented to the network with no delay.

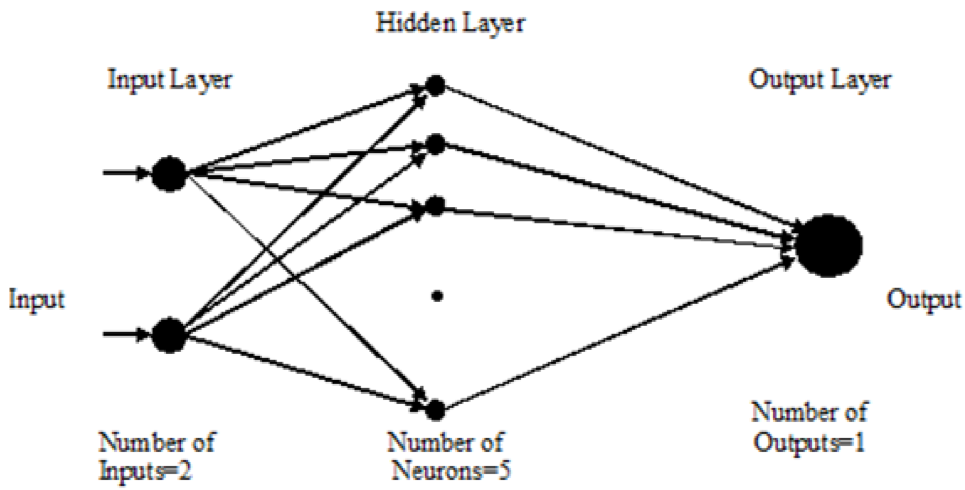


Figure 3.7. Architecture of ANN applied to Jimma City electrical load profile.

3.3.5.5. Performance Metrics

There are a number of error measurements that are relevant for quantifying the performance of the model. The most widely reported error in neural network literature is the MAPE, given in

$$MAPE = \frac{\frac{A-F}{A}\times 100}{N}$$

Where A is a (1xN) set of actual values, F is a (1xN) set of forecast values, and N is the number of points being forecast, which in this case is 24. Three additional performance measures that are informative when looking at the forecasting accuracy are: 1) the maximum error throughout a 24-hour period. 2) The difference in total electric energy consumed over the 24-hour period indicated by the area contained by the load profile curve. MAPE below 5% is the measure of a highly accurate prediction. The MPE is the ratio of the largest residual to the target value occurring at that hour. This metric quantifies the largest error for a day's forecast as a percentage of the total load on the system. The values as well as the time of day that this error is most likely to occur are both informative measures of how and when this forecast tool is appropriate to use.

3.4. Network topologies artificial neural networks (ANN).

3.4.1. Feed forward neural network

The feed forward neural network was the first and arguably most simple type of artificial neural network devised. In this network the information moves in only one direction forward: From the input nodes data goes through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network [9]. In classification problems, the network has to be trained (i.e. generate a set of weights that solves the problem properly) with a set of data to correctly classify their desired outputs. Once trained, the network is ready to classify new data. Since training means to optimize the weights of the network, we should decide which optimization algorithms better perform the task. At present, there are a lot of different strategies used to train a network. One of the most widely used is the back propagation algorithm (BP) [21].

3.4.1.1. Single layer feed forward network

This type's network comprises of two layers, namely the input layer and the output layer, the input layer neurons receive input signal and the output layer neurons receive output signal. The synaptic links carrying the weights connect every input neuron to the output neurons but not vise – versa, such a network is said to be feed forward in type or cyclic in nature. The input layer merely transmits the signals to the output layer, hence the name single layer feed forward network.

3.4.1.2. Multi layer feed forward network

This network, as its name indicates is made up of multiple layers, architecture of this class besides possessing an input and output layers also have one or more intermediary layers called hidden layers. The computational unit of the hidden layers are known as hidden neurons or hidden units, the hidden layer aids in performing useful intermediary computation before directing the input to the out put layer. The input layer neurons are linked to the hidden layer neurons and the weights on these links are referred to as input hidden layer weights, again, the hidden layer neurons are linked to the output layer neurons and the corresponding weights are referred to as hidden output layer weights. A multiple feed forward network with input neuron (I), W_1 neurons in the first hidden layer, and W_2 neurons in the second hidden layer and O output neurons in the output layers in written as I- W_1- W_2- O.

3.4.2. Radial basis function (RBF) network

The Radial Basis Function neural network (RBFNN) is to allocate each *RBF* neuron to respond to each of sub-spaces of a pattern class, formed by the clusters of training samples. As a result of that, learning at the hidden layer, is commonly configured as the problem of finding these clusters and their parameters by certain means of functional optimization. The name RBFNN comes from the fact that the basic functions in the hidden layer neurons are radially symmetric. The Radial Basis Function (*RBF*) network typically has three layers: an input layer, a hidden layer with a non-linear *RBF* activation functions and a linear output layer is a special class of multilayer feed-forward network. The hidden layer neurons receive the input information, followed by certain decomposition, extraction, and transformation steps to generate the output information. RBF networks are very popular for function approximation, curve fitting, time series prediction, and control and classification problems. The radial basis function network is different from other neural networks, possessing several distinctive features. Because of their universal approximation, more compact topology and faster learning speed, *RBF* networks have attracted much attention and they have been widely applied in many science and engineering fields [22].

3.4.2. Recurrent neural network (RNN).

Contrary to feed forward networks, Recurrent Neural Networks (RNNs) are models with bi-directional data flow. While a feed forward network propagates data linearly from input to output, RNNs also propagate data from later processing stages to earlier stages. RNNs can be used as general sequence processors [9].

Chapter 4

Results and Discussion

This chapter presents the results of various 24-hour load forecasts using trained ANNs. Plots for the predictor inputs are presented to visually see the trends the predictors and the load. Matlab analysis results for selected 24-hour load forecast days are tabularized and discussed to show how this step reduces the size and complexity of the predictor matrices. Load forecast results one day of each season (winter, summer and holiday) are presented along with 24-hour load forecast profile plots for selected days.

It also bounds the normal load range for Jimma City from a minimum of approximately 3,400 kW to a maximum of approximately 14,400 kW.

4.1. Load Forecast Results

4.1.1 Selection of Network Architecture and Parametric Values

Different network architectures were experimented with and their performances in terms of MAPE, on the test data set, when other network parameters were fixed, were noted and recorded as in table 4.1 below.

Table 4.1: Tested network architectures and their performances in terms of MAPE.

Layer architecture	MAPE (%) on Test Sets					
	1	2	3	4	5	Average MAPE
5	5.8655	-6.9446	2.1608	-3.9095	0.6171	**3.8995**
7	-4.2862	-5.9749	3.6468	13.2268	-8.1201	7.0509
10	-9.9236	-1.8652	0.0179	-8.9998	-8.6472	5.8967
15	-12.3397	-6.9131	1.1382	0.67183	-7.7350	5.7596
20	5.4595	-3.7583	-16.5521	-1.2265	-10.7328	7.5538
25	-12.8897	-19.2184	-1.0868	-1.4279	4.3720	7.799
30	26.0449	-4.8497	-13.7014	-13.6657	5.4583	12.744
40	9.4125	3.4647	-5.7722	-1.3225	-7.3355	5.4615

DISCUSSION: From table 4.1, it can be seen that the model architecture that gave optimal performance in terms of forecast error is **5** architecture, i.e., a single layered ANN model with 5 neurons in the second/hidden layer. It can be observed from table 4.1 that increasing or decreasing the number of neurons in a layer necessarily affect the model performance significantly.

4.1.2 Selection of Epoch and Performance ratio

Epoch: The epoch was set to a high initial value more than 10000 in this case, and the network performance was monitored. Particularly the number of epoch during which training stopped was observed, and with this as a guide the number of epoch was turned down until an optimal value of **2000** was noted.

Problem of generalization: as stated in the experimental procedure of this paper, the problem of over fitting was solved by regularization technique just as the optimal value of the performance ratio parameter was achieved by trial and error. Table 6 below shows the effect of choice of performance ratio parameter on our model accuracy. From table 6, it can be seen that the model forecasting accuracy was best with the value of performance ratio parameter set to **0.01**.

Table 4.2: Variation in performance ratio parameter with model accuracy

Performance ratio	MAPE
0.1	-4.0672
0.01	**0.6171**
0.001	1.4926
0.9	-3.4461
0.5	-1.4599
0.8	-1.5115
0.05	4.0924
0.09	-18.3095
0.2	-7.5631

Results: Table 4.3 below shows the optimal values of various model parameters used in this research while the test results when the trained model was tested on the 24-hourly load curves of New jimma city for the days of Tuesday 23/9/2007 E.C through Sunday 28/9/2007 E.C Winter season, the days of Tuesday 26/12/2007 E.C through Sunday 01/13/2007 E.C summer season and the days of Wednesday 01/01/2008 E.C new-year holiday the same are depicted in figures 4.1 through 4.13. The results obtained from testing the trained neural network on new data that never participated in the training exercise for 24 hours of a day .below in graphical form (figures 4.1-4.13). Each graph shows a plot of both the actual and forecast load values in MW against the hour of the day.

Table 4.3: Optimal values of our model parameters

Parameter	Optimal value		
	newff	newrb	Newelm
Epochs	2000	2000	2000
Performance ratio	0.01	0.01	0.01
Architecture/Structure	5	5	5
Training algorithm	Levenberg -marquardt	Conjugate gradient	Gradient descent backpropagation with adaptive learning rate

Table 4.4 Actual and Forecasted load (Tuesday 23/09/2007 E.C)

time	Actual load (KW)	Forecasted load (newff) (KW)	Forecasted load (newrb) (KW)	Forecasted load (newelm) (KW)
1	7800	9413	8033	9444
2	9300	11529	9328	9672
3	10100	9413	9874	9444
4	10500	11529	10591	9672
5	11900	11554	11750	10033
6	12000	11554	12433	10370
7	11700	11556	11733	10684
8	11700	9413	10177	9444
9	6900	6474	9339	8280
10	11700	11554	10110	10171
11	11600	11557	11592	10744
12	11700	11811	12341	11198
13	12500	12016	12260	11460
14	12700	12016	12462	11460
15	12500	12145	12791	11304
16	11700	11554	11557	10561
17	10500	11554	10532	10033
18	9000	5963	8995	6382
19	5300	5433	5296	4481
20	5300	6881	5325	9366
21	5300	4956	5214	8964
22	5300	5273	5438	5943
23	5300	5963	5247	6382
24	6400	6688	6217	8103
MAPE		0.7775	**0.5739**	2.8073

Actual and Forecasted Electrical Load Vs Time

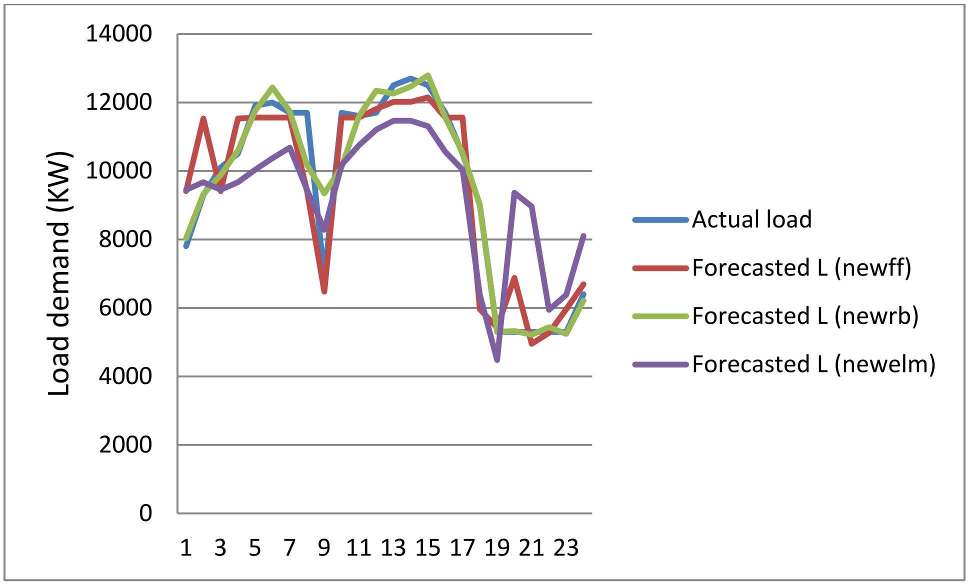


Figure 4-1 Comparison of actual and forecasted (feed forward, radial basis and recurrent) ANN power demand

Table 4.5 Actual and Forecasted load (Wednesday 24/09/2007 E.C)

time	Actual load (KW)	Forecasted load (newff) (KW)	Forecasted load (newrb) (KW)	Forecasted load (newelm) (KW)
1	9000	8957	7936	6297
2	4600	4594	7189	7763
3	10100	7186	6760	8547
4	4600	5251	7452	8937
5	10500	9731	9041	10268
6	10600	9515	10618	10360
7	10700	9967	11246	10083
8	10500	9967	10493	10083
9	9500	9539	8832	5431
10	7100	9967	7511	10083
11	7200	9979	7712	9989
12	10400	9967	9407	10083
13	10600	8907	11272	10809
14	12200	9015	12058	10985
15	12000	8907	11904	10809
16	10600	9967	10678	10083
17	5300	5251	5275	8937
18	4300	3771	4301	7468
19	5300	4896	5305	3924
20	5300	4896	5258	3924
21	5300	4896	5492	3924
22	5300	4896	4816	3924
23	5400	4896	6066	3924
24	7900	8858	7674	4955
MAPE		3.5139	**2.8703**	3.7233

Actual and Forecasted Electrical Load Vs Time

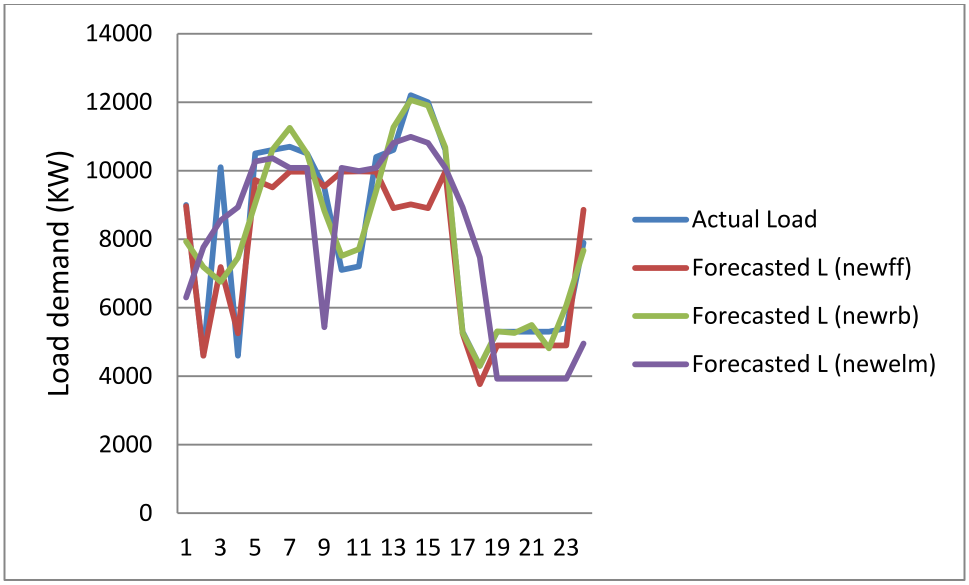


Figure 4-2 Comparison of actual and forecasted (feed forward, radial basis and recurrent) ANN power demand

Table 4.6 Actual and Forecasted load (Tuesday 26/12/2007 E.C)

time	Actual load (KW)	Forecasted load (newff) (KW)	Forecasted load (newrb) (KW)	Forecasted load (newelm) (KW)
1	10600	10969	9791	9973
2	11400	11193	11249	10774
3	10900	11193	11297	10774
4	10600	11790	10907	10401
5	11200	11614	10966	10649
6	12000	11113	11392	11084
7	11100	11113	11444	11084
8	10100	10969	10742	9973
9	10100	10121	9781	9209
10	10000	9031	9418	9152
11	10000	9908	9953	10094
12	9300	9908	10856	10094
13	13300	11790	11497	10401
14	11100	14184	11869	11756
15	11900	11790	11987	10401
16	10600	9908	10375	10094
17	5300	5242	5390	8557
18	5200	5194	5188	7355
19	5300	5305	5320	7049
20	5300	5323	5195	6978
21	5300	5403	5608	6875
22	5300	5278	4930	7160
23	5300	5341	5156	7605
24	6300	6640	7207	7964
MAPE		1.3646	**0.3975**	9.7006

Actual and Forecasted Electrical Load Vs Time

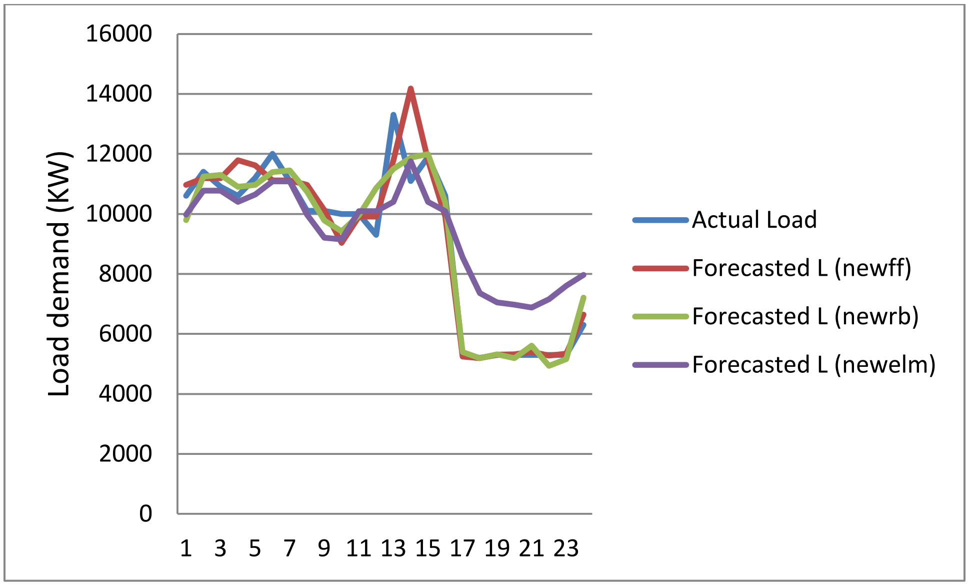


Figure 4-7 Comparison of actual and forecasted (feed forward, radial basis and recurrent) ANN power demand

Table 4.7 Actual and Forecasted load (Wednesday 27/12/2007 E.C)

time	Actual load (KW)	Forecasted load (newff) (KW)	Forecasted load (newrb) (KW)	Forecasted load (newelm) (KW)
1	10600	10738	8250	9786
2	10600	10618	9748	10479
3	10600	9563	11070	10046
4	10600	10738	11946	9786
5	11200	13475	12185	10306
6	12700	12819	11764	10996
7	11700	12318	10823	10219
8	9100	9217	9673	9353
9	8500	9217	8701	9353
10	9500	9798	8284	9266
11	9300	9798	8631	9266
12	6700	6702	9696	8660
13	11700	11616	11091	12108
14	13300	12318	12142	10219
15	11900	11187	12048	10910
16	10500	10738	10281	9786
17	6600	5057	7212	5372
18	5300	4921	5066	5297
19	5000	5057	5176	5372
20	4800	5057	4391	5372
21	4600	5057	4493	5372
22	4800	5057	4971	5372
23	5300	5057	5747	5372
24	5400	5393	6860	6147
MAPE		0.5180	1.4959	**0.2811**

Actual and Forecasted Electrical Load Vs Time

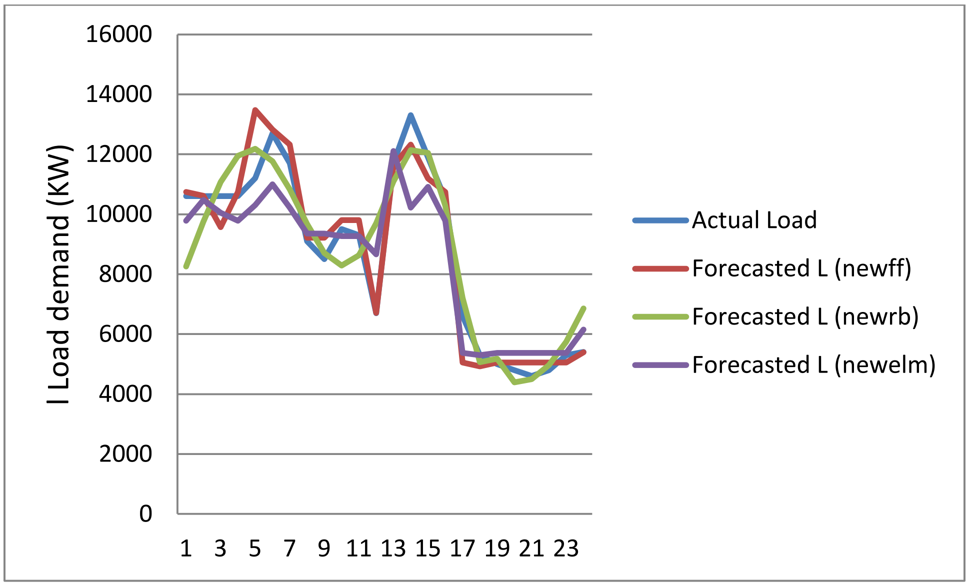


Figure 4-8 Comparison of actual and forecasted (feed forward, radial basis and recurrent) ANN power demand

Table 4.8 Actual and Forecasted load (Wednesday 01/01/2008 E.C)

time	Actual load (KW)	Forecasted load (newff) (KW)	Forecasted load (newrb) (KW)	Forecasted load (newelm) (KW)
1	9000	8079	8133	7400
2	10600	8959	9324	8829
3	10010	9265	10319	9195
4	9800	9622	10915	9553
5	10300	10122	10975	9972
6	10600	10287	10517	10312
7	10600	8901	9701	8756
8	9300	8633	8809	8384
9	7900	8486	8177	8159
10	8400	8633	8074	8384
11	8200	8633	8615	8384
12	8400	9470	9655	9410
13	11700	11028	10756	11329
14	11700	10716	11273	11024
15	10600	10533	10555	10835
16	7900	9622	8389	9553
17	5800	8633	5650	8384
18	5300	5032	5284	4775
19	4800	4947	4912	6030
20	4800	4726	4520	5064
21	4800	5032	4785	4775
22	5300	5226	5302	4632
23	5600	5710	6019	6181
24	6300	7831	6983	6789
MAPE		1.9401	**0.4259**	0.9675

Actual and Forecasted Electrical Load Vs Time

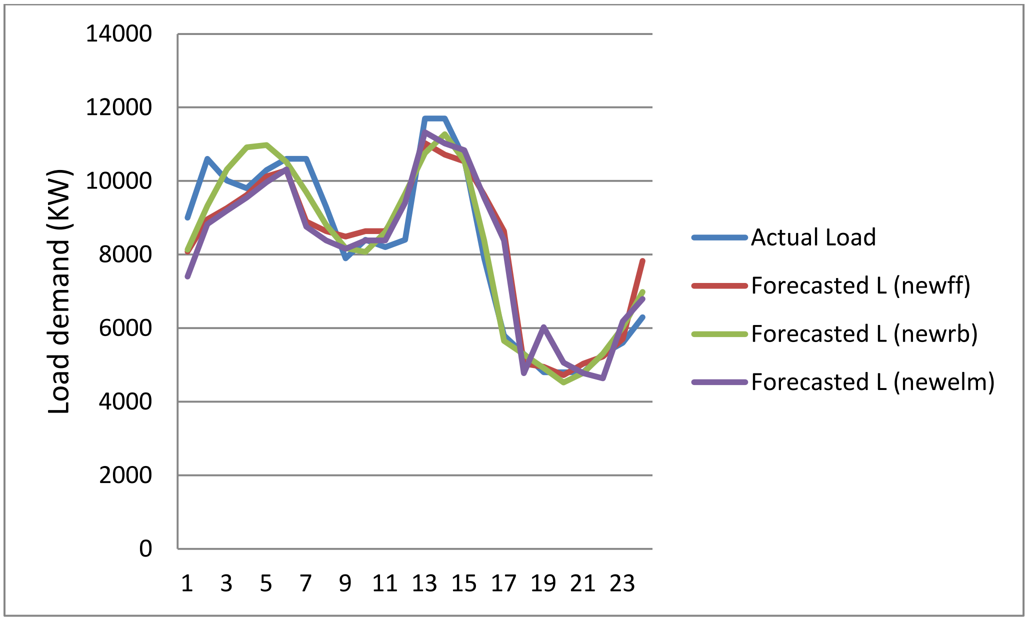


Figure 4-13 Comparison of actual and forecasted (feed forward, radial basis and recurrent) Power demand

The percentage absolute mean error of this model on the test sets have been calculated and tabulated in table 4.6.

Table 4.9: MAPE for the model on the test set

Test Days	MAPE (%)		
	Forecasted load (newff)	Forecasted load (newrb)	Forecasted load (newelm)
Tuesday 23/10/2007 E.C	0.7775	0.5739	2.8073
Wednesday 24/10/2007 E.C	3.5139	**2.8703**	3.7233
Thursday 25/10/2007 E.C	**6.3868**	1.1469	**0.1283**
Friday 26/10/2007 E.C	0.7468	0.2999	9.1751
Saturday 27/10/2007 E.C	3.0121	**0.0861**	1.0112
Sunday 28/10/2007 E.C	0.7857	0.2800	1.6861
Tuesday 26/12/2007 E.	1.3646	0.3975	9.7006
Wednesday 27/12/2007 E.C	**0.5180**	1.4959	0.2811
Thursday 28/12/2007 E.C	3.3875	0.9447	1.3583
Friday 29/12/2007 E.C	2.4496	0.8606	1.6425
Saturday 30/12/2007 E.C	1.1218	1.1392	1.9556
Sunday 01/13/2007 E.C	3.5327	0.5386	**13.8851**
Wednesday 01/01/2008 E.C	1.9401	0.4259	0.9675

Winter, summer and holiday peak load forecasted Data from typical electrical load profile of Jimma City

Table 4.10

Time	Days	Peak load (Actual)	Peak load(Forecasted)
14	Tuesday 23/09/07	12.700 MW	12.462 MW
14	Tuesday 26/12/07	13.300 MW	11.497 MW
14	Wednesday 24/09/07	12.200 MW	12.058 MW
14	Wednesday 27/12/07	13.300 MW	12.142 MW
14	Wednesday 1/1/08	11.700 MW	11.273 MW
14	Thursday 25/09/07	13.000 MW	12.374 MW
14	Thursday 28/12/07	13.000 MW	12.614 MW
14	Friday 26/09/07	13.300 MW	13.285 MW
14	Friday 29/12/07	12.700 MW	12.155 MW
14	Saturday 27/09/07	12.300 MW	12.099 MW
14	Saturday 30/12/07	12700 MW	12244 MW
14	Sunday 28/09/07	12000 MW	11554 MW
14	Sunday 1/13/07	12800 MW	11281 MW

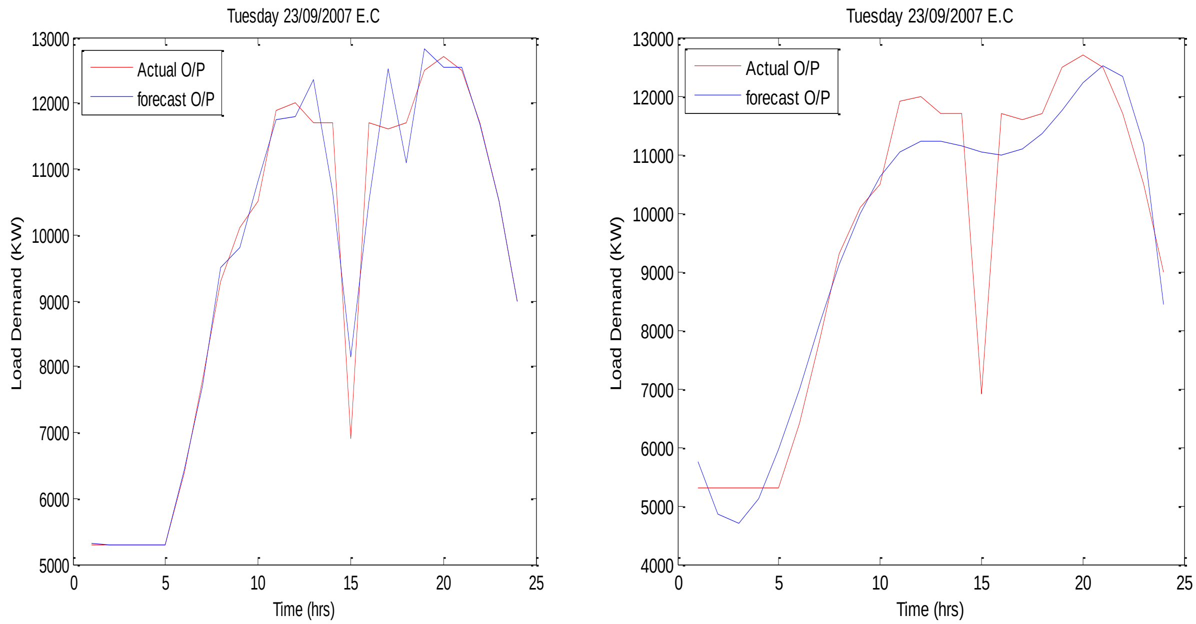
4.2. Load Forecast Discussion

This chapter provided the techniques implemented, and the results, of designing an ANN for a Jimma City. Computer program results for load forecasting of the power system are presented in Fig. 4-4 up to Fig. 4-16 shows a Load between the Actual-time Load and forecast-time load. The forecast includes the weekends, winter, summer and holidays.

Based on these data, the Short-term daily load forecasts are presented. Figure. 4-1 up to Figure. 4-13. The 24-hour-ahead load forecast results for one week from each season are tabularized in Table. 4-4 up to Table. 4.16. The Percent Error column in Table 4.17 is the highest and least integer error value obtained for days from the 24-hour load forecast day. The MAPE results in all Tables 4.17 have an approximate range for feed forward neural network 0.5180 to 6.3868, for radial basis neural network 0.0861 to 2.8703 and recurrent current 0.2811 to 13.8851.

The number of hidden layer neurons in each ANN was set at 5 for feed forward neural network, for radial basis neural network and recurrent current. This value was selected by trial and error to determine the minimum number of hidden-layer neurons that would produce the lowest forecast error. The values selected for the minimum coefficient, number of training days, and number of hidden-layer neurons had a direct affect on the Matlab® program's ANN training runtime. A low minimum value would allow more input variables to be used in the ANN predictor matrices. This added complexity would increase the program runtime and would also present the ANN with so much input data that the resulting forecast error would increase. Increasing the training weeks also required the ANN to process a larger amount of data, which increased the program runtime. If the input data set was too large, the ANN could not generalize its output, and the resulting forecast error would increase. Increasing the number of hidden-layer neurons increased the program runtime because the weights and biases of each neuron have to be calculated and optimized during network training. An overly complex network could not generalize on the out-of-sample data set and would "over fit" the sample data. This information could also be used in customer (users) for energy saving measures with the local electric utility.

The types of NN and the effect of the layers (input, hidden and output), for this reason the thesis works ANN toolbox by using feed forward neural network, radial basis neural network and recurrent neural network. The methods to fix a number of hidden neurons in neural networks. The number of input nodes must match the number of inputs to the function and the number of output nodes must match the number of outputs of the function. Hidden layer of neurons between the input nodes and output nodes is enough to accurately approximate any continuous function. It selects random number of hidden neurons might cause either over fitting or under fitting problems. This paper proposes the solution of these problems. To fix hidden neurons, tested based on the statistical errors. The results show that the MAPE is smallest. The large and the smallest number of hidden units the function which is actually represented by the network is far more wild than the original one particularly in case of learning samples which contain a certain amount of noise which all real city data have the network will be the noise of the learning samples instead of making a smooth approximation.



(a) (b)

Figure 4-14 Effect of the number of hidden unit on the network performance, larger Neural Networks can represent more complicated functions..

(a). 5 hidden unit (b). 50 hidden units more noise

ANN are many types feed forward neural network, Radial basis function (RBF) neural network and recurrent neural network, but this thesis work selects radial basis neural network . Two input layer Neural Network, one hidden layer of 5 neurons (or units) and one output layer), radial basis neural network is connection extends from input to output without any feedback and Static networks ,non linear and very clear (simplest method). radial basis neural network process is instinctively very clear, When a learning pattern is clamped the activation values are propagated to the output units and the actual network output is compared with the desired output values we usually end up with an error is bring to zero.

Chapter 5

Conclusions and Recommendations (Future Research)

5.1 Thesis Conclusions

In this study, the methods for forecasting electric loads on a power system were discussed. Emphasis was placed on short-term load forecasting which is important for real time operation and control of power systems. The result of the Feed forward, radial basis and recurrent network models used for one day ahead short term load forecast for jimma substation, a typical jimma city Power System, shows that Feed forward, radial basis and recurrent network models, which is a Feed forward, radial basis and recurrent network, has a good performance, and reasonable prediction accuracy was achieved for this model.

Its forecasting reliabilities were evaluated by computing the mean absolute error between the exact and predicted values and compare the result of mean absolute error between the three neural networks select the smallest one radial basis its value 0.0861 to 2.8703. The results suggest that ANN model with the developed structure can perform good prediction with least error and finally, this neural network could be an important tool for short term load forecasting. Our experimental results also show that a simple ANN-based prediction model appropriately tuned can outperform other more complex models.

The load forecasting methodology adopted in this study proved its accuracy during the last one week for winter season, one week for summer and new-year holiday implementation. Electric load forecasting plays a central role in the operation and planning of electric power. The country wide energy estimation, the planning for new plants, the routine of maintaining and scheduling daily electrical generation are all dependent on accurate load forecasting in the future.

5.2 Recommendations (Future Research)

From many properties in load forecasting by using the techniques discussed in this research, it is a very promising and worthy of further efforts to put them in to practical usage, The user- friendly software can be built for real on-line load forecasting by utility companies. However, for building a complete functional forecasting software package, several future studies can be carried out, as listed in the following

1. For making the forecaster more complete, other weather information, such as wind speed , humidity, clued covers and rain fall, many possible be included in the training and tasting of the neural network model.

2. Mid-term & Long-term load forecasting should be concerned. This means that forecasting period can be extended from one week to one year or one year-ahead. The actual forecasting period is mainly decided by the utility companies

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Appendix

Appendix A – Matlab Code

```
%************************* Tuesday 23/09/2007 E.C*************************
% program written to short term load forecast in Jimma towen by using ANN
% cells using feed forward,radial basis and recurrent current neural network
%*******************Ermias Shiferaw March 2015*********************
% MATLAB data file given below.
% input, target and actual data
nntool

time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

 input=[    9300    9600    9300    9600    10100   10600   11100   9300    7900    10300   11200   12000
12500   12500   12200   10900   10100   5800 3400   9200    8700    5300    5800    7700];

 target=[ 7800    9300    10100   10500   11900   12000   11700   11700   6900    11700   11600
11700   12500   12700   12500   11700   10500   9000 5300    5300    5300    5300    5300    6400    ];

eg = 0.02; % sum-squared error goal

sc = 5;  % spread constant

net = newrb(time, target,eg,sc);

 forecast = sim(net,time);

plot(time,target,'r');

hold on;

plot(time,forecast,'-');

legend('Actual O/P','forecast O/P');

title('Tuesday 23/09/2007 E.C') ;
xlabel('Time (hrs)');

ylabel('Load Demand (KW)');

 E=(target- forecast)./ target;
```

```
 AE= E*100;
 MAPE=sum(AE)/24
 disp([time' target' forecast' E' AE' ])
nntool
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];
input=[9300   9600   9300   9600   10100  10600  11100  9300   7900   10300  11200  12000
12500  12500  12200  10900  10100  5800 3400  9200   8700   5300   5800   7700   ];
 target=[ 7800   9300   10100  10500  11900  12000  11700  11700  6900   11700  11600
11700  12500  12700  12500  11700  10500  9000 5300   5300   5300   5300   5300   6400   ];
net = newff(input,target, 5);
net.trainParam.epochs=2000;
net.trainParam.goal=0.01;
net = train(net,input,target);
forecast = sim(net,input);
% plot the Actual data values and the pridicted output of the network
plot(time,target,'r');
hold on;
plot(time,forecast,'-');
legend('Actual O/P','forecast O/P');
title('Tuesday 23/09/2007 E.C') ;
xlabel('Time (hrs)');
ylabel('Load Demand (KW)');
E=(target- forecast)./ target;
 AE= E*100;
 MAPE=sum(AE)/24
```

```
 disp([time' target' forecast' E' AE' ])

nntool

time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

input=[9300   9600   9300   9600   10100   10600   11100   9300   7900   10300   11200   12000
12500   12500   12200   10900   10100   5800 3400   9200   8700   5300   5800   7700   ];

 target=[ 7800   9300   10100   10500   11900   12000   11700   11700   6900   11700   11600
11700   12500   12700   12500   11700   10500   9000 5300   5300   5300   5300   5300   6400   ];

net = newelm(input,target, 5);

net.trainParam.epochs=2000;

net.trainParam.goal=0.01;

net = train(net,input,target);

forecast = sim(net,input);

% plot the Actual data values and the pridicted output of the network

plot(time,target,'r');

hold on;

plot(time,forecast,'-');

legend('Actual O/P','forecast O/P');

title('Tuesday 23/09/2007 E.C') ;

xlabel('Time (hrs)');

ylabel('Load Demand (KW)');

E=(target- forecast)./ target;

 AE= E*100;

 MAPE=sum(AE)/24

 disp([time' target' forecast' E' AE' ])

%************************ Wednesday 24/09/2007 E.C************************
```

```
% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];
 input=[   7800   9300   10100   10500   11900   12000   11700   11700   6900   11700   11600
11700   12500   12700   12500   11700   10500   9000 5300   5300   5300   5300   5300   6400];
 target=[ 9000   4600   10100   4600   10500   10600   10700   10500   9500   7100   7200   10400
10600   12200   12000   10600   5300   4300 5300   5300   5300   5300   5400   7900   ];
%************************ Thursday 25/09/2007 E.C************************
% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];
 input=[9000   4600   10100   4600   10500   10600   10700   10500   9500   7100   7200   10400
10600   12200   12000   10600   5300   4300 5300   5300   5300   5300   5400   7900   ];
 target=[  5300   5900   5800   6100   10900   10900   7500   5900   9000   12000   11900   11000
11700   13000   7900   6800   6300   6200 4000   3700   3500   3800   4200   4800  ];

%************************ Friday 26/09/2007 E.C************************
% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];
 input=[5300   5900   5800   6100   10900   10900   7500   5900   9000   12000   11900   11000
11700   13000   7900   6800   6300   6200 4000   3700   3500   3800   4200   4800   ];
 target=[ 8500   9100   9800   9800   10600   11400   11300   10300   6600   6200   6800   11700
11900   13300   12700   10600   10200   7900 6000   5800   5600   5300   5200   5800   ];
%************************ Saturday 27/09/2007 E.C************************
% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];
 input=[8500   9100   9800   9800   10600   11400   11300   10300   6600   6200   6800   11700
11900   13300   12700   10600   10200   7900 6000   5800   5600   5300   5200   5800   ];
 target=[ 9000   9800   10000   10600   9800   12200   11700   11400   10900   10600   10400
10600   10900   12300   11700   8700   6300   6100 5800   5800   5200   5200   5300   6900   ];
%************************ Tuesday 26/12/2007 E.C************************
```

```
% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

 input=[10400   11700   11700   11100   11500   12200   12200   10400   9100    9000    10600   10600   11100   13300   11100   10600   7900    5300 4500   4300    4000    4800    5900    6700    ];

 target=[ 10600   11400   10900   10600   11200   12000   11100   10100   10100   10000   10000   9300    13300   11100   11900   10600   5300    5200 5300    5300    5300    5300    5300    6300    ];

%************************ Wednesday 27/12/2007 E.C************************

% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

 input=[10600   11400   10900   10600   11200   12000   11100   10100   10100   10000   10000   9300    13300   11100   11900   10600   5300    5200 5300   5300    5300    5300    5300    6300    ];

 target=[ 10600   10600   10600   10600   11200   12700   11700   9100    8500    9500    9300    6700    11700   13300   11900   10500   6600    5300 5000    4800    4600    4800    5300    5400    ];

%************************ Thursday 28/12/2007 E.C************************
% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

 input=[  10600   10600   10600   10600   11200   12700   11700   9100    8500    9500    9300    6700    11700   13300   11900   10500   6600    5300 5000   4800    4600    4800    5300    5400  ];

 target=[ 11700   10700   10600   10600   11100   12800   9500    9000    9500    9600    9300    9400    11100   13000   12000   9600    7200    5900 5300    5200    4900    4900    4900    6700    ];


%************************ Friday 29/12/2007 E.C************************
% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

 input=[ 11700   10700   10600   10600   11100   12800   9500    9000    9500    9600    9300    9400    11100   13000   12000   9600    7200    5900 5300   5200    4900    4900    4900    6700   ];

 target=[ 9800    11200   11200   10900   10800   10900   11700   9600    9400    9000    9000    10600   11400   12700   11100   5800    6300    5300 5100    4800    4500    4500    5800    6100    ];

%************************ Saturday 30/12/2007 E.C************************
```

```
% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

 input=[9800   11200   11200   10900   10800   10900   11700   9600   9400   9000   9000   10600
11400   12700   11100   5800   6300   5300 5100   4800   4500   4500   5800   6100   ];

 target=[ 10100   10900   10400   10100   11200   11200   10600   10100   8500   7900   8500   9300
11700   12700   7900   7800   6800   5300 5300   5000   5000   5000   5300   5300   ];


%************************* Sunday 01/13/2007 E.C**************************
% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

input=[9300   11200   11700   12200   12800   13300   11100   10600   10300   10600   10600
12000   14900   14400   14100   12200   10600   5800 7500   6200   5800   5600   7700   8500   ];

 target=[ 9000   10600   10100   9800   10300  10600   10600   9300   7900   8400   8200   8400
11700   11700   10600   7900   5800   5300 4800   4800   4800   5300   5600   6300   ];


%********************** Wednesday 01/01/2008 E.C**********************
% input, target and actual data
time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

 input=[9300  11200  11700  12200  12800  13300  11100   10600  10300   10600  10600  12000
14900  14400  14100  12200  10600  5800  7500   6200   5800  5600  7700  8500  ];

 target=[ 9000  10600  10010  9800  10300 10600  10600  9300 7900   8400   8200   8400  11700
11700  10600  7900  5800  5300 4800 4800  4800  5300  5600  6300  ];

 eg = 0.02; % sum-squared error goal

sc = 5;  % spread constant

net = newrb(time, target,eg,sc);

 forecast = sim(net,time);

plot(time,target,'r');

hold on;
```

```
plot(time,forecast,'-');

legend('Actual O/P','forecast O/P');

title('Wednesday 01/01/2008 E.C');

xlabel('Time (hrs)');

ylabel('Load Demand (KW)');

 E=(target- forecast)./ target;

 AE= E*100;

 MAPE=sum(AE)/24

 disp([time' target' forecast' E' AE' ])

time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

input=[ 9300   11200   11700   12200   12800   13300   11100   10600   10300   10600   10600
12000   14900   14400   14100   12200   10600   5800 7500   6200    5800    5600    7700    8500  ];

target=[9000   10600   10100   9800    10300   10600   10600   9300    7900    8400    8200   8400
11700   11700   10600   7900    5800    5300 4800    4800    4800    5300    5600    6300    ];

net = newff(input,target,5);

net.trainParam.epochs=2000;

net.trainParam.goal=0.01;

net = train(net,input,target);

forecast = sim(net,input);

% plot the Actual data values and the pridicted output of the network

plot(time,target,'r');

hold on;

plot(time,forecast,'-');

legend('Actual O/P','forecast O/P');

title('Wednesday 01/01/2008 E.C');
```

```
xlabel('Time (hrs)');

ylabel('Load Demand (KW)');

E=(target- forecast)./ target;

 AE= E*100;

 MAPE=sum(AE)/24

 disp([time' target' forecast' E' AE' ])

time=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];

input=[   9300   11200  11700  12200  12800  13300  11100  10600  10300  10600  10600
12000  14900  14400  14100  12200  10600  5800 7500  6200   5800   5600   7700   8500];

target=[9000  10600  10100  9800   10300  10600  10600  9300   7900    8400    8200  8400
11700  11700  10600  7900   5800   5300 4800   4800   4800  5300   5600    6300   ];

net = newelm(input,target, 5);

net.trainParam.epochs=2000;

net.trainParam.goal=0.01;

net = train(net,input,target);

forecast = sim(net,input);

% plot the Actual data values and the pridicted output of the network

plot(time,target,'r');

hold on;

plot(time,forecast,'-');

legend('Actual O/P','forecast O/P');

title('Wednesday 01/01/2008 E.C');

xlabel('Time (hrs)');

ylabel('Load Demand (KW)');

E=(target- forecast)./ target;
```

```
AE= E*100;

MAPE=sum(AE)/24

disp([time' target' forecast' E' AE' ])
```