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Short Term Load Forecasting of Distribution Feeder Using Artificial Neural Network Technique

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Abstract

This paper explains the load forecasting technique for prediction of electrical load at Hawassa city. In a deregulated market it is much need for a generating company to know about the market load demand for generating near to accurate power. If the generation is not sufficient to fulfill the demand, there would be problem of irregular supply and in case of excess generation the generating company will have to bear the loss. Neural network techniques have been recently suggested for short-term load forecasting by a large number of researchers. Several models were developed and tested on the real load data of a Finnish electric utility at Hawassa city. The authors carried out short-term load forecasting for Hawassa city using ANN (Artificial Neural Network) technique ANN was implemented on MATLAB and ETAP. Hourly load means the hourly power consumption in Hawassa city. Error was calculated as MAPE (Mean Absolute Percentage Error) and with error of about 1.5296 % this paper was successfully carried out. This paper can be implemented by any intensive power consuming town for predicting the future load and would prove to be very useful tool while sanctioning the load.

Keywords

Load forecasting, artificial neural network, MAPE, back propagation, MATLAB

1. Introduction

The most used thing in today's world is energy. We use energy in various forms in our day-to-day life, electricity, electricity, solar energy, wind energy, chemical energies in form of batteries and many other forms. Sometimes we are extravagant and sometimes we are careful. But to provide users uninterrupted supply of electricity there must be proper evaluation of present day and future demand of power. That's why we need a technique to tell us about the demand of consumers and the exact capability to generate the power and this need load forecasting techniques [1].

Electric load forecasting is the process used to forecast future electric load, given historical load, weather information along with current and forecasted weather information. Load forecast accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets. The Energy Management System demands accurate load forecasting and short-term Load Forecasting provides better and truthful results [2].

Load forecasting is however a difficult task as the load series is complex pattern and exhibits several levels of system seasonably. Several conventional techniques had been used for the load forecasting. However, the advantages of those techniques have led to the use of the artificial intelligence techniques [3]. An artificial neural network (ANN) is the piece of a computing system designed to simulate the way the human brain analyzes and processes information. It is the foundation of artificial intelligence (AI) and solves problems that would prove impossible or difficult by human or statistical standards. And the artificial neural network is an attempt to simulate the network of neurons that make up a human brain so that the computer will be able to learn things and make decisions in a humanlike manner. ANNs are created by programming regular computers to behave as though they are interconnected brain cells [4].

Short-term electrical load forecasting is vital for the efficient operation of electric power systems. A power grid integrates many stakeholders who can be affected by an inaccurate load forecast. Power generation utilizes 24-hour or 48-hour ahead forecasts for operations planning, i.e., to determine which power sources should be allocated for the next 24 h transmission grids need to know in advance the power transmission requirements in order to assign resources end users utilize the forecast to calculate energy prices based on estimated demand. Contingency planning load shedding management strategies and commercialization strategies are all influenced by load forecasts. Forecast errors result in increased operating costs [2]. predicting a lower load than the actual load results in utilities not committing the necessary generation units and therefore incurring higher costs due to the use of peak power plants ;on the other hand, predicting a higher load than actual will result in higher costs because unnecessary baseline units are started and not used. Reliable forecasting methods are essential for scheduling sources and load management [5]. The key function of an electric power company is to supply customers with high quality electric energy in secured and economical manner. In order to do so, an electric power company faces economical and technical problems in planning, control and operation of electric power system. For the purpose of optimal planning and operation of electric power system, there is need for proper evaluation of present day and future electric power load [1, 6].

Load forecasting has always been important for planning and operational decision conducted by utility companies. However, with the deregulation of the energy industries, load forecasting is even more important Load forecasting for vision load demand prerequisite is the most imperative key for power system planning. The ability of the generation, transmission and distribution capacities are strictly dependent on the precise energy and load forecasting for that system. Power system expansion planning starts with a forecast of anticipated future load requirements. Estimates of both demand and energy requirements are crucial to valuable system planning [7]. An electric load forecasting is used by an electric power company to anticipate the amount of electric energy needed to supply so as to meet up the demand [8].

2. Related work and Background

2.1 Theoretical Background

Load forecasting in power system is an important subject and has been studied from different point of view in order to achieve better load forecasting results [9]. Techniques such as regression analysis, expert system, artificial neural network and multi-objective evaluations have been used based on different choices of inputs and available information. Distribution system load forecasting has been challenging problem due to its spatial diversity and sensitivities to land usage and customer habits. Different tools have been developed to assist utilities to simulate and estimate the future land, usage land and load growth in their territory, so that distribution system planners can plan according to their goal and interests. Many factors need to be considered for this purpose, namely.

- Land usage in the future
- Type of power consumption
- Building of new feeder and substation or reinforce the existing ones
- Planning of the new feeders and structures

Electric load forecasts can be divided into three categories based on the planning perspective of the duration:

- Short Term Load Forecasts (STLF): This is usually from one hour to one week.
- Medium Term Load Forecasts (MTLF): This is usually from one week to a year.
- Long Term Load Forecasts (LTLF): This is longer than a year.

Short-term load forecasting at the distribution level predicts the load of substations, feeders, transformers, and possibly customers with a typical forecasting horizon ranging from half an hour to one week. High quality load forecasting is important for the planning and operation of distribution systems. Fig. 1 presented the view of Hawassa distribution substation.

Figure 1. Hawassa distribution substation view

Need for efficient and accurate load forecasting for the power system are as flows.

- Distribution System Planning
- Distribution System Expansion
- Operation and Maintenance
- Financial Planning
- Load Management

2.2 Related work

At the case study of Hawassa city, the electric power company faces economical and technical challenges in planning, control and operation of an electric power system. Further, for the purpose of optimal planning and operation of an electric power system, there is need for proper evaluation of present status and future electric power load. Other problems, which are faced by the system like over loading and under loading, no proper power arrangement and the capacity of power distribution sub-station is not equal to power demand. Ref. [8] focused on the study of electrical power load at Hawassa city distribution feeder and the appropriate forecasted power loads by studying the short-term forecasting by using ANN method. Also, it develops the load curve on the 24 hours [8]. Ref. [9] was introduced the efficient approach to short-term load forecasting at the distribution level. Ref. [10] was presented on the title of short-term load forecasting using a hybrid model based on support vector regression. Ref. [11], introduced on the title of Short-Term Load forecasting using SVM based PUK kernel. In this paper, Support Vector Machine (SVM) model based on Pearson VII universal kernel known as PUK kernel has been proposed for Short Term Load Forecasting (STLF). Also, it was introduced the Machine learning algorithms have been applied in two parts. The performance is verified with simulation on a case study based on 6 weeks' load pattern of distributed grid station in Pakistan. The forecasting results of PUK based SVM model are proved to be better than the other models and indicate that the forecasting precision of the proposed methods is much efficient to other methods.

3. Methodology

3.1 Characteristics of Power System Load

In this paper a number of techniques are included and analyses the implementation of the following methodologies [12-16].

- Test data input
- Neural network formation
- Train neural network
- Next iteration of artificial neural network
- Error calculation
- Error comparison
- Output of neural network
- Load prediction of desired period

In general forecasting methods can be divided into two broad categories: Parametric methods and artificial intelligence-based methods. Based on analyzing qualitative relationships between the load and the factors affecting the load, the parametric methods formulate mathematical or statistical models of load. Then the parameters of the built model are estimated from historical data.

3.2 Data Collection and Preparation

To perform this work, the historical data (load data and temperature) were collected from Hawassa city. The historical load data of the distribution feeder was obtained from the transmission and distribution office of Hawassa city, and the temperature was obtained from the internet, and Hawassa city metrology agency office. The data collected is the actual load data of the 132/33/15 kV substation, more focusing in the 33kV and 15 kV in the Hawassa city for the different month of 2019 Gagarin calendar (2011 Ethiopian calendar). The load data of first 21 days of a month and temperature will be used for training the network and the load data and temperature for the remaining days in the month will be used for the network validation.

3.3 Input Data

The input data is of one week winter (02/05/2011 to 08/05/2011), One week summer (25/12/2011 to 01/11/2011) and One Holiday of 2011 EC of electrical load of the distribution feeder. Load data was recorded for Hawassa city, so there is 15 days of data are selected from a year. This data was used for training and testing of the 24-hour load forecasting using ANN. The load data was collected from a database containing data recorded from power meters located at the Hawassa city substation and organization office. Table 1 presented the Hawassa city distribution feeder name with its rating. Table 2 presented the Hawassa city climate conditions. Table 3 presented the winter, summer and holiday Measured Data from typical electrical load profile of Hawassa City.

- Maximum Voltage
- Minimum Voltage
- Maximum Current
- Minimum Current
- MWh. consumption and availability of DSF (distribution system feeder)

Table 1. Hawassa city distribution feeder name with its rating

Number of feed-ers	Name of the feeder Hawassa city	Feeder rate in kV
1	FEEDER R3 A	15
2	FEEDERM2 B	15
3	FEEDERR6 C	15
4	FEEDERT3 D	15
5	FEEDER Y5E	15
6	FEEDER P3F	15
7	FEEDER Y4H	15
8	FEEDER R2I	15
9	FEEDER JR5	15
10	FEEDER M3K	15
11	FEEDER I1L	33
12	FEEDERR4 M	15
13	FEEDERI2 N	33

Table 2. Hawassa city climate conditions

Month	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Average Max Tem-perature in °C and °F	27 (80)	27 (80)	28 (82)	28 (82)	28 (82)	29 (84)	28 (82)	27 (81)	26 (79)	24 (75)	24 (75)	25 (77)
Daily Mean Temperature in °C and °F	23 (73)	23 (73)	23 (73)	22.5 (72.5)	23 73	24 75	24 75	23.5 74.5	23 73	21.5 (70.7)	21.5 (70.7)	22 (72)
Average Lower Temperature in °C and °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)

Table 3. Winter, summer and holiday Measured Data from typical electrical load profile of Hawassa City

Hr s.	2/5/19 (MW) in feeder AR4	8/5/19 (MW) in	23/6/19 sum-mer(Tuesday)	26/9/19 (MW)Y	Holyday 2011	Holyday 2011win

		feeder AR	(MW)M3		summer	ter
1	14.24	0	14.8	11.9	16.23	18
2	12	11.2	13.8	14.2	16.3	17.9
3	11	8.5	13.7	11.1	15	17.3
4	11.5	8.3	16.78	16.23	16	17
5	13.5	8.07	16.6	13.34	17	16.7
6	14.6	8.15	13	13.54	16.3	15.9
7	12.5	8.15	12.4	13.54	17.9	16.5
8	13	8	8	15.4	18.8	18.9
9	15	10.7	12.43	12	18.4	19.5
10	15.5	11.45	15.2	14	17	18.9
11	0	13.45	12.4	13	15	19.5
12	14.5	0	13.9	12.4	18.7	16.83
13	15	12.46	13.4	8.9	15.9	18
14	15.25	15.46	14.6	9.8	17.8	19.8
15	15.5	16.45	14.4	16.1	17.9	18
16	16	16	13	16	17.09	19.3
17	16.5	16.48	15.23	9.8	17.8	18.7
18	16.4	16.58	11.2	7.9	17.6	14.7
19	17.4	16.9	14.2	9	18.9	19.9
20	18	18	13.5	11	18.9	18.99
21	15.49	17.45	12.4	12	17	17.6
22	14.5	19.6	12.4	16	18.9	18.6
23	13	18.53	14.23	12.9	18.9	19.4
24	14.9	11.2	13.24	12.34	17.7	19.7

The output of summer and winter measured data from typical electrical load profile of Hawassa City for Monday is presented by the figures 2 and 3. Table 4 presented the Maximum load profile for distribution feeders (DF).

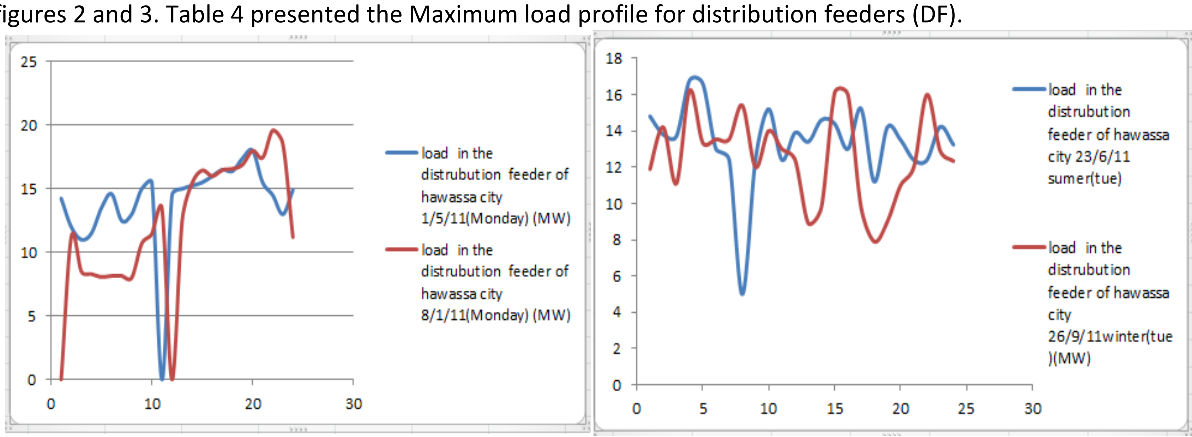

Figure 2. winter and summer of measured data typical electrical load profile of Hawassa city

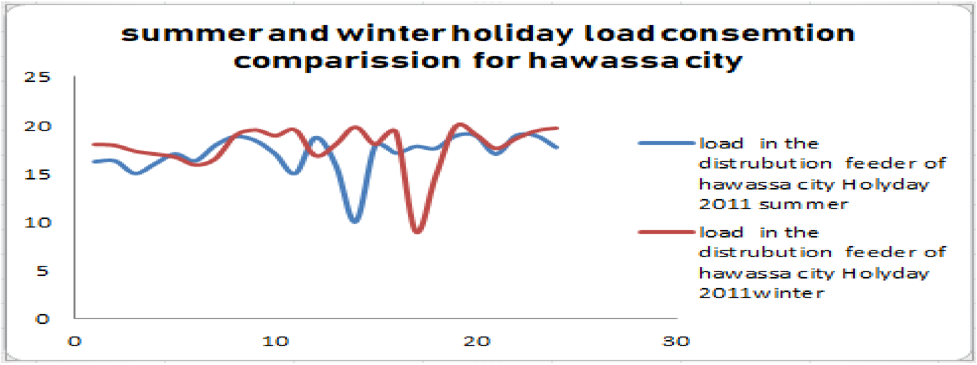

Figure 3. winter and summer of measured data typical electrical load profile comparison

Table 4. Maximum load profile for DF

Time	Day	Peak load in MW	Peak load in kW
20	Monday DF1 R61/05/11	18	18000
22	Monday DF 2 R12 8/05/11	19.6	19600
04	Tuesday DF3 RM223/06/11	16.78	16780
04	Tuesday DF4 IL126/09/11	16.2	16200
19	Holyday DF5 R3sum-mer	18.9	18900
19	Winter holy DF6 I1day 2011	19.9	19900
21	Wednesday 15/05/11	22.3	22300
23	Wednesday N2 27/09/11	19.82	19200
22	Wednesday DFT3 25/12/11	19.4	19400
22	Thursday TR505/09/11	20.1	20100
21	Thursday M3 05/10/11	20.9	20900
21	Thursday M4 05/12/11	19.32	19320

3.4 Factors Affecting Short Term Load Forecasting

These factors can be categorized as Time factor, weather, economy, Humidity and random disturbances. In this research paper these factors and their impact on consumption of electric power and their significance in short term load forecasting is evaluated. Generally the factors affecting to the load forecasting are concluded in the figure 4.

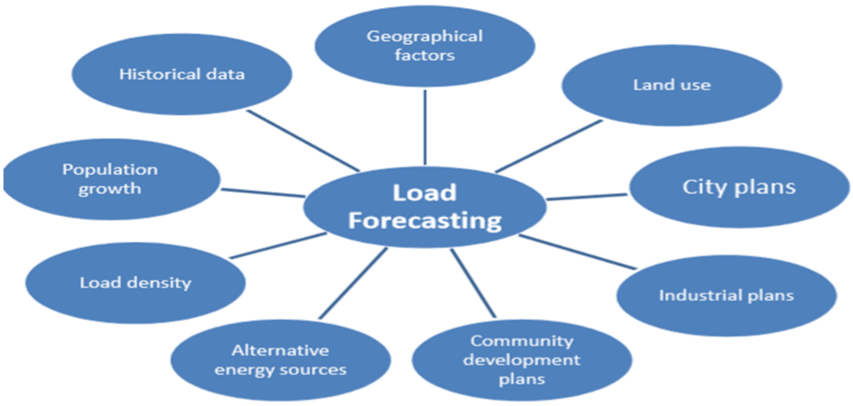

Figure 4. Factor affecting of load forecasting [3]

3.5 Artificial Neural Network

An artificial neural network (ANN) is the piece of a computing system designed to simulate the way the human brain analyzes and processes information. It is the foundation of artificial intelligence (AI) and solves problems that would prove impossible or difficult by human or statistical standard [13, 17-20].

The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique. 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. Artificial Neural Networks (ANN) is a soft technique used in various optimization processes. This method is able to perform non-linear modeling and adaptation. It does not require assumption of any functional relationship between load and weather variables in advance. The most popular artificial neural network architecture for electric load forecasting is back propagation. Back propagation neural networks use continuously valued functions and supervised learning.

3.6 ANN Forecasting Using Model

The developed forecasting model which considers temperature and humidity as input data since the load demand does not depend only on temperature and humidity and in order to account for other factors. Figure 5 presented the model arrangement of ANN for load forecasting.

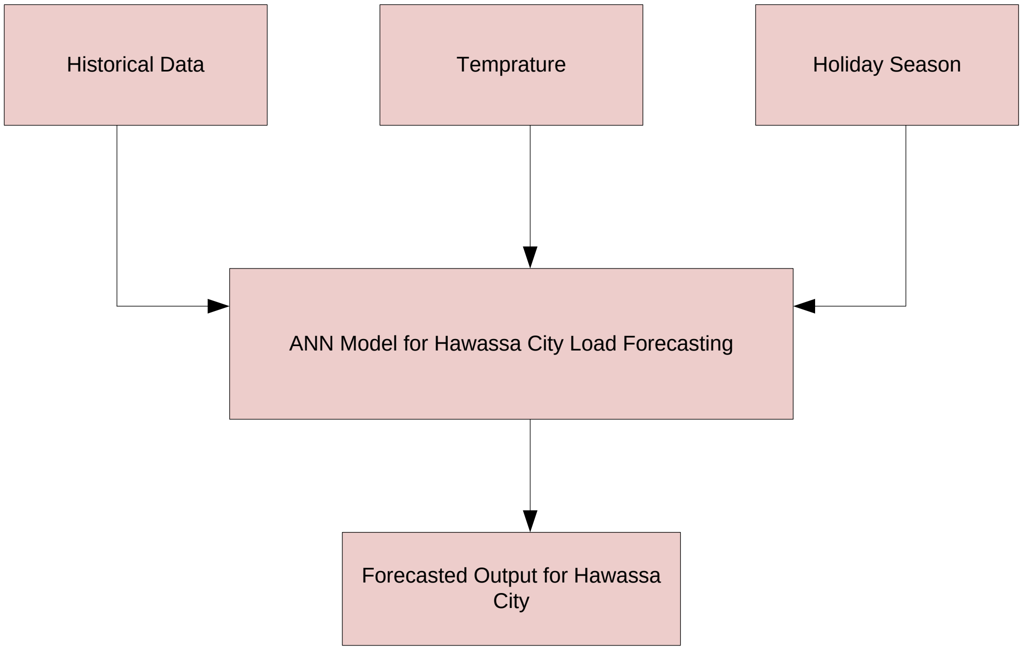

Figure 5. Model arrangement of ANN

3.7 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 x_j connected to neuron k is multiplied by the weight w_{kj}. 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

The architecture of the ANN comprises of:

- Input layer: Contains neurons equal to the number of inputs.
- Hidden layer(s): The number of hidden layers and the number of neurons in each layer depends on the complexity.
- Output layer: Usually it has one neuron, and its output ranges from 0 to 1, that is, greater than 0 and less than 1. But multiple outputs can be present.

3.8 Network Structure

Network is 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 architecture of the ANN comprises of

- Input layer: Contains neurons equal to the number of inputs
- Hidden layer(s): The number of hidden layers and the number of neurons in each layer depends on the complexity
- Output layer: Usually it has one neuron, and its output ranges from 0 to 1, that is, greater than 0 and less than 1. But multiple outputs can be present [15, 21-30].

3.9 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 the below equation,

$$MAPE = \frac{\frac{A-F}{A}*100}{N} \quad (1)$$

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.

3.10 ANN Evaluation Process

Contrary to feed forward networks, Recurrent Neural Networks (RNNs) are models with bidirectional 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. Figure 6 presented the evaluation process of the ANN.

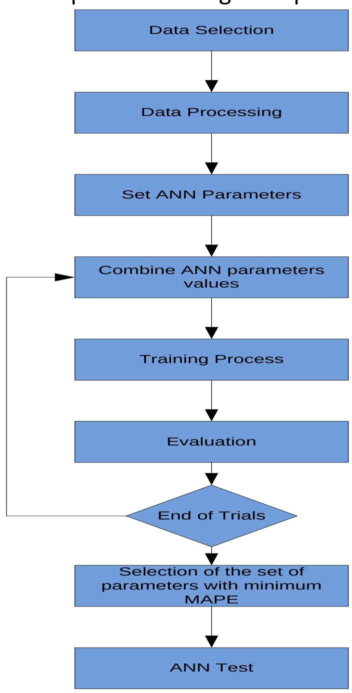

Figure 6. flow chart and evlution process of ANN

3.11 Calculation of absolute error

This method has been implemented in MATLAB. The forecasting performance is evaluated by using the standard mean absolute percentage error (MAPE).

$$MAPE\% = \frac{1}{T}\sum\left(L(t) - \frac{La(t)}{La(t)}\right) * 100 \quad (2)$$

where, L(t) is actual data and La(t) is predicted data

3.12 Short Term Load Forecasting in Hawassa City

Short term load forecasting is basically a load predicting system with a leading time of one hour to seven days, which is necessary for adequate scheduling and operation of power systems. For proper and profitable management in electrical utilities, short-term load forecasting has lot of importance [31-38].

Some of the techniques that have been proposed and implemented to create STLF for the planning of distribution feeder are:

- Similar-day approach

- Regression methods
- Time Series
- Neural Network
- Fuzzy logic

3.13 Factors

Amongst several factors which impact consumption, there are two high level components which are highly significant [39-45]:

- Seasonality
- Weather

These factors can be expressed as:

$C = F(S, W) + W$ (3)

where, C is consumption, S is season/TOD, W is weather, and **ε** is error or residue.

3.14 Mean Absolute percentage error (MAPE)

The MATLAB output display the MAPE according to the forecasted result based on the following equation [46-48]:

$$ERROR = \frac{TARGET-FORCAST}{TARGET} = \frac{T-F}{T} \quad (4)$$

$$MAPE\ (day) = \frac{SUM(AE)}{24} \quad (5)$$

4. Results and Discussion

In this section, we make use of the empirical electric load data of Hawassa city to examine the performance of the proposed methods by using the ANN. The short-term load forecasting is performed for planning of the distribution feeder. The 24 hours actual versus predicted ANN based load forecast for output in MW for feeder A is shown in figure 7. Figure 8 presented the simulation results of the feeder A.

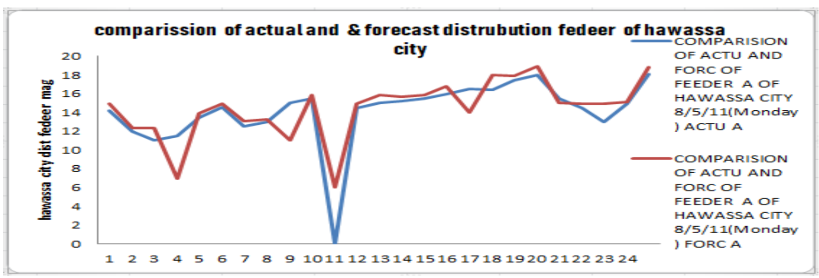

Figure 7 forecasting and actual compression distribution feeder A

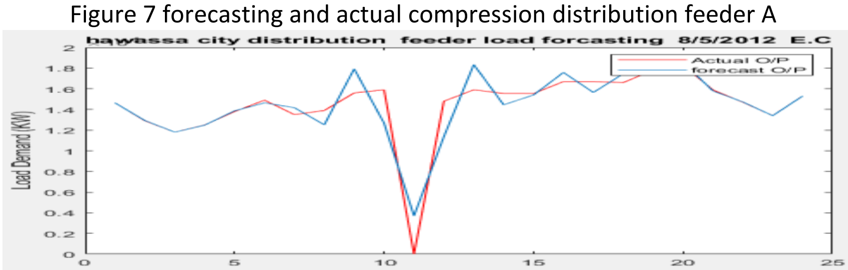

Figure 8. simulation result of feeder A

The DF forecasting of the Hawassa city of 2012 EC (2020 GC) and 2013 EC (2021 GC) on January feeder compression will be the above in the local time expectation the 11:00 hour is zero (means there is no power or light in feeder A) but the forecasted result will be not zero that means it has forecasted result around 5.43MW and the maximum load forecasting for the feeder A is 18.9 MW at the time of 20:00 the forecasting power feeder of the year is more accurate because the MSE and MAPE will be level value that means MAPE is1.0e+04 , 0.0024, 1.5296. Figure 9 presented the distribution feeder A to D, actual & forecasting values comparison.

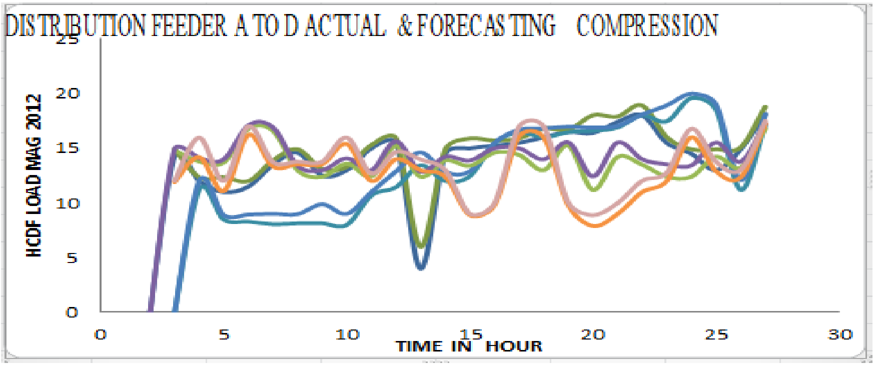

Figure 9. DF of actual and forecast compression different feeder

In the figure 10 we have actual and forecasted graph. The actual and forecasted result has slight difference because the forecasted result will be presented the minimum forecasting fluctuation of the minimum amount of feeder rate in the forecasting process. It indicates that the feeder distributes the required amount of electric power to the customer according to the historical data or input. The actual and forecasted distribution feeder load comparison is presented for the date of 23/6/2012 EC.

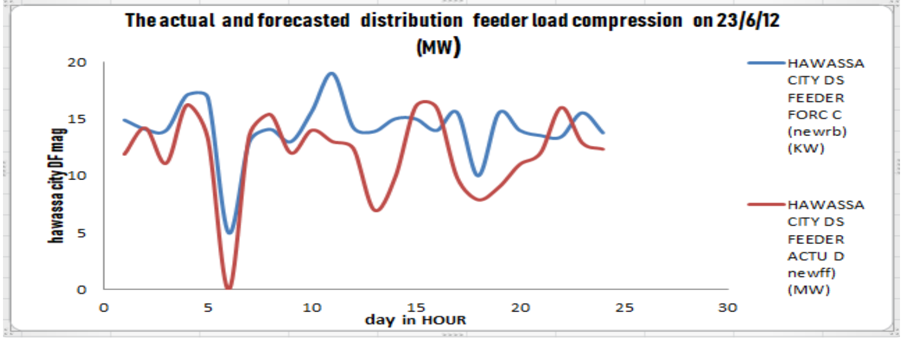

Figure10. Comparison of actual and forecast for the Hawassa city feeder

Figure 11 presented the simulation result of the feeder on the 23/06/12 EC (Ethiopian calendar). The distribution feeder of simulation result in the above figure shows the light color to represent the forecasted result of distribution feeder and the red color to represent the actual data of the DF. The starting point of the feeder have related value then the forecasted result is same as differ and the actual data in the mid time of day season (6^{th} hour of day season) has not any power that means 0 MW in the feeder, but the forecasted result will be around 12.8MW. This high forecasting difference show that in the day of 23/06/12 E.C feeder B needs to distribute the forecasted amount of power to the Hawassa city and when we see the 11^{th} hour the actual power in the feeder will be large amount, but the forecasted value will be less than the actual value. During this time the large amount of power will be save because the forecasted process input will be considered.

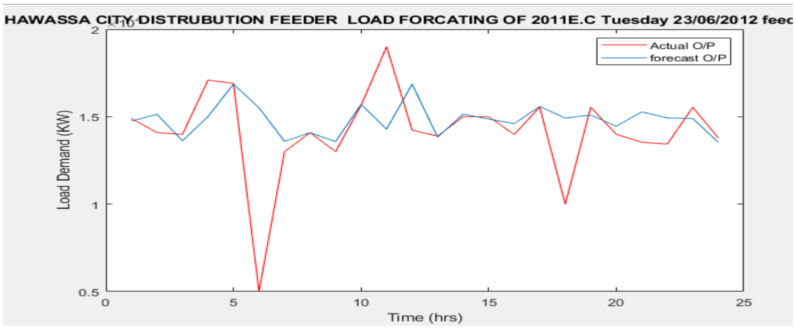

Figure 11. simulation result of the feeder on the 23/06/12 EC (Ethiopian calendar)

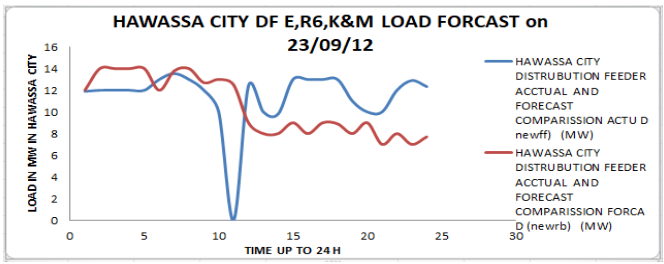

Figure 12. the actual and forecasted distribution feeder load compression on 23/09/ 2012 EC (MW)

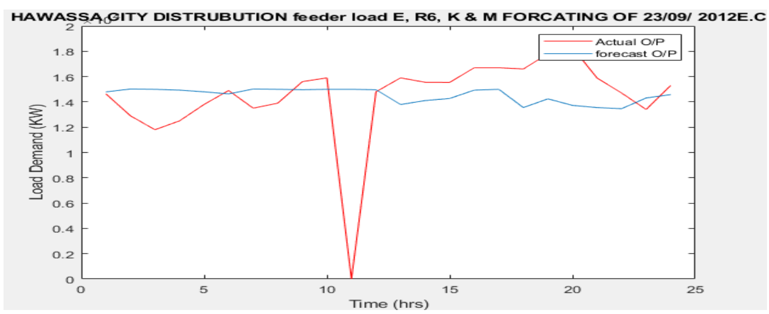

Figure 13. Simulation result of the feeder on the 23/09/ 2012 same mage feeder E

The figures 12 and 13 show the distribution feeders simulation results. The starting point of the feeder has related value in the forecasting process. The forecasted result is differed and the actual data in daytime around 11th hour has not any power that means 0 MW in the feeder but the forecast forecasted result will be around 14.38MW. This high forecasting difference show that in the day of 23/09/2012 EC of feeder E, R6, K, and M need to distribute the forecasted amount of power to the Hawassa city and when we see the 20$^{th\ hour}$, the actual power in the feeder will be large but the forecasted value will be less than the actual value. During this time the large amount of power will be saved according to the future expectation historical input forecasting performances of ANN forecasting process.

Also, the input layer contains neurons equal to the number of input hidden layer(s). The number of hidden layers and the number of neurons in each layer depends on the complexity output layer. Usually it has one neuron, and its output ranges from 0 to 1. The neural network structure in the figure 14 has five hide neuron each newer on path has input point that is weight and base arrangement that means forward recurrent and back propagation that are including feed forward neural network radial basis neural network and recurrent.

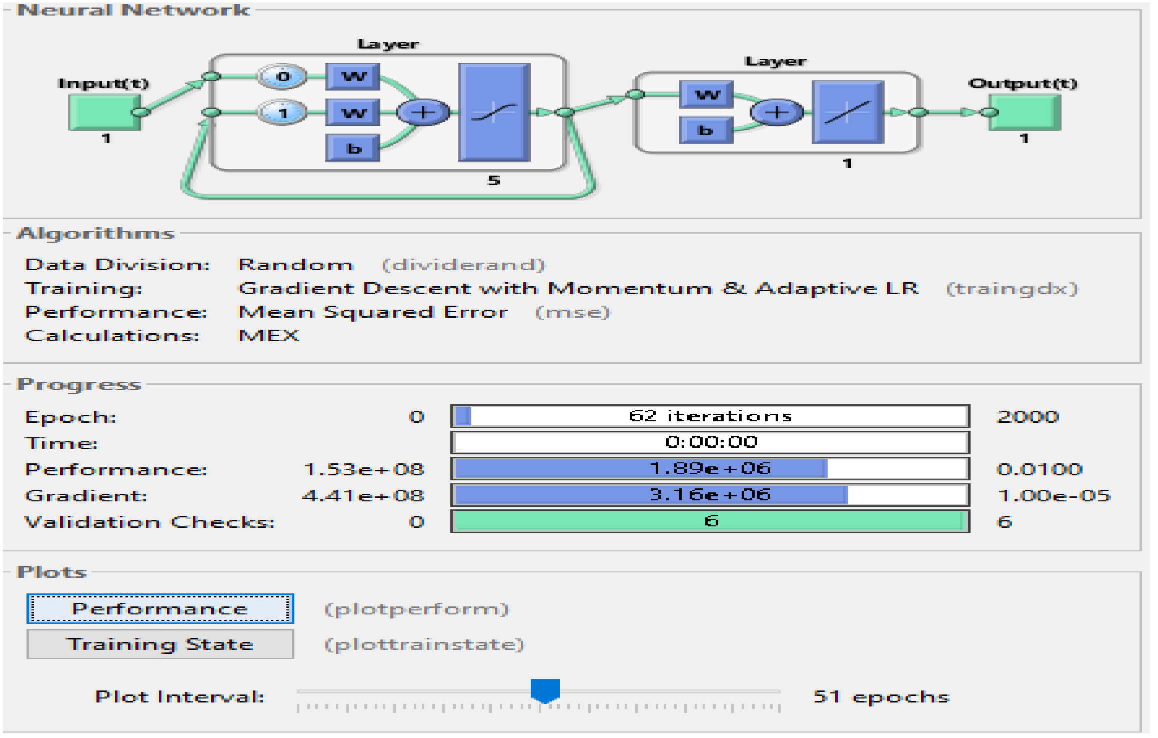

Figure 14. Neural network structures in the MATLAB

Epoch number 0 and 42 is Has the same result of gradient and performance rate because the turning rate of neural network point is zero to forty-two that means one turning rate has 42 center pick point (just like 0 degree and 360 degree cos (0) & cos (360) has the same value that is 1).

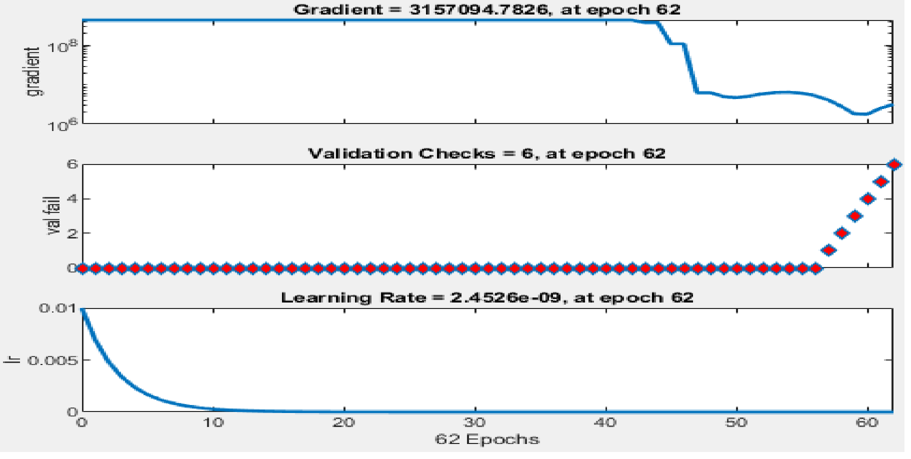

Figure15. Turning state of validation checker in the ANN

In figure 15 shows turning stat of validation checker in the ANN to keep epoch iteration of the graph and network and to count each turning point in the three hidden neurons. Built-in MATLAB training function was used to perform the feed forward (newff), radial basis (newrb) and recurrent training (newelm) of the ANN in the graphical representation the forecasting data and in the turning state present gradient, validation, epoch iteration and learning rate according to epoch iteration number. Table 5 presented the summer and winter time holidays load forecasting.

Table 5: Summer and winter time holidays load forecasting

Time	Holiday forecasting using newff for 2011 EC summer	Holiday forecasting using newrb for 2012 EC summer Forecast of feeder	Holiday forecast-ing using newff for 2011 EC win-ter of feeder	Holiday forecasting using newrb for2012 EC winter of feeder
1	16.23	16.54	18	18.54
2	16.3	16.59	17.9	18.3
3	15	15.43	17.3	17.754
4	16	16.23	17	17.3
5	17	17.43	16.7	17.23
6	16.3	16.59	15.9	16.34
7	17.9	18.33	16.5	16.87
8	18.8	19.5	18.9	19.23
9	18.4	18.99	19.5	19.89
10	0	17.43	18.9	19.23
11	15	15.43	19.5	19.89
12	18.7	19.44	16.83	17.12
13	15.9	16.21	18	18.34
14	17.8	18.3	19.8	20.12
15	17.9	18.3	18	18.34
16	17.09	17.53	19.3	19.54
17	17.8	18.43	18.7	18.99
18	17.6	17.98	14.7	15.05
19	18.9	19.65	19.9	20.2
20	18.9	19.65	18.99	19.34
21	17	17.43	17.6	17.89
22	18.9	19.65	18.6	18.93
23	18.9	19.65	19.4	19.78
24	17.7	18.43	19.7	20.02
MAPE	**0**	**0.039**	**0**	**0.0159**

The actual and forecasted distribution feeder load comparison for holiday summer season is presented by the figure 16. Figure 17 presented the simulation results of the feeder on the 2012 EC summer season.

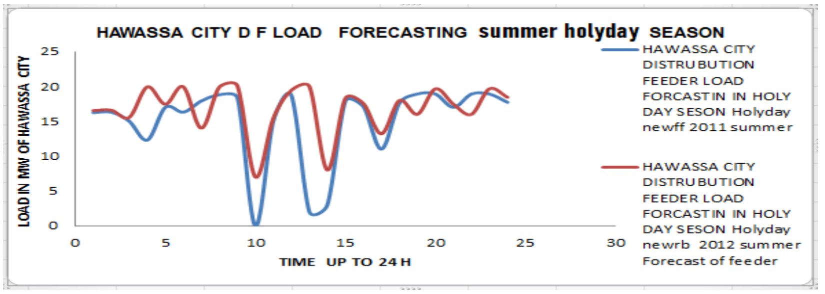

Figure 16. Actual and forecasting distribution feeder load comparison for holiday summer season

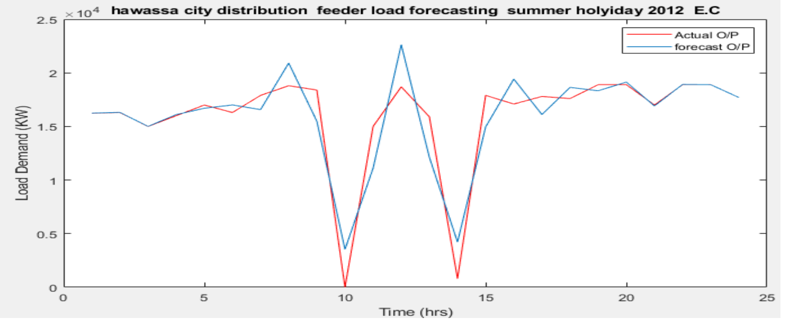

Figure 17. The simulation result of the feeder on the 2012 EC summer season

The simulation results show the gray line that represents the forecasted result and the light red color represented the actual data of the distribution feeder in the summer season. The forecasted result will be more standardized because of the relationship between actual and forecasted value. The MAPE will be under to IEEE standard. For the distribution feeder at the 14th bus, the actual data will be less the forecasted result and around 17 MW and the maximum forecasted value around 19.7MW. It means for the summer season, the distribution feeder required to distribute the forecasted amount of power according to the proposed technique. Therefore, it is important to plan the distribution feeder at the substation level. Figure 18 presented the actual and forecasting load of distribution feeder load comparison for holiday winter season. Figure 19 presented the simulation result of the feeder on the holiday winter season.

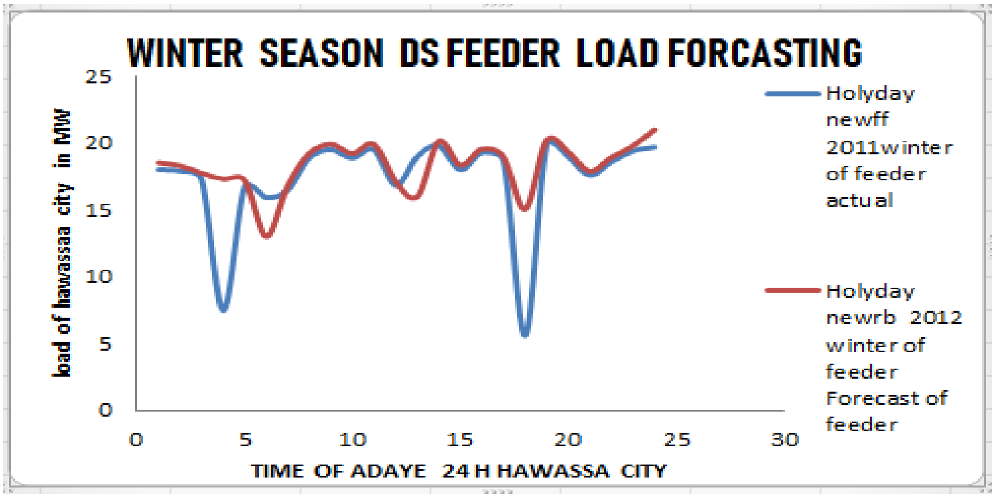

Figure 18. Actual and forecasting load of distribution feeder load comparison for holiday winter season

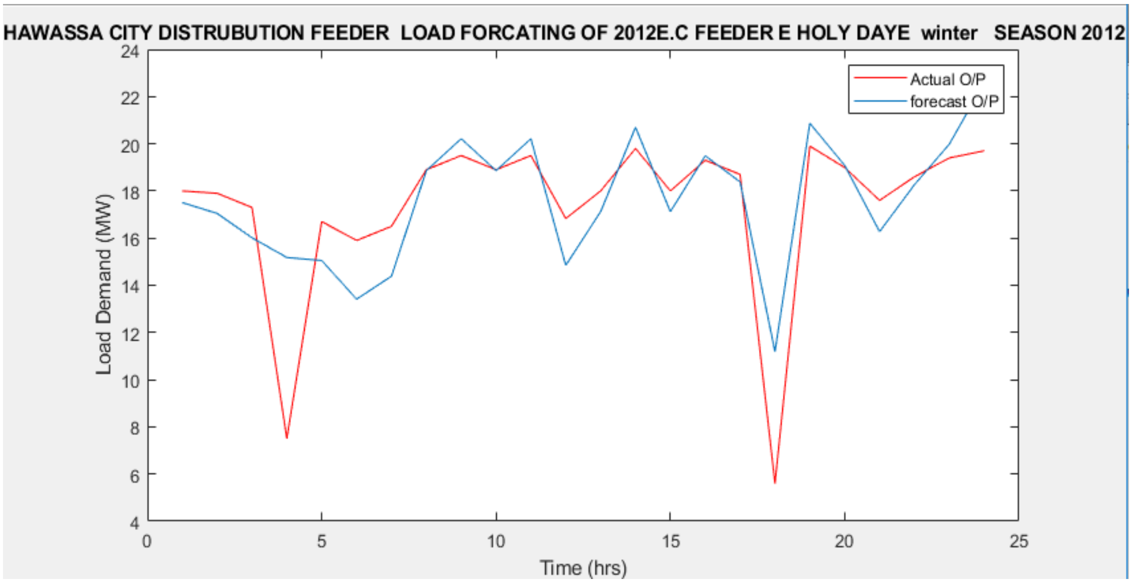

Figure 19. Simulation result of the feeder on the holiday winter season

The forecasted result will be more standardized because of the result relation between actual and forecasted value and the MAPE of error will be under the IEEE standard. The distribution feeder at the 18th hour had actual data less than the maximum forecasted result which is around 20.2MW. It means for the summer time the distribution feeder required to distribute the forecasted amount of power according to the MATLAB simulation. It is important to plan the distribution feeder at the substation level. Table 6 presented the MAPE for the feeder on the case study. Table 7 presented the distribution feeder load forecast.

Table 6. MAPE for the feeder on the case study

Feeder Test	MAPE %		
	Fore-casted load (newff)	Fore-casted load (newrb)	Forecasted load (new-elm)
Feeder 1 11kv	0.7775	0.5739	2.8073
Feeder 2 11kv	3.5139	2.8703	3.7233
Feeder 3 11kv	6.3868	1.1469	0.1283
Feeder 4 11kv	0.7468	0.2999	0.1751
Feeder 5 11kv	3.0121	0.0861	1.0112
Feeder 6 11kv	0.7857	0.2800	1.6861
Feeder 7 11kv	1.3646	0.3975	9.7006
feeder 8 11kv	0.5180	1.4959	0.2811
feeder 9 11kv	3.3875	0.9447	1.3583
feeder 10 11kv	2.4496	0.8606	1.6425
feeder 11 33kv	1.1218	1.1392	1.9556
feeder 12 11kv	3.5327	0.5386	13.8851
feeder 13 33kv	1.9401	0.4259	0.9675

Table 7. Distribution feeder load forecast

Time	Target D	Forecast deviation	Forecast deference	Absolute error	DF MAPE
001	1.4640	1.4664	0.0024	0.000	0.00100
002	1.2900	1.2924	0.0024	-0.000	0.00100
003	1.1800	1.1900	0.010	0.000	0.0004
004	1.2500	1.2480	-0.0108	-0.000	0.00450
005	1.3800	1.3872	0.0072	0.001	0.00300
006	1.4900	1.4636	-0.064	0.002	0.00270
007	1.3500	1.4172	0.0672	0.005	0.00280
008	1.3900	1.2512	-0.1388	0.010	0.00578
009	1.5600	1.7928	0.2328	0.015	0.00966
010	1.5900	1.2667	-0.3323	0.020	0.01380
011	0	0.3693	.3693	0.001	0.01530
012	1.4800	1.3420	-0.138	0.0023	0.00575
013	1.5900	1.1368	0.4532	0.0015	0.01883
014	1.5500	1.8345	0.2845	0.0070	.011854
015	1.5540	1.4449	-0.1091	0.001	0.00454
016	1.6700	1.5402	0.1298	0.0005	0.00540
017	1.6700	1.5642	-0.1059	0.0006	0.00440
018	1.6600	1.7452	0.0852	0.0005	0.00350
019	1.7800	1.7280	-0.0520	0.0003	0.00210
020	1.8300	1.8548	0.02480	0.0001	0.00100
021	1.5890	1.5796	-0.0094	0.0001	0.0004
022	1.4800	1.4728	-0.0072	0.0000	0.0003
023	1.3400	1.3430	0.0030	0.0000	0.00012
024	1.5300	1.5269	-0.0031	0.0000	0.00013

5. Economic Analysis

Economic analysis of the forecasting distribution feeder to calculate the cost of each forecasted feeder based on the forecasting deviation (FD) and distribution feeder MAPE are calculated based on the simulation result output. Figure 8 presented the economic analysis of the forecasted feeders.

Table 8. Economic analysis

TIME	DF MAPE	FD	POWER DIFF. IN kW	BIRR/kW	T COST
1	0.001	0.0024	2.4	0.65 cent	1.56
2	0.001	0.0024	2.4	0.65 cent	1.65

3	0.004	0.010	10	0.65 cent	65
4	0.0045	.0208	20.8	>>	13.52
5	0.003	.00720	7.2	>>	4.68
6	0.0027	0.0640	64	>>	41.6
7	0.0028	0.0672	67	>>	43.55
8	0.00578	0.01288	12	>>	7.8
9	0.00966	0.02328	23.38	>>	15.197
10	0.0138	.3323	332.3	>>	210.145
11	0.01530	0.36930	369.3	>>	240
12	0.00575	.138	138	>>	89.7
13	0.0883	0.45320	452	>>	293.8
14	0.1185	0.2845	284.5	>>	161.525
15	0.0054	0.1091	5.4	>>	3.51
16	0.0054	0.1298	129.8	>>	84.37
17	0.0044	0.1059	105.9	>>	68.835
18	0.0035	0.08520	85.2	>>	55.38
19	0.0021	0.0526	52.26	>>	34
20	0.001	0.0248	24.8	>>	16.12
21	0.0004	0.0094	9.4	>>	6.11
22	0.0003	0.0072	7.2	>>	4.7
23	0.00012	0.003	3	>>	195
24	0.00013	0.0031	3.1	>>	2.015
Total birr single DF/ DAY				1467	ET.BIRR
Total Forecasted Saving Per Year				**6960905 ET. BIRR**	

6. Conclusion

The main purpose of this study is to investigate an intelligence method for the short-term load forecasting, by using three layer feed-forward and back-propagation neural networks for Hawassa city, Ethiopia. It takes into account the effect of the amount of period of disconnected time of load. The results show that neural networks can be considered an efficient and applicable method to short term load forecasting. 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. The results suggest that ANN model with the developed structure can perform good prediction with least error. Finally, this neural network could be an important tool for the short-term load forecasting. Results also show that a simple ANN-based prediction model, appropriately tuned, can outperform other more complex models.

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