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Short Term Load Forecasting using Artificial Neural Network and Time Series Methods: A Case Study of Bishnumati Feeder in Balaju Substation, Nepal

by

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The undersigned certify that they have read, and recommended to the Institute of Engineering for acceptance, a thesis entitled "**Short Term Load Forecasting using Artificial Neural Network and Time Series Methods: A Case Study of Bishnumati Feeder in Balaju Substation, Nepal.**" submitted by Mr. Suman Adhikari, in partial fulfillment of the requirements for the degree of Master of Science in Renewable Energy Engineering.

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ABSTRACT

Electrical load forecasting takes a crucial role in planning, controlling and operation of electric power system. The accuracy of actual and forecasted load be very essential for economically effective control and efficient operation. Short term electric load forecasting takes an importance role in power system operation and planning of Utilities Company. Short term load forecasting (STLF) be always one of most critical, sensitive and accuracy demanding factors of the power systems. An accurate short term load forecasting improves not only the systems economic viability but also its safety, stability and reliability. The researcher presented in this works support Artificial Network and Time Series Methods techniques in forecasting of short term load. This analysis represents a load forecast using hourly, daily and weekly load of Bishnumati Feeder of Balaju Substation, by using artificial neural network & time series methods.

Load forecasting be very important and crucial for efficient and necessary operation for electric power system. This can be taken by obtaining the most effective forecast which help in minimizing the risk in decision making and changes the prices of operation of the electric power system. Then the comparison of artificial neural network and time series method for short term load forecasting that can be used out in this thesis using actual time electric power in this feeder. Moving average, exponential smoothing are analyzed in excel and ANN are analyzed in MATLAB software toolbox. The analysis to be done for the hour-to-hour operation to day to day of the soon be completed of the Bishnumati feeder. The ANN and time series methods, different analyzing models were used for forecasting.

For validation of this model it can be used to forecast of an 11kV Bishnumati Feeder of Nepal for November 10, 2018 and the output is compared to Conveaant University of Nigeria such as Multilayer feed forward Model. The proposed model of ANN for Bishnumati Feeder gives weeekly MAPE of 3.67% which is lower than the MAPE value obtained by the ANN models in Conveant Univesity of 8.37%, but it is within the limit of acceptance. Again, the value of %MAPE for moving average and exponential smoothing be 9% & 6.22% in Bishnumati Feeder which is lower than the MAPE value obtained by the models of Conveant University of 10.3% & 8.31%% but it is within the limit of acceptance.

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LIST OF ACRONYMS AND ABBREVIATIONS

AC	Alternating Current
AEPC	Alternative Energy Promotion Centre
DG	Distributed Generation
GoN	Government of Nepal
kW	Kilo Watt
kVAR	Kilo Volt Ampere - Reactive
IEEE	Institute of Electrical and Electronics Engineers
LV	Low Voltage
NEA	Nepal Electricity Authority
ANN	Artificial Neural Network
MA	Moving Average
ES	Exponential Smoothing
TSM	Time Series Method
Pf	Power Factor
RE	Renewable Energy
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
APE	Absolute Percentage Error
MSE	Mean Squared Error
RMSE	Root Mean Squared Error

LF	Load Forecasting
STLF	Short Term Load Forecasting
MTLF	Medium Term Load Forecasting
LTLF	Long Term Load Forecasting
LC	Load Curve
LV	Lagging Variable
NNT	Neural Network Training
RLF	Regional Load Forecasting

CHAPTER ONE

INTRODUCTION

1.1 Background

Electrical energy always takes place an important role for economic and sustainable development of power sector. To enhance and give the possible feedback in profitable economic rate and continuously meeting the power demand load in future, prediction of data have become a difficult work in electric utility sector. If the predicted value of load is mismatched this can affect whole of the system monitoring and planning .However, an effective value of power forecast can also be helpful for making different power strategy, financing, the future market source and the different electricity management techniques. However, in the present condition, the forecasting can be done on the base of aggregate value of the past lag and lead power. Such forecasting cannot only to identify whether the power load takes place or not but also it can be used to identify the power sector identification, planning & assisting the location of the system. Besides, many of the people are uses the power load for different type of purposes, but no one of the company and person does not constructed the backyard regional load forecasting. Regional forecasting can identify the reserve capacity of the electricity that can be used in power shortage area. The amount of equity that can be take how much size of power source is produced by efficiently and precisely (Hsu and Chen, 2003).

Load forecasting, for different items of the power methods became a very special tools for the upgradation of the latest system operation. The load demand of these method be increasing day by day because that they will meet the emergency of the energy markets & they will uses for higher demanding scores, which will benefit in the power market. Load forecast that can give and achieve the energy transactions system, competitive market portfolio share & earning of benefit from competitive market. Forecasting can play important role in daily and yearly markets to know the power quality in daily energy market and the completive electricity per unit prices.

The short term refers to the prediction of the electrical power of hourly, daily, weekly using the previous and the past value of load. Again, midterm load forecasting can be used to forecast daily, weekly, monthly and also forecast up to the some years. Finally, the long term forecast refers to forecast the load up to one years to the many years using the previous and past value of electrical power.

A power system plays as important role of supplying for these consumers like large and small types with inexpensive and efficient amount of electrical energy with abundant as possible. Sufficient amount of electricity can applied to consumers, when the demand load on the system may be found. The process of calculation in upcoming load value is also called the forecasting of load. Load forecasting can also defined as the prediction of load that can be necessary by a certain geographical considering area uses the preceding value of electrical load that can be use in projected region. Again forecasting can give the necessary decision for that system and give the very good plan for efficient and effective plan and policy for development of energy sector. If the prediction of electrical load is high, the network can do promise the production of power which will accidently goes to expensive running of large energy system management. On the other hand, if the system electric load forecasting takes place below estimation, security and trust ability of system decreases, there should be high value of power cutout in the system and there should be high value of customer dissatisfaction. The time that can be required for forecasting be hourly weekly yearly that will provide the security in the power sector, efficient and the reliable power supply to consumers, there should be maintain power system security. Short term forecast spans the time of hour to day and day to week. In medium term forecast spans from week to year that can be concerned with time schedule of fuel applied and maintenance operation of system. Long term forecast up to the different years and, this forecast is important for planning of operations of system (Purva Sharma, 2008).

The forecasted load accuracy greatly depend upon size of power system network, reliability and outages. Forecasting becomes more complex with the smaller system. Hence, more accurate methods and additional information is required to get acceptable outputs. It becomes more complex with unpredictable occurrence of anomalous events. The quality and quantity of available load data, metrological data, sociological data etc. directly affect the quality of result. Identification of proper tool, management of information system has another important role in the model development. Good forecasting with limited information and with large number of constraints is major challenge faced by the all the power system engineers all around the world. The challenges is more pronounced by the fact that the information and constraints are

completely different from one power system to other or one part of the world to other. No general algorithm or tool can be developed. Hence, for each system a specific method and algorithm has to be developed regarding information collection, data management, data filtration, model development and scope of implementation.
There are different techniques of mathematical model that can be applied in load forecasting, if improvement and starting of very effective analytical techniques that takes the progress of further précised load forecasting category. If precise value of load forecasting depends on in which techniques that can be adopted to forecast the power and how much accuracy of the parameter like temperature, humidity and method be most commonly adopted technique for electric load forecasting. This methods include the fuzzy logic, support vector regression and neural network. Above these method neural network gives the accurate forecasting using the different parameters like temperature, humidity, pressure etc. on the short term forecast.

1.2 Power System Load Forecasting

A secure and highly reliable source of electricity is an essential part of our modern system. Providing a reliable supply of electricity at the lowest possible price would require sufficient generation to exactly meet customers fluctuating demand and system losses. One way that facilitates achieving this exact match between demand fluctuation and energy generation is to estimate the demand in advance. In principle this can be done using the known demand patterns and the factor affecting demands. For long and medium term demand estimation, factors such as economic growth, gross domestic product, purchasing power off people along with many other factors including economical, demographical , social and load consumption have to be taken into account while for short term estimation metrological factors are considered. In a broad sense, this practice of anticipating the future load demand be broadly referred to as load forecasting.

Load forecast be a region of great profitable service to electrical power utility. This is also tackling of problem on the basis of daily changes in load. Different forecasting methods will show electric power utilities to make plan for necessary peak demand to achieve more economical unit allocation, scheduling and pre-dispatching.

The lead time in load forecasting arranging from few minutes past for security assessments, several years for long economic operation and planed for future activities.

This could constitute a very short and a very long term time frame for power systems load forecasting.

1.3 Load Dispatch Practice in Nepal

It is because of monopoly market that prevails in Nepal in case of electricity distribution no such efficient, accurate and widely accepted load dispatching techniques has been utilized. NEA, perform load dispatch all across the country via its integrated system of transmission and distribution line leaving behind very few area of Syangja and Pyuthan. Load Dispatch Centre (LDC) of system operation department of NEA is fully responsible for load dispatch. Power trading, power plant operation, loading of transmission line, flow of power along with co-ordination for shutdowns of generating units and substation equipment is perform by LDC. The management of demand and supply side depends upon the operator choice. Instant decision made by the system operator's plays role in power dispatch. Trading of power to other private electricity company and cross-border is not in practice till now so no such economical and technical analysis is done before the load dispatch all across the country (NEA, 2076).

1.4 Problem Statement

The load demand in the system fluctuating in nature. It is changed by a various factors arranging on different metrological conditions above seasonal affects to all of the factors and which make to take the parameters be difficult, if there should be error on taking weather parameter, this can be affect the whole of the system forecasting. Short term forecasting be very important in reliable, efficient and effective operation of power system. Load forecasting can gives the result on the basis of previous lag data, lead data. If this data should not be uniform there should be effect on the outcome of forecasting.

If there should be find the large amount of forecasted error, this can be indicates that the system be overload and the operation be risky. High level of estimation can give to startup off the system, therefor invaluable reserve capacity should be connected to maintain the accuracy of forecast. In power system network there should contains power generation capacity and resources, to minimize the concurrent This must be done with economic analysis with optimization of operating money, because accuracy of forecasted load be the important value in load forecasting. If the emergency power be closed then there should be fluctuation in the effective load of the system, then the reserved capacity cannot be worked properly as compared to the timely scheduled routine.

Many different power company treated with different challenges in the aspect of condition such as planning, operation of the system. There is no need of present evaluation that can be compared with future forecast power. Various different method can be adopted for the short term forecasting, but different parameters like temperature, humidity, pressure etc. can play the vital role on producing the error on the system. The weather parameters are fluctuating in day to day, hour to hour etc. So that drawbacks can be minimized by using the proper data set can be used and taken.

Forecasting daily conditions of load be the series of hourly values assumed variable in a given day is very much difficult than forecasting the load bounded by small values, as this can be forecast with the different complex working plane models. ANN and FUZZY LOGIC are two such algorithms that deals with highly nonlinear and noisy data set. Their good generalization ability has convinced researchers all around the world for load forecasting applications. Properly tuned parameters have proven these algorithms to end up at global optimal solutions.

1.5 Scope of Work

Load dispatch procedure of Nepal does not follow the technical procedure of anticipating the load demand of an hour or a day ahead because our power dispatching environment does not have any competitive market. Application of short load forecasting technique to the establishment provincial grid & unbundling of electric power system short term forecasting will come in the account.

A research will play role in selecting appropriate technique for short term forecasting in our case that will contribute near future for our nation as their will be reform in power sector.

1.6 Rationale of the Study

The quality of short term load forecasting plays a very vital role in the economic operation of the system, there should be many operations are related on this factor. So that for decision making forecasting make the very largely significance on the economic viability. The rationale includes the economic scheduling of the plant, scheduling of generating capacity, system security. The lack of demand accuracy, no any tradition method cannot be used because model for the one side only cannot be changed the parameter.

Short term load forecasting can be used to specify the application of the load forecasting e.g. model generation system forecasts on day to day or hour to hour. They can be minimize the spinning reserve capacity and daily routine and maintenance within the prescribed time. In a competitive open market system short term forecasting gets attention. This can give the appropriate value of forecasting on the basis of electricity trading and spot price, which will decreasing the purchasing cost of electricity. So that the consumers can take the electricity consumption in a low cost price.

The daily load have been reliable, price that can be forecast on the given information, power services company are deliver to the good bilateral contract and that can be used for the good decision on the load forecast. Forecasting technique can also be used to bidding the generating company to take over market strategically and also manage of this assets. Again, the forecasting of the electrical price can give the important strategy on the bidding of electricity in pool market.

Hence, very efficient and technical methods can be adopted to know the future price, which will give the efficient and reliable supply of load to the side of consumers.

1.7 Objectives

1.7.1 Main Objective

To calculate Short term load forecasting using Artificial Neural Network and Time Series Method of Bishnumati Feeder and compare results.

1.7.2. Specific Objectives

- To find the hourly basis data of temperature, humidity and power of this area.
- To develop the artificial neural network and time series model for Short Term Load Forecasting.
- To forecast the day ahead of 24 hours, weekly and monthly load demand of Bishnumati feeder with basic feed forward back propagation and time series model and compare the result.

1.8 Limitation of the Study

Limitation in this thesis are shown below:

- A research can be done on the basis of primary data, there should not be the validation of data because of human error and other factors.
- In this study we can consider the limited factor, but other factors can also be affect the system.
- The necessity of human begins be increasing drastically, so these method cannot be take over.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview of Load Forecasting

Power load demand are always fluctuating with time quantity. Power load varies throughout the day. The demand for electrical load not only varies throughout the day but hour by hour. Socioeconomic factor, metrology, network reconfiguration, failure in power system component make the electrical demand fluctuating. Penetration of Distributed generation as well as production of deregulated market makes it more unpredictable and variable. For this season, the issue of load forecasting have been one of forecasted area of post electrical utilities in the power industries. There is a continuous need of electric load, because the load is always fluctuating. This forecasted load should be timely dispatched, meet the unit commitment and satisfy freed energy transactions in terms of energy transfer scheduling within the constraints of system are working (D. Ayeni and A., 2016)

There are namely three types of forecast these are short, medium and long term prediction of load. From the given above type, short type prediction be more urgent and critical.

The short term load forecasting refers to the hourly prediction of load by using short time duration like day to several days. The mid-term forecasting can be done either by peak load forecast horizon for either days to month. Long term forecast refers to the forecast from one year to the several years of a week.

Short term electric load forecasting is crucial for the judgement of reliability of the system, because this forecasting output can be done on the basis of off line technique. In order to determine whether the forecasting load may vulnerable to the system or not can be identified. These process of action unit may be bringing peaking loads unit online, load management on scheduling, switching operation so that the value of the reliability in the system does not fluctuate.

Medium Term Forecasting can be used to predict the demand that can be required to maintenance and other network work perform by any other power suppliers. It can be used to forecasting the system load and sometime bulk power interexchange levels that could be used.

Long Term Load Forecasting helps to formulate long term decision plans like infrastructure development because forecast can be done for long time duration, there should be more difficult on off peak demand and mainly focuses on the annual peak demand system load.

2.2 Review of Literature

There are different studies are conducted to do the short term forecasting of the electrical load. This study can be done in foreign and the other international agency on this topic, to increase the theoretical concept, and the method used, in combination to the previous studies. Therefore, some articles research paper view are summarized as bellows:

Electric load forecasting that can be use by the power production company to find new value of forecasted load by using the lag and lead power. This research article presents another concept for short load forecasting by ANN method to forecast the hourly load into the daily load. The hidden layer of ANN can give the genetic theories, which can be apply to forecast the load; the ANN model was trained by Levenberg Marquardt. The daily load data of the Ganmo, Kwara state of Nigeria Transmission and Directorate company substation of 132/11 kV substation can be calculated. The best design for this method can be implemented on the Matlab software. The best method that can be applied for the short term load forecasting be the neural networks training and the support vector regression method (Moshood A. Hambali 2016).

This article describes the new and the latest approach on the short term load forecasting using neural network and analysis on the feasibility of the different analytical methods. From the different analytical model, different results that can be obtained. The best method that can be selected on the basis of percentage error. Different kinds of error can be calculated from the different method. Therefore the minimum error on this technique indicates that this is the best method on forecasting. The input and trained data parameters are given to the matlab software, where input be the temperature, pressure, humidity and trained parameters be power or load respectively. Back propagation algorithm can be applied for load forecast (Reddy and Momoh, 2014).

Power System planning and scheduling done to find future load by using the lead and the lag power. The accurate method of the load forecasting be challenging for the supply of electricity, reliability and efficient operation of the load. There are different factors that can be affect the load forecasting, this can be conclude that forecasted load should not be actual load, but future load demand will rise in this ratio can be found. Per capital consumption capacity of electricity, in which season can be run, population growth rate etc. plays a vital role for forecasting of short term load. In this research regression analysis of load forecasting and the neural network method can be used to compare results. The best method be neural method for short type of load forecasting. Comparison of these forecasting method can be based on the error, such as mean absolute percentage error, absolute error be used the judgement of different method. The minimum value of error which can be give, this is the best method for the load forecasting & analysis of the power sector technique (S. Saravanan, S. Kannan, 2020).

A. K. And Mao, J. (1996). This article is very important for those readers when there is no knowledge or little knowledge on ANN method easy to understand in effective way. The writer discuss the motivational in the development of ANNs. These paper describes the basic method of artificial intelligence method and different computational technique. In a recent modern days, artificial network can be commonly used in modern research and other analytic methods (A. K. and Mao, J., 1996)

ANN method is described and emphasized on the different research paper article. They can described statistical and other modern methods are failed to describe the non-linearity problem that can be directly affecting on the load demand of the system. These are human and weather error condition (Buhari and Adamu 2012)

Kumar (2019) addressed the different approach of load forecasting technique to solve the linear and nonlinear equation. This method in load forecasting can be done by using ANN method. The result obtained from this method is good and efficient and validate with previous load (Gupta, 2019).

Short term forecasting can be used for prediction of the short term load. This method can also be used for the planning, scheduling and operation of the actual power system. These type of forecasting have a greater accuracy, give a very fast response to study the parameter of load and different factor that can affect (Sruthi, 2015).

A paper by (LU,et al., 2011) data are separated in two forms linear and nonlinear. Nonlinear are dealt by ANN while the linear data are dealt by ARIMA, combination of both ARIMA and ANN used to study the forecasted load (Yang, 2011).

This is carried out study of North Vietnam using the feed technique by using the Back Propagation Algorithm. This result shows that ANN technique for hourly, daily, monthly load forecasting problem is important with near validate result (Bhattacharyya, 2011)

This method describes the forecasting the load at distribution level using ANN technique (Sun, 2015).

A paper by (Yuhang Yang, 2011) describes an efficient approach of term load forecasting techniques used by ANN techniques. For this study load curve in a time interval before the target hour is regarded as the training data and the data are normalized before training. Experiment is carried out for Duke Energy Carolina is found satisfactory (Yuhang Yang, 2011)

Study carried out by Anil K Pandey (Pandey, et al., 2104) describes the ANN techniques of forecasting short term load of UPPCL, India. Data from UPPCL that can be used to forecast the load for linear system can be described. The only input data is used as load (Pandey, 2014).

A paper by Martin T. Hagan and Suzanne M. in ref (Martin & Suzzane, 1987) recommend Box and Jenkins time series statistical models, as the suitable time series model of load forecasting. Drawback of this model i.e. the non-linearity of both load and temperature parameters and simply way to eliminate it has be described (Hagan, 2013).

ANN is an artificial intelligence technique that can be using the value of neurons for the time of load forecasting. Human cannot be analyzed a different problems facing on these technique, but in latest days different application can be used for the proper method of load forecasting. By using the previous lead and lag load for predicting the future load be very efficient and effective operation of the power system (Elmolla, 2011).

Load forecast plays a vital role for the different activities of planning, operation monitoring of the power system. If there should be done on accurate load forecasting, then we can be determine the reliability and efficient of the load system can be determined efficiently. For the operation of the system be very economical (Karady, 1996).

Forecasting in the distribution system be very efficient and very important for prediction the load at small system in England. The large number of the node points

and there should be difficult switching operation may can hold the problems on the load forecasting. There should be high accuracy on the large load forecasting, because the load should be constant and aggregated data can be taken as validated (Sun, 2015).
Prediction of future load be the important analyzing factor for the load forecasting. This method plays a very crucial technique for the unit commitment, reducing the installation of devices for reserve capacity. They can also be reduces the generation cost and the reliability should be high in this system (Modelling, 2014).
The load demand on the power system should be very efficient and effective operation on load forecasting. The accuracy of the forecasted load should be high because this can be uses the modern method of forecasting. Conventional method cannot be used different parameters while the modern method can be uses the different parameters affecting the system load (Girraj, 2017).
Forecasting of electric load on the summer season gives the high value of accuracy. Because in this season load can be fluctuating high and also demand be increasing drastically. Therefore for load forecasting highly fluctuating time load can be taken as a input and the targeted parameters. Different affecting parameter that can be used such as temperature humidity, pressure etc. They can be give the accurate and the efficient value of operation of the system that can be used. The hourly load can be used to forecast the future load using the method of ANN time series, end use methods. ANN method be the best method for load forecasting (Ilunga, 2018).
The decision making process on the power sector mainly depends on the actual value of forecasted load. Forecasting can give important help on the load flow analysis, contingency analysis, unbalance power in the system, switching process & strategy, to give the effective and efficient system for greater reliability & balancing the load in the system (Bhandari,Shakya, 2018)
Long value of time series that can be used by the Belgian transmission management operation (TSO) ELIA, are described in this paper for the determination of lone linear system for STLF (Chaudahri, 2017).

2.3 Different Approach of Load Forecasting

There are different methods of forecasting technique can be used, which can be included the similar day approach, neural network, support vector regression, fuzzy logic & different algorithms. These techniques are used for load forecasting using different parameter.

2.3.1 Classical Approach

Classical approach includes time series methods, trend analysis, similar day approach, and regression based approach and end use methods

2.3.2 Modern Approach

Modern Approach includes artificial intelligence, machine learning algorithms, fuzzy logic and expert systems genetic algorithms etc.

2.3.3Artificial Neural Network

The investigation on the forecasting involves a different categories of the research fields, uses the different action on engineering, economic conditions, metrology parameters and respectively other values. This method describes the imaginable forecasting methods that can be more scattered on literature.

The most appropriate tools in the field, artificial neural networks (ANNs) have been replace the very long traditional technique in different type of applications. In the method, the output of the ANN may be verified and adapting capacity, capacity of tolerance nosy level of data or unnecessary formal model. However, the forecasting can be done by ANN be the top former and other be the rare performer. In the real field, it is rear that performance of ANN be better than comparison with other methods. In research one of the best method on the load forecasting be the neural network applications that can be applied in power system.

2.3.4. ANN for forecasting

Artificial neural network is best technique that can be inspired by biological nervous systems. Neural network are composed of small element called neurons. Neuron is an information gathering and processing device which can be used to operate the neural network. Three elements parameter of neuron methods are given below

- A reset of the parameter weights
- An summing point can be added for input parameter
- Activation functions like sigmoid can be used to limit the amplitude of neuron

As in nature, the connection between elements largely determine the network function. A neural network function can be trained by applying the function which can adjust the values of the connection between different elements. In ANN method of load forecasting, usually, many input/targeted pair parameters are to be taken (Kuldeeep Saini, 2016).

2.3.5 ANN Forecasting Model

For load forecasting technique, which can be used as a temperature, humidity are placed as input parameter as shown in Fig. 2.1. Again, the power does not depends on the temperature. This means that if temperature does not effect on the fluctuation of load. The input parameters are taken into the neural network toolbox, where the power load can be used for training purpose. Then after comparison of the actual and forecasted load.

For the fitting of the problems using ANN toolbox, neural network can give the best result and evaluation of the system. The results of neural network be, as an output of linear and nonlinear function of input parameter. Neural network parameters are divided into different number of layers between input and output. The number of layer used in practice by ANN method be relatively small.

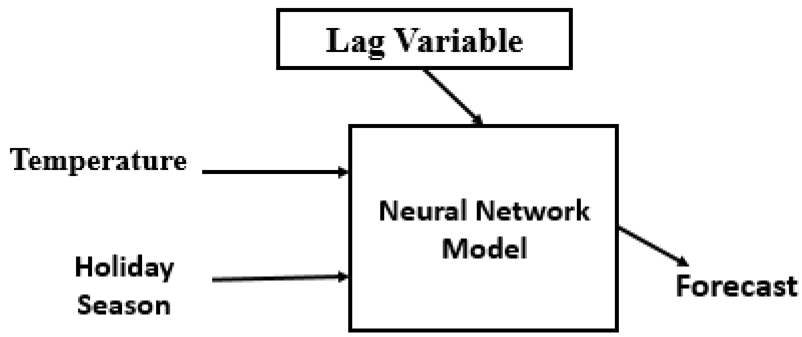

Figure 2.1: The Proposed ANN Models

ANN be the best method of load forecasting using the MATLAB software. ANN can be used the model to learn the input and the targeted perimeter and find the best fitting weight value as output. Further, that new input parameter can be used to forecast the later load.

2.3.6 Mapping Algorithm Selection for ANN

In problems of fitting, neural network can be compared with the data set of numerical inputs and again the numerical values of the target sets. The fitting tool of neural network consists of feed forward methods network with the hidden layer and linear output of neurons. This can be fit the multidimensional matching problems that can be used arbitrarily well, given that more data and more neurons are given to hidden layer. The network be trained by using the Levenberg-Marquardt back propagation algorithm. For a perfect mapping of all four graph, all of testing, validation and resulting graph should lies in a forty five degree line, which can be done in neural network (A.K. Srivastal, 2016).

Back Propagation Algorithm

These algorithm, is merged with a viewed error-correction learning rule, is the one of the best, very popular and very strong methods in the important process like training of artificial networks. This algorithm gives the inaccuracy of signal reverse through the system in the training time in which there should be update the weight parameter of the system. For these system two way directional data flow during the training period, so that the back propagation algorithm should not be a reasonable duplication of different biological studying techniques. When there should be discussion in back propagation algorithm, this is very effective to learn the interlayer of the neurons and the respected input value of the respected weight to the given hidden layer.

The Algorithm, in theory is as follows:

i. Randomly initialize all the weights to prevent the algorithm from focusing at a local minima.

ii. For every training set,

iii. Compute the output using forward propagation

iv. Error = Output obtained – Actual output

v. Back calculate the error associated with each unit from the in front layer until the input layer is reached.

vi. These error measurements can be used to calculate the partial derivate which can be used by gradient slopping technique to decrease cost function & update the weight values of load.

vii. Break, if gradient descent reports convergence.

Radial Basic function Neural Network

RBFs are used for activation function to the hidden layer of RBFN. The connection between the inputs to the hidden layer cannot be weighted but in link between hidden & the output layer be weighted. The hidden layer functions provide function set to makeup random basis for input parameters. Radial basic function neural network are the simple class of functions. These can be applied to both linear and nonlinear data. The learning technique of this method involves both supervised and non-supervised learning methods. Broomhead and Lowe first introduced this technique in 1988. The RBFNN method is a fixed three layered structure. The RBFNN method is similar to working as K-Nearest Neighbor Algorithm.

2.3.7 Characteristics of Short Term Load

Short-term load basically defined as the electric power of a day or an hour ahead a highly unpredictable in many of the case. The load depends upon weather to unpredictable condition that arises day to day in our life and varies largely because of the human daily activities. Although the load is highly fluctuating in nature some of the basic characteristics is shown by it. Below are the characteristics of short term load.

Uncertainty: This can be uncertain to find out future development of load dispatch. The changes are related with a lot of factors that is also constantly developing and changing. Although several of these factors can be predicted, the remaining is difficult to predict, which makes our prediction results uncertain.

Conditionally: The future load change occurs under the necessary conditions and the assumed conditions when predicting it. The necessary condition is the ability to predict the essential rules of change in load, and prediction results obtained in this case are usually effective. In many cases, the load change in the future is difficult to determine. Assumed conditions are based on some certain research and obtained through repeated analysis.

Temporality: The short term load forecasting is conducted by applying scientific prediction method during a certain period of the time scale, such as minutes, hours and days. In this way, the temporality is one important characteristics of the short term electric power forecasting.

Multi-scheme: In various environments, sometimes this can be very useful & important, judge later load patterns according to uncertainty and conditionality of the short term power forecasting. Thus, variety of load forecasting technique be finding and used. Load forecasting can be done by using the previous and past data. The short type load forecast method might fail to fulfil its function while the load characteristics changes over time. Therefore, to ensure an accurate prediction during the change in load characteristics, it is necessary to choose an appropriate short term load forecasting methods & make respondent changes, forecasting can be done on the previous value of load.

2.3.9 Parameters Chosen for Short Term Load Forecasting

The input parameters chosen for Short Term Load Forecasting are as follows:

1. Hourly Dry Bulb Temperature

2. Hourly Dew Point Temperature

3. Hour of the day (Value between 1 to 24)

4. Day of the Week (Valued from 1 to 7)

Coding that can be used for seven day of a week be 1 to 7 from Sunday to Saturday.

5. Working Day or Not

a. Working Day has value 0

b. Weekend or Holiday has value 1

6. Previous Day Same Hour Load

2.3.10 Overfitting Problem

If results in training set is satisfactory, but performance of data set is relatively bad, which indices the overfitting, and then decreasing the number of value of neurons which show the effective outcomes.

2.3.11 Significance of Regression Line

Regression R gives the very close relation between the output value and target parameters. If regression value 1 indices that there should be close relation between the input and the targets and if the value of 0 indicates that there should not be exact relation between input and outputs but random relation between output and the target parameters.

2.3.12 Deficiency of hidden neuron

If training result is not good as compared with testing performance, then deficiency of hidden neuron units can be identified. Increase in number of hidden units can give more accurate results. These can be applied to both linear and nonlinear and nonlinear data.

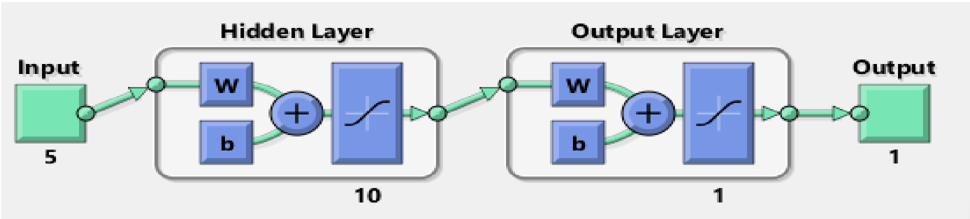

Figure 2.2: Simulation Model of Neural Network

2.4 Time Series Methods

A time series can be predefined as the data value can be regenerated with the respect in the manner of time. Time series methods defines the rejection of the most of the obstacles and hurdles of very difficult parameters of a present event, the value of this time in the previous be related to over activities and the value of these methods can be calculated on the basis of previous value of load. For these comparison of analysis time series methods like moving average & exponential smoothing can be used for this methods (Alex D, 1989).

2.5. Fuzzy Logic

This method uses the Boolean logic algorithm, this is used for the digital circuit modelling. The output into the fuzzy logic may be represents in the form of '1' & '0'. Where 1 represents the better truth & 0 represents the failure of the system.

This fuzzy logic method of short term forecasting that can applied into the different graph like weather parameters like temperature, pressure, humidity and output parameters be the power. The main disadvantages of these method be the sharing of the data on the input and the target parameter. Fuzzy logic be the multi value system of forecasting if the forecasting be true but the value of answer be true and if wrong but the value of answer be false. Fuzzy logic generation creates a Bollean algebra which can be used for the design of digital circuit. The main advantages of these method be there should not be need of mathematical modelling, for the precise of the input and the outputs. Fuzzy logic method can be used the IF-THEN rule to convert fuzzy input into the fuzzy output.

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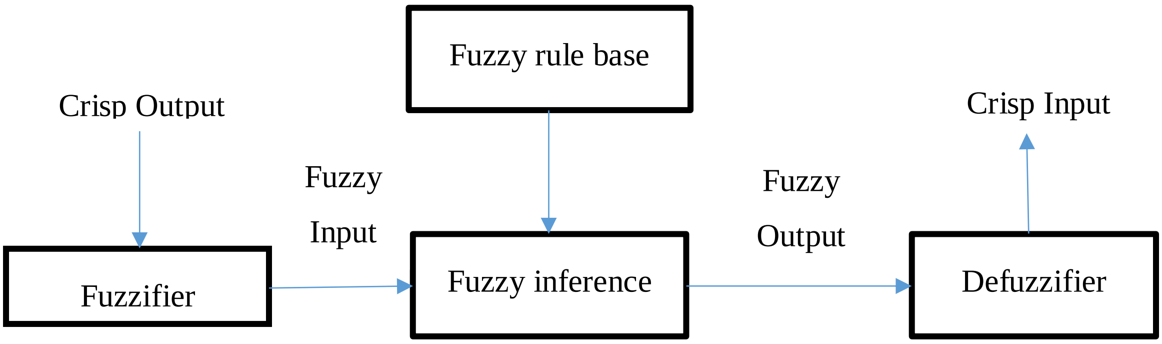

Figure 2.3: Configuration of Fuzzy logic

These are the different techniques used for short term forecasting. Fuzzy logic method uses previous value of load data, temperature, wind speed, humidity etc. (I. SAamuel, 2016).

2.6 Support Vector Regression

In this technique, support vector machine be the software technique that can be used on the machine, to forecast the load for the future years. This can be used to supervise different learning methods with related to learning algorithms that can be used to find the data. The given set of training parameters are set one or other categories. SVM methods can be set the different models for the load forecasting, using different techniques. An SVM technique be the representation of the point of the space, so that the points are scattering on different point in space. So that we can be fit the regression line and mapped into the same space. For the forecasting of load using support vector regression analysis, kernel function parameter that can be used to fit regression line.First of all to analyzing the linear classification for short term load forecasting, SVMs can perform very efficiently by using the kernel function, their outputs are matched into the high space of dimensions. These support vector machines method can be used as a load forecasting. The support vector regression method give the best value of load forecasting as compared with time series and the ann method (Cosmis, 2013).

2.7. Nepal Study on Load Forecasting

GoN, ministry of energy, water & irrigation commission head person has been forecasted power consumption rate up to 2040. Different method for power request investigation has been applied for that analysis. Three scenarios of economic development have been applied for assumptions of that forecasting – (a) occupation as previous (4.6% Gross Domestic Product increase percent), (ii) References (7.3% Gross Domestic Product increase percent), and (iii) Large increase (9.3% Gross Domestic Product growth rate). An ultra-examination that can be do with different rules and regulation assumption, example. 100% cooking in electricity & 75% of water heating can be done with electrical energy in city area like 2020, highly dense are by 2026, etc., at 7.3% and 9.3% Gross Domestic Product increasing rate. The plan making period for 26 years that can be always in consideration, which always gives the electricity demand value forecast in the ratio of time frame like 2016-2041.

Energy Demand Projection up to 2030 using MAED based approach is carried out by Nepal Investment Board in 2068 (NIB, 2068). The model present a framework for evaluating the impact on energy demand by certain changes in the overall macroeconomic picture of a country as well as the standard of living population. Demand for energy is disaggregated into a various end use categories. The total demand for energy is combined into four different energy consumer sector viz. industry (agriculture, construction, mining and manufacturing). Transportation, service and household.

Nepal Electricity Authority, system planning department on 2015 has published a report on demand forecasting up to year 2033/34 AD (NEA, 2015). Demand of energy is divided in to three categories; domestic, irrigation and industrial commercial and other sector. Mathematical equation is formulated to forecast the consumption scenario of energy in three different models and the load is forecasted based upon it. Some university level study have been carried out in short term forecasting using ANN and other conventional technique but this study that can be compare the result between the various techniques of forecasting.

2.8. Research Gap

In context of Nepal unbundling of power system is not yet been implemented. NEA, an undertaking of Government of Nepal is the only one institution for power generation, transmission and distribution. Although Private sectors are involved in power generation but for evacuation of power they are fully dependent with NEA governed by the power purchase agreement between them. In some district of Nepal like Pyuthan and Syanga, Butwal Power Company (BPC) has distributed its generated power to some extend to local consumer (AEPC, 2017). Some part of the very remote area of Nepal has been electrified by micro hydro and some standalone small power plant of NEA. Short term load forecasting i.e. forecast of an hour or a day ahead load which plays vital role in managing load distribution to the consumer at distribution level has been widely utilized all over the world by distribution companies is not in practice in context of Nepal in both private and government sector. So for application levels no such research activities has been carried out in area of short term load forecasting. As mentioned above all the agencies of Nepal has studied the long term demand forecast and no any single research or analysis could be found in STLF by any agencies of legal.

Some studies have been done by the university's student for fulfilment of the requirement in Master or Bachelor level. Some traditional method along with the predefined model of ANN that is multilayer perception that can be utilized to forecast short term demand in Bishnumati feeder located in Balaju substation, Balaju with or without considering the parameters that can affecting on load demand. Because of very few study in the field of short term forecasting using artificial network and other hybrid model there remains some question regarding finding out the suitable model among the various models. This opportunity is utilized in this research where the ANN and time series methods of moving averages and exponential smoothing technique has been selected among the different model and the load for a day ahead, a weekly load and a monthly load can also has been forecasted by analyzing seasonal effect.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Data Collection

Combined hourly feeder data from 1st January 2018 to 29th December 2019 of the Bishnumati feeder of 132/11 kV, collected from Balaju Substation, Nepal Electricity Authority in Banasthali Kathmandu Nepal Electricity Authority. The raw data obtained had been recorded manually in Balaju Substation containing single excel sheet for daily load diagrams. The obtained data was then converted into single time series data.

Similarly, hourly metrological data (temperature, humidity) was collected from department of Meteorology, Government of Nepal.

3.2. Data Analysis

First, the obtained time series data of load and temperature is checked thoroughly to get the basic picture of the load and temperature variations.

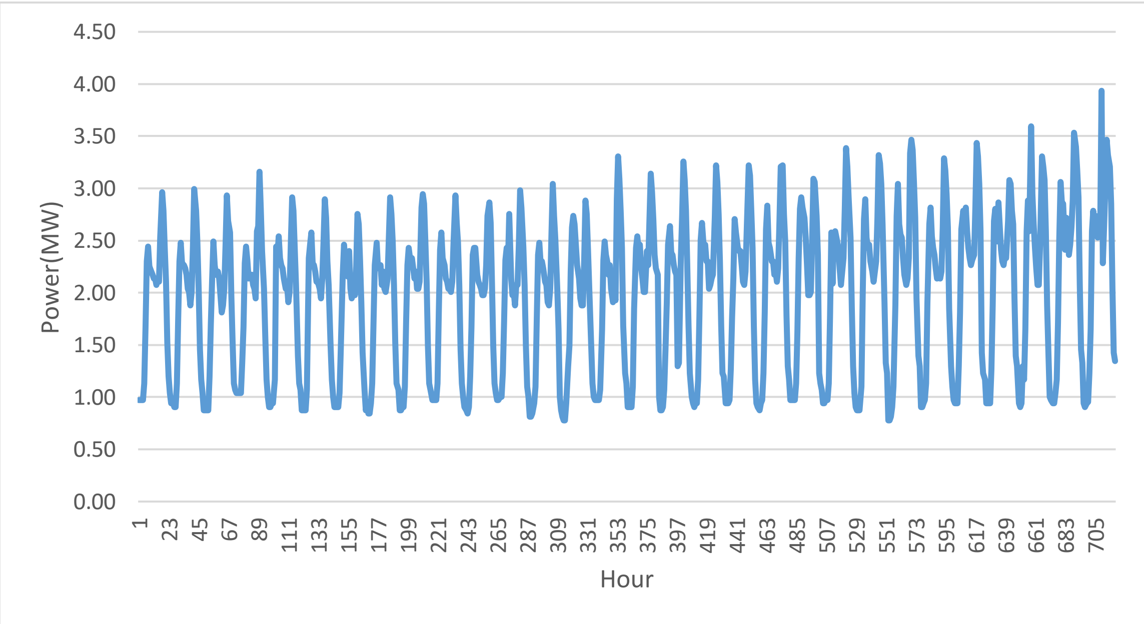

Figure 3.1: Basic pictorial view of available one month load data

Again, the pictorial view of temperature for one month can be listed as follows:

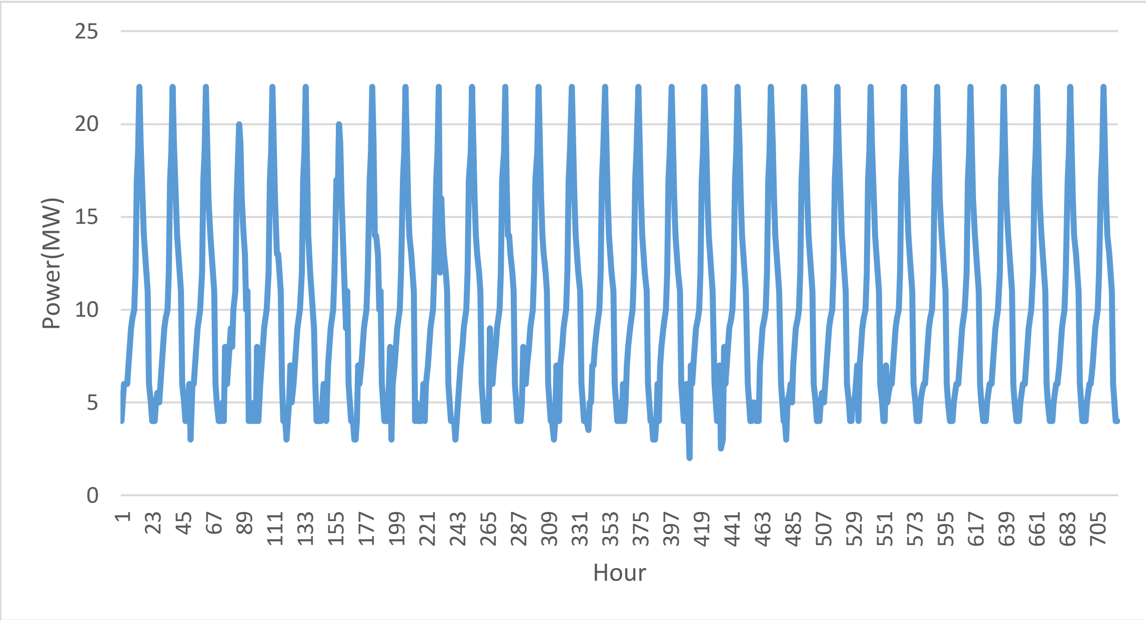

Figure 3.2: Basic pictorial view of available one month temperature data

3.3 Methodology

This study is focused on short term load forecasting techniques using different methods of forecasting like ANN and time series methods. Similar day approach to modern artificial intelligence has been studied and implemented all over the world in various power grid best suit. In Nepal, short term load forecasting is not implemented in real hour to hour or day to day forecasting because no accurate model and technique cannot be implemented in power sector of Nepal.

In this research different analytical technique are analyzed on the basis of mean absolute percentage error (MAPE) and mean absolute deviation (MAD) between the actual & forecasted load. Both technique are used the feed forward neural network algorithm for data training and data forecasting.

The basic Framework for this research methodology shown in flowchart.

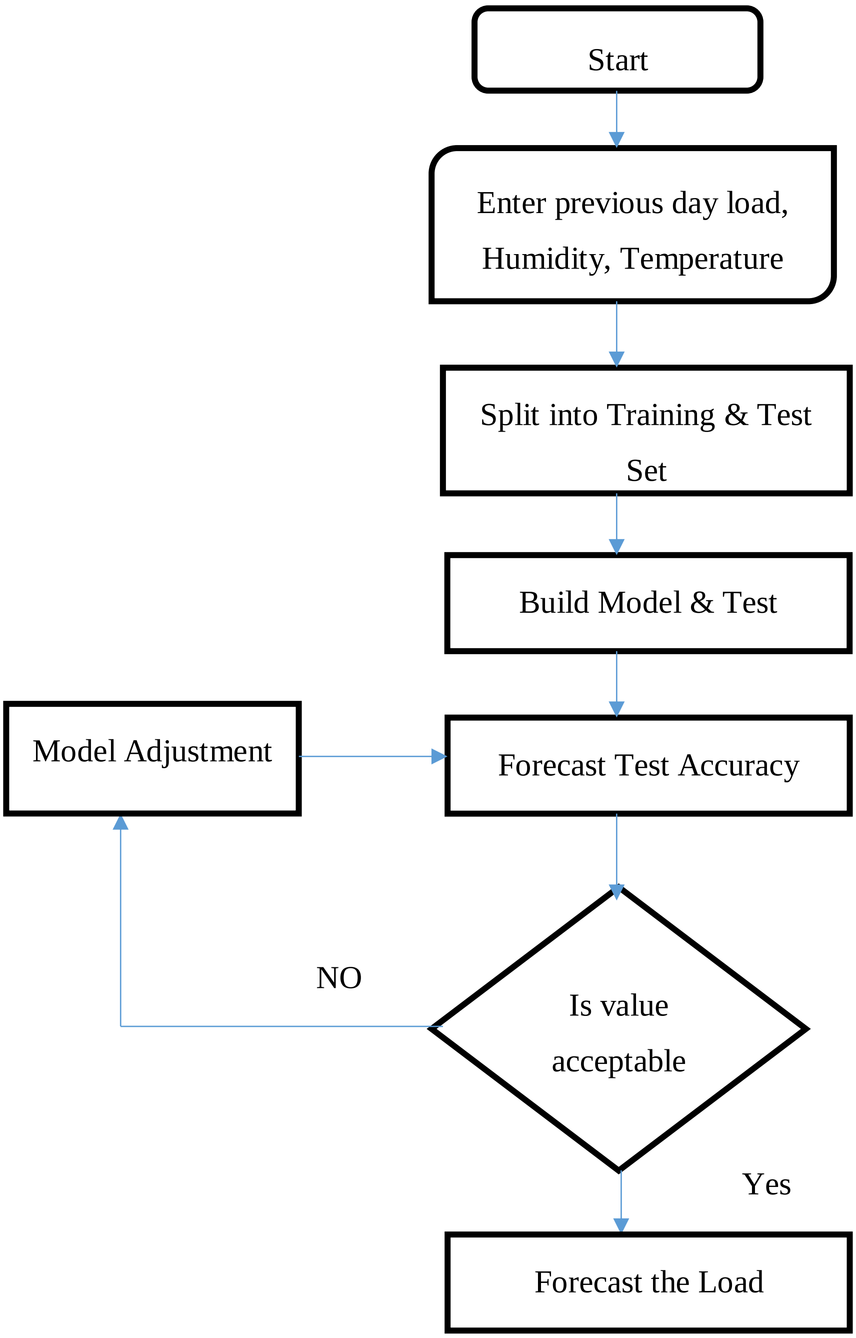

Figure 3.3: Forecasting Methodology by Artificial Neural Network (ANN)

The load forecasting methodology by moving averages and exponential smoothing technique can be shown in flow chart:

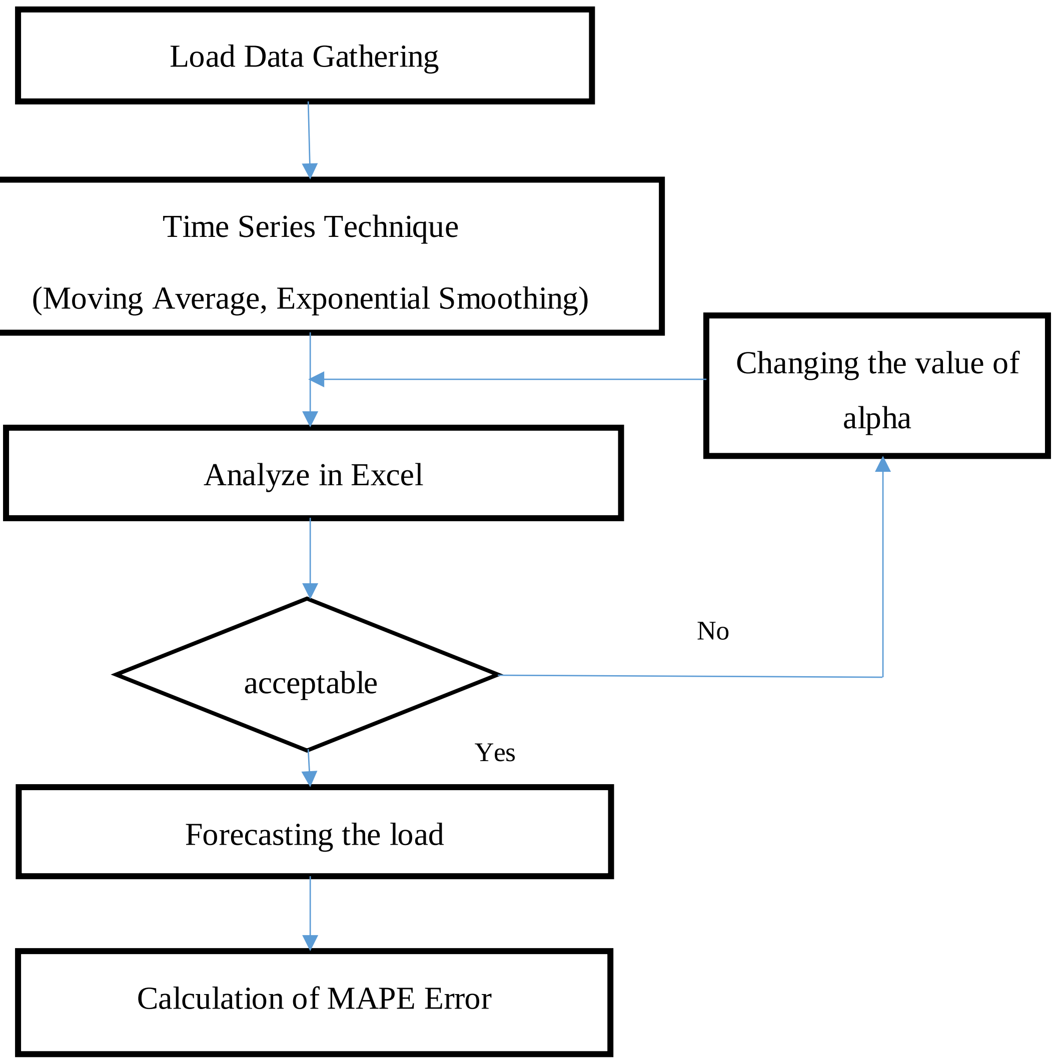

Figure 3.4: Load Forecasting Steps for Moving Average & Exponential Smoothing

Electric load forecasting by using artificial network and time series methods (moving averages & exponential smoothing) the error can be calculated. The least efficient error method is the appropriate method of load forecasting. Therefore ANN method be best method of the load forecasting because this method having minimum error on the forecasting.

3.4 Tool Selection

For, all the predictions related to ANN Matlab 2018a is used and for time series methods statistical tool excel is used.

3.5 Evaluation of Predicted Performance

The forecasting results of the training network that could be analyze by calculating errors on the given data set or those which can be used as a period of training. Various different error can be calculated on the basis of actual or original load and the forecasted load. There are different error can be analyzed on the basis of mape, absolute error, mean square error, root mean square error and absolute mean error..

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\text{actualload}-\text{forecastedload}|}{(\text{actualload})} * 100\ , \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (3)$$

$$\text{APE} = \frac{|\text{actualload}-\text{forecastedload}|}{(\text{actuallload})} * 100\ , \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (4)$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\text{actualload(i)}-\text{forecastedload(i)}|}{(\text{actualload})(\text{i})}\ , \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (5)$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(t_i - O_i)^2 \ \text{ or } \ \sqrt{\text{MSE}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (6)$$

Where *n* represents the total number of sample that could be taken in forecast and *i* represents the total time period in which time electric load can be forecasted, *t* represents the target parameter and O represents the neural network output

In case of load forecasting the system that can be assumed as accurate, the relative error is found on the basis of hour. If the positive error means, the forecasted load is greater than the actual rated load, and if the negative sign of error indicates that forecasted load should be less than the actual load.

3.6 Forecasting next hour using ANN

Two input methods are tested for forecasting next hour load is set that the effects of power variables and additional input parameters. The forecast is done with historical load variables along with temperature variables, day type & cyclic values in hour of day and day of week as input.

For properly synchronized additional variables the performance error MAPE, MSE etc. gets improved automatically. The training method of the network and number of layers that can be used in this forecasting technique are shown in below figure.

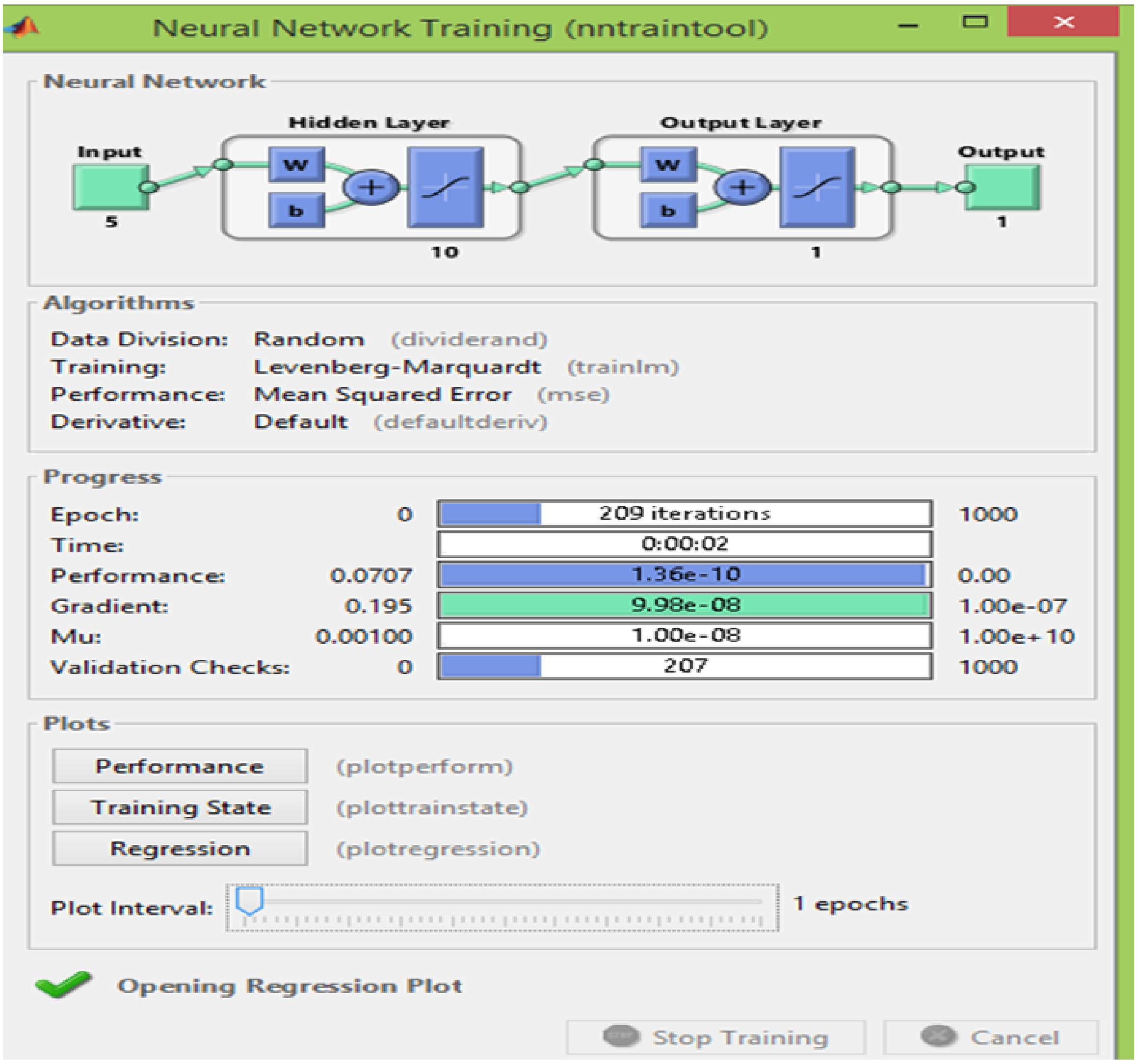

Figure 3.5: Neural Network Training Process

For, neural network training analysis 50% of data are divided into the training process, 25% of data can be used to forecast for validation and 25% of data are used for forecasting load. For this training process input layer and output layer are given. Then for forecasting of hourly load number of iterations can be increased until the coefficient of correlation is much closed to unity.

Thus the formulated input vector and target variable is feed in the ANN to get predicted values using feed forward layer model network with using hidden neurons and linear output layer of neurons. It can be analyzed by analyzing the mapping problems abnormally well given constant data and there should be enough neurons in the hidden layer. The neural network is trained based on Levenberg-Marquardt back propagation algorithm.

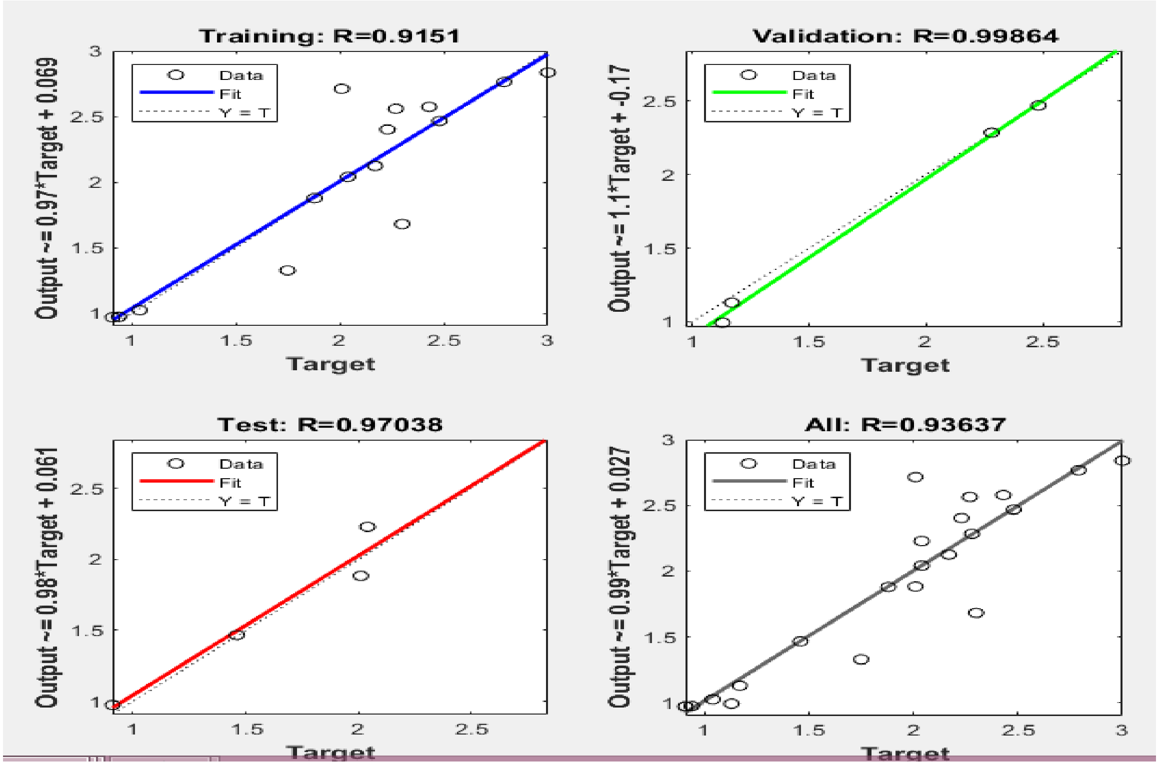

Figure 3.6: Neural Network Training Regression

Training of the Network: It is a process of the weight adjustment on the basis of coefficient of correlation between input, target and validation. This analysis can be done in Matlab software. Then temperature, humidity, pressure and other parameters are taken as input. 50% of these data can be used for the training of the neural network, 25% data can be used for validation and remaining 25%, for forecast. The performance of neural network was trained by different activation function and number of layers till the system does not give the best performance. Figure above shows the method of neural network being trained.

3.7. Neural Network Architecture

In this method of load forecasting using ANN method, we can be split the data into the inputs set, hidden layer sets, output layer and the output. For, this load forecasting using ANN methods we can be use temperature, previous hour load, humidity, in which days of load be forecast and whether the day be working day or not. The overall parameter of the neural network that can be listed in table.

Table 3.1: Neural Network Architecture

Number of Inputs	Number of Hidden layer Neurons	Number of Output Neuron	Activation Functions
5	10	1	Sigmoid

The basic structure in ANN that can be used to forecast the load can be shown below:

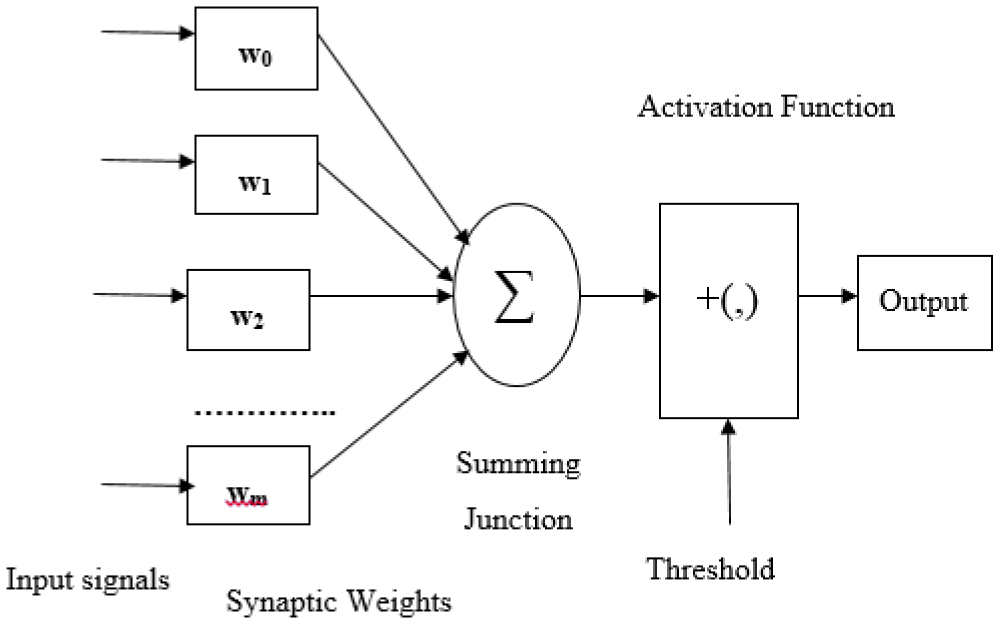

Figure 3.7: Mathematical Model of ANN

In this neural network mathematical model, can give the input parameters, the input can be divided into the training and testing set. If there is variation in actual and the forecasted load, the value of weight set can be change. Therefore, we can be give the input to the summing junction point and the activation function called sigmoid function that can be gives the actual forecasted load hour output.

The actual model for the forecasting gives the five inputs value, the number of hidden layers be ten then we can be give the sigmoid activation function that will be give the actual forecasting load. Therefore, there should be only one output function that will give the forecasted load for hour or day. All of the five inputs are summing up with this weightage value, then give to the activation function with the threshold value and gives the output or forecasted load.

3.8. Time Series Architecture

In this method of load forecasting we can be used two methods of time series analysis. They are moving average and the exponential smoothing technique. In this method of load forecasting the moving of three item can be analyzed and then be take into the fourth column. The exponential smoothing technique can also be used the same technique, at the starting we can be take the averages of hourly load and forecasted the load for next hour, next day and the next month.

This analysis of time series be the statistical method of load forecasting. These method can only base on the previous load, but doesn't depends upon the other affected factor. The validation of the forecasted load on this method be low precious as compare with the artificial neural network method or the support vector machines method or fuzzy logic method. In other method of analysis temperature, humidity, working hour or not can be analyzed but in this method only the input power can be used. Therefore the actual validation result be poor as compare with other method. But in comparison of two method like moving average and exponential smoothing, exponential method can analyze by changing the value of alpha but in moving average can be divided into three point, four point and the five point average. If the average can be taken as three point this is called three point average, if the average can be taken as four and five point respectively called as four and five point moving average.

CHAPTER FOUR

RESULTS AND DISCUSSION

As discussed earlier in methodology load forecasting is done by using the feed forward propagation algorithm of ANN and the time series methods. Although the short term forecasting depends upon a temperature, holidays and greatly to the human behavior in our study, then include time of day, day of week and load of input parameters for both forecasting technique.

4.1 Forecasted load with ANN Model

The hourly load data of the Bishnumati Feeder 132/11 Kv is collected from the Balaju Substation, located in Banastahli Kathmandu. First of all, set the input and the target parameter for load forecasting. Then, the input parameters are day, previous load, temperature, humidity and the hour is working hour or not. The input and targeted parameter of the 2018 January 1st are as follows:

Table 4.1: Input and Target Parameter for ANN Model

Hour	Previous Load(MW)	Temperature(degree centigrade)	Humidity (%)	Working hour/not	Target(MW)
1	0.97	4	88	0	0.97
2	0.97	5	87	0	0.97
3	0.97	6	88	0	0.97
4	0.97	6	86	0	0.97
5	0.94	6	89	0	1.13
6	1.10	7	84	0	1.67
7	1.68	8	88	1	2.30
8	2.32	9	89	0	2.45
9	2.46	9.5	85	0	2.25

10	2.20	10	67	0	2.20
11	2.19	12	70	0	2.17
12	2.07	17	73	0	2.14
13	2.09	18.5	75	0	2.14
14	2.17	22	76	1	2.07
15	2.06	19	77	0	2.14
16	2.04	16	76	0	2.11
17	2.02	14	74	0	2.54
18	2.36	13	76	0	2.96
19	2.91	12	74	0	2.79
20	2.75	11	75	0	2.43
21	2.38	6	74.5	0	2.11
22	2.04	5	74.6	1	1.52
23	1.49	4	74.2	0	1.20
24	1.17	4	74.5	0	1.04

The load Forecasting can be done on the following basics scheme. The input and target value are given to the matlab toolbox and then analyzing the regression line. If the regression line is very close to unity, then there could be the accuracy of forecasted load. If the regression line is not closed to unity, we can be change the value of neuron then the value of training, validation, testing of regression line is very close to unity. For these forecasting, we can give the different parameter of input and target parameter are given and forecast the load for next hour of the day, and week. If all the affecting parameter to be consider, these method of load forecasting gives the actual value of load for next hour, day and week of a month. The forecasted load and error can be shown in table:

Table 4.2: Calculation of Forecasted load & APE

Hour	Actual load, MW	Forecasted load, MW	Absolute Percentage Error
1	0.94	0.974823	0.037859
2	0.94	0.975202	0.038262
3	0.91	0.974341	0.074394
4	0.91	0.971354	0.0711
5	1.13	0.993563	0.123528
6	1.75	1.32966	0.239749
7	2.30	1.68225	0.268452
8	2.48	2.468294	0.003801
9	2.28	2.283354	1.23E-05
10	2.27	2.563162	0.130547
11	2.23	2.403972	0.075699
12	2.17	2.126062	0.020258
13	2.04	2.042409	0.000951
14	2.01	2.714401	0.351739
15	1.88	1.880662	0.001137
16	2.01	1.883253	0.062163
17	2.43	2.577683	0.061155

18	3.00	2.839645	0.052165
19	2.79	2.766072	0.00694
20	2.48	2.469414	0.003349
21	2.04	2.22909	0.09244
22	1.46	1.466409	0.006128
23	1.17	1.129685	0.031131
24	1.04	1.02559	0.010458

%MAPE = 6.34%

This table shows the original load, forecasted load and absolute error which is also called deviation in actual and forecasted load. The first day of January 1st hourly load are forecasted by using the artificial network training method, where input and the targeted parameter are given. Then the hourly forecasted load can be obtained. After that we can be calculate the mean absolute percentage error, the value of percentage mape for first day of January be 6.34%. The value of 6.34 indicates that there should be least variation in actual load and forecasted load.

For, the load forecasting the load can be forecasted on the basis of regression line. If the coefficient of correlation is not very close to unity, then to increase the iteration. If there should not variation in actual and forecasted load, then there wouldn't be variation in original and forecasted load. The mean absolute percentage error of 6.34% indicates that there should be least variation in actual and forecasted load.

Load curve that can be compare the actual load and forecasted load of the January 1st load, the maximum load occurs in 9th hour and minimum in 1st hour. There should not be large variation in actual and forecasted load.

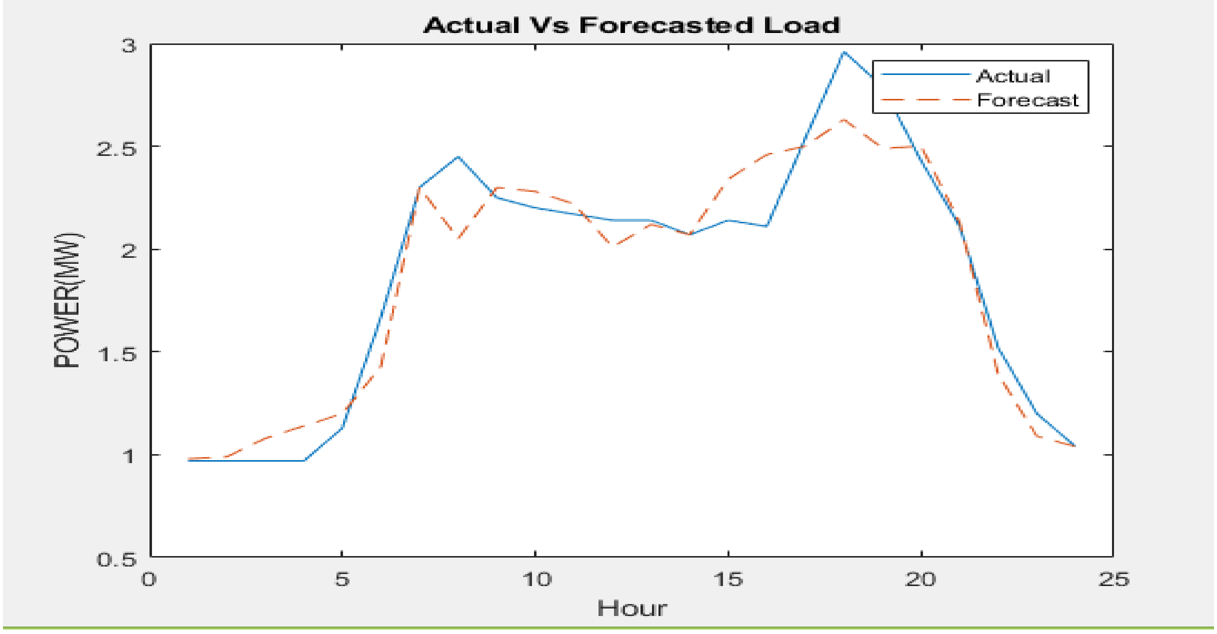

Figure 4.1: Actual Load Vs Forecasted Load Graph of January 1st

In this graph, the regression line between the input and the target are very close to unity. In 7th and the 20th hour there should be changes in other different parameter. So that in this hour there should be variation in actual and forecast load. If we can be consider all of the parameter for load forecasting, there should be small variation in actual and the forecast load. For analyzing the forecasted load, there should be analyze on the basis of regression line on matlab. Graph shows that the input and target graph are originated as origin and the coefficient of correlation between the actual load and the targeted parameter are very close to unity.

Actual and Forecasted load for January 2nd

Actual and the forecasted load for the January 2nd can be analyzed on the basis of the regression line. If the coefficient of correlation between target and the input be very close to unity. In this condition accuracy between the original and forecasted load. .Therefore the original load and forecasted load for these hour of Bishnumati feeder can be listed in table:

Table 4.3: Calculation of Actual and Forecasted load of January 2nd

Hour	Actual load(MW)	Forecasted load(MW)	Absolute Percentage Error
1	0.94	0.95	0.006
2	0.94	0.94	0.001
3	0.91	0.95	0.042
4	0.91	0.94	0.034
5	1.13	0.99	0.130
6	1.75	1.00	0.427
7	2.30	2.29	0.006
8	2.48	2.54	0.024
9	2.28	2.39	0.046
10	2.27	2.17	0.041
11	2.23	2.26	0.009
12	2.17	2.22	0.024
13	2.04	2.03	0.004
14	2.01	1.96	0.025
15	1.88	1.87	0.003
16	2.01	2.04	0.015
17	2.43	2.73	0.126
18	3.00	2.95	0.014
19	2.79	2.78	0.001

20	2.48	2.47	0.005
21	2.04	2.06	0.012
22	1.46	1.45	0.005
23	1.17	1.26	0.085
24	1.04	1.10	0.059

% MAPE = 4.76%

This MAPE indicates that there is most accurate forecasting can be done by analyzing the input and the targeted value. The comparison of load curve for actual and forecasted load are drawn as below:

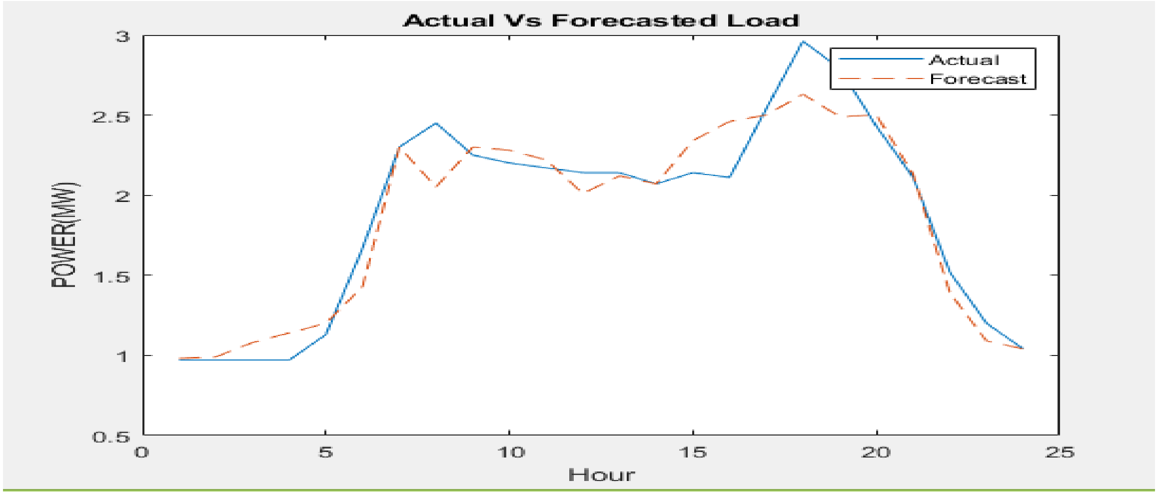

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Figure 4.2: Actual Vs Forecasted Load of January 2nd

There should be small variation in actual and the forecasted load because that different parameter can affect the load forecasting. These parameter are temperature, humidity, working hour or not and the previous year's same days load. From these graph we can be conclude that peak time hours holds the few fluctuation in load, but in normal hours there should not be fluctuate the actual and the forecasted load. In this graph in 8th hour peak there should be fluctuation in load. The mean absolute percentage of error in the second day of January 2nd be 4.34%. The meaning of mape indicates that there should be least variation in actual and the forecasted load.

Actual and Forecasted Load for January 3rd:

The forecasted load and absolute percentage error for the January 3rd are calculated as follows. The load can be forecasted on the basis of regression line and the load can be forecasted on the basis of coefficient of correlation.

Table 4.4: Forecasted load of January 3rd and Absolute Percentage Error

Hour	Actual load(MW)	Forecasted load(MW)	Absolute Percentage Error
1	0.87	0.93	0.07
2	0.87	0.94	0.08
3	0.87	0.94	0.08
4	0.87	0.96	0.09
5	1.20	1.15	0.04
6	1.70	1.76	0.03
7	2.12	2.21	0.04
8	2.49	2.53	0.01
9	2.27	2.42	0.07
10	2.17	2.18	0.00
11	2.20	2.20	0.00
12	2.14	2.12	0.01
13	1.98	1.97	0.00
14	1.81	1.82	0.00
15	1.88	1.86	0.01
16	2.04	2.00	0.02

17	2.46	2.40	0.03
18	2.93	2.73	0.07
19	2.69	2.68	0.00
20	2.57	2.58	0.00
21	1.98	1.95	0.01
22	1.52	1.31	0.14
23	1.13	1.16	0.02
24	1.07	1.12	0.05

%MAPE = 3.67%

The comparison graph between the actual and forecasted load of January 3rd drawn in below. There should be least variation in original & forecast load in third day of January. Then, mean absolute percentage error 3.67% indicates that there should be least variation in original and forecast load. In first and second day of a week, percentage mape is high but in 3rd day of a week the value of mape is decreased.

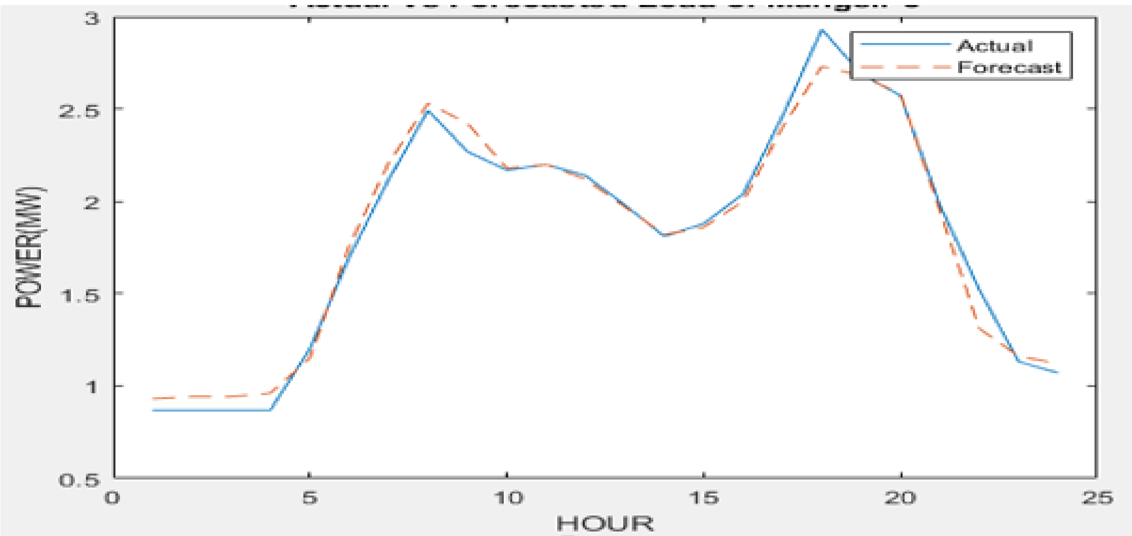


Figure 4.3: Actual Vs Forecasted Load of January 3rd

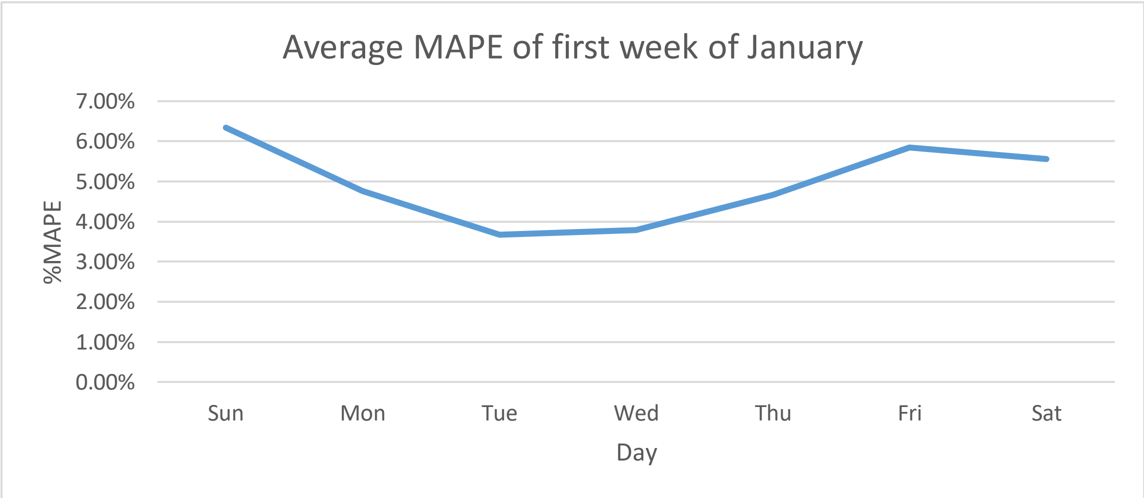
Again the forecasted load MW for the January 4th, 5th, 6th & 6th day are calculated as follows. This can be shows that there should be least variation in actual and the forecasted load in this day. Again these load can be same as to the previous week same days.

Table 4.5: Calculation of forecasted load for different day of January

Hour	January 4th	January 5th	January 6th	January 7th
1	1.01	0.93	0.92	0.94
2	1.01	0.92	0.92	0.92
3	1.02	0.97	0.91	0.96
4	1.01	0.93	0.92	0.92
5	1.26	1.14	0.91	1.04
6	1.62	2.41	2.50	1.39
7	2.28	2.34	2.46	2.17
8	2.50	2.60	2.38	2.63
9	2.22	2.34	2.24	2.13
10	2.17	2.25	2.31	2.27
11	2.17	2.23	2.27	2.20
12	2.17	2.16	2.17	2.27
13	2.02	2.06	2.24	2.22
14	2.04	2.07	2.23	1.80
15	1.84	1.91	2.13	1.85
16	2.10	2.03	2.19	1.83
17	2.65	2.34	2.36	2.50

18	3.16	2.90	2.70	2.66
19	2.76	2.76	2.49	2.65
20	2.47	2.34	2.32	2.10
21	2.03	2.32	2.09	1.66
22	1.58	1.53	0.91	1.39
23	1.06	1.10	1.21	0.97
24	1.01	1.00	1.13	0.95
%MAPE	3.78%	4.66%	5.84%	5.56%

This table indicates the forecasted load of different day, month and minimum acceptable percentage error. Then, the value of mape indicate that there is a minimum variance in actual and forecasted load and the coefficient of correlation be very close



to unity. The figure below shows the graph of mape in first week of January

Figure 4.4: Average MAPE of first week of January by ANN Method

Graph shows the value of mean absolute percentage error be high in starting and ending days in a week. The value of percentage mape be 6% in Sunday, at the middle of the week the value of mape be 4% but in ending of the week the value of mape be highest.

4.2. Forecasted load on the basis of Moving Average

Load can be forecasted on the basis of moving average and the exponential smoothing. This type of method uses the load at input and the output can be analyzed on the basis of three, four, five point moving averages. Exponential analyzing technique is very efficient and beneficial method.

The January 1st load can be analyzed on the basis of Moving point averages. This method be the statistical method for load forecasting. In this method load can be forecasted on the basis of the 3, 4 and 5 point averages. There should be least deviation in percentage MAPE between first day of 3, 4 and 5 point moving averages. The forecasted load of their 3 method of moving averages are shown in below table. The load can be forecasted on the basis of three technique on moving averages method. This method gives the accurate forecasted load and we can be calculate the mean absolute error that can be measures the differences in the original and the forecasted power.

Table 4.6: Load forecasting using Moving Averages of January 1st

		3Point MA	4 Point MA	5 Point MA
Time (hrs.)	Actual(MW)	Forecast(MW)	Forecast(MW)	Forecast(MW)
1	0.97	1.57	2.17	2.49
2	0.97	1.21	1.77	2.32
3	0.97	1.04	1.42	1.97
4	0.97	0.97	1.15	1.61
5	1.13	0.97	0.97	1.33
6	1.67	1.03	1.01	1.00
7	2.30	1.26	1.19	1.14
8	2.45	1.70	1.52	1.41
9	2.25	2.14	1.89	1.70

10	2.20	2.33	2.17	1.96
11	2.17	2.30	2.30	2.17
12	2.14	2.21	2.27	2.27
13	2.14	2.17	2.19	2.24
14	2.07	2.15	2.16	2.18
15	2.14	2.12	2.13	2.14
16	2.11	2.12	2.12	2.13
17	2.54	2.11	2.11	2.12
18	2.96	2.26	2.21	2.20
19	2.79	2.54	2.44	2.36
20	2.43	2.76	2.60	2.51
21	2.11	2.73	2.68	2.57
22	1.52	2.44	2.57	2.57
23	1.20	2.02	2.21	2.36
24	1.04	1.61	1.81	2.01
%MAPE		12%	11.23%	11.44%

The MAPE of these forecasted load be slightly higher than the ANN method, again the other five days of one week MAPE are given in table.

Table 4.7: Forecasted Value for different day of January

	Moving Average MAPE%		
Date	3 Point	4 Point	5 Point
January 2nd	10.34%	10.55%	11%
January 3rd	9%	9.04%	10.35%
January 4th	10%	9.55%	11%
January 5th	11%	10.45%	12%
January 6th	10.5%	10.50%	11%
January 7th	9.5%	11%	10.42%

Again, the graph can be plotted between the days and the percentage MAPE can be plotted.

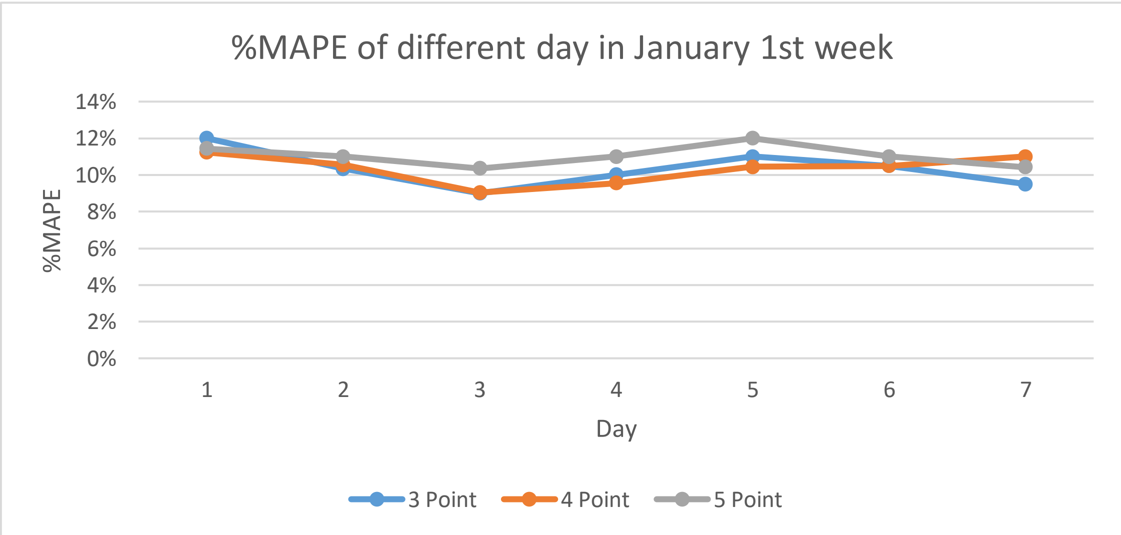


Figure 4.5: %MAPE of different day in January 1st week

From, the graph percentage mape be highest in starting and the ending day of the week using the 3, 4 or 5 point moving averages methods. Because of from these three methods the value of percentage mape be slightly change. The weekly chart of mean absolute percentage error that can be shown in above graph. So that we can be take the average of three error.

4.3. Forecasted load on the basis of Exponential Smoothing

Exponential Smoothing is the best technique for electrical load forecasting. The forecasted load for seven days of January first week be listed as follows. The forecasted load can be calculated on the basis of different value of alpha. The forecasted load for the seven days can be calculated as follows & all the forecasted load are in Mega Watt.

Table 4.8: Forecasted load on the basis of Exponential Smoothing

		a=0.1	a=0.2	a=0.3
Time(Hr.)	Actual load	Forecast load	Forecast load	Forecast load
1	0.972	0.972	0.972	0.972
2	0.972	0.972	0.972	0.972
3	0.972	0.972	0.972	0.972
4	0.972	0.972	0.972	0.972
5	1.134	0.972	0.972	0.972
6	1.668	0.988	1.004	1.520
7	2.300	1.056	1.140	2.215
8	2.445	1.180	1.389	2.540
9	2.251	1.307	1.642	1.812
10	2.202	1.401	1.831	1.943
11	2.170	1.481	1.991	2.021
12	2.138	1.550	2.129	2.066
13	2.138	1.609	2.246	2.087
14	2.073	1.662	2.352	2.102

15	2.138	1.703	2.434	2.094
16	2.105	1.746	2.521	2.107
17	2.542	1.782	2.593	2.106
18	2.964	1.858	2.745	2.237
19	2.785	1.969	2.966	2.455
20	2.429	2.051	3.129	2.554
21	2.105	2.088	3.205	2.517
22	1.522	2.090	3.208	2.393
23	1.198	1.233	3.095	1.432
24	1.036	1.250	1.928	1.852
%MAPE		8%	9%	8.46%

The graph that can be plotted between actual and the forecasted load of the January 1st are drawn as below.

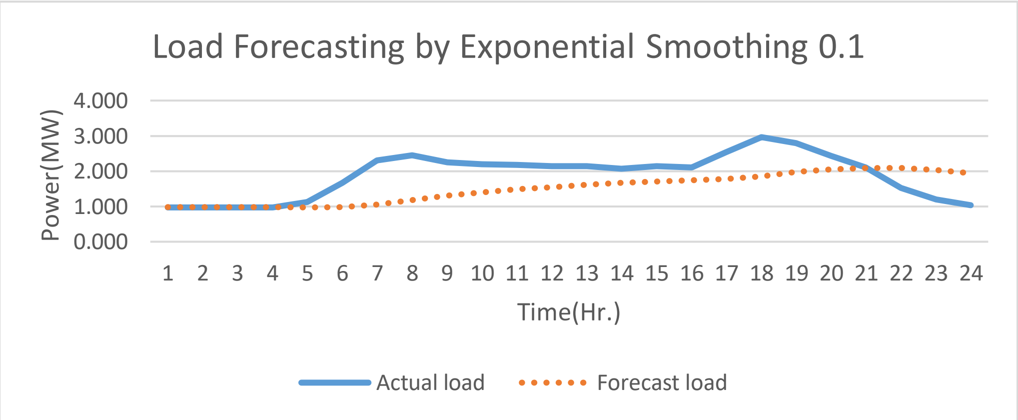


Figure 4.6: Comparison between Actual load and Forecasted load at alpha 0.1

When the value of alpha be 0.3, the graph can be plotted as

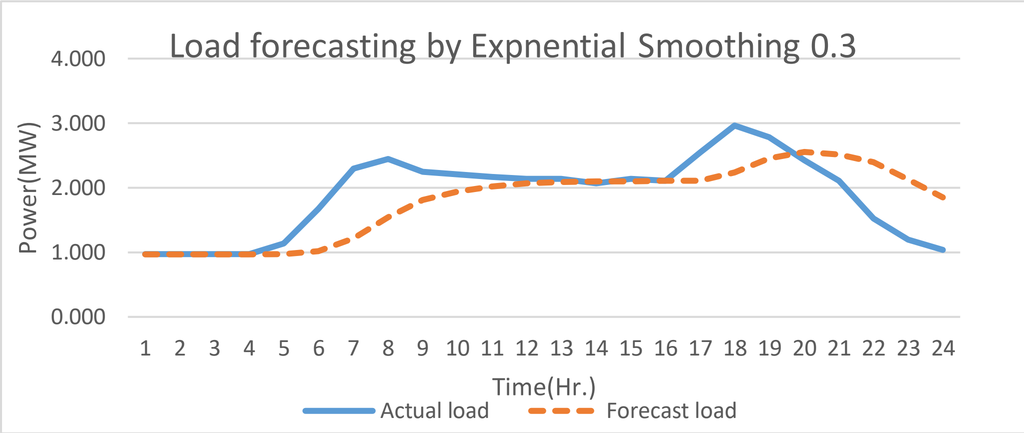


Figure 4.7: Forecasting using exponential smoothing using alpha 0.3

The two graph that can be compares the forecasted load using the exponential smoothing, when the value of alpha be 0.1 & 0.3. There is small variation in actual and the forecasted load because of the previous days load can be used to forecast the next day load.

Table 4.9: Forecasted load by exponential smoothing

	Forecasted MAPE%		
	0.1	0.2	0.3
January 1st	8%	9%	8.46%
January 2nd	7.46%	7.99%	8.20%
January 3rd	6.22%	7%	7.79%
January 4th	6.89%	8%	8%
January 5th	6.42%	7%	8.22%
January 6th	7.02%	7.40%	8.11%
January 7th	7.49%	8.42%	8.5%

Figure below shows the percentage mape calculated by the exponrntial smoothing.

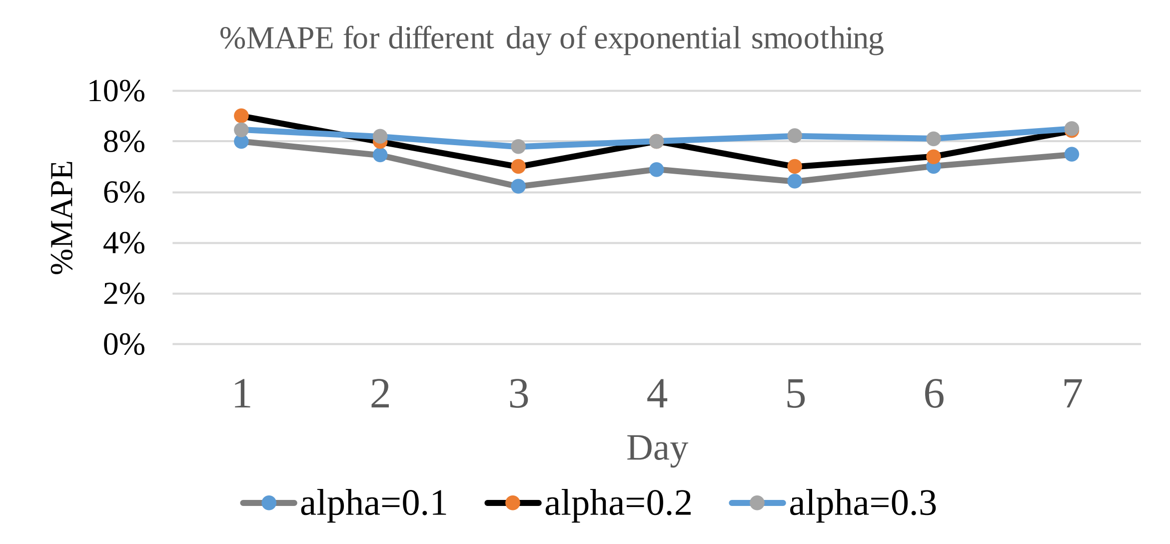


Figure 4.8: %MAPE for different day of Exponential Smoothing

This can be indicates that MAPE is maximum on the January 1st load and indicates minimum in the Tuesday of the normal week. Therefore the mape is maximum on Sunday, because Sunday be the starting period of the week, but the Tuesday be normal days of week. Therefore mape is maximum in starting and minimum in Tuesday of a week.

Comparison of Forecasted load by different method:

Table 4.10: Comparison of different Forecasting Method of January 1st

Day	ANN	Moving Average	Exponential Smoothing	Actual Load
1	0.974823	1.57	0.972	0.97
2	0.975202	1.21	0.971965	0.97
3	0.974341	1.04	0.971934	0.97
4	0.971354	0.97	0.971906	0.97
5	0.993563	0.97	0.97188	1.13
6	1.32966	1.03	0.988052	1.67
7	1.68225	1.26	1.056047	2.30

8	2.468294	1.70	1.1804	2.45
9	2.283354	2.14	1.306892	2.25
10	2.563162	2.33	1.401302	2.20
11	2.403972	2.30	1.481413	2.17
12	2.126062	2.21	1.550274	2.14
13	2.042409	2.17	1.60901	2.14
14	2.714401	2.15	1.661873	2.07
15	1.880662	2.12	1.702971	2.14
16	1.883253	2.12	1.746437	2.11
17	2.577683	2.11	1.782318	2.54
18	2.839645	2.26	1.858335	2.96
19	2.766072	2.54	1.968856	2.79
20	2.469414	2.76	2.05051	2.43
21	2.22909	2.73	2.088372	2.11
22	1.466409	2.44	2.09006	1.52
23	1.129685	2.02	2.033279	1.20
24	1.02559	1.61	1.949788	1.04

The comparison of forecasted load by artificial neural network method, moving average method and the exponential method of January 1st can show in table. From table there is minimum variation in actual load and the forecasted load in ANN method and the exponential smoothing method, but variation in moving average methods due to the variation in different affecting parameter.

4.4. Comparison of MAPE for different days

Electric load can be forecasted with the reference of next hour forecast and next day forecast. MAPE error of the next hour error is less than the next day error, because in next day error there should neglected different parameters of input. In this method of load forecasting technique the mean absolute percentage error pf different day of a week can be calculated on the basis of the next day and the next hour forecast method. The next hour method can give the actual forecasting also called minimum variation in actual and the forecasted load. From the below table the variation in actual and forecasted load in next day is higher because in this method for forecasting different parameter can be neglected.

Table 4.11: Comparison of MAPE for different days

MAPE for different days						
	Next hour			Next day		
Day	ANN	Moving Average	Exponential smoothing	ANN	Moving Average	Exponential smoothing
Sun	**6.34%**	**12%**	**8%**	**7.34%**	**12.24%**	**9%**
Mon	4.76%	10.34%	7.46%	6.67%	11.32%	7.55%
Tue	**3.67%**	**9%**	**6.22%**	**5.43%**	**9.40%**	**7%**
Wed	3.78%	10%	6.89%	6.34%	10.72%	7.22%
Thu	4.66%	11%	6.42%	6.46%	11.22%	6.66%
Fri	5.84%	10.50%	7.02%	7%	10%	7.42%
Sat	5.56%	9.50%	7.49%	6.86%	9%	8%

From these three methods of load forecasting using next day forecasting and using hourly basis. The ANN have a minimum error as compared with moving average and exponential smoothing method. Maximum error occurred in Sunday because of peak day and minimum error in Tuesday. In Nepalese society there should holiday on the Saturday, but starting of the days are peaking day, then there should be actual variation in actual and the forecasted load. But in normal days like Tuesday, Wednesday the variation in actual and the forecasted load be very low. So that the percentage MAPE becomes low in normal days and the highest in the starting and the ending days of the week. The below histogram diagram shows the comparison of mean absolute percentage error in next hour and the next day method. From the below histogram comparison between three method the MAPE must be maximum in the moving average method. The best method or the lowest percentage MAPE be found in the artificial neural network method.

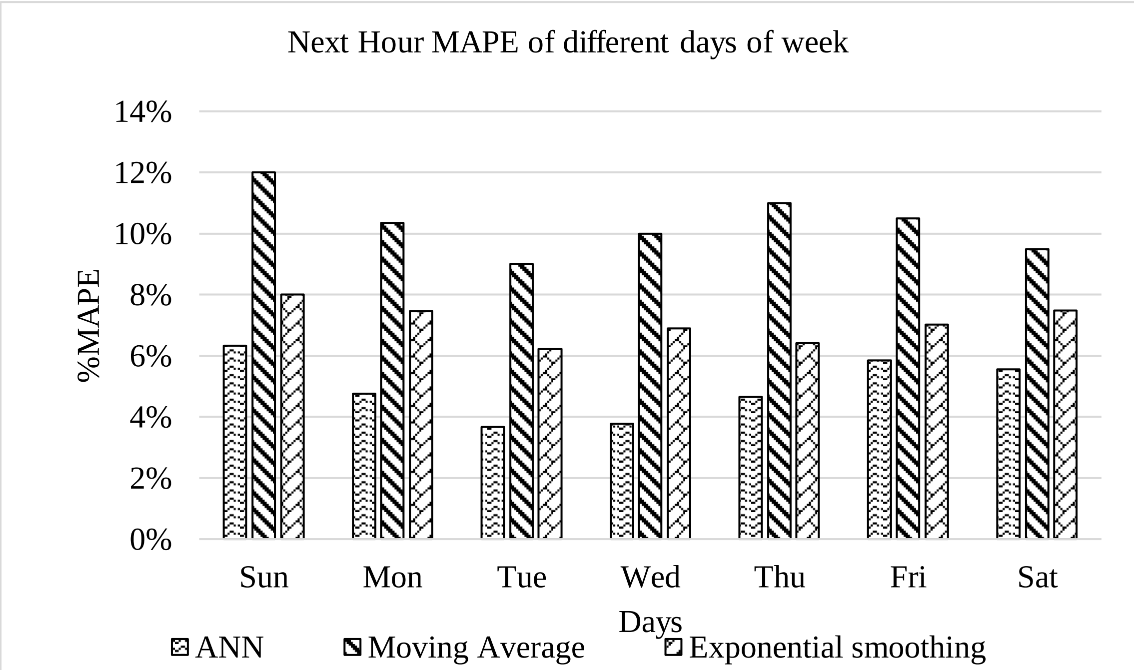


Figure 4.9: Next hour MAPE of different days of week

Again, the load forecasting can be done rather than the average of hour and can be used directly previous days load

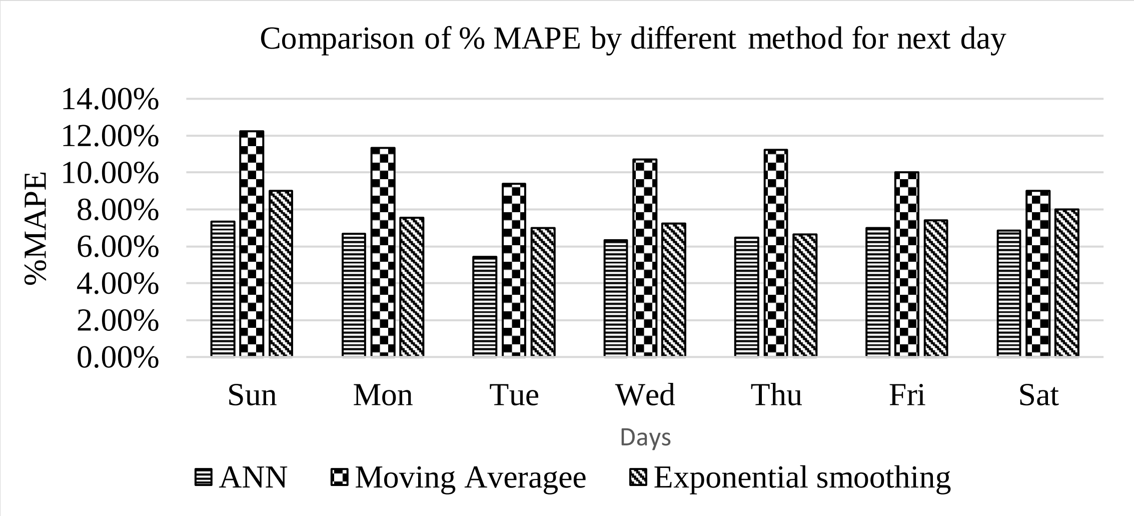


Figure 4.10: Comparison of MAPE for next day

From the histogram chart, there should be very high error is occurred in starting and the ending day of the week. The error can be high in Sunday and Monday of starting day of week and Thursday and Friday because in these days there should be high variation in load. These days are peaking load day in the Nepal society.

4.5. Calculation of MAPE for different Month

The calculation of MAPE for different month can be calculated on the basis of input and the target parameters. The input parameter be previous month load, temperature, humidity, whether the working day be worked or holiday, the number of days that can be used, considering the effect of four seasons. The value of MAPE for the different month can be listed as follows.

Table 4.12: %MAPE for different month

Month	ANN	Moving Average	Exponential Smoothing
January	4.76%	7%	5%
February	6.74%	9%	8%
March	5.76%	9.20%	6%
April	6.76%	10%	10%

May	7.44%	9%	8%
June	8.95%	12%	11%
July	6%	12%	12%
August	6%	10%	8%
September	6.50%	10.92%	7%
October	6.67%	10.62%	6%
November	6%	8%	8%
December	5.52%	8.72%	6.42%

The monthly load can be forecasted on the basis of previous month, yearly load. The error that can be obtained on forecasting and actual load are shown in table.

The percentage MAPE for different month are shown in histogram chart as shown in figure. There is variation in actual and forecast load which also called deviation or mean absolute percentage error, mape.

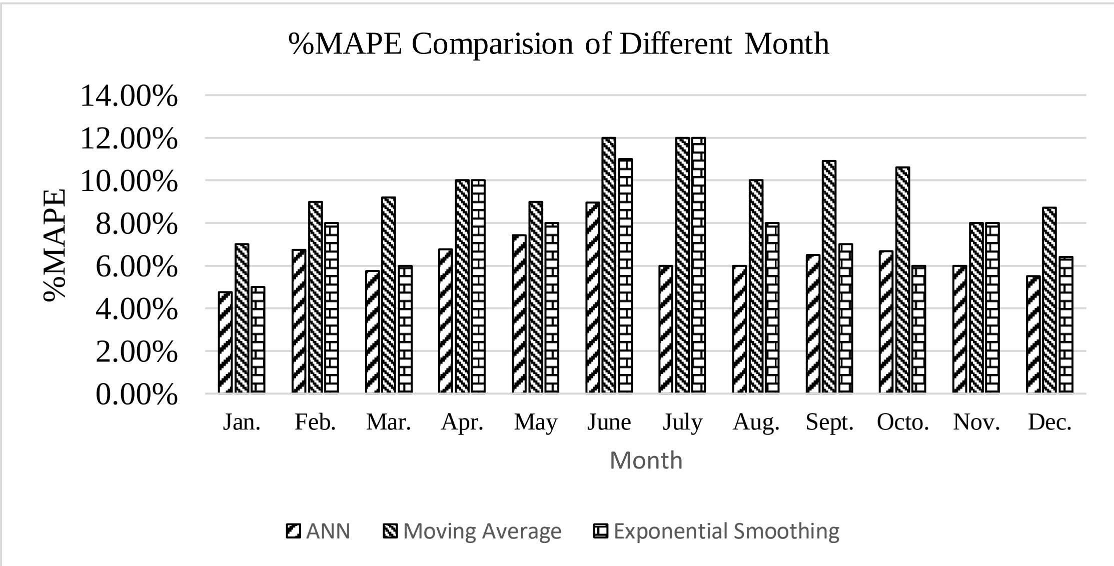


Figure 4.11: %MAPE comparison of different month

From the table and figure, conclude that maximum MAPE occurs in June month and the minimum MAPE on January. Because of monsoon change in June and July month and load will be fluctuated, then there will be maximum error occur. The histogram plot of MAPE of different method are shown in figure 4.11. For the monthly load forecasting there are different parameter to be considered such as seasonal effect, previous month load, temperature, humidity, working month or not. These are the parameter that affect the different type of load forecast. For these forecast they can be give the input and the target parameter by the neural network tool box and increase the iteration, if the coefficient of correlation is very close to unity. Then there should be validation of actual and forecast.

From the discussion, the mean absolute percentage error be lowest in ANN methods as compared with time series methods. ANN is the best method for forecasting. Minimum error is found in the normal days of a week and month.

4.6. Research Validation

In literature section, we have discussed about the various methods that can be apply for short electric power forecast.

For further examine proposed feed forward back propagation neural network using electric load of Convenant University, Canaan land, Ota, Ogun state, Nigeria are used. The purpose of these method, load data of previous day are used as forecast the value of electric load for next day. This analysis of forecast load can be used to validate the forecasted load on the basis of ANN and time series method. Therefore, the forecasted load that can be forecast on the basis of neural network in this method are shown in below:

Table 4.13: Actual load and forecasted load of Ogun State by ANN Method

Time	Actual(MW)	Forecast(MW)
1	2.2	2.26
2	2.2	2.18
3	1.9	2.19
4	2.4	2.01
5	2.6	2.32
6	2.9	2.48
7	3.1	2.77
8	2.7	2.92
9	3.7	2.62

10	3.3	3.18
11	2.9	3.06
12	2.6	2.81
13	2.7	2.48
14	2.8	2.57
15	2.9	2.86
16	2.9	2.71
17	2.9	2.73
18	2.9	2.68
19	2.9	2.65
20	3.2	2.63
21	2.8	2.84
22	2.9	2.65
23	2.7	2.56
24	2.6	2.46

Therefore, mean absolute percentage error mape for these method be 6.34%, which is less than the mape obtained in this method of 8.34%. The forecasted load is smaller than the comparable load, with the acceptable limit. There is also no variation in the one or two week of load. This can be compares that there should be validation of research.

Again, the forecasted load by using the time series methods of moving average in this international research paper are shown in table below. The percentage mape of this paper and the model that can be used in research are compared to validate.

Table 4.14: Forecasted load of Ogun by Moving Average

Time	Actual(MW)	Forecast(MW)		
		3 Point MA	4 Point MA	5 Point MA
1	2.1	2.47	2.55	2.76
2	2.1	2.27	2.38	2.48
3	1.8	2.13	2.23	2.32
4	2.3	2	2.05	2.14
5	2.5	2.07	2.08	2.1
6	2.8	2.2	2.18	2.16
7	3	2.53	2.35	2.3
8	2.6	2.77	2.65	2.48
9	3.6	2.8	2.73	2.64
10	3.2	3.07	3	2.9
11	2.8	3.13	3.1	3.04
12	2.5	3.2	3.05	2.94
13	2.6	2.83	3.03	2.94

14	2.9	2.63	2.78	2.8
15	2.8	2.67	2.6	2.72
16	2.8	2.77	2.7	2.72
17	2.8	2.83	2.78	2.78
18	2.8	2.8	2.83	2.82
19	2.8	2.8	2.8	2.8
20	3.1	2.8	2.8	2.85
21	2.9	2.9	2.88	2.88
22	2.8	2.93	2.9	2.88
23	2.6	2.93	2.9	2.84
24	2.5	2.77	2.85	2.88

The research paper, the percentage mape of this be 10.3%, 11.02% and 11.55%. But the actual mape of the forecasted load on this model be 12%, 11.23% and 11.44%. Which is within the acceptable limit and there shouldn't be the wild variation in daily loads. This can be shows the validation of the result (Osarndo, 2014).

Again, the load can be forecasted on the basis of exponential smoothing with changing the value of alpha 0.1, 0.2 & 0.3. Then forecasted power be listed in the tables below:

Table 4.15: Forecasted load of Ogun by Exponential Smoothing

Time	Actual(MW)	alpha 0.1	alpha 0.2	alpha 0.3
		Forecast(MW)	Forecast(MW)	Forecast(MW)
1	2.2	2.3	2.22	2.21
2	2.2	2.18	2.17	2.18
3	1.9	2.19	2.15	2.16
4	2.2	2.15	2.08	2.05
5	2.4	2.17	2.14	2.16
6	2.9	2.18	2.22	2.25
7	3.1	2.26	2.34	2.5
8	2.7	2.34	2.45	2.57
9	3.7	2.37	2.48	2.58
10	3.1	2.46	2.32	2.88
11	2.9	2.54	2.80	2.99
12	2.4	2.56	2.82	2.94
13	2.5	2.56	2.76	2.83
14	2.8	2.55	2.73	2.75
15	2.7	2.60	2.76	2.78
16	2.7	2.61	2.77	2.8
17	2.7	2.63	2.76	2.8
18	2.7	2.64	2.79	2.9
19	2.7	2.66	2.79	2.89
20	3.0	2.67	2.77	2.89
21	2.8	2.74	2.86	2.86

22	2.8	2.80	2.75	2.79
23	2.6	2.61	2.84	2.86
24	2.5	2.51	2.80	2.9

The percentage mape obtain from this research paper be 10.69%, 8.56%and 8.32% and the percentage mape obtained from these model be 8%, 9% and 8.46% respectively. Therefore, the value of mape are within the limit of this research paper and forecasted load is validated.

CHAPTER FIVE

CONCLUSIONS & RECOMMENDATION

5.1. Conclusion

The short term load is forecasted by using the Artificial Neural Network and Time series methods. Artificial Neural Network is used to forecast the load of daily, weekly and hourly of first January 2018. ANN methods of forecasting gives the mean absolute percentage error. The mape be 3.67% in normal days of a week and for peak hour of a day's mape becomes highest 6.37%. Again, for the monthly load forecasting there is highest mape in September be 10.92% and minimum in January be 4.76%.

Again, the load can be forecasted by using time series method, in this method only one parameter can be taken as input. There should be high value of mape in third day be 9% and minimum in starting and ending of the week. The percentage mape be 8% in starting and 7.02% in ending of the week.

For validation of this model it can be used to forecast of an 11kV Bishnumati Feeder of Nepal for November 17, 2018 and the output is compared to Conveaant University of Nigeria such as Multilayer feed forward Model. The proposed model of ANN for Bishnumati Feeder gives weekly MAPE of 3.67% which is smaller than the MAPE value obtained by Conveant University be of 8.37%, but it is within the limit of acceptance. Again, the value of %MAPE for moving average and exponential smoothing be 9% and 6.22% in Bishnumati Feeder which is higher than the MAPE value obtained by the models of Conveant University be of 10.3% & 8.31%% but it is within the limit of acceptance.

From these analysis can be concluded that load forecasting can be done on the basis of neural network. The accuracy of artificial neural network is higher than time series methods.

5.2. Recommendation

1. This research can also help to make important suggestions in area of routine rescheduling, other small factor analysis, and load flow analysis in electric power system also can be useful for the energy utility companies for trading energy on the basis of future electric power load demand in dynamic energy markets.

2. This research is limited to only one feeder of Kathmandu Valley for academic purpose. If the recording of past data can be done properly of other stations of Nepal, similar forecasting can be carried out for whole NEA stations.

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Appendix A: Daily load Sheet Data

The hourly load data of different month are listed as follows, where the power in Mega Watt. The first 12 hours of the January are shown in table below:

Hour/Day	1	2	3	4	5	6	7	8	9	10	11	12
1	0.97	0.94	0.87	1.04	0.91	0.87	0.91	0.96	0.87	0.97	0.91	0.97
2	0.97	0.94	0.87	1.04	0.91	0.87	0.91	0.84	0.87	0.97	0.87	0.97
3	0.97	0.91	0.87	1.04	0.94	0.87	0.91	0.84	0.91	0.97	0.84	1.00
4	0.97	0.91	0.87	1.04	0.94	0.87	0.91	0.94	0.91	0.97	0.91	1.00
5	1.13	1.13	1.20	1.33	1.17	1.07	1.04	1.13	1.10	1.13	1.20	1.23
6	1.67	1.75	1.70	1.67	2.45	2.33	1.47	1.70	1.73	1.81	1.67	1.73
7	2.30	2.30	2.12	2.28	2.35	2.46	2.17	2.27	2.27	2.41	2.36	2.32
8	2.45	2.48	2.49	2.45	2.54	2.57	2.46	2.48	2.43	2.57	2.43	2.43
9	2.25	2.28	2.27	2.32	2.33	2.28	2.30	2.23	2.28	2.33	2.43	2.27
10	2.20	2.27	2.17	2.14	2.27	2.27	2.19	2.23	2.33	2.27	2.17	2.75

11	2.17	2.23	2.20	2.17	2.23	2.20	2.15	2.27	2.23	2.14	2.11	2.14
12	2.14	2.17	2.14	2.17	2.14	2.11	2.40	2.07	2.14	2.11	2.07	1.98
13	2.14	2.04	1.98	2.07	2.04	2.11	2.04	2.20	2.20	2.04	2.04	2.01
14	2.07	2.01	1.81	2.04	2.07	2.04	1.94	2.04	2.04	2.04	1.98	1.88
15	2.14	1.88	1.88	1.94	1.91	1.94	2.04	2.01	2.04	2.01	1.98	2.07
16	2.11	2.01	2.04	2.59	2.01	2.14	1.98	2.14	2.11	2.11	2.04	2.07
17	2.54	2.43	2.46	2.64	2.49	2.49	2.25	2.53	2.82	2.48	2.27	2.46
18	2.96	3.00	2.93	3.16	2.91	2.90	2.75	2.91	2.95	2.93	2.74	2.98
19	2.79	2.79	2.69	2.80	2.79	2.72	2.66	2.75	2.85	2.67	2.87	2.82
20	2.43	2.48	2.57	2.40	2.43	2.30	2.32	2.49	2.49	2.48	2.67	2.45
21	2.11	2.04	1.98	2.04	2.07	2.07	1.91	2.07	2.11	2.07	2.11	2.07
22	1.52	1.46	1.52	1.59	1.39	1.49	1.43	1.52	1.49	1.46	1.49	1.49

23	1.20	1.17	1.13	1.17	1.13	1.17	1.07	1.13	1.13	1.13	1.13	1.10
24	1.04	1.04	1.07	1.00	1.07	1.00	0.87	1.07	1.07	1.00	1.04	1.00

Again, the next 12 days load of month January are listed as follows:

13	14	15	16	17	18	19	20	21	22	23	24
0.81	0.81	0.97	0.91	0.87	0.94	0.94	0.91	0.97	0.94	0.91	0.78
0.81	0.78	0.97	0.91	0.87	0.91	0.94	0.87	0.97	0.94	0.87	0.78
0.84	0.78	0.97	0.91	0.91	0.94	0.94	0.94	0.97	0.97	0.87	0.81
0.94	0.94	0.97	0.91	1.07	0.94	0.97	0.97	0.97	0.97	0.87	0.91
1.10	1.30	1.07	1.10	1.46	1.17	1.26	1.23	1.13	1.13	1.10	1.10
1.75	1.49	1.65	1.85	1.89	1.78	1.77	1.81	1.62	1.78	1.98	1.88
2.36	2.20	2.32	2.43	2.46	2.51	2.14	2.61	2.33	2.57	2.70	2.74
2.48	2.62	2.49	2.54	2.64	2.67	2.70	2.83	2.80	2.09	2.90	3.04
2.28	2.74	2.36	2.41	2.38	2.41	2.57	2.48	2.91	2.56	2.53	2.66
2.30	2.66	2.30	2.46	2.36	2.46	2.43	2.43	2.82	2.59	2.43	2.56
2.23	2.46	2.17	2.23	2.27	2.30	2.40	2.30	2.72	2.53	2.46	2.53
2.11	2.27	2.27	2.14	2.20	2.30	2.40	2.30	2.53	2.43	2.30	2.33
2.07	2.14	2.04	2.01	2.17	2.04	2.27	2.17	2.27	2.23	2.20	2.17
1.91	1.94	1.91	2.01	1.30	2.07	2.11	2.20	1.98	2.07	2.11	2.07
1.88	1.88	1.99	2.40	1.33	2.14	2.07	2.11	1.98	2.20	2.20	2.14

2.04	1.88	1.93	2.27	2.33	2.17	2.20	2.23	2.01	2.33	2.30	2.33
2.57	2.30	2.90	2.70	2.74	2.72	2.62	2.69	2.48	2.80	2.72	3.34
3.04	2.88	3.30	3.14	3.26	3.22	3.22	3.21	3.09	3.38	3.32	3.47
2.74	2.75	3.09	2.96	3.08	3.06	3.13	3.22	3.06	3.21	3.24	3.37
2.51	2.41	2.79	2.70	2.79	2.75	2.79	2.75	2.74	2.91	3.04	3.06
2.04	2.04	2.43	2.36	2.27	2.30	2.43	2.49	2.36	2.53	2.66	2.72
1.65	1.49	1.68	2.23	1.68	1.68	1.68	1.78	1.23	1.85	1.91	1.94
1.00	1.13	1.23	2.17	1.23	1.23	1.17	1.30	1.13	1.30	1.33	1.39
0.87	1.00	1.13	1.00	1.00	1.20	0.94	1.17	1.07	1.04	1.23	1.30

Again the next 6 days of month are listed as follows:

25	26	27	28	29	30
0.91	0.97	0.94	0.94	0.97	0.94
0.91	0.94	0.94	0.91	0.94	0.91
0.94	0.94	0.94	0.94	0.94	0.94
0.97	0.94	0.94	1.30	1.04	0.96
1.13	1.30	1.26	1.17	1.17	1.23
1.89	1.81	1.88	1.65	1.72	1.65
2.66	2.61	2.69	2.59	2.53	2.59
2.82	2.79	2.80	2.88	3.06	2.79
2.54	2.62	2.49	2.59	2.87	2.57

2.43	2.82	2.87	3.60	2.85	2.74
2.36	2.59	2.64	2.95	2.41	2.53
2.23	2.43	2.41	2.66	2.72	2.64
2.14	2.33	2.30	2.43	2.59	2.67
2.17	2.27	2.27	2.23	2.36	3.94
2.14	2.32	2.35	2.07	2.46	2.28
2.20	2.36	2.33	2.07	2.62	2.64
2.62	2.83	2.69	2.46	2.88	3.04
3.29	3.43	3.08	3.30	3.53	3.47
3.17	3.30	3.04	3.21	3.40	3.32
2.95	3.04	2.79	3.08	3.17	3.21
2.62	2.59	2.66	2.59	2.91	2.85
1.85	1.43	1.94	1.88	2.07	2.04
1.30	1.23	1.39	1.43	1.46	1.43
1.10	1.17	1.30	1.00	1.33	1.34

Load data for the other month are as follows:

Hour /Day	1	2	3	4	5	6	7	8	9	10	11	12
1	0.95	0.94	0.87	1.02	0.91	0.86	0.90	0.96	0.87	0.97	0.91	0.97

2	0.96	0.94	0.87	1.04	0.91	0.87	0.91	0.84	0.87	0.97	0.87	0.97
3	0.97	0.91	0.87	1.04	0.94	0.87	0.91	0.84	0.91	0.97	0.84	1.00
4	0.97	0.91	0.87	1.04	0.94	0.87	0.91	0.94	0.91	0.97	0.91	1.00
5	1.13	1.13	1.20	1.33	1.17	1.07	1.04	1.13	1.10	1.13	1.20	1.23
6	1.67	1.75	1.70	1.67	2.45	2.33	1.47	1.70	1.73	1.81	1.67	1.73
7	2.3	2.30	2.12	2.28	2.35	2.46	2.17	2.27	2.27	2.41	2.36	2.32
8	2.4	2.48	2.49	2.45	2.54	2.57	2.46	2.48	2.43	2.57	2.43	2.43
9	2.2	2.28	2.27	2.32	2.33	2.28	2.30	2.23	2.28	2.33	2.43	2.27
10	2.2	2.27	2.17	2.14	2.27	2.27	2.19	2.23	2.33	2.27	2.17	2.75
11	2.1	2.23	2.20	2.17	2.23	2.20	2.15	2.27	2.23	2.14	2.11	2.14
12	2.1	2.17	2.14	2.17	2.14	2.11	2.40	2.07	2.14	2.11	2.07	1.98
13	2.1	2.04	1.98	2.07	2.04	2.11	2.04	2.20	2.20	2.04	2.04	2.01

14	2.0	2.01	1.81	2.04	2.07	2.04	1.94	2.04	2.04	2.04	1.98	1.88
15	2.1	1.88	1.88	1.94	1.91	1.94	2.04	2.01	2.04	2.01	1.98	2.07
16	2.1	2.01	2.04	2.59	2.01	2.14	1.98	2.14	2.11	2.11	2.04	2.07
17	2.5	2.43	2.46	2.64	2.49	2.49	2.25	2.53	2.82	2.48	2.27	2.46
18	2.9	3.00	2.93	3.16	2.91	2.90	2.75	2.91	2.95	2.93	2.74	2.98
19	2.7	2.79	2.69	2.80	2.79	2.72	2.66	2.75	2.85	2.67	2.87	2.82
20	2.4	2.48	2.57	2.40	2.43	2.30	2.32	2.49	2.49	2.48	2.67	2.45
21	2.1	2.04	1.98	2.04	2.07	2.07	1.91	2.07	2.11	2.07	2.11	2.07
22	1.5	1.46	1.52	1.59	1.39	1.49	1.43	1.52	1.49	1.46	1.49	1.49
23	1.20	1.17	1.13	1.17	1.13	1.17	1.07	1.13	1.13	1.13	1.13	1.10
24	1.04	1.04	1.07	1.00	1.07	1.00	0.87	1.07	1.07	1.00	1.04	1.00

The input and target parameter of January 1st are shown in below:

S.N.	Input parameter			Target	Forecast Load
	Temperature	Humidity	Working day		
1	4	0.88	0	0.94	0.95
2	5	0.87	0	0.94	0.94
3	6	0.88	0	0.91	0.95
4	6	0.86	0	0.91	0.94
5	6	0.89	0	1.13	0.99
6	7	0.84	0	1.75	1
7	8	0.88	1	2.3	2.29
8	9	0.89	0	2.48	2.54
9	9.5	0.85	0	2.28	2.39
10	10	0.67	0	2.27	2.17
11	12	0.9	0	2.23	2.26
12	17	0.73	0	2.17	2.22
13	17	0.75	0	2.04	2.03
14	22	0.76	1	2	1.96
15	19	0.77	0	1.88	1.87
16	16	0.76	0	2.01	2.04
17	14	0.74	0	2.43	2.73
18	13	0.76	0	3	2.95

19	12	0.74	0	2.79	2.78
20	11	0.75	0	2.48	2.47
21	6	0.745	0	2.04	2.06
22	5	0.746	1	1.46	1.45
23	4	0.742	0	1.16	1.26
24	4	0.7	0	1	1.1

Coding

Matlab coding for plotting the Actual vs Forecasted load in day 1 by ANN method

```
n=24;
target=randn(n,1);
forecasted=randn(n,1);
plot(target)
plot(forecasted)
plot(target)
hold on
plot(forecasted)
hold off
xlabel("Hour")
ylabel("Power(MW)")
title("Actual vs forecasted load of first day")
legend("actual","forecast")
```

Matlab coding that can be used to plot the graph of second day are

```
n=24;
target=randn(n,1);
```

forecasted=randn(n,1);

plot(target)

plot(forecasted)

plot(target)

hold on

plot(forecasted)

hold off

xlabel("Hour")

ylabel("Power(MW)")

title("Actual vs forecasted load")

legend("actual","forecast")

Calculation of Error in Matlab:

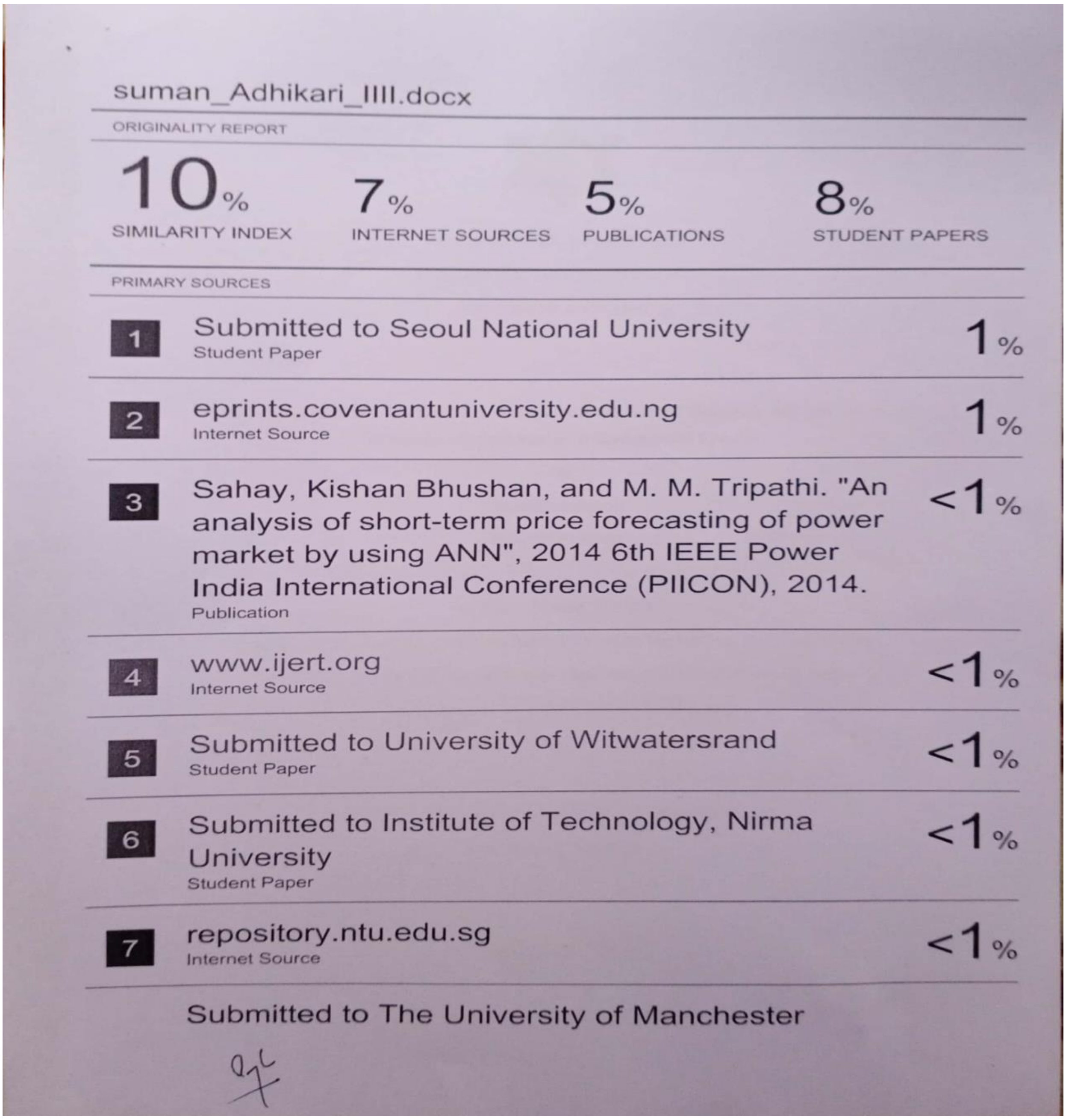
Calculation of mape in matalb be as follows;

Mean absolute percentage error, mape

function mape(forecasted, actual)

mape= 1/24(sum(abs(actual(:) – forecasted(:))/actual(:))

Appendix B: Plagiarism Test Report



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Appendix C: Published Research Paper

quantity of available load data, metrological data, sociological data etc. directly affect the quality of result. Identification of proper tool, management of information system has another important role in the model development. Good forecasting with limited information and with large number of constraints is major challenge faced by the all the power system engineers all around the world. The challenges is more pronounced by the fact that the information and constraints are completely different from one power system to other or one part of the world to other. No general algorithm or tool can be developed. Hence, for each system a specific method and algorithm has to be developed regarding information collection, data management, data filtration, model development and scope of implementation.

There are large varieties of mathematical methods that are used for load forecasting, the development and improvements of suitable mathematical tools will lead to the development of more accurate load forecasting techniques. The accuracy of load forecasting depends on the load forecasting techniques used as well as on the accuracy of forecasted weather parameters such as temperature, humidity etc. As per the recent trends artificial intelligence methods are the most pronounced for the STLF. From different artificial intelligence methods, fuzzy logic and artificial neural network are the most used. Among the two methods fuzzy logic for STLF is gaining.

II. METHODOLOGY

This study is focused on the short term load forecasting techniques using the different model of short term load forecasting. Similar day approach to the modern artificial intelligence has been studied and implemented all over the world in various power grid best suit. In Nepal, short term load forecasting is not implemented in real hour to hour or day to day forecasting because no accurate model and technique cannot be implemented in power sector of Nepal.

In this research different analytical technique are analyzed on the basis of Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) between the actual and forecasted load. Both techniques use the feed forward back propagation neural network algorithm for both data training and data forecasting.

The basic Framework for this research methodology are listed is shown below

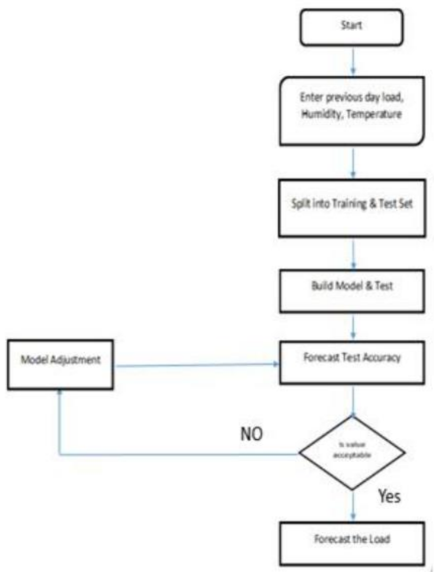

Figure 1: Forecasting Methodology by Artificial Neural Network (ANN)

The load forecasting methodology by moving averages and exponential smoothing technique can be shown in flow chart:

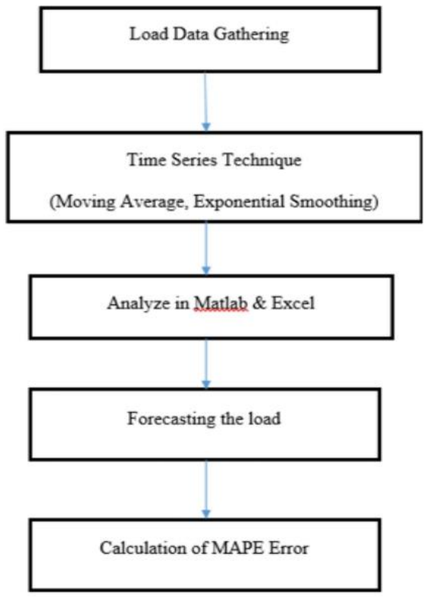

Figure 2: Load Forecasting Model for Moving Average & Exponential Smoothing

From these two method of short term load forecasting technique by artificial neural network & time series method (moving averages & exponential smoothing) the error can be calculated. The least efficient error method be the most appropriate method for the load forecasting. Therefore the ANN method be the best method of the load forecasting because these method having minimum error on the forecasting.

2.1. Tool Selection

For, all the predictions related to ANN Matlab 2018a is used and for time series methods statistical tool excel is used.

2.2. Evaluation of Predicted Performance

The forecasting performance of the trained network could be assessed by calculating the prediction error on samples other than those used during the training phase. Various error metrics between the actual and forecasted loads are presented and defined but the most commonly adopted by load forecasters are the Mean Absolute Percentage Errors (MAPE), the Absolute Percentage Errors (APE), the Mean Absolute Error (MAE) and the Mean Squared Error (MSE) or Root Mean Squared Error (RMSE).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|actualLoad(i) - forecastedLoad(i)|}{(actualLoad)(i)} \times 100,$$

$$APE = \frac{|actualLoad - forecastedLoad|}{(actualLoad)} \times 100,$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\frac{|actualLoad(i) - forecastedLoad(i)|}{(actualLoad)(i)} ,$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - O_i)^2 \ \ or \ \sqrt{MSE} ,$$

Where n is the number of the data points and i is the period at which the load is produced or forecasted, t is the target and O the NN output.

To make sure that the system is accurate, the relative error is retained on the hourly basis. In the case of positive error, it means the forecasted load is greater than the actual consumption load, and the opposite is true when the forecasted load was less than the actual load.

2.3. Forecasting next hour using ANN

Two input methods are tested for forecasting next hour load is set that the effects of power variables and additional input parameters. The forecast is done with historical load variables along with temperature variables, day type & cyclic values of hour of day and day of week as input.

With properly synchronized additional variables the performance error MAPE, MSE etc. gets improved automatically.

Thus the formulated input vector and target variable is feed in the ANN to get predicted values using 2- layer feed forward network with sigmoid hidden neurons and linear output neurons. It can fit multi-dimensional mapping problems abnormally well given consistent data and enough neurons in its hidden layer. The neural network is trained with Levenberg-Marquardt back propagation algorithm.

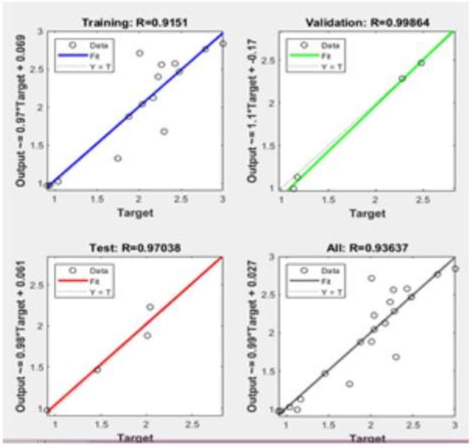

Fig 3: Neural Network Training Regression

Training of the Network: This is just a process of weight adjustments with respect to the targeted output by the neural network. The training of the network is carried out using the MATLAB software. The load data collected is the input data to the neural networks. 50% of this data was used for the training of the neural network, 25% was used for the validation and the remaining 25%, for the forecast. The neural network was trained using different activation functions and number of layers till the best performance was obtained. Figure 5 shows the neural network being trained.

2.4. Data Collection

Combined hourly feeder data from 1st Poush 2075 to 29th Poush 2076 of the Bishnumati feeder of 132/11 Kv, collected from Balaju Substation, Nepal Electricity Authority. The raw data obtained had been recorded manually in Balaju Substation containing single excel sheet for daily load diagrams. The obtained data was then converted into single time series data.

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8	2.48	2.468294	0.003801
9	2.28	2.283354	1.23E-05
10	2.27	2.563162	0.130547
11	2.23	2.403972	0.075699
12	2.17	2.126062	0.020258
13	2.04	2.042409	0.000951
14	2.01	2.714401	0.351739
15	1.88	1.880662	0.001137
16	2.01	1.883253	0.062163
17	2.43	2.577683	0.061155
18	3.00	2.839645	0.052165
19	2.79	2.766072	0.00694
20	2.48	2.469414	0.003349
21	2.04	2.22909	0.09244
22	1.46	1.466409	0.006128
23	1.17	1.129685	0.031131
24	1.04	1.02559	0.010458

%MAPE = 6.34%

The graph that can be compares the Actual Load and Forecasted load of the Mangsir 1st load, the maximum load in 9 hour and minimum in 1st hour.This gives actual forecast:

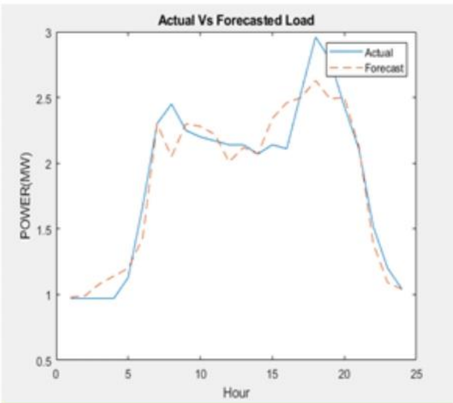

Figure 4: Actual Vs Forecasted Load of mangsir 1st

4.2. Forecasted load on the basis of Moving Average

Load can be forecasted on the basis of moving average and the exponential smoothing. This type of method uses the load at input and the output can be analyzed on the basis of 3 point, 4 point, 5 point moving averages. Exponential smoothing technique is very efficient and beneficial method.

The mangsir 1st load can be analyzed on the basis of Moving point averages:

Table 4: Load forecasting using Moving Averages of mangsir 1st

		3Point MA	4 Point MA	5 Point MA
Time(hrs.)	Actual(MW)	Forecast(MW)	Forecast(MW)	Forecast(MW)
1	0.97	1.57	2.17	2.49
2	0.97	1.21	1.77	2.32
3	0.97	1.04	1.42	1.97
4	0.97	0.97	1.15	1.61
5	1.13	0.97	0.97	1.33
6	1.67	1.03	1.01	1.00
7	2.30	1.26	1.19	1.14
8	2.45	1.70	1.52	1.41
9	2.25	2.14	1.89	1.70
10	2.20	2.33	2.17	1.96
11	2.17	2.30	2.30	2.17
12	2.14	2.21	2.27	2.27
13	2.14	2.17	2.19	2.24
14	2.07	2.15	2.16	2.18
15	2.14	2.12	2.13	2.14
16	2.11	2.12	2.12	2.13
17	2.54	2.11	2.11	2.12
18	2.96	2.26	2.21	2.20
19	2.79	2.54	2.44	2.36
20	2.43	2.76	2.60	2.51
21	2.11	2.73	2.68	2.57
22	1.52	2.44	2.57	2.57
23	1.20	2.02	2.21	2.36
24	1.04	1.61	1.81	2.01
%MAPE		12%	11.23%	11.44%

The MAPE of these forecasted load be slightly higher than the ANN method again then other 5 days of one week MAPE are listed in table below.

Table 5: Forecasted Value for different day of Mangsir

	Moving Average MAPE%		
Date	3 Point	4 Point	5 Point
Mangsir 2nd	10.34%	10.55%	11%
Mangsir 3rd	9%	9.04%	10.35%
Mangsir 4th	10%	9.55%	11%
Mangsir 5th	11%	10.45%	12%
Mangsir 6th	10.5%	10.50%	11%

Mangsir 7th	9.5%	11%	10.42%

4.3. Forecasted load on the basis of Exponential Smoothing

Exponential Smoothing is the best technique for electrical load forecasting. The forecasting of load for seven days of Mangsir be listed as follows. The forecasted load can be calculated on the basis of different value of alpha. The forecasted load for the seven days can be calculated as follows & all the forecasted load are in Mega Watt.

Table 6: Forecasted load on the basis of Exponential Smoothing

		a=0.1	a=0.2	a=0.3
Time(Hr.)	Actual load	Forecast load	Forecast load	Forecast load
1	0.972	0.972	0.972	0.972
2	0.972	0.972	0.972	0.972
3	0.972	0.972	0.972	0.972
4	0.972	0.972	0.972	0.972
5	1.134	0.972	0.972	0.972
6	1.668	0.988	1.004	1.520
7	2.300	1.056	1.140	2.215
8	2.445	1.180	1.389	2.540
9	2.251	1.307	1.642	1.812
10	2.202	1.401	1.831	1.943
11	2.170	1.481	1.991	2.021
12	2.138	1.550	2.129	2.066
13	2.138	1.609	2.246	2.087
14	2.073	1.662	2.352	2.102
15	2.138	1.703	2.434	2.094
16	2.105	1.746	2.521	2.107
17	2.542	1.782	2.593	2.106
18	2.964	1.858	2.745	2.237
19	2.785	1.969	2.966	2.455
20	2.429	2.051	3.129	2.554
21	2.105	2.088	3.205	2.517
22	1.522	2.090	3.208	2.393
23	1.198	1.233	3.095	1.432
24	1.036	1.250	1.928	1.852
%MAPE		8%	9%	8.46%

The graph that can be plotted below in figure:

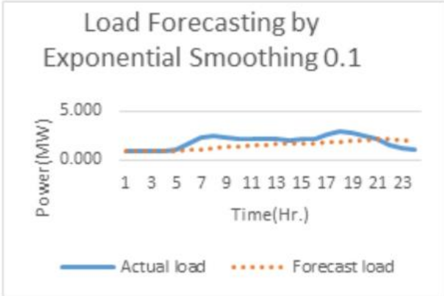

Figure 5: Comparison between Actual load and Forecasted load at alpha 0.1.

When the value of alpha be 0.3, the graph that can be plotted as:

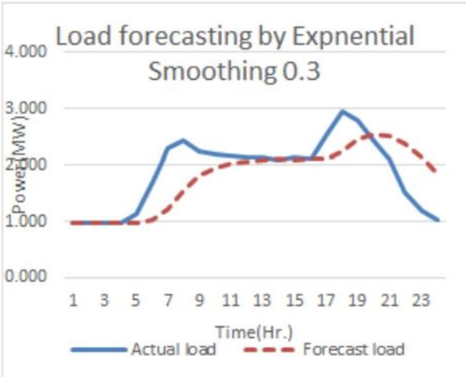

Figure 6: Forecasting using exponential smoothing using alpha 0.3

Others day of the mangsir are listed are as follows:

Table 7: Forecasted load by exponential smoothing

	Forecasted MAPE%		
	0.1	0.2	0.3
Mangsir 1st	8%	9%	8.46%
mangsir 2nd	7.46%	7.99%	8.20%
mangsir 3	6.22%	7%	7.79%
mangsir 4	6.89%	8%	8%
mangsir 5	6.42%	7%	8.22%
mangsir 6	7.02%	7.40%	8.11%
mangsir 7	7.49%	8.42%	8.5%

This can be indicates that MAPE is maximum on the mangsir 1st load and indicates minimum in the Tuesday of the normal week. Therefore the mape is maximum on Sunday, because of Sunday be the starting period of the week, but the Tuesday be normal days of week. Therefore mape is maximum in starting and minimum in Tuesday of a week. Other day are fluctuating in-between these maximum and minimum ranges.

Day	ANN	Moving Average	Exponential Smoothing	Actual Load
1	0.974823	1.57	0.972	0.97
2	0.975202	1.21	0.971965	0.97
3	0.974341	1.04	0.971934	0.97
4	0.971354	0.97	0.971906	0.97
5	0.993563	0.97	0.97188	1.13
6	1.32966	1.03	0.988052	1.67
7	1.68225	1.26	1.056047	2.30
8	2.468294	1.70	1.1804	2.45
9	2.283354	2.14	1.306892	2.25
10	2.563162	2.33	1.401302	2.20
11	2.403972	2.30	1.481413	2.17
12	2.126062	2.21	1.550274	2.14
13	2.042409	2.17	1.60901	2.14
14	2.714401	2.15	1.661873	2.07
15	1.880662	2.12	1.702971	2.14
16	1.883253	2.12	1.746437	2.11
17	2.577683	2.11	1.782318	2.54
18	2.839645	2.26	1.858335	2.96
19	2.766072	2.54	1.968856	2.79
20	2.469414	2.76	2.05051	2.43
21	2.22909	2.73	2.088372	2.11
22	1.466409	2.44	2.09006	1.52
23	1.129685	2.02	2.033279	1.20
24	1.02559	1.61	1.949788	1.04

4.4. Comparison of MAPE for different days.

The electric load can be forecasted on the basis of next hour forecast and the next day forecast. The MAPE error of the next hour error is less than the next day error, because in next day error there should neglected different parameters of input.

MAPE for different days						
	Next hour			Next Day		
Day	ANN	Moving Average	Exponential smoothing	ANN	Moving Averagee	Exponential smoothing
Sun	**6.34%**	**12%**	**8%**	**7.34%**	**12.24%**	**9%**
Mon	4.76%	10.34%	7.46%	6.67%	11.32%	7.55%
Tue	**3.67%**	**9%**	**6.22%**	**5.43%**	**9.40%**	**7%**
Wed	3.78%	10%	6.89%	6.34%	10.72%	7.22%
Thu	4.66%	11%	6.42%	6.46%	11.22%	6.66%
Fri	5.84%	10.50%	7.02%	7%	10%	7.42%
Sat	5.56%	9.50%	7.49%	6.86%	9%	8%

From these three methods of load forecasting using next day forecasting using hourly basis. The ann method have a minimum error as compared with the moving average and the exponential smoothing method. The maximum error occurred in Sunday because of peak day and minimum error in Tuesday. The comparison graph as shown in below:

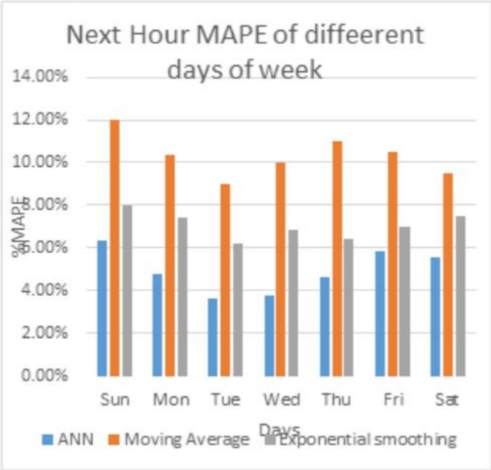

Figure 7: Next hour MAPE of different days of week

Again, the load forecasting can be done rather than the average of hour and can be used directly previous days load

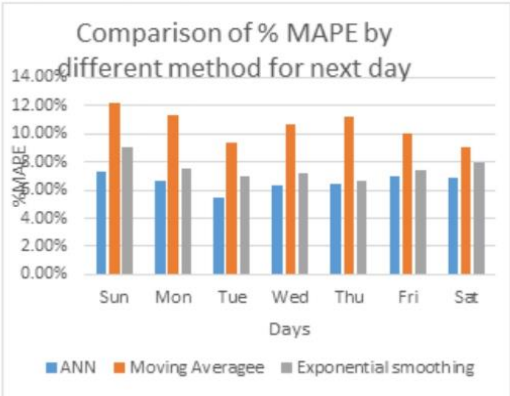

Figure .8: Comparison of MAPE for next day

4.3. Calculation of MAPE for different Month

The calculation of MAPE for different month can be calculated on the basis of input and the target parameters. The input parameter be previous days load, temperature, humidity, whether the working day be worked or holiday, and the number of days that can be used. The forecasted load can be calculated on the basis of regression line. The MAPE for the different month can be listed as follows.

Table 4.12: %MAPE for different month

Month	ANN	Moving Average	Exponential Smoothing
Poush-1	4.76%	7%	5%
Magh-1	6.74%	9%	8%
falgun-1	5.76%	9.20%	6%
chaitra -1	6.76%	10%	10%
Baisakh -1	7.44%	9%	8%
Jestha-1	8.95%	12%	11%
Asadh-1	6%	12%	12%
Shawan-1	6%	10%	8%
Bhadra -1	6.50%	10.92%	7%
Ashwin -1	6.67%	10.62%	6%
Kartik-1	6%	8%	8%
Mangsir-1	5.52%	8.72%	6.42%

From these table, we can be conclude that the maximum MAPE occurs in jestha month and the minimum MAPE on poush. Because of monsoon change in jestha ashar month and load will be fluctuated, then there will be maximum error occur. The histogram plot of MAPE of different method are shown bwlow

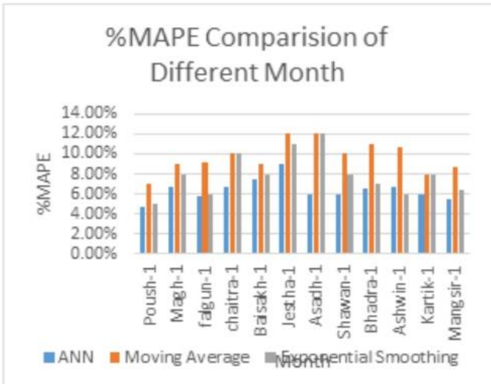

Figure 9: %MAPE comparison of different month

These shows the maximum and minimum value of MAPE for different month can be listed in above figure.

5. Conclusion

Artificial Neural Network model was developed incorporating the statistical method. In this research we can be compared the statistical method and the artificial method, the mean absolute percentage error of the ANN be less than as compare with the moving average and the exponential smoothing technique.

An artificial neural network method can be used different parameters as an input while the statistical method can only use one input. Therefore the accuracy of the ANN method of load forecasting can be more accuracy than the other methods.

The MAPE of the mangsir 1st be 6.34% and 12% for ANN method and the moving averages method. From these we can be concluding that load forecasting can be done on the basis of neural network.

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