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THESIS NO: M-361-MSREE-2019-2023

Short-term load forecasting of Gothatar feeder of Nepal Electricity Authority using Recurrent Neural Network

by

Sudarshan Acharya

A THESIS

SUBMITTED TO THE DEPARTMENT OF MECHANICAL AND AEROSPACE ENGINEERNIGIN IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN RENEWABLE ENERGY ENGINEERING

DEPARTMENT OF MECHANICAL AND AEROSPACE ENGINEERING

LALITPUR, NEPAL

OCTOBER, 2023

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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 of Gothatar feeder of Nepal Electricity Authority using Recurrent Neural Network**" submitted by Sudarshan Acharya in partial fulfillment of the requirement for the degree of Masters of Science in Renewable Energy Engineering.

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DECLARATION

I declare that the work hereby submitted for Master of Science in Renewable Energy Engineering (MSREE) at IOE, Pulchowk Campus entitled "**Short-term load forecasting of Gothatar feeder of Nepal Electricity Authority using Recurrent Neural Network**" is my own work and has not been previously submitted by me at any university for any academic award.

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ABSTRACT

This paper mainly focuses on short-term forecasting, gives an hourly demand forecast of electricity. Forecasting using Recurrent Neural Network (RNN) is helpful for making important decisions in the field of preventing misbalancing in load and power generation, scheduling, load switching strategies, preventing imbalance in the load demand and power generation, thus leading to greater power quality and network reliability. We use a method called Recurrent Neural Network (RNN) to anticipate the future hourly demand of Gothatar feeder, Nepal Electricity Authority (NEA). The RNN Network is build, trained and test with historical hourly demand data along with six different input variables and used for the prediction of day ahead hourly demand. The output from RNN model is validated with the real hourly demand data collected from NEA. In addition, the load forecasting is performed for short term load forecasting (STLF) using some other time series methods like: Single Exponential Smoothing (SES), Double Exponential Smoothing (DES) and Holt-Winter's method as well, and whose output was compared with that of RNN. The Root Mean Square Error (RMSE) of SES, DES and Holt-Winter's method was found to be 188.033 kVA, 181.066 kVA and 169.759 kVA respectively, degree of Determination (R^2) was 0.609, 0.618 and 0.634 and Mean Average Percentage Error (MAPE) was found to be 15.421%, 13.31% and 11.502% respectively. The RNN method proved to be the accurate and best forecasting method when the results are compared with other forecasting methods in terms of different error measurements i.e., RMSE, R^2 and MAPE. Root Mean Square Error (RMSE) of 69.03 kVA, R^2 of 0.876 and MAPE of 4.35% obtained from RNN. So, the RNN model proved to be the most accurate and best method with very less error and better R^2 in this study.

ACKNOWLEDGEMENT

I would like to thank the Department of Mechanical and Aerospace Engineering, Pulchowk campus, Institute of Engineering, Tribhuvan University for providing me an important platform to study Master of Science in Renewable Energy Engineering program.

I would like to express my sincere thankfulness to **Prof. Dr. Mahesh Chandra Luintel** and **Assoc. Prof. Mahammad Badrudoza** for continuously supervising my thesis work.

I would also like to extend my sincerest of gratitude towards external examiner **Mr. Tek Nath Tiwari** sir for his invaluable suggestions and feedback which has helped a lot in improving the quality of this thesis work.

I would like to thank NEA, Gothatar feeder for providing Electricity demand data and Department of Hydrology and Meteorology for providing temperature and rainfall data.

I would also like to express my special thanks to **Asst. Prof. Shahabuddin Khan**, **Mr. Pravin Shrestha, Mr**. **Om Prakash Dhakal and Mr. Ravi Lal Pokhrel** for their help in my thesis work.

Last, but not least, I am very thankful to my family members for their support, encouragement and help in each step of my thesis work.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
DES	Double Exponential Smoothing
GDP	Gross Domestic Product
kVA	Kilo-volt Ampere
LSTM	Long Short-term Memory
NEA	Nepal Electricity Authority
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
NN	Neural Networks
RF	Random Forest
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SES	Single Exponential Smoothing
STLF	Short Term Load Forecasting
SVM	Support Vector Machine
VAR	Vector Auto Regress
SES	Single Exponential Smoothing
DES	Double Exponential Smoothing
R^2	Coefficient of Determination

CHAPTER 1 : INTRODUCTION

1.1 Background

In last few years, the electrical short-term load forecasting is evolving as one of the most important field of research for the reliable and efficient power operation. It plays crucial role in the field of scheduling, load flow analysis, contingency analysis, maintenance and planning of power system. In the specific places, the hybrid networks i.e., a combination of neural network with stochastic learning techniques such as genetic algorithm (GA), particle swarm optimization (PSO) etc. are being successfully applied in forecasting of short-term load (Baliyan, Gaurav, & Mishra, 2015).

Short-term load forecasting (STLF) requires a short interval of time to a couple of days, which plays a vigorous and important role in the effective power system operation. It is also very helpful in solving problems in unit commitment and security problem assessment related to the power system network. Any player will be established in a market if they predict the electrical demand accurately. Therefore, almost all kind of load forecasting decisions are made in the energy markets.

To forecast the load accurately, many methods have been used in the past. These include statistical methods such as regression analysis, support vector machines, fuzzy logic, expert systems, econometric models, end-use models, artificial neural network (ANN), SES, DES, Holt's-winter method, Recurrent Neural Network (RNN) etc. This proposal mainly focuses on the short-term demand forecasting which can be referred as short-term load forecasting using Recurrent Neural Network (RNN) algorithm.

Although many efforts have been done in past to forecast the load using numerous methods around the world, Neural Network method is not being used well enough to forecast the electrical load in context of Nepal. In addition, the load forecasting has been done in Nepal by Government owned Utility Nepal Electricity Authority (NEA) for the purpose of only long term. Very rare attempts have been done to forecast the load for short-term in context of Nepal so far.

RNN is an algorithm class that uses manifold layers to extract higher feature level progressively from the raw input. Recurrent Neural network (RNN) algorithms are used in the field mentioned above. So, here RNN model will trained with around eighteen months of historical input data by considering the load affecting factors like hour, day of the month, week of the month, month of the year, temperature, rainfall, previous day load etc. The network is trained and will able to make predictions of demand based on the patterns learned during training. To check whether the forecasted load catches the pattern of tested load accurately, validation will be performed just by comparing the forecasted load with the real test data.

Types of Forecasting

Demand forecasting are mainly of three types i.e., Short-term demand forecasting, Mid-term demand forecasting and Long-term demand forecasting.

i) Short-term Forecasting

This type of forecasting usually forecasts the load from half an hour to a week of the month.

ii) Medium-term Forecasting

This type of forecasting usually forecasts load from week of the month to a year.

iii) Long-term Forecasting

This type of forecasting usually forecasts loads for more than a year.

1.2 Problem Statement

Power forecasting is a topic of great interest nowadays in the perspectives of supplier of electricity for reliable, loss free and continuation of supply. Load forecasting plays vulnerable role in the decision making, purchasing of power, demand side management, generating electric power, switching of load, to reduce errors and improve stability of power system. Furthermore, the forecast must be efficient which can be done efficiently using efficient algorithm of RNN and which has not been done yet for forecasting in Nepal.

1.3 Scope of Study

Our country is a developing country and we must follow the appropriate forecasting techniques but in fact our country does not effectively follow the suitable load dispatching methods for the prediction of load. Because there is no any competitive market. So, to reduce the uncertainties like, unnecessary tripping of power system, we must predict the load. It will not only solve unnecessary tripping but also help to reduce losses.

This research will play very important role for selecting the suitable techniques for short-term load forecasting in our country, that will contribute in near future for our country and help to reduce cost, improve stability, increase power consumption and reduce losses.

As we know, RNN algorithm is very useful and best model but in our country this model has not been used to predict the demand. This thesis emphasis on the usefulness of RNN algorithm and compares other models of forecasting with the RNN model and select the best model among them.

1.4 Objectives

Main Objective:

To obtain the hourly forecasted load of Gothatar feeder of Nepal Electricity Authority using Recurrent Neural Network algorithm.

Specific Objectives:

i) To prepare Recurrent Neural Network model using MATLAB software.

ii) To obtain the short-term forecasted hourly load using Single Exponential Smoothing, Double Exponential Smoothing and Holt-winter’s algorithms.

iii) To compare the result of Single Exponential Smoothing, Double Exponential Smoothing and Holt-winter’s algorithms with the result of Recurrent Neural Network algorithm to conclude the best model for forecasting the load.

1.5 Limitations

i. During the shutdown or maintenance of feeder, the feeder will be off, at this hour the demand is considered as previous demand.

ii. A Research can't be performed on the basis of primary data because there is no validation data and there is possibility of human errors.

iii. Input parameters like population growth, humidity, GDP, seasonal parameters and festivals data range are not considered in this research.

iv. During the smoothing of demand, we use moving average smoothing technique by taking 5 data at a time.

v. Expert human beings are required to run the program. i.e., the method can't be taken over.

vi. This thesis is limited to the Gothatar feeder for forecasting the load.

CHAPTER 2 : LITERATURE REVIEW

Electricity demand forecasting is now becoming the topic of interest in recent days to predict the power demand ahead for the stability and reliable of the supply system with low loss and outage. Many researchers have been working for forecasting of demand. It is very essential to forecast the demand with best result and for that new tool for forecasting is growing on. Earlier, power demand was forecasted using general time series forecasting analysis but in recent trend the short-time demand forecasting is being done by Neural Network and machine learning algorithms. Short-time demand forecasting is recently being done in many countries with various algorithms of machine learning like support vector machine (SVM), random forest (RF), neural networks (NN) etc.

For the best operation of power system, generation of electrical power must fulfill the electrical demand of load. The generation, transmission, and distribution system require some algorithms for forecasting the electrical power demand so that they can utilize the transmission and distribution infrastructure securely, efficiently, and economically. The short-term load forecast (STLF) indicates the forecasting of demand few hours to the few days (Muhammad, haruna, Sharif, & Mohammed, 2022).

The forecasting of power system is essential to predict the future demand of electrical power, which help to reduce the overall costs and electricity resources and also help to improve the electrical distribution of load for different electric companies. Mainly three algorithms are used to predict the electrical demand; namely: (1) Long Short-Term Memory (LSTM), (2) Gated Recurrent Units (GRU), and (3) Recurrent Neural Networks (RNN) (Lee & Choi, 2020).

To provide the required electrical demand to the customer in a safe and economic manner, many electrical companies face many technical and financial problems in an operation. Among these problems, load flow analysis, stability analysis, planning, scheduling and controlling of electrical power demand are the most common. In last few years, electrical load forecasting is also one of the most crucial, important and challenge field of the research. Forecasting of electricity demand will help in the optimization of the startup cost of generating units, and can also save the investment in the construction of required number of power plants and facilities. It can also helpful for checking the risk of the operation, fluctuation of the demand, spinning reserve and susceptibility to the failures. Forecasting of load provides the very important information for delivering the power demand and planning. It also plays an important role in demand side as well as energy management system (Baliyan, Gaurav, & Mishra, 2015).

2.1 Forecasting using Neural Network (NN)

Neural Network (NN) is an area of computer science, is used to forecast the load on the basis of statistical techniques. Unlike conventional statistical techniques, first of all we must understand the basic concepts of algorithms to forecast the load. Neuron is the simplest unit of a Neural Network (NN), which is shown in figure below. Neuron consist of many inputs X_i and weights W_i. The activation function used here is a command that generates only one output by summing the input, weight and bias variable

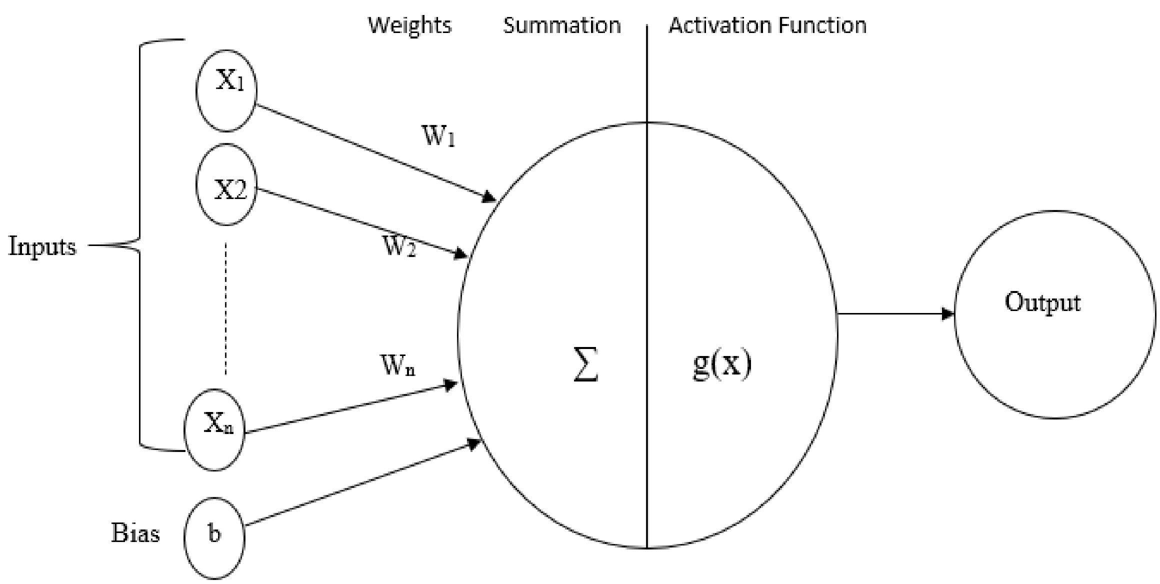

Figure 2.1: Simple Neural Network

The function which is used to generate output by adding inputs, weights and bias value is simply called an activation function. Many activation functions are there i.e., tansig, logsig, trainscg, sigmoid, tanh, etc. The most common, popular and effective in recent research is the rectified linear unit (ReLU) (http://www.deeplearningbook.org, 2016).This is denoted by the following equation.

$$\mathrm{ReLU(x)} = \begin{cases} \mathrm{x} & \text{if } \mathrm{x} > 0 \\ 0 & \text{if } \mathrm{x} \leq 0 \end{cases} \qquad (1)$$

The Neural Network can be capable of dealing with the large amount of data and hence they are used in big data analytics. Characteristically gives computer systems with some specific features of data to learn. Mainly NN can perform the load forecasting in to two ways. They are: supervised forecasting and unsupervised forecasting. Supervised forecasting permits the computer to learn from the sample dataset, where the required output or targets of data are known already. The classifications and regression are main difficulties are the subcategories of supervised forecasting problems. Regression analysis deals with the continuous predicting while classification problems focus to forecast categorical class labels. Both algorithms can perform the process of forecasting by using the historical past demand dataset before performing the predictions of new targets. Unsupervised forecasting deals with the data with no known targets. By using the unsupervised demand forecasting algorithms, suitable information with no supervision of a known result will extract the structured data. The training part applies on a fraction of dataset. In contrast, the remaining dataset are utilized to test and validate the proposed model before selecting the forecasting method. The recent scenario of demand forecasting leads with Neural Network algorithms. The NN algorithms are used in demand forecast are ANN, SVM, SVR, RF, SVM-SMO, RNN, LSTM etc. The simple process used in NN algorithm for forecast are:

i)Pre-processing of data

We have to arrange all the data in the format that the algorithm suggesting. Some values of data may be missing, which must be fill up using the most common mathematics technique like extrapolation, interpolation etc. Then, the data will be ready in the required format.

ii) Training and Testing

From the available dataset, the complete data is separated into two different group: training and testing group. The training and testing ratios may be 70:30, 80:20 etc. First of all, the dataset is trained according to the given input and then testing is carried out in remaining data set. The model learns from the training data set and fits best according to that.

iii) Forecasting

After performing the validation of the model, the demand forecasting part is carried out. The validation of the model is based on Mean Average Percentage Error (MAPE), Coefficient of determination (R^2), Mean Square error (MSE), Root Mean Square Error (RMSE) etc.

2.2 Basic of RNN

Recurrent Neural Network (RNN) is a part of the Neural Network (NN) architecture which is used for load forecasting. Although it is not different from ANN in terms of working logic, but it allows the feedback system to work. RNN models has ability to store information for a certain period of time. Due to this feature, RNN is extremely useful while dealing with time series or sequential data (Niu, Zhao, & Liu, 2009).

Recurrent Neural Network is (RNN) is a part of Neural Network in which the output of a neuron feeds into its input. In simple terms, let's consider we have a problem where the document is damaged and some of the words on the documents were unreadable. As we are humans, we would may solve the problem by reading of the document and we can make the guess based on knowledge that we have. The RNN algorithm able to solve this problem by taking the series of words to recognize the context of the sentence, and then the unreadable word can be predicted. They perform this action through loops in neurons, which allows the information from the first word to the last word. This structure of RNN can be very confusing since we self-reference, but can be unfold this by using Recurrent Neural Network. Once we unfold the word, many copied layers passing an extra input into their normal neural network successor as shown in figure 2.2.

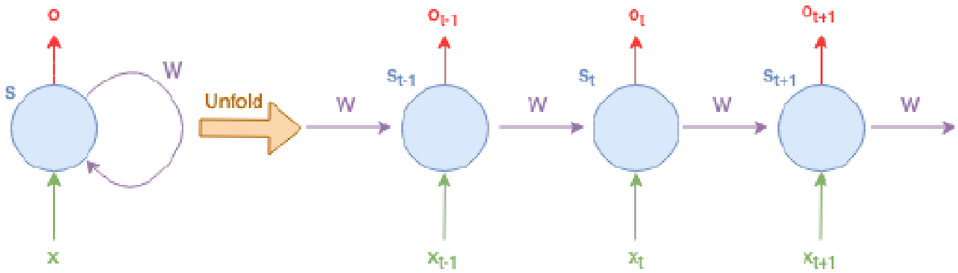

Figure 2.2: Unfolded recurrent neural network

2.3 Forecasting using Time-series modeling

2.3.1 Single Exponential Smoothing Method (SES)

Single exponential smoothing method for forecasting was mostly being applied (Dhakal, Gautam, & Bhattarai, 2021). SES is a forecasting technique used for the smoothing of time series data by the use of excel. Whereas, in case of moving average technique, the past dataset is weighted equally and exponential functions are applied to decrease the weights over time in exponentially. This method is very easily learned and is easily used procedure for the demand prediction depending on the previous assumptions made by the user i.e., seasonality. To predict the time series demand smoothly, Exponential smoothing method is often used.

The basic equation for single exponential smoothing method is given by,

$$St = \alpha . Xt + (1 - \alpha) . St - 1 \qquad (2)$$

Where α is smoothing factor, whose value lies between 0 and 1, and S_t is a weighted average of present observation X_t and previous smoothed demand S_{t-1}.

Single exponential smoothing algorithm does not perfectly predict when there is a certain trend in a dataset (Dhakal, Gautam, & Bhattarai, 2021). In such circumstances, numerous methods are developed under the name "double exponential smoothing" or "second-order exponential smoothing," which is the application of an exponential filter twice, thus being named "double exponential smoothing (DES)". Double exponential smoothing is also called Holt's linear trend model.

DES is given by following equations,

$S0 = X0$

$b0 = X1 - X0$

$For\ t > 0,$

$St = \alpha.Xt + (1 - \alpha)(St - 1 + bt - 1)$ (3)

$bt = \beta(St - St - 1) + (1 - \beta)bt - 1$

$Ft = St + bt$

To forecast beyond X_t,

$Ft + m = St + m.bt$ (4)

where, α and β are data smoothing factor and trend smoothing factor whose values lies between 0 and 1.

2.3.2 Holt-Winter's Method

This is a model of time series behavior. Demand forecasting always requires a special model, and Holt-Winter's is a way of modeling time series data of three aspects: a typical value (average), a slope (trend) over time, and a cyclic repeating pattern (seasonality). Holt and winter's extended Holt’s method for capturing the seasonality (Shakya, Jha, & Bhandari, 2018). The Holt-Winter's seasonal method includes the equation of forecast and three smoothing formulae in terms of equations. E_t is used for the level, T_t is used for the trend, S_t is used for the seasonal component, with equivalent parameters of smoothing α, β and γ.

Mainly two variations are there to this model that alter the seasonal component. If there is any seasonal variation, then additive method is preferred because during this condition, the seasonal variations are almost constant, while during the seasonal variations proportional to the series level, another method is preferred which is known as multiplicative method. The seasonal component is always represented in absolute terms with additive method. The seasonal factor will be added up to nearly zero within every year. The seasonal factor is written in relative terms (i.e., percentages) with the multiplicative method, and the series can be adjusted seasonally by dividing through by the seasonal factor.

General equations for Holt-winter's additive seasonal method are given below:

$$\hat{Y}_{t+n} = E_t + nT_t + S_{t+n-p}$$

$$E_t = \alpha\left(Y_t - S_{t-p}\right) + (1\text{-}\alpha)(E_{t-1} + T_{t-1}) \qquad (5)$$

$$T_t = \beta\left(E_t - E_{t-1}\right) + (1\text{-}\beta)T_{t-1}$$

$$S_t = \gamma\left(Y_t - E_t\right) + (1\text{-}\gamma)S_{t-p}$$

Where E_t is level, T_t is trend, S_t is seasonality, α, β and γ are smoothing parameters whose value is between 0 and 1 and $\hat{Y}_{t+n}$ is the forecasted value.

The equations for Holt-winter's multiplicative seasonal method are given below:

$$\hat{Y}_{t+n} = (E_t + nT_t)S_{t+n-p}$$

$$E_t = \alpha\left(Y_t / S_{t-p}\right) + (1\text{-}\alpha)(E_{t-1} + T_{t-1}) \qquad (6)$$

$$T_t = \beta\left(E_t - E_{t-1}\right) + (1\text{-}\beta)T_{t-1}$$

$$S_t = \gamma\left(Y_t / E_t\right) + (1\text{-}\gamma)S_{t-p}$$

Where E_t is level, T_t is trend, S_t is seasonality, α, β and γ are smoothing parameters whose value is between 0 and 1 and $\hat{Y}_{t+n}$ is the forecasted value.

2.4 Previous Approaches (Related works)

Many approaches have been used in STLF: Autoregressive integrated moving average (ARIMA), Artificial Neural Network (ANN), Recurrent Neural Network (RNN), Feed Forward Neural Network (FFNN), Long Short-Term Memory (LSTM), extreme learning etc.

1. Researchers compares the performance of a Feed Forward Neural Network and Recurrent Neural Network (Din & Marnerides, Jan 2017). They use the New England-ISO data set from 2007 to 2012. They take data-set including date, consumption hour, electricity price, dew point, dry bulb and system load. They consider temperature effects, time effects, holiday effects, and lagged load. They include previous week and previous day same hour load, and previous 24-hour average load. They also include data distribution effects over the past 24 hours. They use, kurtosis, skewness, and periodicity and variance. They conclude that weather, time, holidays, lagged load, and data distribution are found to be the most dominant factors. They also show that the RNN has less error than the FFNN on all domains and error calculations.

2. They design a long short-term network (LSTM) based on an RNN for STLF (Liu, Jin, Gu, & Oiu, Sept. 2017). LSTMs models are a type of RNN where some variables from one iteration are fed into the next. An LSTM unit is composed of an input gate, output gate, forget gate, an activation function, remembered input, and previous output. The goal is to remember the previous input values and forget some of the values using forget gate and to factor the previous input into the output. LSTMs were proposed to deal with the exploding and vanishing gradient problems that were encountered with traditional RNNs (Hochreiter & Schmidhuber, 12, 1997). An exploding gradient is a problem where the gradient, which is used to change the weights of the model, becomes too big and results in a numeric overflow. A vanishing gradient is one where the gradient gets too small, so much so that all training stops and the weights are not updated. This is the result of the chain rule when back propagating through the unfolded layers of an RNN. One advantage they propose is that the RNN architecture introduces self-loops where they are able to produce different paths that the gradient can flow for a long duration. This means that the model improves its accuracy at a constant rate. their conclusion they state that LSTMs can be used to forecast hour-ahead values with high precision.

3. This paper mainly focuses both on short term and monthly forecasting, proposing an LSTM-RNN (Bouktif, Fiaz, Ouni, & Serhani, 2018) model. They use a large data set from a metropolitan area from France of nine-year period at a 30-minute resolution.

They use a genetic algorithm to generate models with different time lag intervals, then pick the best lag time of the bunch. A genetic algorithm (GA) generates slight differences in the model, trains them, then picks the most accurate one, then repeats the process. GA works much like evolution. They found that the LSTM-RNN had lesser forecasting errors in the medium and short term when compared to the best machine learning algorithms.

4. Short-term load forecasting of Kathmandu valley using Artificial Neural Network (ANN) has been done (Shakya, Jha, & Bhandari, 2018). They compared results obtained from ANN with moving average, weighted moving average, exponential smoothing and Holt's winter. They took temperature, hour of a day, day of week, flag indicating holidays/festivals, load from same hour of previous day as input features in modeling. They concluded that the Artificial Neural Network proved to be the more accurate forecast method when the results are compared in terms of error measurements with a MAD having 1.23, MSE having 1.79 and MAPE having 1.17.

5. This paper focused on generating a long-term load forecasting using hourly demand predictions (Agrawal, Muchahary, & Tripathi, 02, 2018). They found that the most important feature was the load demand for the same day and hour of the previous year. They proposed a model of an RNN with LSTM cells. They also mention that FFNN assumes that the training and test data are independent. Since electricity load demand is a time series data - the assumption fails so FFNN is not suitable. Ultimately, they find that LSTM-RNNs are suitable for forecasting with a mean absolute percentage error of 6.54 %. They concede that incorporating weather parameters into the data-set can be beneficial. It is noted that the LSTM networks are well suited to classifying, processing and making predictions on time series data, since there can be lags of unknown duration between important events in a time series.

6. Short-term load forecasting (STLF) with 24 hours duration is done by ANN algorithm (Singla, Gupta, Nijhawan, & Oberoi, 2019) . They take live load data from a typical 66 kV sub-station of the Punjab State Power Corporation Limited (PSPCL) for a selected

site at Bhai Roopa sub-station, Bathinda, situated in the Punjab state of India, was procured for the presented simulation study. The collected data was divided into three main categories, i.e., validation, training, and testing for study by considering a neural network approach. The results obtained from the modeling were validated with the live data of load of the selected area and found to be within the allowable limits. To find the effectiveness, mean absolute percentage error (MAPE) and root-mean-square error (RMSE) were calculated and examine the errors. It can be safely concluded that the proposed methodology gives reasonably accurate results, and is reliable in predicting the electric demand forecasting.

7. The researchers presented the research work which focuses on the prediction of power consumption using time series forecasting methods for the ˆIle-de-France region with publicly available energy data from RTE, France (Theile, et al., 2018). The two machine learning algorithms Support Vector Machine (SVM) and Recurrent Neural Network (RNN) are implemented and tested for their accuracy in predicting day-ahead half-hourly power consumption data. The MAPE is used for the performance measure. The results from this model indicate a higher accuracy of the RNN.

8. This thesis research mainly focuses on the short-term forecasting to predict a day ahead peak demand of electricity (Bhattarai, Dhakal, & Shrestha, 2022). A method called Long Short-term Memory (LSTM) of deep learning is used to anticipate the future peak demand of Panchkhel distribution Centre, NEA. The LSTM Network is built, trained with historical peak demand data along with five different input variables and used for prediction of day ahead peak demand. The output is validated with the real peak demand data collected from NEA. They concluded that the LSTM model proved to be the more accurate forecast method with a RMSE having 68.86 kVA and R^2 of 0.88.

2.5 Research Gap

In above literature reviews (Bhattarai, Dhakal, & Shrestha, 2022) prepared a model of short-term load forecasting of Peak load for Panchkhel distribution Centre, NEA. They used LSTM Algorithm to forecast the load. (Agrawal, Muchahary, & Tripathi, 02, 2018) focused on generating a long-term load forecasting using hourly predictions. They proposed a model of an RNN with LSTM cells. (Shakya, Jha, & Bhandari, 2018) presented their study on Short-term load forecasting of Kathmandu valley using artificial neural network where they concluded that artificial neural network (ANN) algorithm.

Recurrent Neural Network (RNN) uses feedback in neurons and is considered to be very accurate and effective than other time series forecasting. This thesis is related to short-term load forecasting using Recurrent Neural Network (RNN) which is not carried in our country till now. The main aim of this thesis is to test the RNN algorithm with other time series forecasting algorithms and select the best forecasting algorithm.

CHAPTER 3 : METHODOLOGY

3.1 Flowchart

The flowchart of the thesis is shown in Figure 3.1.

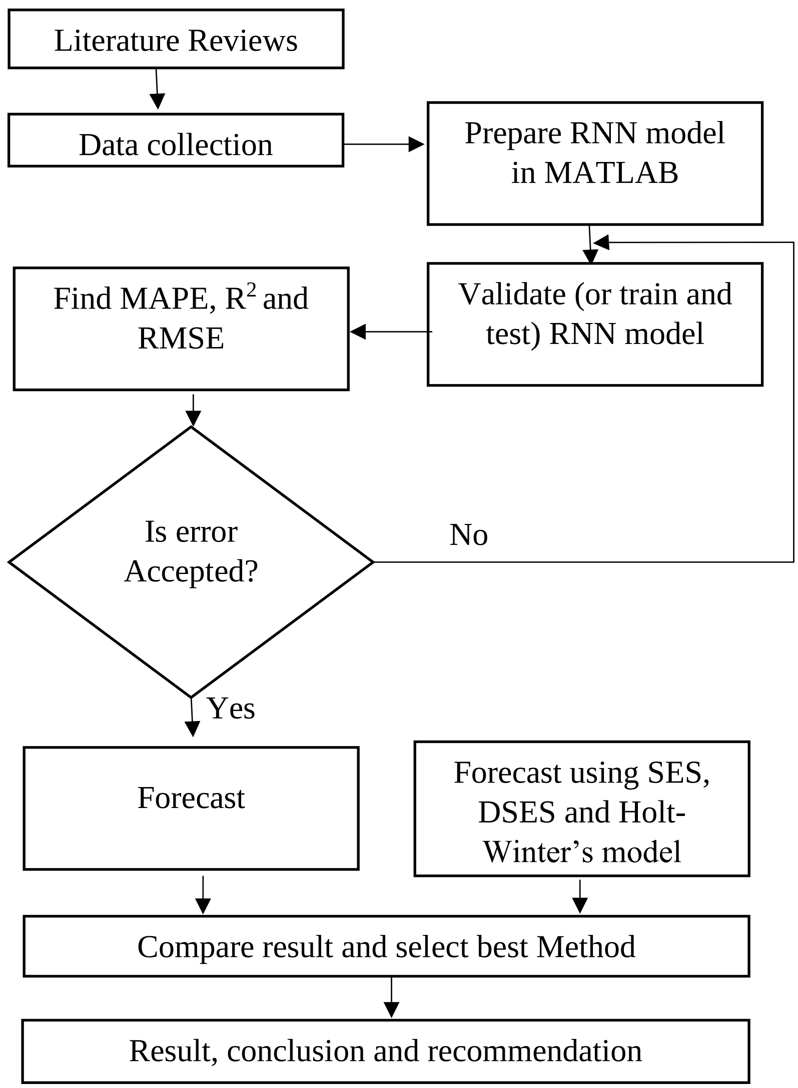

Figure 3.1: Flowchart of thesis

The overall methodology of the research is presented in Figure 3.1 as flowchart of research. First of all, historical hourly demand data is collected from Gothatar feeder, NEA. Thus, hourly collected demand data are pre-processed for analyzing the past demand patterns, trends and periods. The methodology in detail is described in the following sections below.

3.2 Data Collection

The Power demand data required for the research are collected from secondary source i.e., from Gothatar feeder of Nepal Electricity Authority (NEA) and weather data are collected from meteorology department. The demand of Gothatar feeder for the period of last 18 months (1.5 years) data collected in hourly basis of a day for this research and then data is kept in required format.

3.3 Data Normalization

Data Normalization is simply a technique which is often employed as portion of data preparation for MATLAB. The main goal to perform normalization is to convert the input dataset of numeric columns to a common scale, without altering the original data. This technique is normally used when dataset have dissimilar ranges. In the dataset, Input features like month have value from 1 to 12, day has value from 1 to 31, maximum and minimum temperature has different numerical values and rainfall has some positive value i.e., 0 and positive value. So, here we can see that different features have different ranges of values. So, using normalization, these values come in common scale. It is always performed on a dataset to normalize the input data within the range of 0 to 1. The data is normalized here using formula,

$$\text{normalize data} = (\text{Actual data} - \text{minimum data}) / (\text{maximum data} - \text{minimum data})$$

3.4 Input Features for Model

The electricity demand depends on many factors like seasonal demand that can be included by taking hour, day, month or year as features, weather conditions like rainfall, humidity, temperature of day, Actual power demand etc. are considered during study, and other factors like population, GDP growth which generally don’t play big role in short term forecasting. After analyzing the hourly demand pattern and by reviewing the previous literatures, following factors are considered as input features for the model:

- Hour of the day
- Day of the month

- month of the year
- Year
- Rainfall
- Temperature

Here, altogether six features are selected for the model. Using these input data features, the RNN model is designed to forecast the hourly demand.

3.5 RNN Modeling

Mathematical modeling (Equation) of Recurrent Neural Network

The standard modeling equation of a basic Recurrent Neural Network (RNN) involves, updating the hidden state in each time period and calculating the output based on that hidden state.

The basic RNN can be shown by following equation:

$$\mathbf{h_t = Activation\ (W_{hx}X_t + W_{hh}h_{t-1} + b_h)}$$

$$\mathbf{Y_t = OutputLayer(h_t)}$$

Where;

X_t is the input of a system at time t

h_{t-1} is the hidden state from the previous time t-1

W_{hx} is the weight matrix connecting the input to the hidden state

W_{hh} is the weight matrix connecting the previous hidden state to the current hidden state

b_h is the bias term for the hidden state

Activation is an activation function (e.g., tanh or ReLU) applied to the computed sum

$Y_{t\ is}$ the output

Above RNN equation can be shown in Figure 3.2 as:

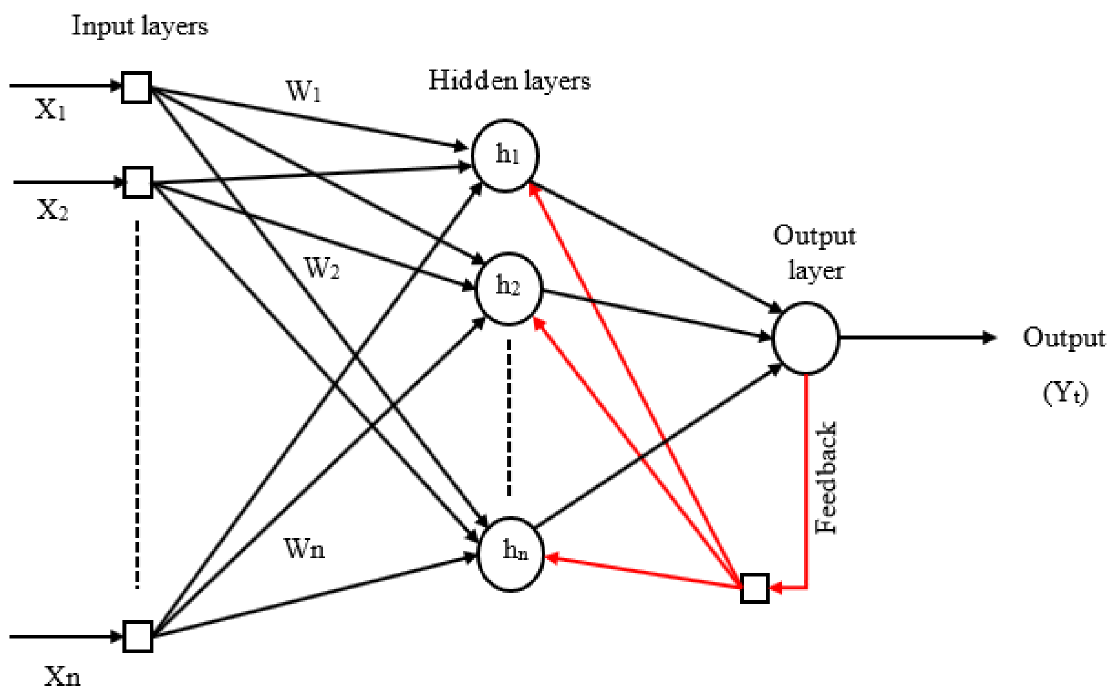

Figure 3.2: Modeling of RNN

Forecasting of Gothatar feeder of NEA using RNN modeling

To forecast the demand using RNN model, all the dataset are divided into two parts: Training dataset (used for training the network) and Testing dataset (for validation with real data that is not used in the training process of the RNN model). The training and testing dataset are split in 80:20 ratio. Data equivalent to 2021/12/16 to 2023/2/26 A.D. is considered as training data set, and data equivalent to 2023/2/27 to 2023/6/15 A.D. is considered for the purpose of testing and a day 2023/04/11 is taken as validation purpose. The methodology to forecast load using RNN is divided in to: collection of data, data pre-processing, RNN modeling and Training, Forecasting and testing (validation).

There are altogether three models are developed and they are trained with the past dataset along with the consideration of different factor consideration. There are six input parameters are used as inputs dataset to the input layer of RNN model. The days of the month are assigned numerical values from 1 to 30/31. The months of the year are assigned numerical values from 1 to 12. The rainfall is assigned with o to positive number. The forecast model is then developed and trained using the RNN algorithm and which can be done in ‘MATLAB 2023’. Adjustments are now made to RNN model until the best result with less error is achieved. In order to get the best model, hidden layers, activation functions, no. of neurons and optimizer and so on are adjusted.

3.6 Performance Measure

Different performance measuring parameters like R^2, Root Mean Square Error (RMSE) and Mean Average Percentage error (MAPE) are used to estimate the performance of the model. Validating techniques like MAPE is a performance measure that tells us about the how far the predicted values are from the original observed value in percentage, lesser the MAPE, better will be the result. RMSE is a performance measure that tells us how far apart the average of predicted values is from the observed values in a dataset. The better model fits a dataset if it has lower RMSE. R^2 is a performance measure that tells us about how accurately the forecasted data fitted and its value ranges from 0 to 1. The better model fits if a dataset have higher R^2 value. RMSE and R^2 is calculated by formula,

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Yi - \hat{Y}i)^2} \qquad (7)$$

$$R^2 = 1 - (RSS/TSS) \qquad (8)$$

$$\text{MAPE} = (\text{Actual error}/\text{Actual demand}) * 100\% \qquad (9)$$

Where, Y_i is the actual consumption, $\hat{Y}_i$ is the forecast value, N is the total fitted point number, RSS is sum of square of residuals and TSS is total sum of squares.

3.7 Comparison of Models

The forecasted value obtained with RNN algorithm is compared with traditional approaches of forecasting i.e., SES, DES and Holt-Winter's multiplicative seasonal method for the validation of best model. The hourly demand is forecasted using SES, DES and Holt-Winter's multiplicative seasonal method with help of MS-Excel SOLVER and RMSE and R^2 values are also obtained. Then all the four of the methods are compared with each other to validate the best method for forecasting.

CHAPTER 4 : RESULTS AND DISCUSSION

4.1 Data Preparation and Data smoothing

4.1.1 Data Preparation

Data preparation is the first step of the research. The hourly electricity demand dataset is collected from NEA, Gothatar distribution substation, and rainfall data and temperature dataset are collected from, Department of Hydrology and Meteorology. Original raw data measured from Gothatar feeder; NEA needs to be pre-processed so as to improve the efficiency. Therefore, the process of pre-processing is one of the crucial phases that deals with the preparation and transformation of the original dataset. The hourly demand data collected is shown in the Figure 4.1. The figure shows the hourly demand pattern of Gothatar feeder, NEA. From the figure, it is noticed that there are some spikes of hourly demand.

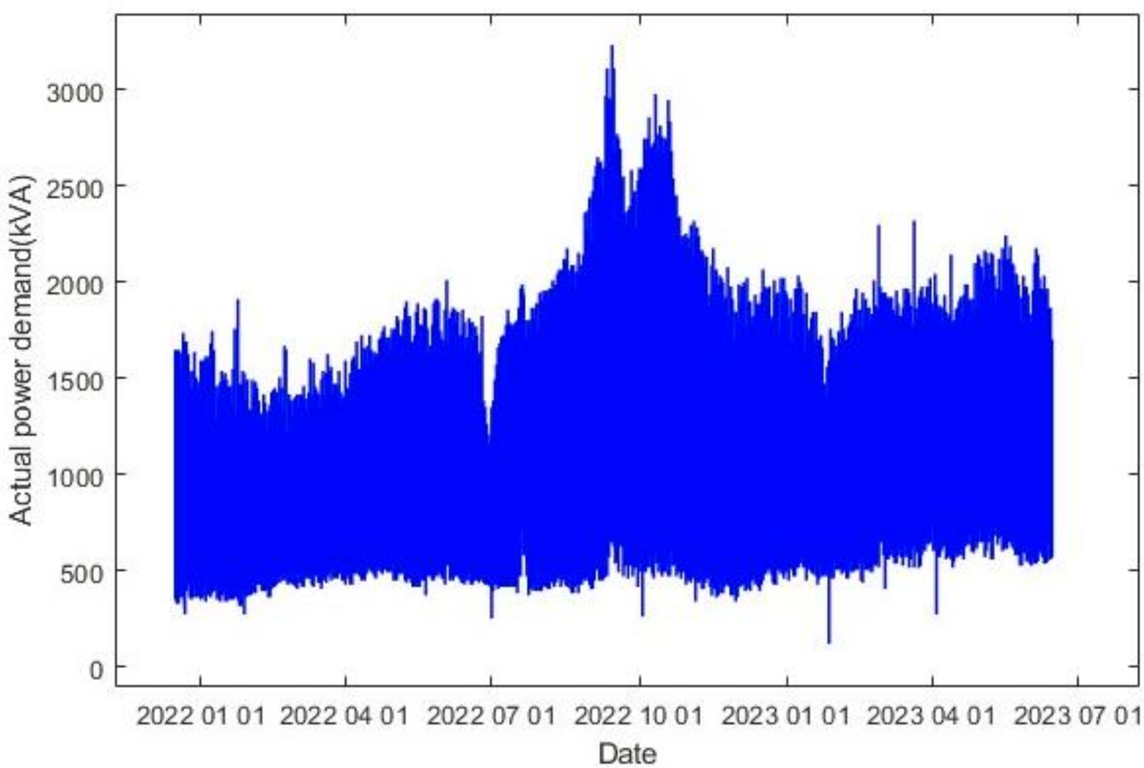

Figure 4.1: Actual Demand of Gothatar feeder

There are altogether 13129 hourly demand data. Maximum hourly value is 2766 kVA and minimum demand 282 kVA.

4.1.2 Data Smoothing

As we see in Figure 4.1 of hourly demand data, there are some random spikes in the hourly demand pattern. Due to these random spikes of hourly demand data, the model will not fit well to predict as these random spikes are on some random days only. So, these random spikes need to be smoothed out first to prepare the best model. The hourly demand is smoothed by simple moving average by taking smoothing window of 5 and the smoothed hourly demand pattern is shown in the Figure 4.2. Here we can see the hourly demand pattern of smoothed data is same as original one but the random spikes are not there in the smoothed hourly demand data.

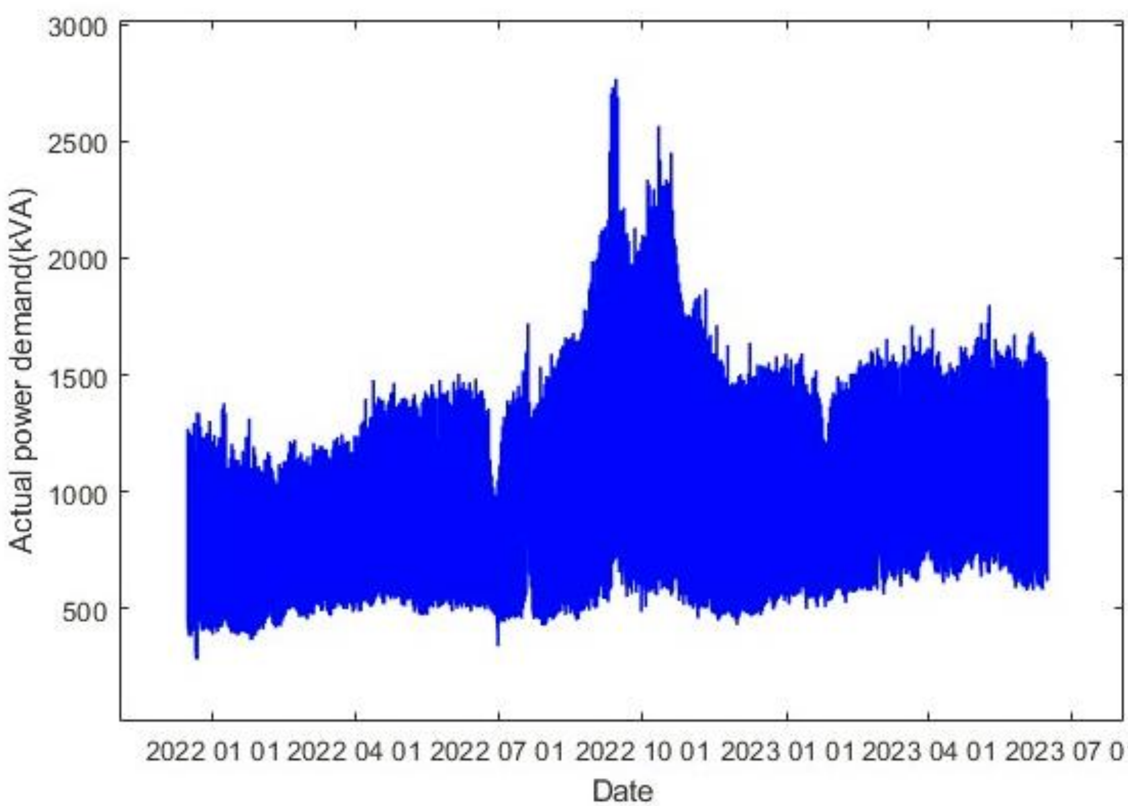

Figure 4.2: Smoothed hourly demand pattern

4.2 Comparison of power demand with respect to months of previous year

The Power demand data required for the research are collected for the period of last 18 months (1.5 years) in hourly basis of a days from 2021/12/16 to 2023/6/15 A.D. The comparison of power demand in different months of year is shown in Figure 4.3.

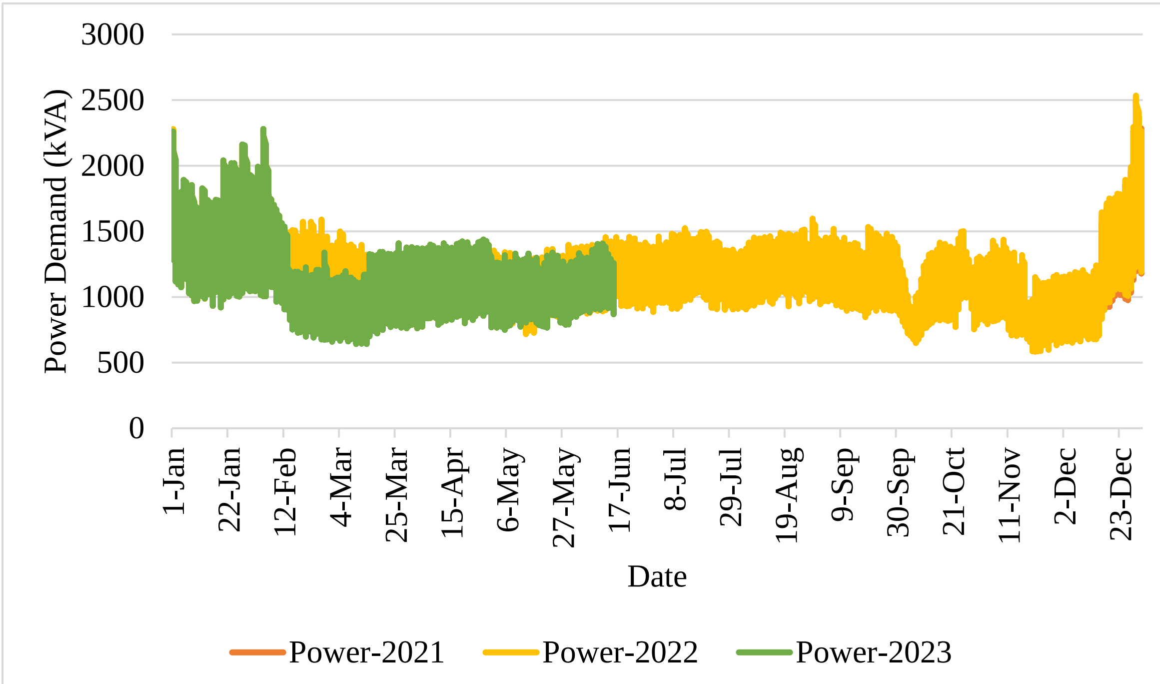

Figure 4.3: Comparison of Power demand of different months of different years

In Figure 4.3, green color represents the power demand of Gothatar feeder from January to June of 2023, yellow color indicates the power demand of feeder from January to December of 2022 and Orange color represents the power demand of Gothatar feeder from December 16 to December 31 of 2021.

From above Figure, it is clearly seen that the power demand of feeder is increases each year with comparison to previous year. The demand in last 2 years i.e., December 16 to 31of 2021 and 2022 is increases slightly. The demand of feeder from January to June 15 of 2022 and 2023 is also slightly increases. This is mainly due to the population growth and increment of use of induction stoves.

4.3 Results of Recurrent Neural Network (RNN)

The coding of Recurrent Neural Network (RNN) model is performed in 'MATLAB 2023'. The hidden layers, activation function, number of neurons, different loss etc. are varied to obtain the best model on hit and trial basis with their performance measures as MAPE, RMSE and R^2. The six different model's parameters used to obtain best model is tabulated in Table 4.1.

Table 4.1: Selection of activation functions, epochs, learning rate, number of hidden layers and best model for forecasting

Model	**Activation Function**	**No. of Neurons**	**No. of Epoch**	**Learning rate**	**MAPE (%)**	**R^2**
1	a) tanh b) logsig c) tansig d) purelin	a) 100 b) 50 c) 25 d) 1	500	0.032	8.66	0.789
2	a) tansig b) logsig c) tansig d) logsig e) trainscg	a) 150 b) 75 c) 50 d) 25 e) 1	2150	0.032	7.02	0.81
3	a) tansig b) sigmoid c) tansig d) sigmoid e) purelin	a) 30 b) 25 c) 20 d) 15 e) 1	2500	0.032	5.34	0.851
4	a) tanh b) logsig c) tanh d) logsig e) trainscg	a) 30 b) 30 c) 20 d) 15 e) 1	2600	0.032	6.82	0.829

Model	Activation Function	No. of Neurons	No. of Epoch	Learning Rate	MAPE (%)	R^2
5	a) tansig b) logsig c) tansig d) logsig e) purelin	a) 25 b) 25 c) 20 d) 15 e) 1	4800	0.032	4.35	0.876 (Best)
6	a) tansig b) logsig c) tansig d) Maxout	a) 15 b) 15 c) 15 d) 1	4850	0.032	5.01	0.84

In Model 1, there are 3 hidden neurons and one output layer. The first layer has activation function as 'tanh' and which has 25 neurons. The second layer has activation function as 'logsig' which has 25 neurons. The third layer has activation function as 'tansig' which has 25 neurons the last layer has activation function as 'purelin' which has only 1 neuron and functions as output layer.

Now, the model is run and fitted by taking learning rate 0.032 and epochs of 500. The epochs size is generally taken by visualizing the loss after running the model. There may be the less value of loss for certain epochs and after that the loss may increase i.e., that point is local minima but we are interested in global minima. So, by considering this epochs size here taken as 500.

The optimizer selected here is 'adam' as it is best optimizer used in recurrent neural network. The training loss for model 1 is shown in Figure 4.4.

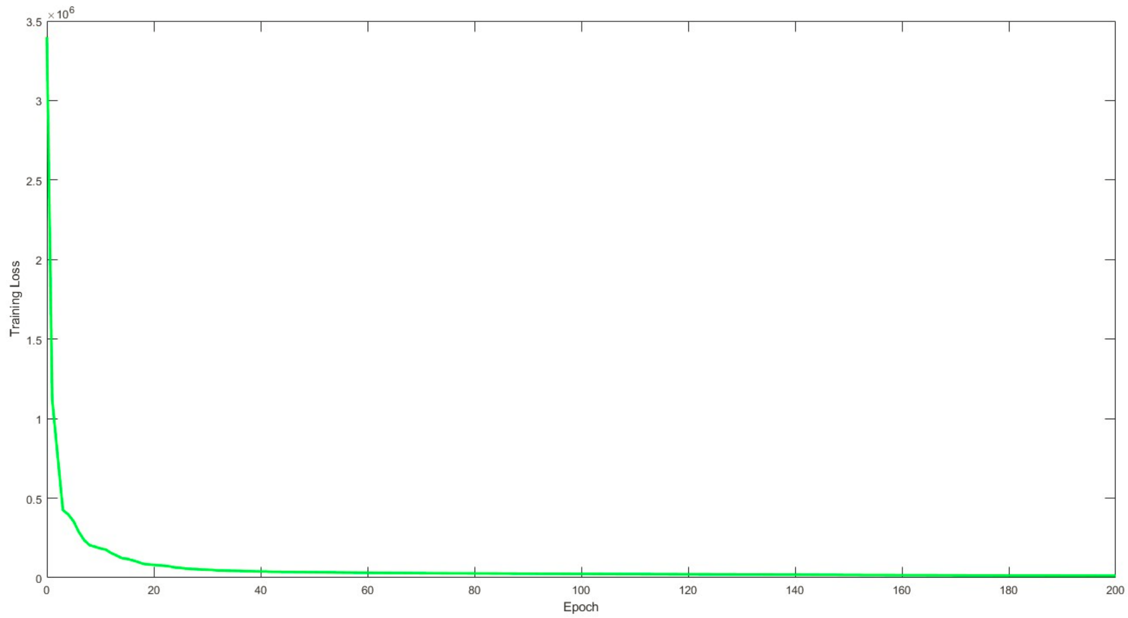

Figure 4.4: Training Loss curve for Model 1

From the loss curve seen in Figure 4.4, it is clearly seen that loss is decreasing as epochs increases and finally settles at constant loss value. So, it is concluded that model is well trained. After the training of RNN model, it is then tested with the test dataset. The model is then used to predict the hourly power demand. Then the performance measures i.e., MAPE, RMSE and R^2 are then calculated using test and predicted dataset.

The R^2 value obtained for model 1 is 0.789. The trained dataset, and test dataset curve is then plotted which is shown in the figure below. From the figure, it is clearly seen that the actual and predicted values are close but not much accurately. The predicted values follow almost same pattern as the actual one.

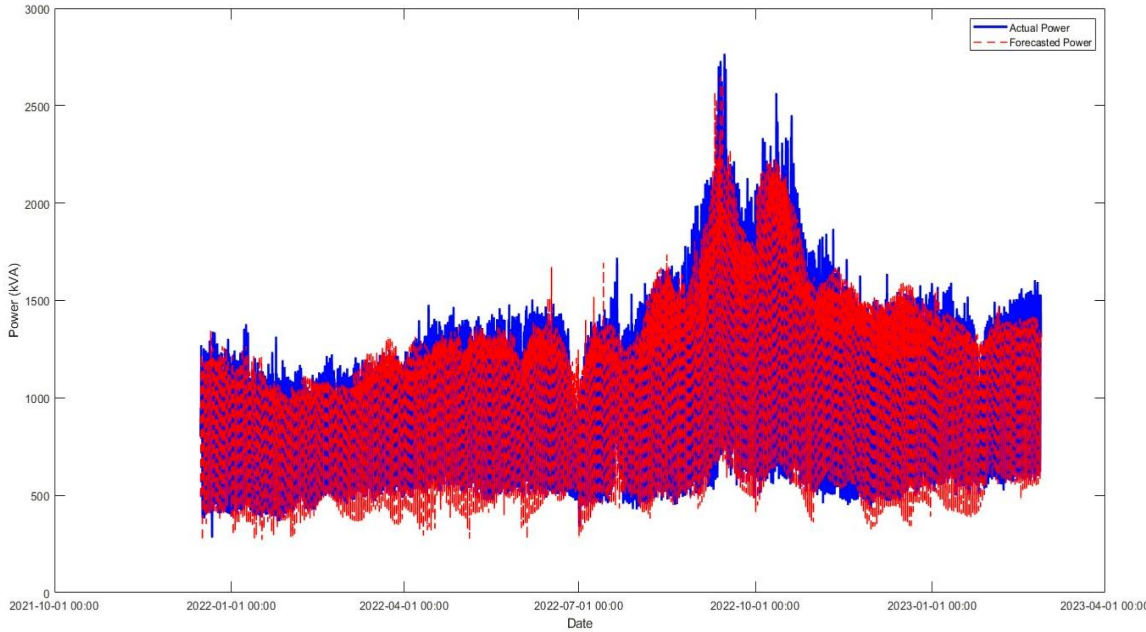

Figure 4.5: Training graph for model 1

From Figure 4.5, we can clearly see this model catches the pattern and trained very well. Red line represented the predicted data and blue line represents the actual power demand.

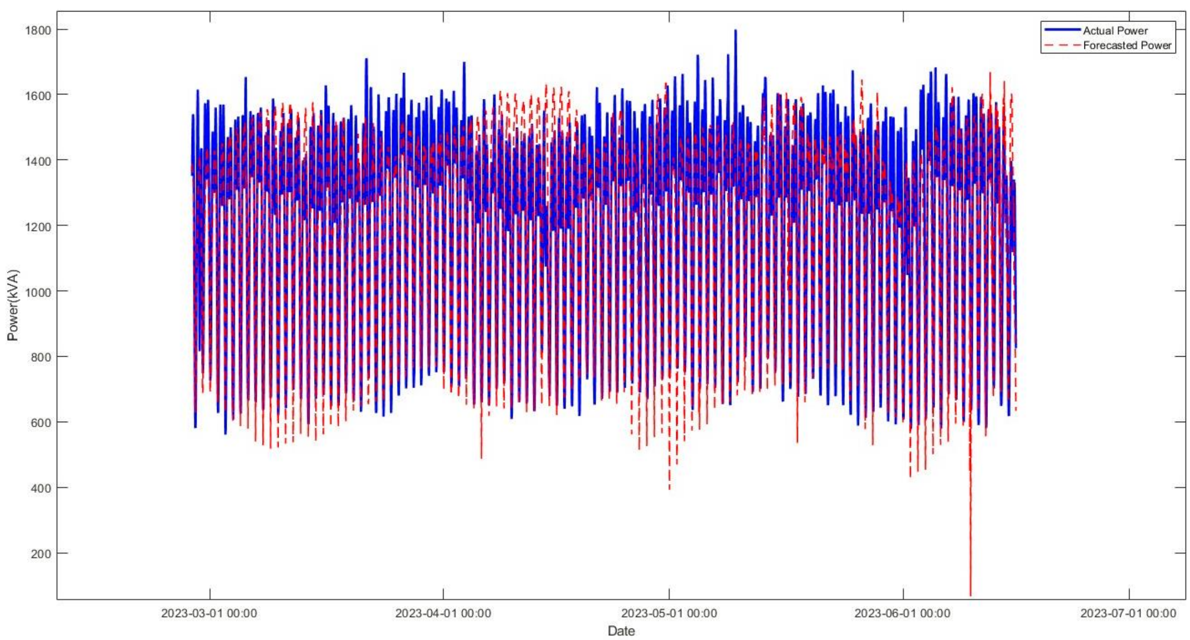

Figure 4.6: Testing graph for model 1

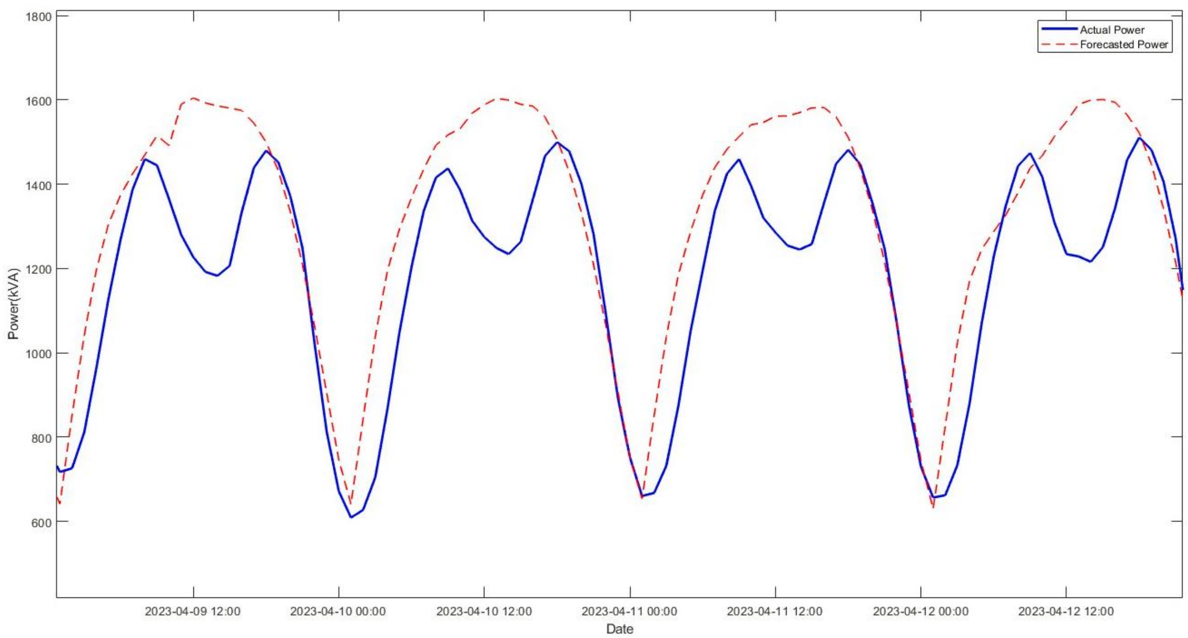

Figure 4.7: Training graph for model 1 when zoomed

Red line represented the predicted data and blue line represents the actual power demand in Figure 4.6 and Figure 4.7. In testing data also, the predicted demand almost catches the pattern of actual demand.

In model 2, there are four layers and one output layer. The first layer has activation function as ‘tansig’ which has 150 neurons. The second layer has activation function as ‘logsig’ which has 75 neurons. Third layer has activation function as ‘tansig’ which has 50 neurons. The fourth layer has activation function ‘logsig’and it has 25 neurons and last layer has activation function ‘trainscg’ which has only 1 neuron and functions as output layer. Then the model is run and fitted by taking epoch of 2150 and learning rate 0.032. The optimizer selected here is ‘adam’ as it is best optimizer used in deep learning forecasting. The training loss for model 2 is shown in Figure 4.8.

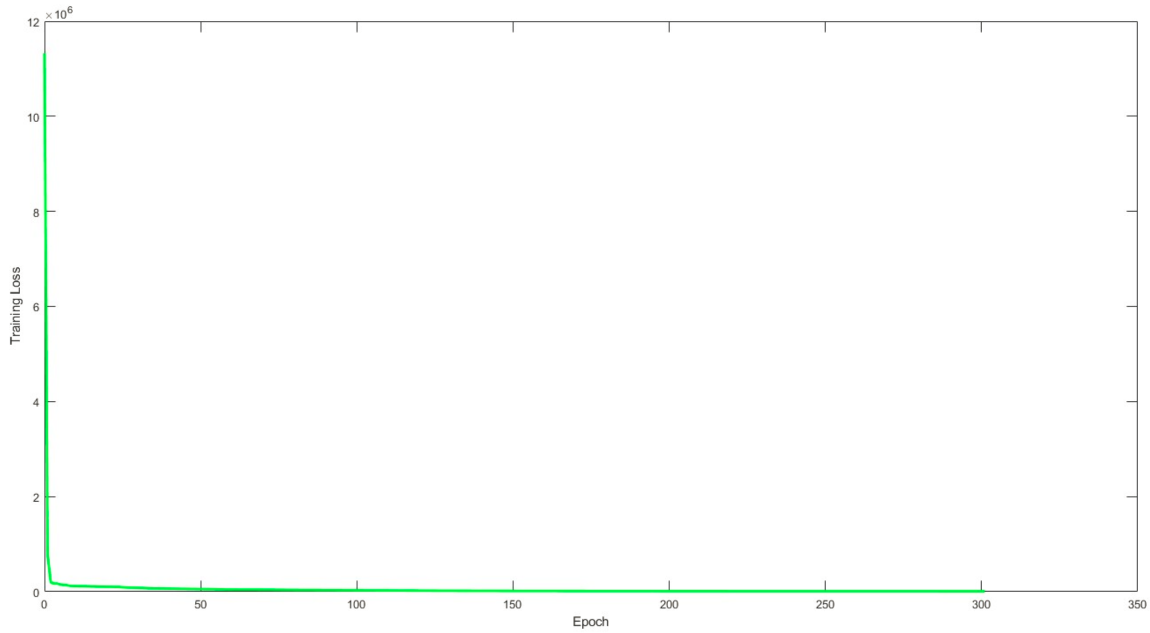

Figure 4.8: Training Loss curve for Model 2

From the Figure 4.8, it is clearly seen that loss is decreasing as epochs increases and finally settles at constant loss value. So, it is concluded that model is well trained. After the training of RNN model, it is then tested with the test dataset. The model is then used to predict the hourly power demand. Then the performance measures i.e., MAPE, RMSE and R^2 are then calculated using test and predicted dataset.

The R^2 value obtained for model 2 is 0.81. The trained dataset, and test dataset curve is then plotted which is shown in the figure below. From the figure, it is clearly seen that the actual and predicted values are close but not much accurately. The predicted values follow almost same pattern as the actual one.

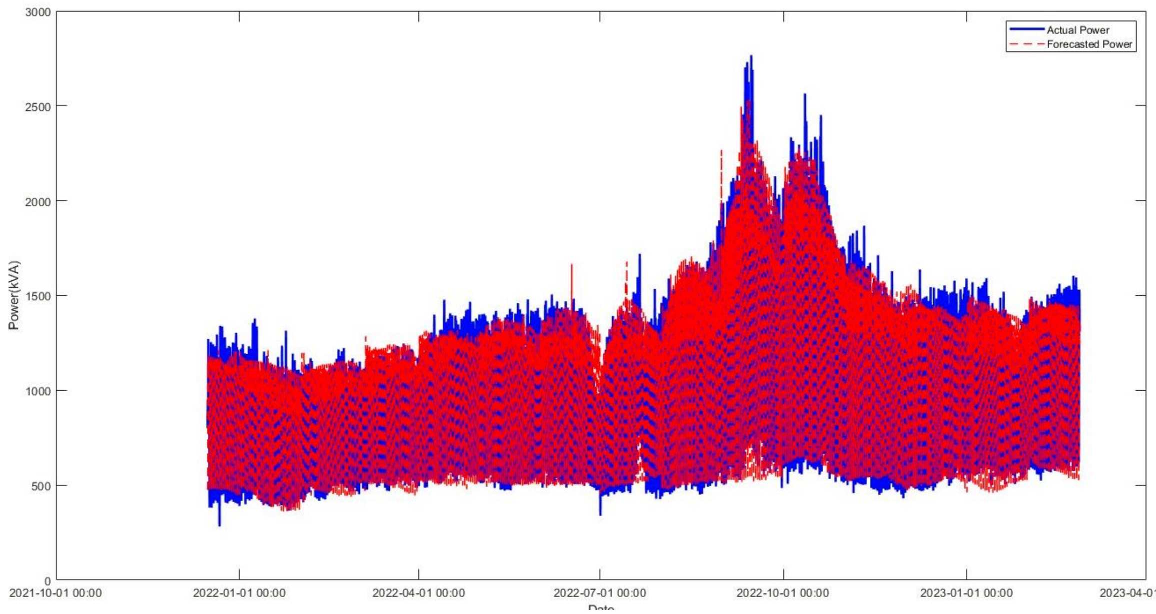

Figure 4.9: Training graph for model 2

From Figure 4.9, we can clearly see this model catches the pattern and trained very well. Red line represented the predicted data and blue line represents the actual power demand.

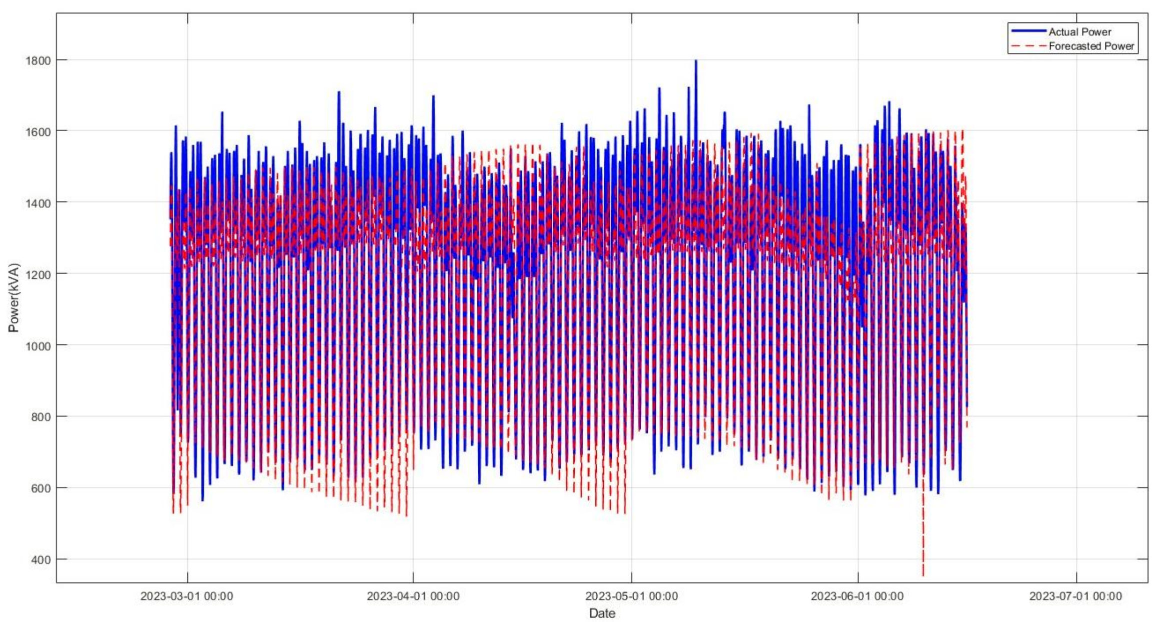

Figure 4.10: Testing graph for model 2

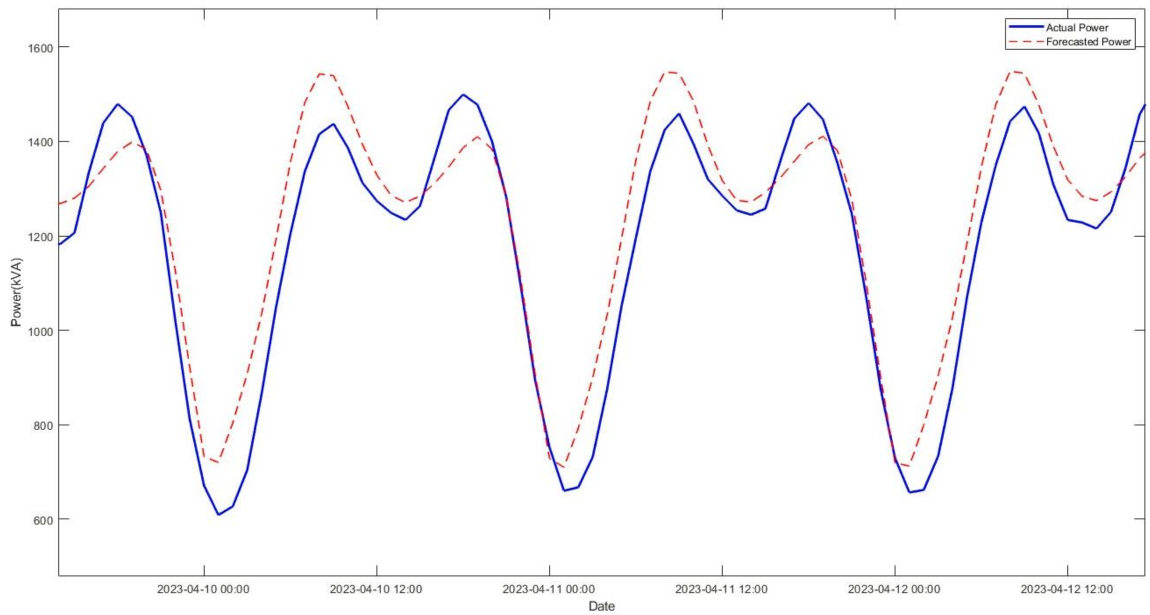

Figure 4.11: Testing graph for model 2 when zoomed

Red line represented the predicted data and blue line represents the actual power demand in Figure 4.10 and Figure 4.11. In testing data also, the predicted demand almost catches the pattern of actual demand.

In model 3, there are four layers and one output layer. The first layer has activation function as ‘tansig’ which has 30 neurons. The second layer has activation function as ‘sigmoid’ which has 25 neurons. Third layer has activation function as ‘tansig’ which has 20 neurons. The fourth layer has activation function ‘sigmoid’ and it has 15 neurons and last layer has activation function ‘purelin’ which has only 1 neuron and functions as output layer. Then the model is run and fitted by taking epoch of 2500 and learning rate 0.032. The optimizer selected here is ‘adam’ as it is best optimizer used in deep learning forecasting. The training loss for model 3 is shown in Figure 4.12.

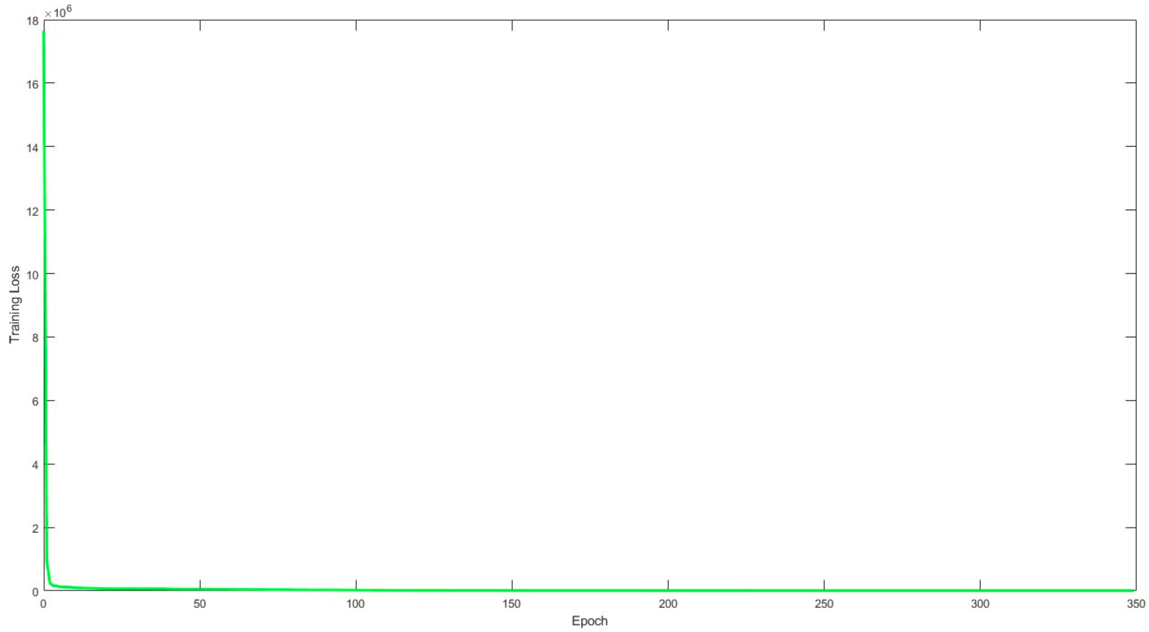

Figure 4.12: Training loss curve for model 3

From the Figure 4.12, it is clearly seen that loss is decreasing as epochs increases and finally settles at constant loss value. So, it is concluded that model is well trained. After the training of RNN model, it is then tested with the test dataset. The model is then used to predict the hourly power demand. Then the performance measures i.e., MAPE, RMSE and R^2 are then calculated using test and predicted dataset.

The R^2 value obtained for model 3 is 0.851. The trained dataset, and test dataset curve is then plotted which is shown in the figure below. From the figure, it is clearly seen that the actual and predicted values are close but not much accurately. The predicted values follow almost same pattern as the actual one.

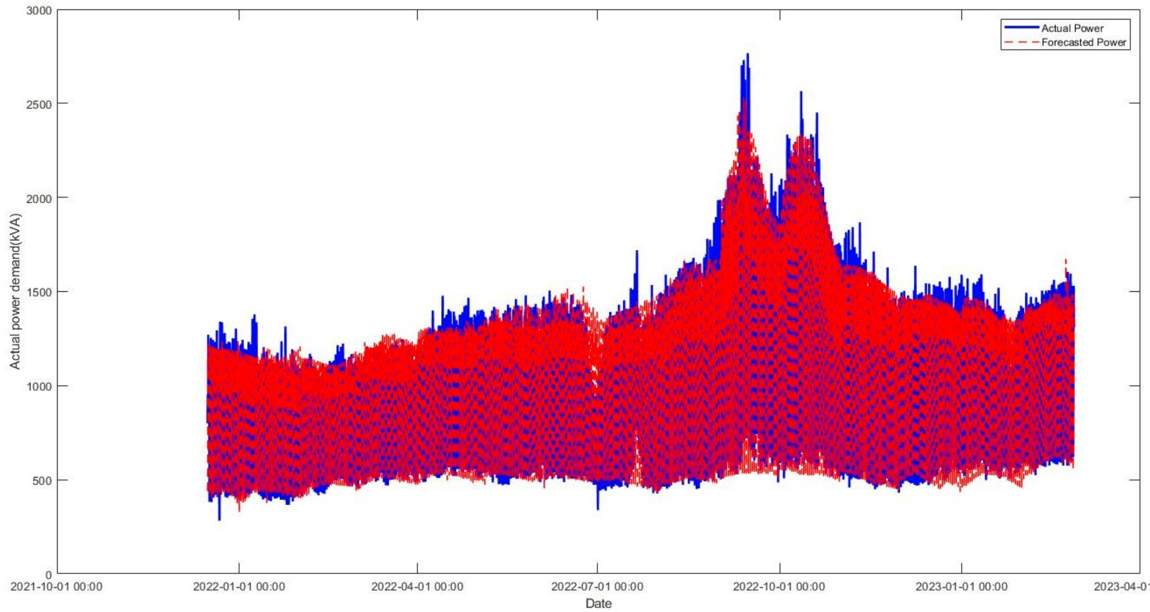

Figure 4.13: Training graph for model 3

From Figure 4.13, we can clearly see this model catches the pattern and trained very well. Red line represented the predicted data and blue line represents the actual power demand.

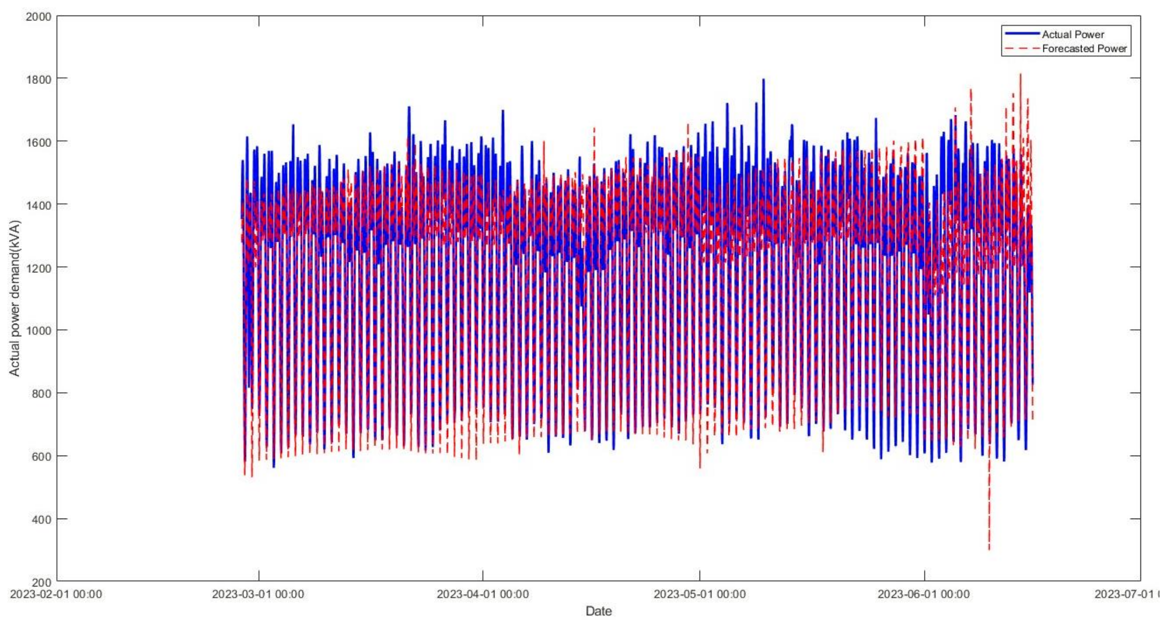

Figure 4.14: Testing graph for model 3

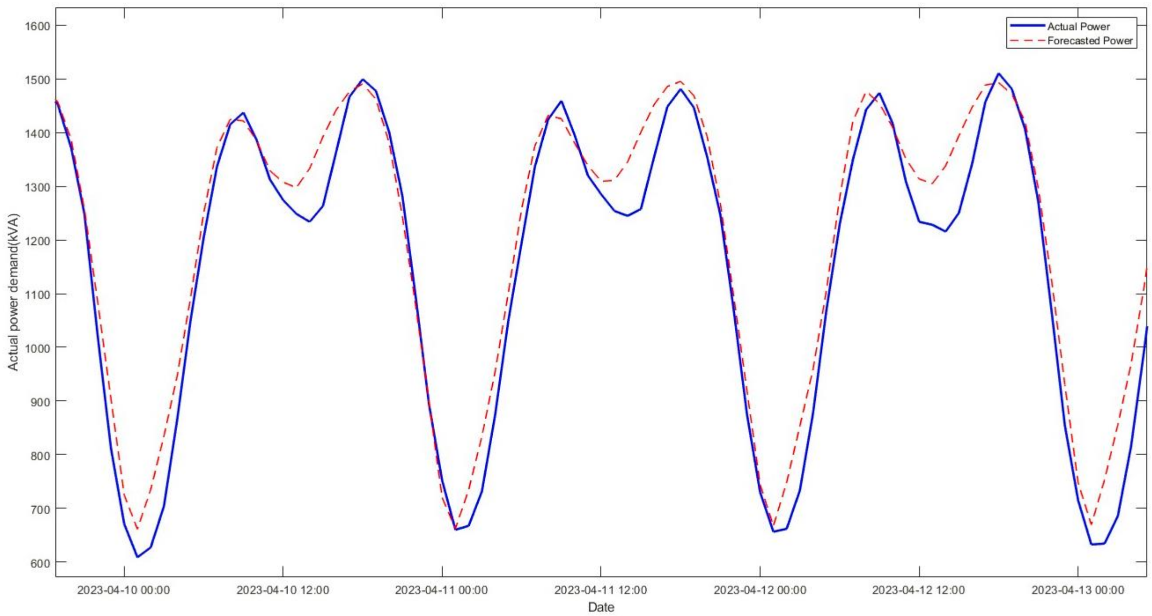

Figure 4.15: Testing graph of model 3 when zoomed

Red line represented the predicted data and blue line represents the actual power demand in Figure 4.14 and Figure 4.15. In testing data also, the predicted demand almost catches the pattern of actual demand.

In model 4, there are four layers and one output layer. The first layer has activation function as ‘tanh’ which has 30 neurons. Second layer has activation function as ‘logsig’ which has 30 neurons. Third layer has activation function as ‘tanh’ which has 20 neurons. The fourth layer has activation function ‘logsig’and it has 25 neurons and last layer has activation function ‘trainscg’ which has only 1 neuron and functions as output layer. Then the model is run and fitted by taking epoch of 2600 and learning rate 0.032. The optimizer selected here is ‘adam’ as it is best optimizer used in deep learning forecasting. The training loss for model 4 is shown in figure 4.16.

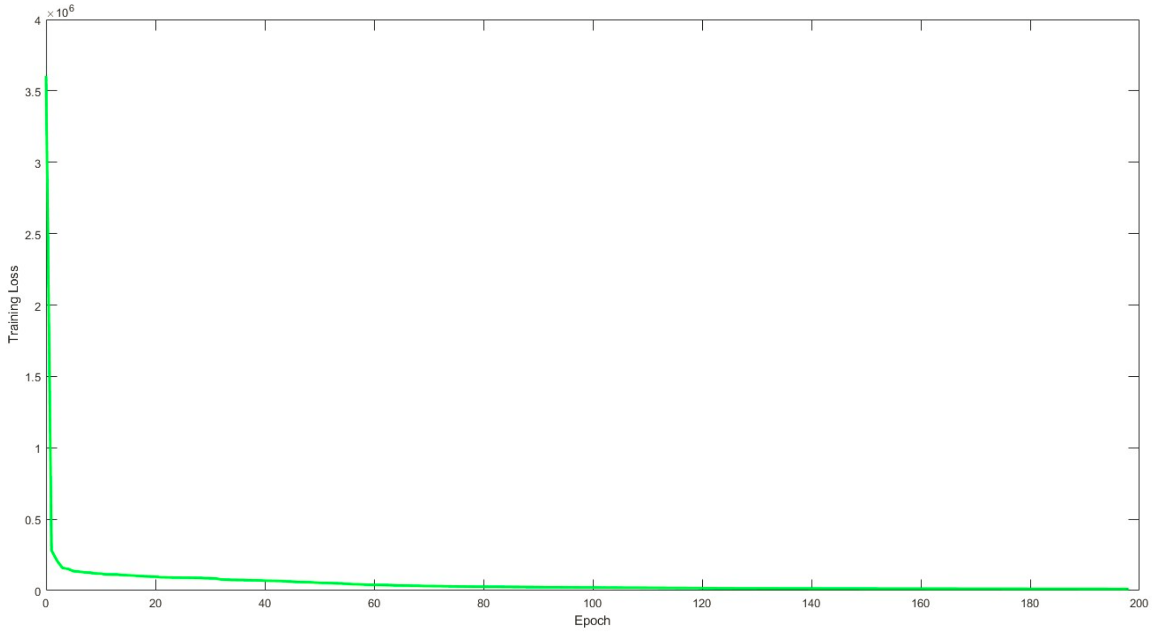

Figure 4.16: Training loss curve for model 4

From Figure 4.16, it is clearly seen that loss is decreasing as epochs increases and finally settles at constant loss value. So, it is concluded that model is well trained. After the training of RNN model, it is then tested with the test dataset. The model is then used to predict the hourly power demand. Then the performance measures i.e., MAPE, RMSE and R^2 are then calculated using test and predicted dataset.

The R^2 value obtained for model 4 is 0.829. The trained dataset, and test dataset curve is then plotted which is shown in the figure below. From the figure, it is clearly seen that the actual and predicted values are close but not much accurately. The predicted values follow almost same pattern as the actual one.

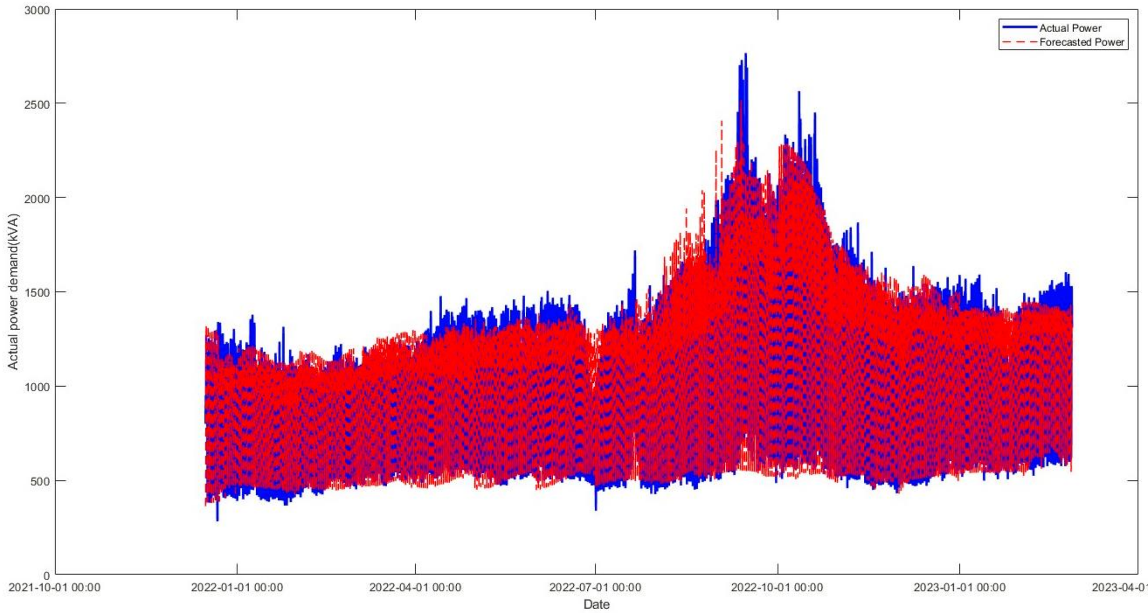

Figure 4.17: Training graph for model 4

From Figure 4.17 we can clearly see this model catches the pattern and trained very well. Red line represented the predicted data and blue line represents the actual power demand.

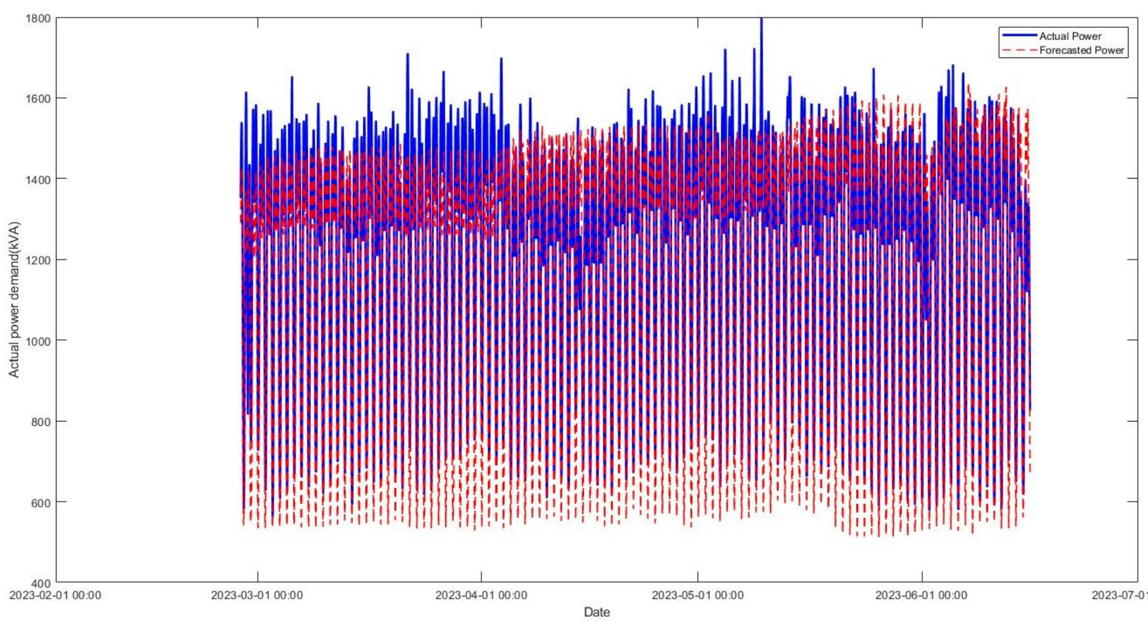

Figure 4.18: Testing graph of model 4

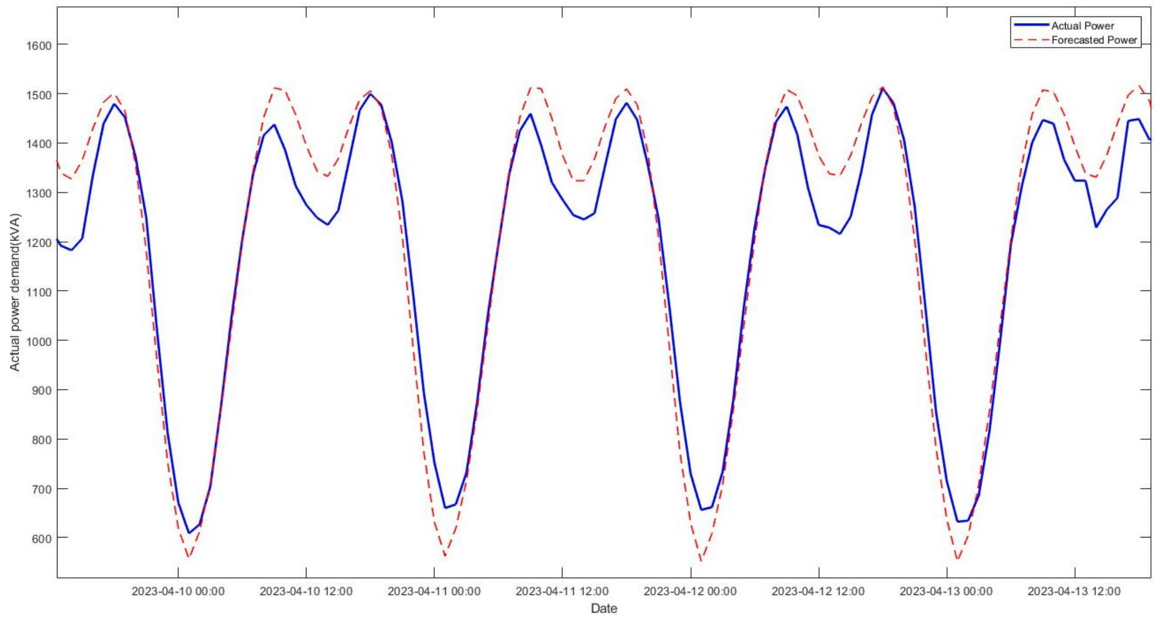

Figure 4.19: Testing graph of model 4 when zoomed

Red line represented the predicted data and blue line represents the actual power demand in Figure 4.18 and Figure 4.19. In testing data also, the predicted demand almost catches the pattern of actual demand.

In model 5, there are four layers and one output layer. The first layer has activation function as ‘tansig’ which has 25 neurons. The second layer has activation function as ‘logsig’ which has 25 neurons. Third layer has activation function as ‘tansig’ which has 20 neurons. The fourth layer has activation function ‘logsig’ and it has 15 neurons and last layer has activation function ‘purelin’ which has only 1 neuron and functions as output layer. Then the model is run and fitted by taking epoch of 4800 and learning rate 0.032. The optimizer selected here is ‘adam’ as it is best optimizer used in deep learning forecasting. The training loss for model 5 is shown in figure 4.20.

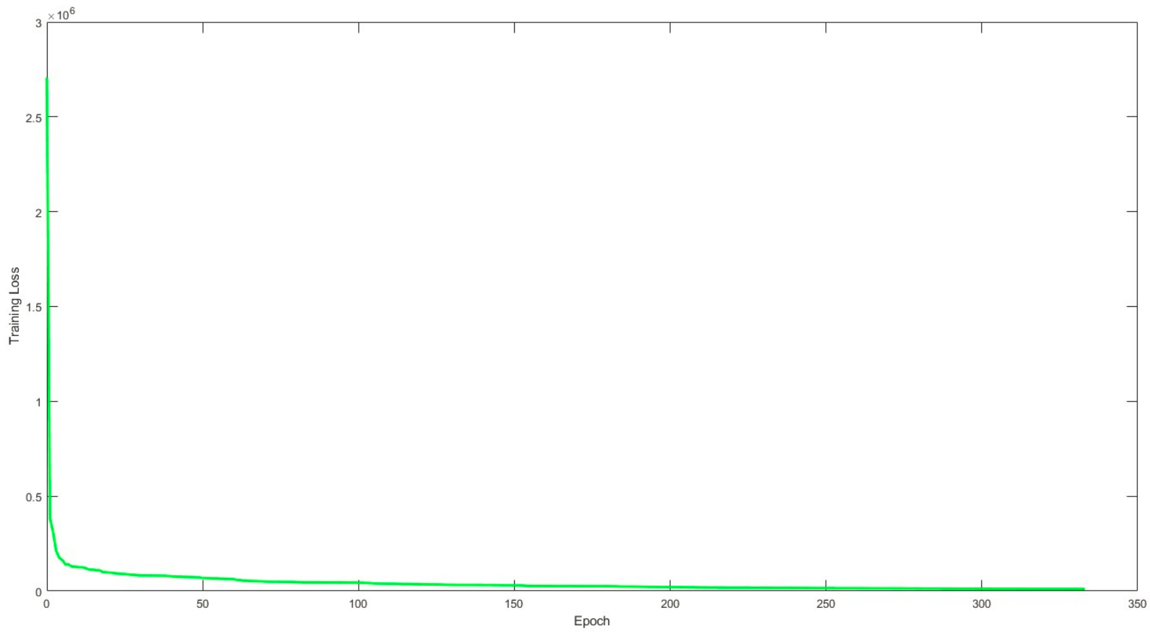

Figure 4.20: Training loss curve of model 5

From figure 4.20, it is clearly seen that loss is decreasing as epochs increases and finally settles at constant loss value. So, it is concluded that model is well trained. After the training of RNN model, it is then tested with the test dataset. The model is then used to predict the hourly power demand. Then the performance measures i.e., MAPE, RMSE and R^2 are then calculated using test and predicted dataset.

The R^2 value obtained for model 5 is 0.876. The trained dataset, and test dataset curve is then plotted which is shown in the figure below. From the figure, it is clearly seen that the actual and predicted values are close but not much accurately. The predicted values follow almost same pattern as the actual one.

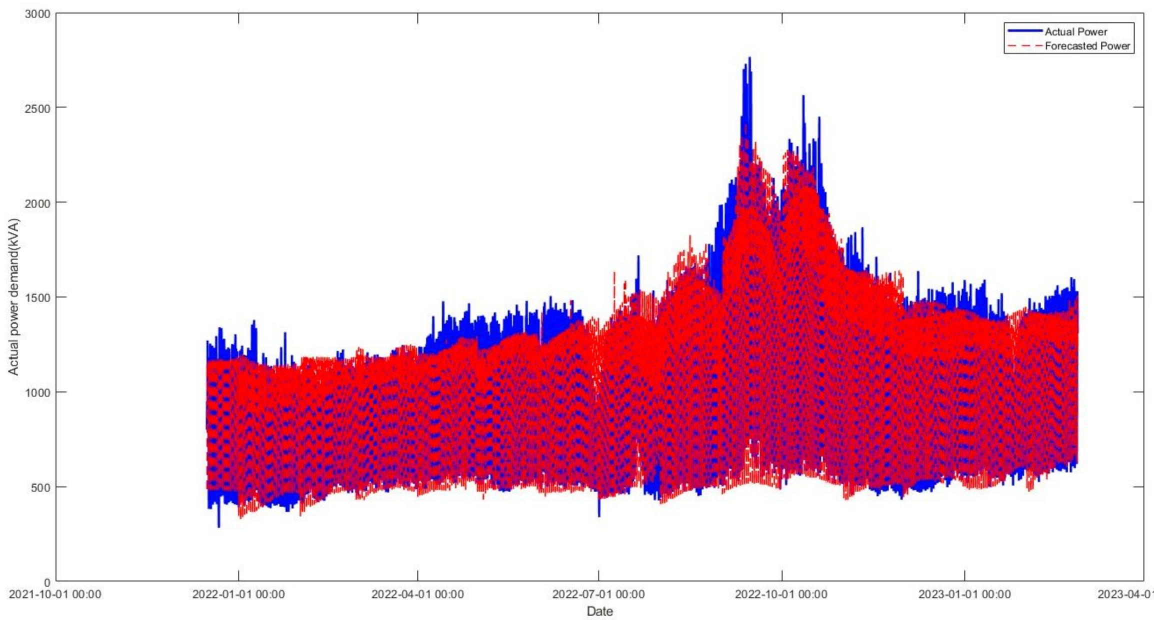

Figure 4.21: Training graph of model 5

From Figure 4.21, we can clearly see this model catches the pattern and trained very well. Red line represented the predicted data and blue line represents the actual power demand.

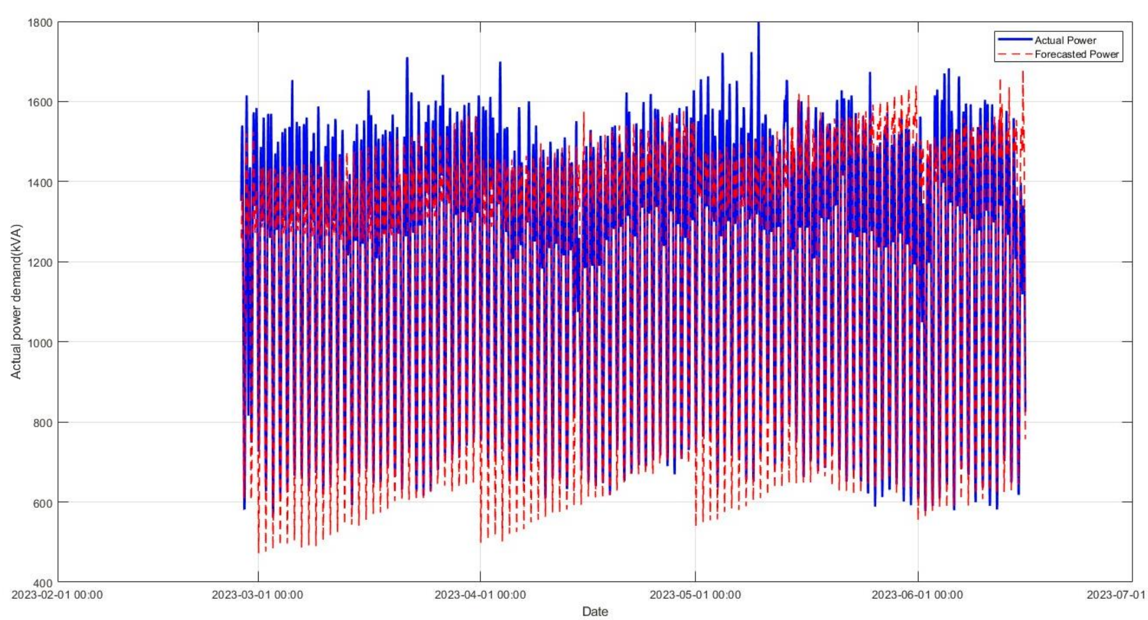

Figure 4.22: Testing graph of model 5

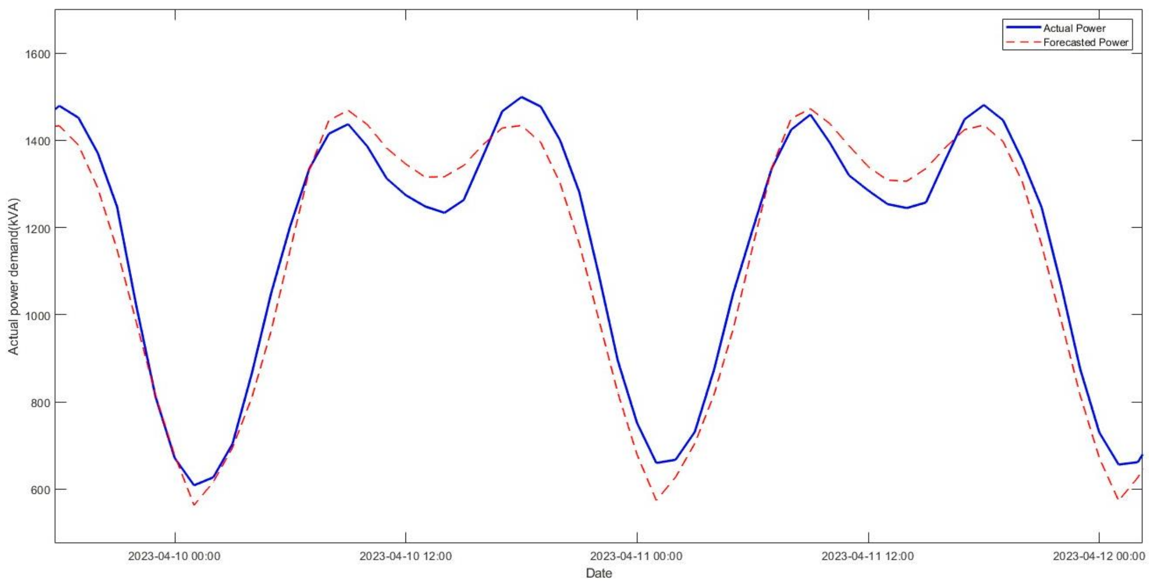

Figure 4.23: Testing graph of model 5 when zoomed

Red line represented the predicted data and blue line represents the actual power demand in Figure 4.22 and Figure 4.23. In testing data also, the predicted demand almost catches the pattern of actual demand.

In model 6, there are three layers and one output layer. The first layer has activation function as 'tansig' which has 15 neurons. The second layer has activation function as 'logsig' which has 15 neurons. Third layer has activation function as 'tansig' which has 15 neurons and last layer has activation function 'Maxout' which has only 1 neuron and functions as output layer. Then the model is run and fitted by taking epoch of 4850 and learning rate 0.032. The optimizer selected here is 'adam' as it is best optimizer used in deep learning forecasting. The training loss for model 6 is shown in figure 4.24.

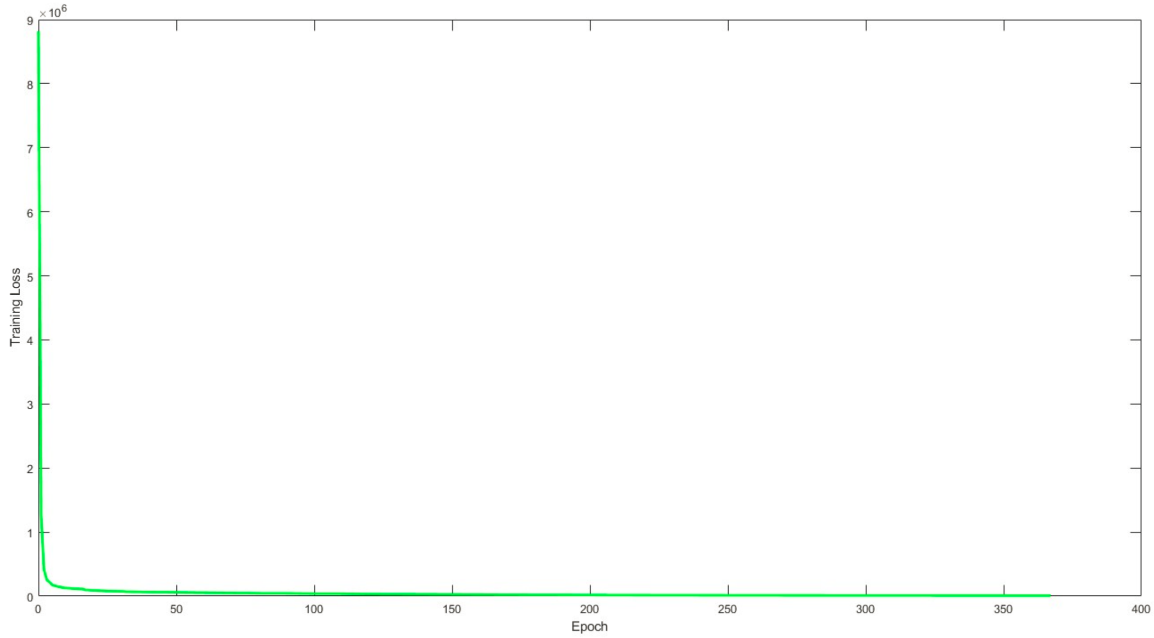

Figure 4.24: Training loss curve of model 6

From Figure 4.24, it is clearly seen that loss is decreasing as epochs increases and finally settles at constant loss value. So, it is concluded that model is well trained. After the training of RNN model, it is then tested with the test dataset. The model is then used to predict the hourly power demand. Then the performance measures i.e., MAPE, RMSE and R^2 are then calculated using test and predicted dataset.

The R^2 value obtained for model 6 is 0.84. The trained dataset, and test dataset curve is then plotted which is shown in the figure below. From the figure, it is clearly seen that the actual and predicted values are close but not much accurately. The predicted values follow almost same pattern as the actual one.

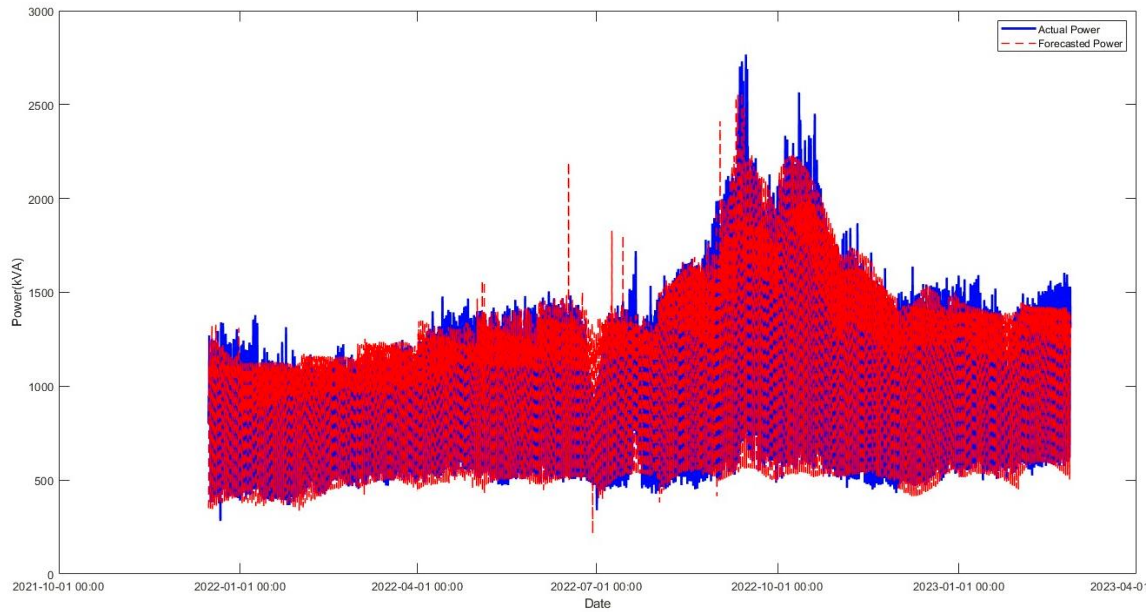

Figure 4.25: Training graph of model 6

From Figure 4.25, we can clearly see this model catches the pattern and trained very well. Red line represented the predicted data and blue line represents the actual power demand.

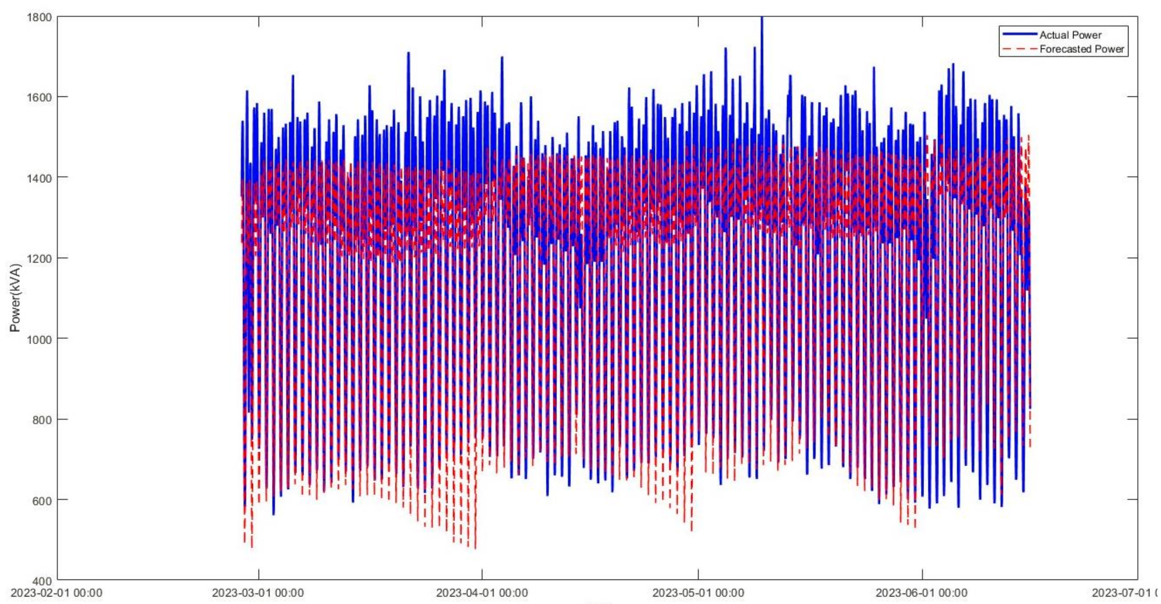

Figure 4.26: Testing graph of model 6

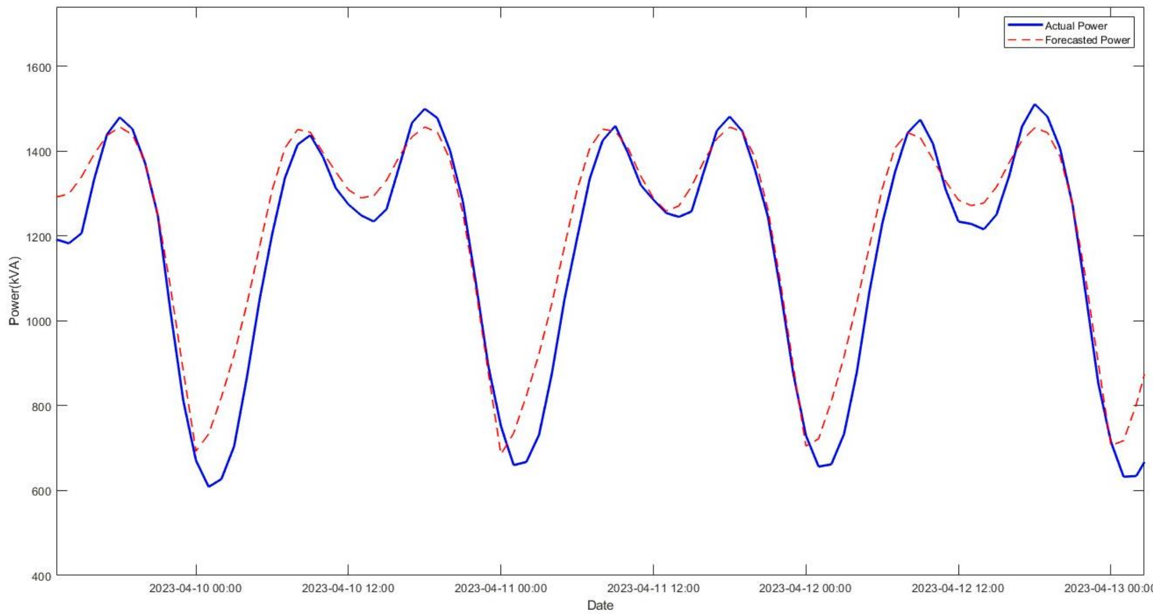

Figure 4.27: Testing graph of model 6 when zoomed

Red line represented the predicted data and blue line represents the actual power demand in Figure 4.26 and Figure 4.27. In testing data also, the predicted demand almost catches the pattern of actual demand.

Among all RNN models i.e., model 1, model 2, model 3, model 4, model 5 and model 6, the model 5 gives higher R^2 i.e., 0.876 value with less MAPE i.e., 4.35% and low RMSE i.e., 69.03 kVA. It means model fitted bitterly than other models.so, prediction of model by using model 5 giver best result with less errors. Hence, we choose model 5 to predict the hourly demand of Gothatar feeder, NEA.

The performance measure i.e., R^2 for all the models is shown in histogram form in the figure 4.28.

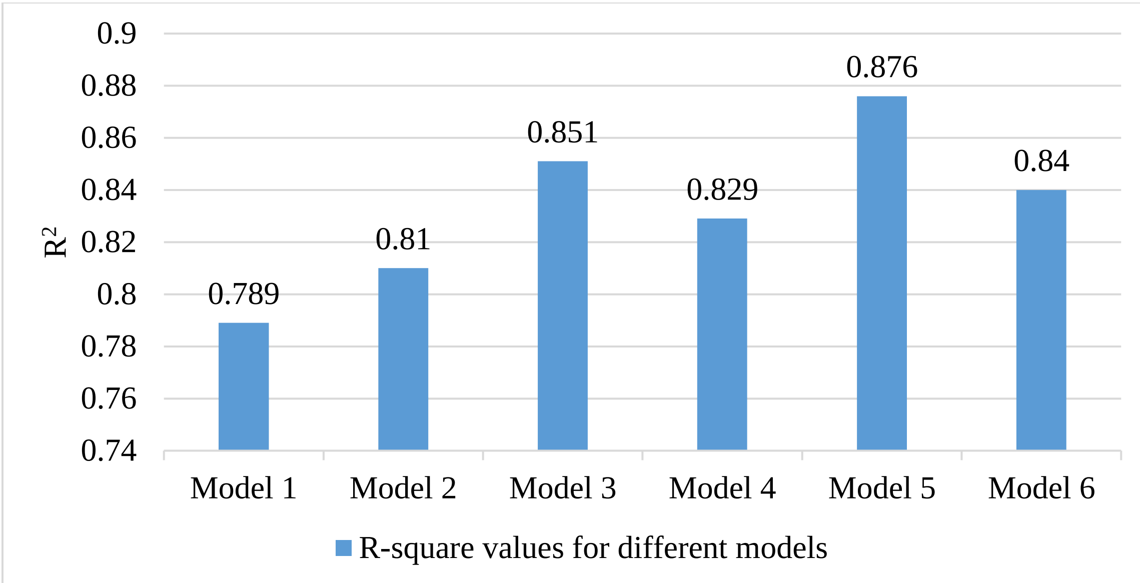

Figure 4.28: Comparison of R^2 values of all Models

Hence, from above figure 4.28, we can say that model 5 is the best one for forecasting of hourly demand of Gothatar feeder, NEA.

4.4 Results of Traditional Approaches

Apart from the RNN model, forecasting is also performed with the help of other time series models for comparing their accuracies with RNN model output. Following are the time series models that is used to forecast the hourly demand of Gothatar feeder, NEA:

4.4.1 Single Exponential Smoothing (SES) Method

Single Exponential Smoothing Method is considered traditional method and which is used for the time series forecasting. The hourly demand of Gothatar, NEA is predicted using single exponential smoothing. The hourly demand is predicted using MS-Excel SOLVER tool. The value of smoothing factor i.e., alpha (α) is optimized using SOLVER by minimizing the mean squared error. The value of α obtained after running SOLVER is 1. The actual and predicted demand curve obtained using SES method is shown in figure 4.29.

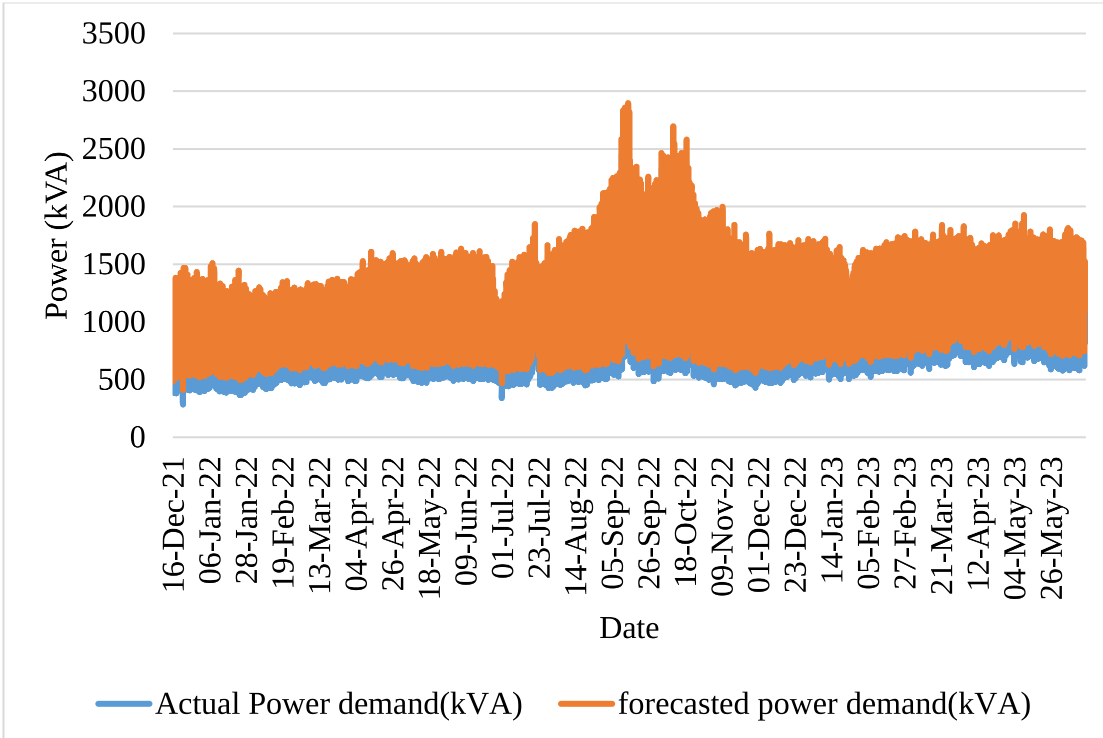

Figure 4.29: Actual vs forecasted power demand using Exponential smoothing

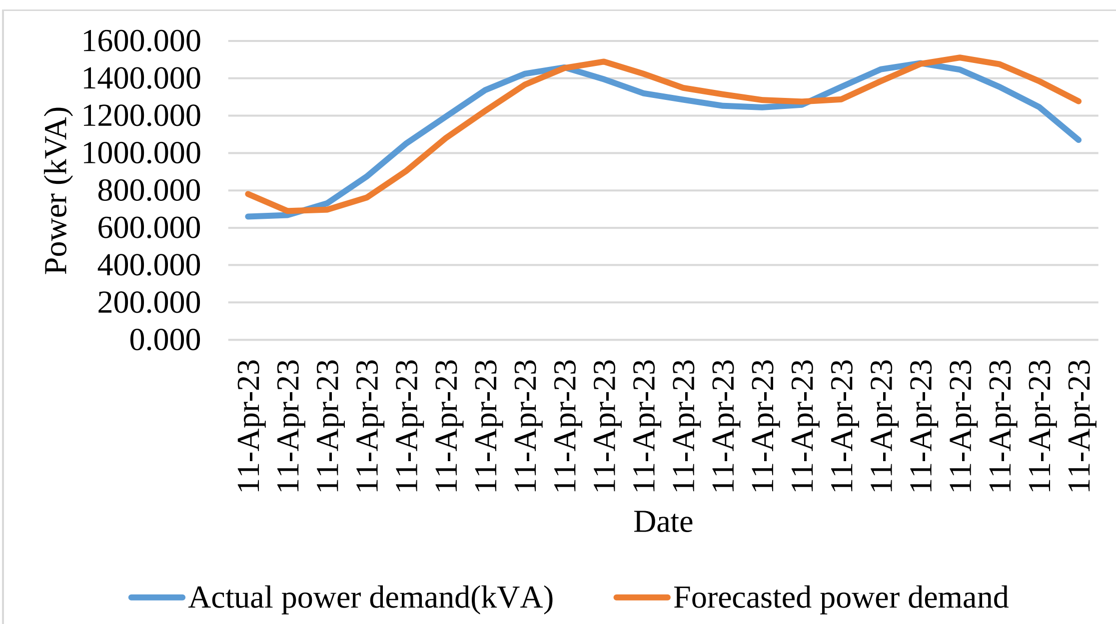

Figure 4.30: Actual vs forecasted power demand using ES for 24 hours

In the above Figure 4.29 and Figure 4.30, actual demand is shown by blue color whereas the predicted one is shown by orange color. From the figure above, it is clearly seen that the predicted demand value follows the same pattern as actual one but not that much close to actual demand value. The performance measures i.e., $R^{2,}$ MAPE and RMSE for SES method is expressed in table 4.2.

Table 4.2: Performance measure of SES Method

Performance Measures	**SES Method**
R^2	0.6098
MAPE	15.421%
RMSE	188.033 kVA

The R^2 value obtained for SES method is 0.6098 which symbolizes that the SES method is 60.98 % accurate for forecasting of hourly power demand. The MAPE for SES method obtained is 15.421%. RMSE for SES method obtained is 188.033 kVA. The actual and predicted hourly demand for day 2023/04/11 which is used for comparison with other methods is shown in table 4.3.

Table 4.3: Actual and predicted hourly power demand using SES

Date	**Time**	**Actual Hourly Load (kVA)**	**Predicted Hourly Load using SES (kVA)**
2023/04/11	06:00 AM	1195	1030

The predicted hourly demand for day 2023/04/11 is 1030 kVA which has around 165 kVA deviation with the actual demand of that day.

4.4.2 Double Exponential Smoothing (DES) Method

Double Exponential Smoothing method is considered as another traditional method and is used to forecast the time series data. After implementation of trend part in SES method, it becomes double exponential smoothing method. The hourly demand Gothatar feeder, NEA is predicted also using double exponential smoothing to see if this method catches some trend in dataset and predict more better hourly demand. The demand is predicted using MS-Excel SOLVER tool. The value of data smoothing factor i.e., alpha(α) and trend smoothing factor beta(β) are optimized using SOLVER by minimizing the mean squared error. The value of α obtained after running SOLVER is 0.645 and that of β obtained is 1. i.e., The actual and predicted demand curve obtained using DES method is shown in figure 4.31.

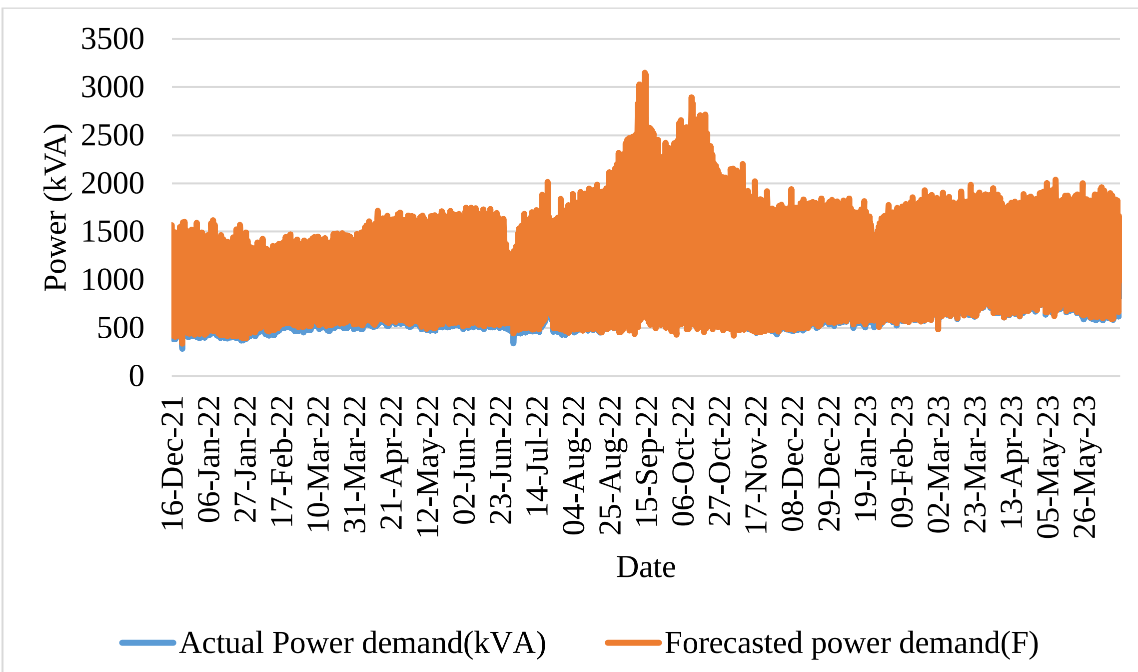

Figure 4.31: Actual vs forecasted demand by Double exponential smoothing

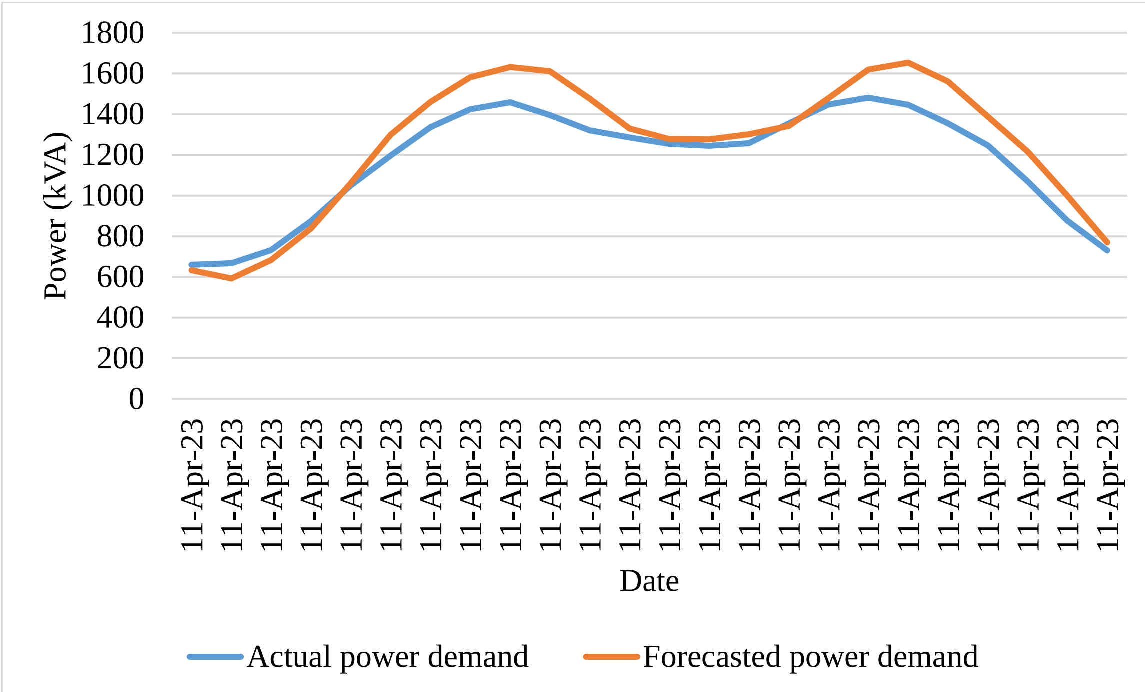

Figure 4.32: Actual vs forecasted demand using DES for 24 hours

In the above Figure 4.31 and Figure 4.32, actual demand is shown by blue color whereas the predicted one is shown by orange color. From the figure above, it is clearly seen that the predicted demand value follows the same pattern as actual one but not that much close to actual demand value. The performance measures i.e., R^2, MAPE and RMSE for SES method is expressed in table 4.4.

Table 4.4: Performance measure of DES method

Performance Measures	**DES Method**
R^2	0.618
MAPE	13.31 %
RMSE	181.06 kVA

The R^2 value obtained for DES method is 0.618 which symbolizes that the DES method is 61.8 % accurate for forecasting of demand. The RMSE for DES method obtained is 181.06 kVA. The actual and predicted demand for day 2023/04/11 which is used for comparison with other methods is shown in table 4.5.

Table 4.5: Actual and predicted load using DES

Date	**Time**	**Actual Hourly Load (kVA)**	**Predicted Hourly Load using SES Method (kVA)**
2023/04/11	06:00 AM	1195	1298

The predicted demand for day 2023/04/11 obtained using DES method is 1298 kVA which has around 103 kVA deviation with the actual demand of that day.

4.4.3 Holt-Winter's Multiplicative Seasonal Effect Model

Holt-Winter's multiplicative seasonal effect model is another traditional method used for time series forecasting. In Holt-winter's model, there is addition of multiplicative seasonality factor. After visualizing the actual hourly demand curve of Gothatar feeder, NEA, there is seen some multiplicative seasonality. Here the monthly seasonality is taken. The hourly demand of Gothatar feeder, NEA is predicted also using Holt-Winter's multiplicative seasonal effect method to see if this method catches seasonality in dataset and predict more better hourly demand. The hourly demand is predicted using MS-Excel SOLVER tool. The value of smoothing factors i.e., alpha(α), beta(β) and gamma(γ) are optimized using SOLVER by minimizing the MSE. The value of α, β and γ obtained after running SOLVER are 1, 0.00145 and 0.85615. The actual and predicted hourly demand curve obtained using Holt-Winter's multiplicative seasonal effect method is shown in figure 4.33.

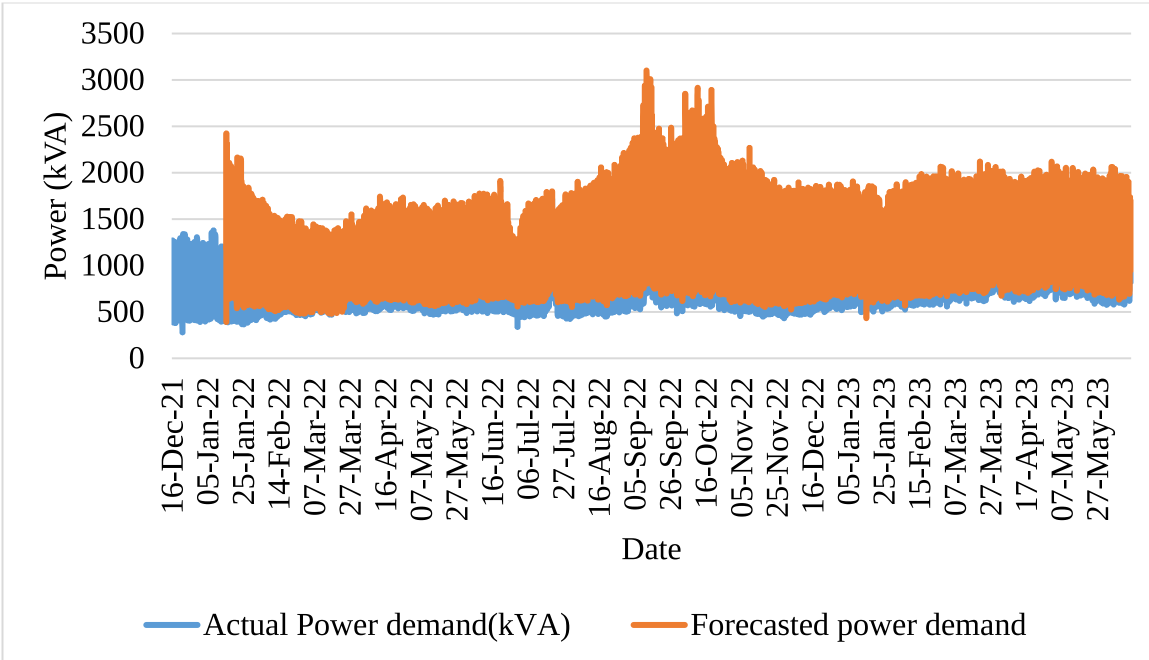

Figure 4.33: Actual vs forecasted load using Holt-winter's method

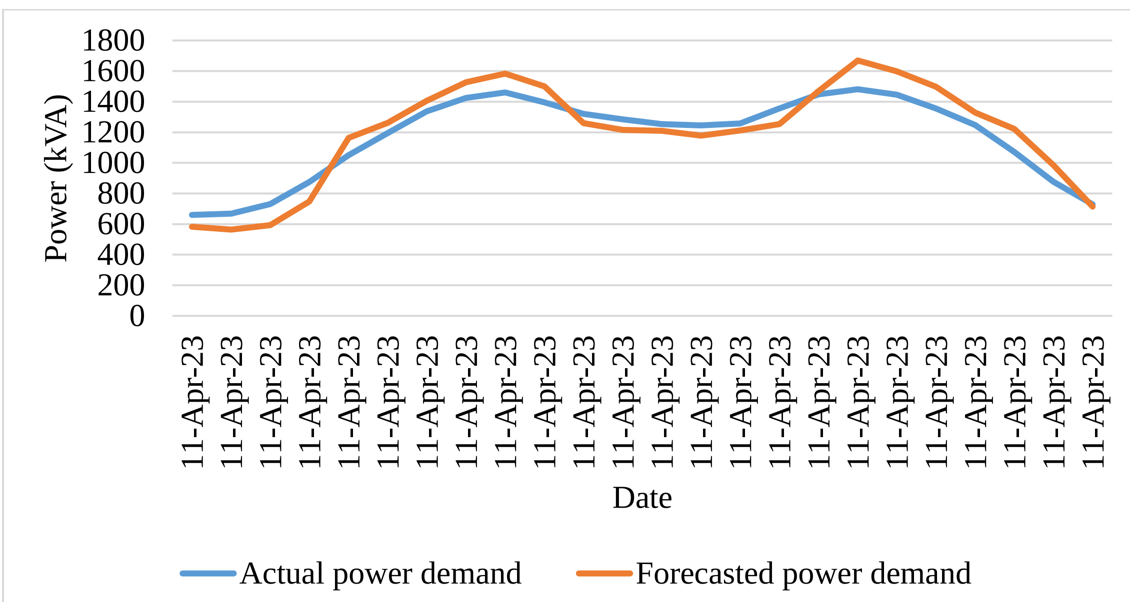

Figure 4.34: Actual vs forecasted load using Holt-winter's method for 24 hours

In the above Figure 4.33 and Figure 4.34, actual demand is shown by blue color whereas the predicted one is shown by orange color. From the figure above, it is clearly seen that the predicted hourly demand value follows the same pattern as actual one but not that much close to actual hourly demand value. The performance measures i.e., $R^{2,}$ MAPE and RMSE for Holt-Winter's method is expressed in table 4.6.

Table 4.6: Performance measure of Holt-Winter's method

Performance Measures	**Holt-Winter's Method**
R^2	0.634
MAPE	11.502 %
RMSE	169.759 kVA

The R^2 value obtained for Holt-Winter's Method is 0.634 which symbolizes that the Holt-Winter's Method is 63.4 % accurate for forecasting of hourly demand of Gothatar feeder, NEA. The RMSE for Holt-Winter's Method obtained is 169.759 kVA. The actual and predicted hourly demand using Holt-Winter's method for day 2023/04/11 which is used for comparison with other methods is shown in table 4.7.

Table 4.7: Actual and predicted hourly load using Holt-winter's method

Date	**Time**	**Actual Demand (kVA)**	**Predicted Hourly Demand using Holt-Winter's Method (kVA)**
2023/04/11	06:00 AM	1195	1261

The predicted hourly demand for day 2023/04/11 obtained using Holt-Winter's method is 1261 kVA which has around 66 kVA deviation with the actual hourly demand of that day.

4.5 Comparison among All Methods

To compare the forecasted demand of the same day from all the methods are presented in Tabular form. The performance measures of all methods are presented in Table 4.8.

Table 4.8: Comparison between performance measure of all methods

Validation date	Actual hourly Demand (kVA)	Predicted hourly Demand using RNN (kVA)	Predicted hourly Demand using SES (kVA)	Predicted hourly Demand using DES (kVA)	Predicted hourly Demand using Holt-Winter's Method (kVA)
2023/04/11	1195	1155	1030	1298	1261

Table 4.9: Comparison between performance measure of all methods

Performance Measures	RNN Method	SES Method	DES Method	Holt-Winter's Method
R^2	0.876	0.6098	0.618	0.634
RMSE	69.03 kVA	188.033kVA	181.066	169.759 kVA
MAPE	4.35 %	15.421 %	13.31 %	11.502 %

The predicted hourly demand obtained using SES, DES and Holt-Winter's method for day 2023/04/11 are 1030 kVA, 1298 kVA and 1261 kVA which has higher deviation with actual load than that obtained in case of RNN method which has predicted hourly demand of 1155 kVA. Also, the R^2 values for SES, DES and Holt-Winter's method are 0.6098, 0.618 and 0.634 respectively which is smaller than the R^2 obtained from RNN method i.e., 0.876. The RMSE values obtained using SES, DES and Holt-Winter's method are 188.033 kVA, 181.066 kVA and 169.759 kVA respectively which is lot higher than that obtained in case of RNN method i.e., 69.03 kVA.

CHAPTER 5 : CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The model was formed with Recurrent Neural Network algorithm in 'MATLAB 2023' through coding and trained with very large dataset by assuming different input features that has effect on the hourly electricity demand of Gothatar feeder, NEA and selected the best Recurrent Neural Network model for forecasting of hourly power demand.

The hourly power demand of Gothatar feeder, NEA, was also forecasted by other time series methods i.e., Single Exponential Smoothing, Double Exponential Smoothing and Holt-Winter's method.

The trained model forecasted hourly demand of Gothatar feeder, NEA, which was validated with actual demand of Gothatar feeder, NEA. In addition, the prediction of demand was also, done with the help of other time series methods i.e., Single Exponential Smoothing, Double Exponential Smoothing and Holt-Winter's method whose performance measures were compared with Recurrent Neural Network model. The Recurrent Neural Network model is found to be the best forecasting method when the performance was compared in terms of performance measures with a R^2 having 0.876, RMSE having 69.03 kVA and MAPE having 4.35%. While the R^2, RMSE and MAPE were 0.609, 188.033 kVA and 15.421%, 0.618, 181.066 kVA and 13.31% and 0.634, 169.75 kVA and 11.502% respectively for Single Exponential Smoothing, Double Exponential Smoothing and Holt-Winter's method.

Thus, the Recurrent Neural Network (RNN) method was found as the best among all the methods for forecasting of hourly demand showing the robustness of the model with non-linear demand data.

5.2 Recommendation

i. It is recommended that the forecasting using Recurrent Neural Network can be carried out by taking humidity, GDP, population growth, seasonal parameters, holidays etc. can also use as input features in addition to the input features to forecast the short-term demand.

ii. Also, there is window for forecasting by taking different features for same model and concluding the best features for the forecasting. Furthermore, the forecasting can be done with other models and result can be compared with result of this research to validate best model.

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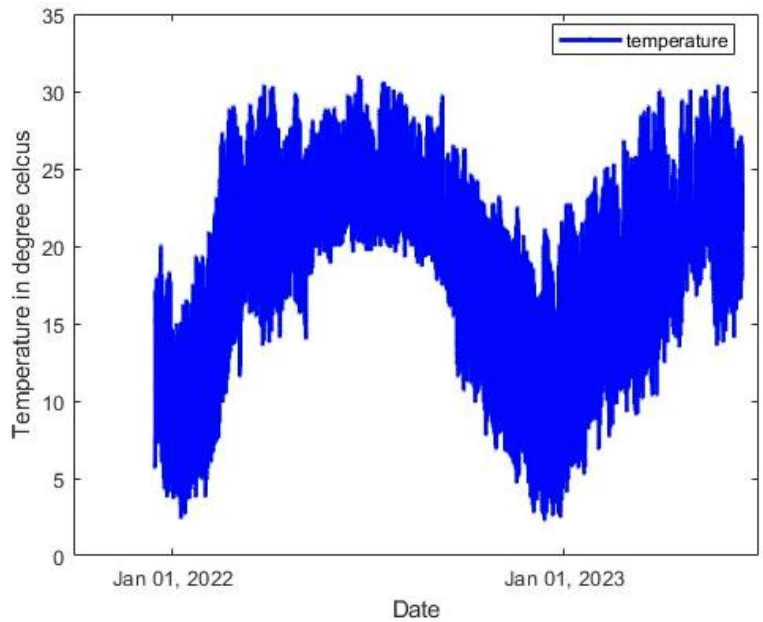
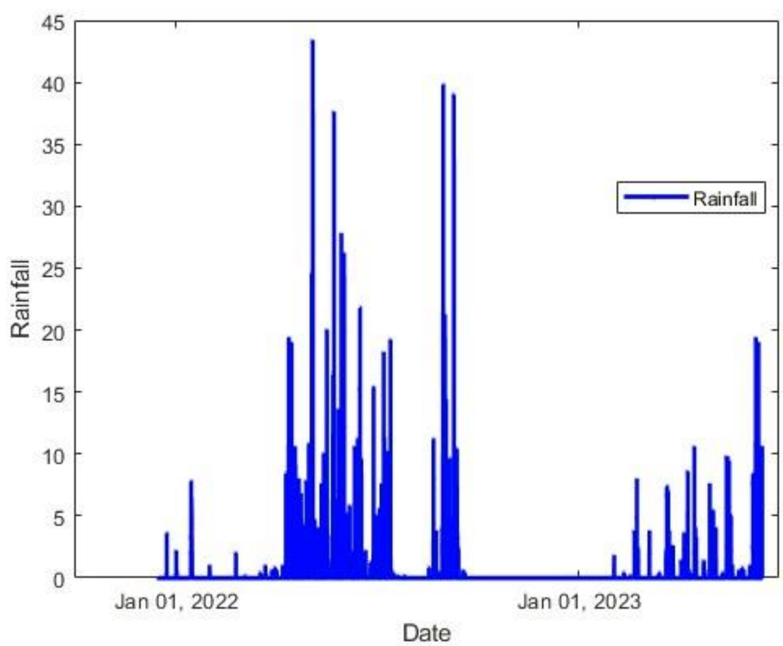
APPENDIX

A. Temperature and Rainfall Graph of last 18 months is shown below:

Temperature Graph of last 18 months is shown below:



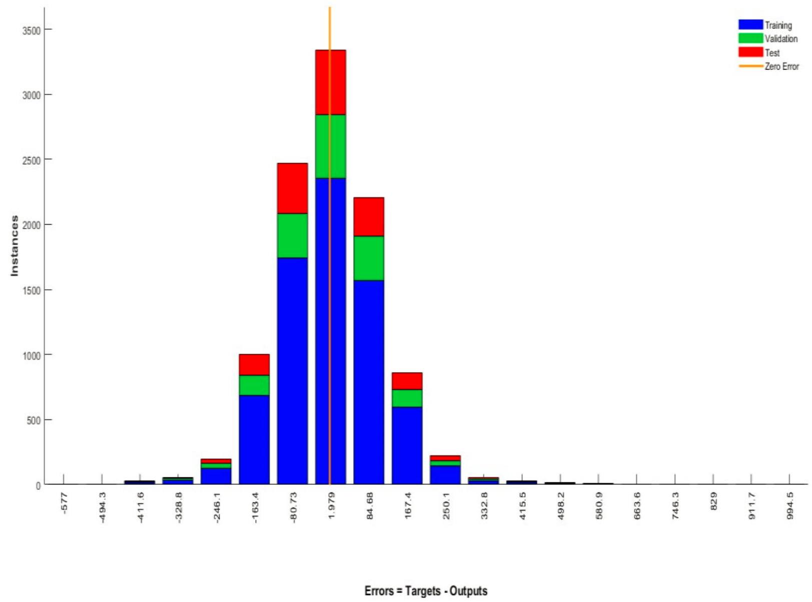
Rainfall Graph of last 18 months is shown below:



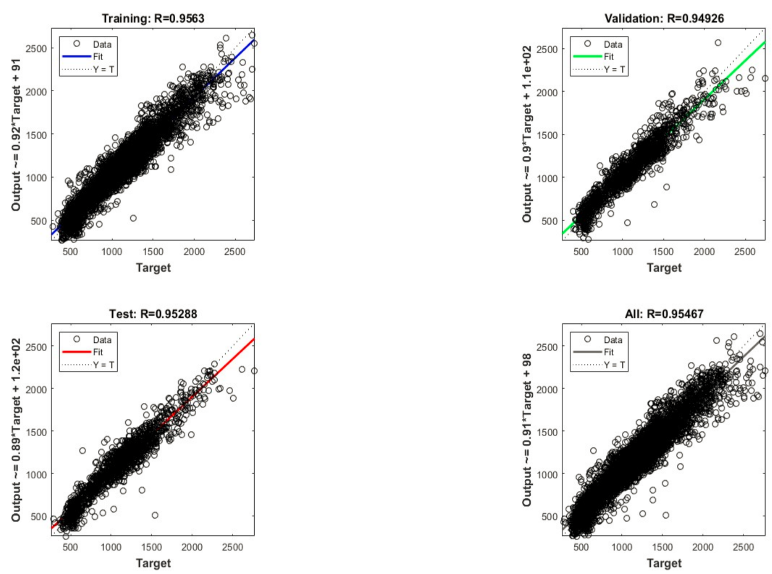
B. Loss histogram, Regression diagram of different models:

1. Model 1:

Error histogram of mode 1 is shown below:

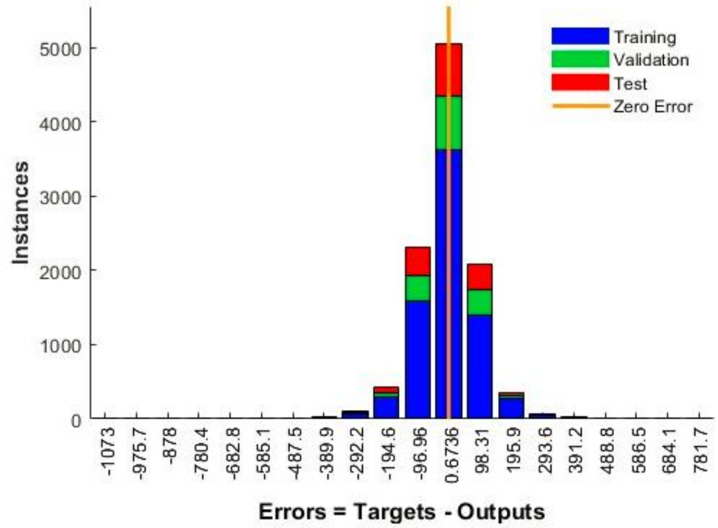


Regression graph for model 1:

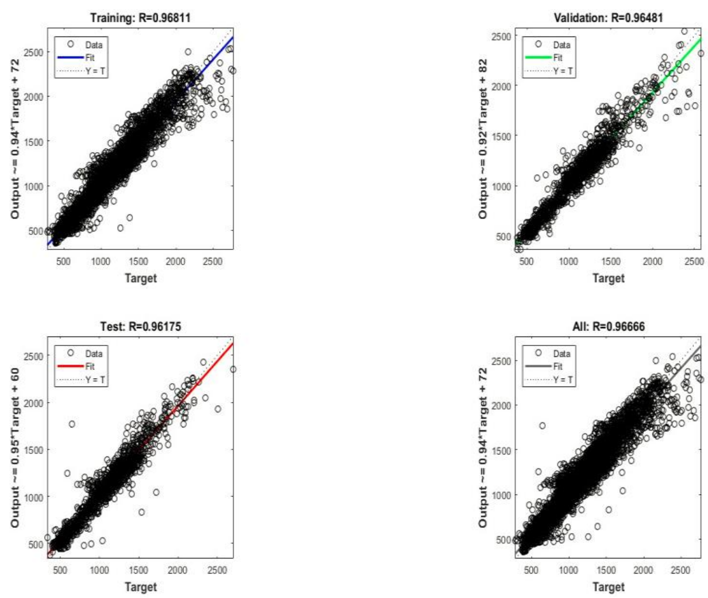


2. Model 2:

Error histogram of model 2 is shown below:

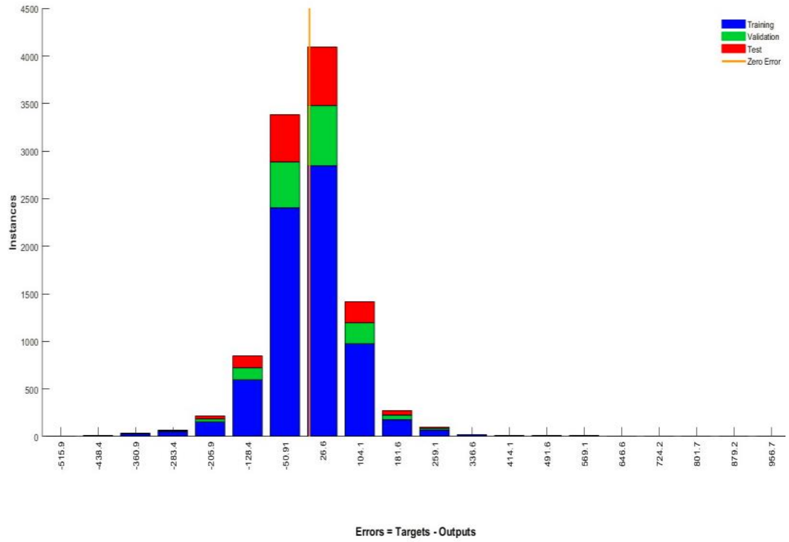


Regression graph of model 2

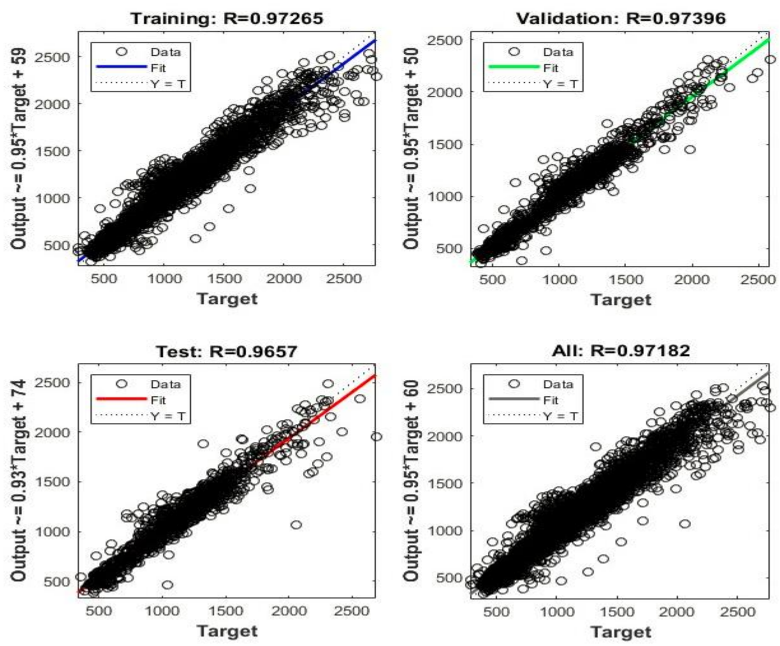


3. Model 3:

Error Histogram of model 3 is shown below:

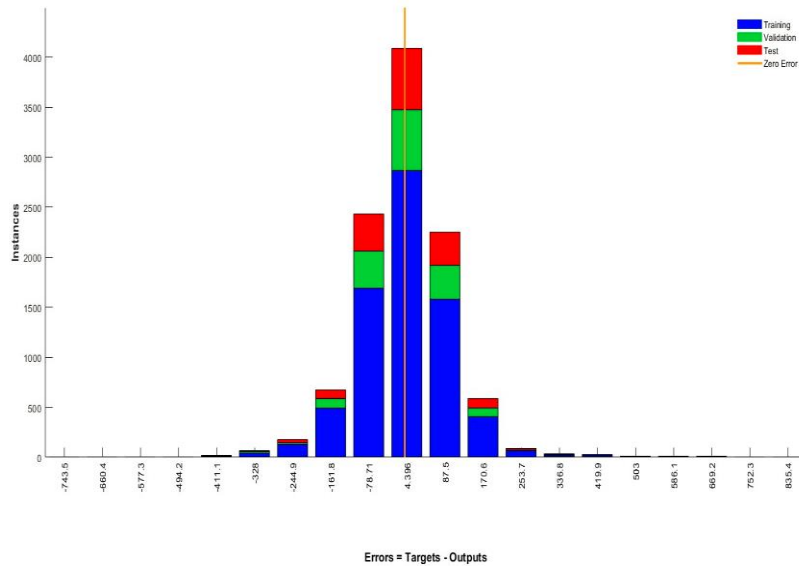


Regression graph for model 3 is:

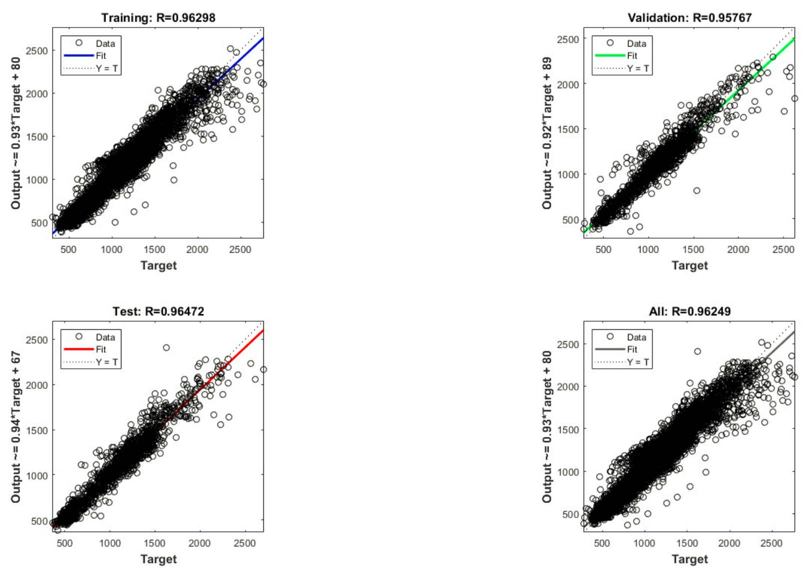


4. **Model 4:**

   Error histogram of model 4 is shown below:

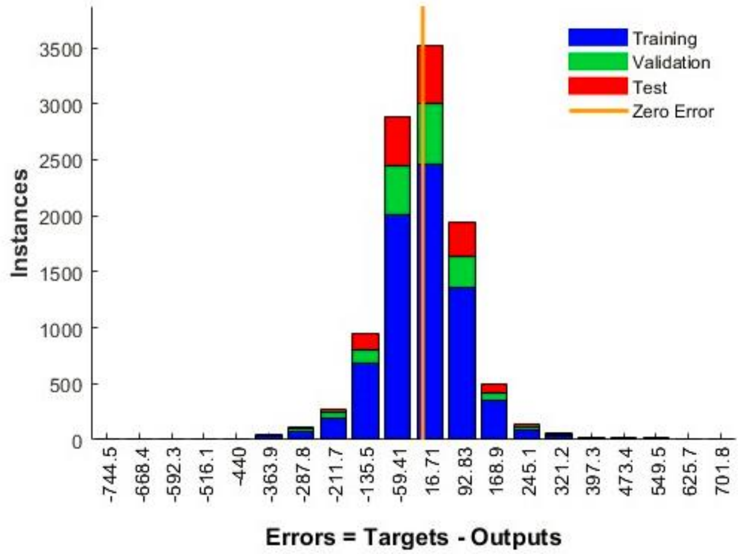


Regression graph of model 4:

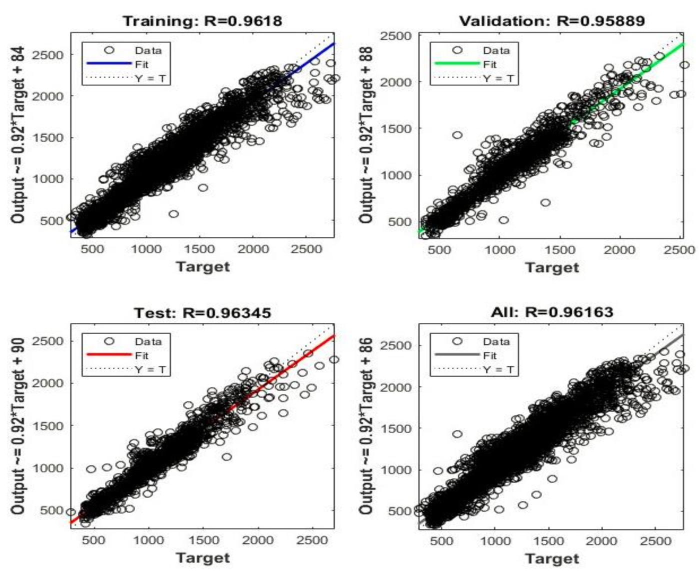


5. **Model 5:**

Error histogram is shown below:

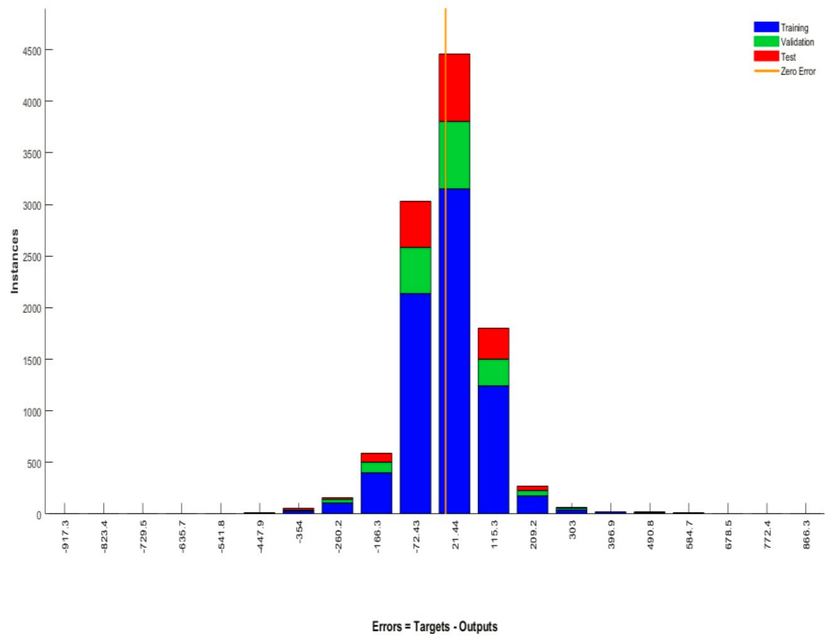


Regression graph for model 5 is shown below:

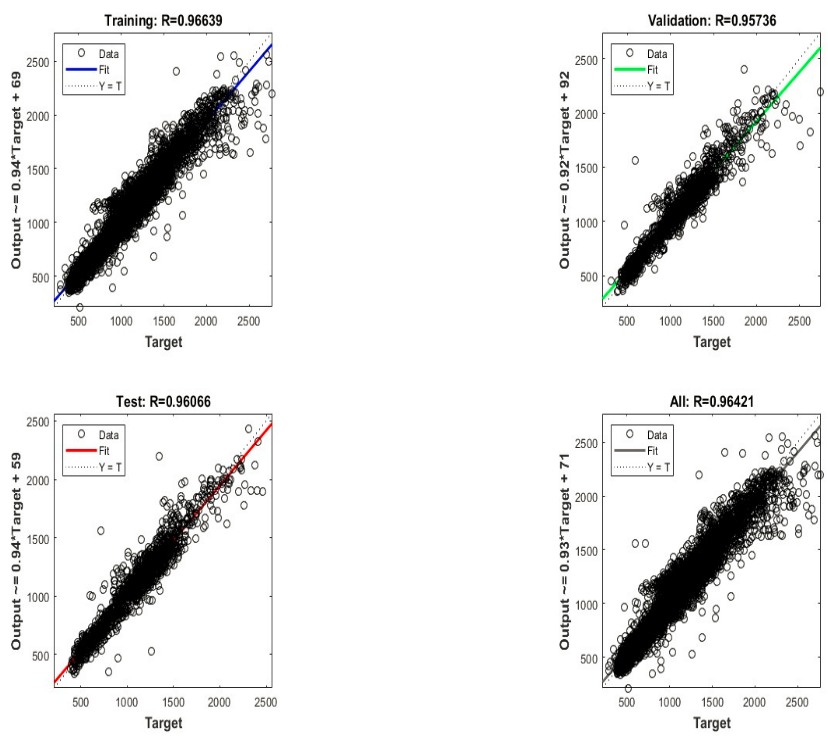


6. **Model 6:**

Error histogram for model 6 is shown below:



Regression graph is shown below:



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