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

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Abstract

This paper mainly focuses on Short-term forecasting and gives an hourly demand forecasting of electricity. We use a method called Recurrent Neural Network (RNN) to anticipate the future hourly demand of the Gothatar feeder, Nepal Electricity Authority (NEA). Forecasting using a Recurrent neural network helps make important decisions in the field of preventing unbalancing in load and power generation, scheduling, load switching strategies, and preventing imbalance in the load demand and power generation, thus leading to greater power quality and network reliability. Other time series methods like Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Holt-Winter's (HW) method, as well, and whose output was compared with that of Recurrent Neural Network. The Root Mean Square Error (RMSE) of Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Holt-Winter's method was found to be 188.033 kVA, 181.066 kVA, and 169.759 kVA respectively and the coefficient of determination (R^2) was 0.609, 0.618, and 0.634 respectively. The RNN algorithm has The Root Mean Square Error 69.03 kVA and R^2 of 0.876 obtained from the Recurrent Neural Network. So, the Recurrent Neural Network model proved to be the most accurate and best method with very little error and better R^2 in this study.

Keywords

kVA, Recurrent Neural Network, Single Exponential Smoothing, Double Exponential Smoothing, Holt Winter's, Root mean Square Error, Nepal Electricity Authority, R^2

1. Introduction

Short-term load forecasting (STLF) requires a short interval of time to a couple of days, which plays a vigorous and vital role in the compelling power system operation.

It is also very helpful in solving problems in unit commitment and security problem assessment related to the power system network.

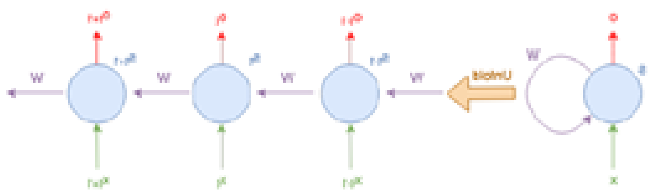

Figure 1: Simple recurrent neural network

Neural network (NN) is an area of computer science, used to forecast the load based on statistical techniques. Although it is not different from Artificial Neural Network (ANN) in terms of working logic, it allows the feedback system to work [1]. Its basic structure is shown in Figure 1.

In the last few years, electrical short-term load forecasting has evolved as one of the most important fields of research for reliable and efficient power operation [2].

The forecasting of power systems is essential to predict the future demand for electrical power, which helps to reduce the overall costs and electricity resources and also helps to improve the electrical distribution of load for different electric companies. [3].

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

Recurrent Neural Network is an algorithm class that uses manifold layers to extract higher feature levels progressively from the raw input. RNN algorithms are used in the field mentioned above. So here RNN model will train 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. by visualizing their correlation.

The network is trained and will be able to make predictions of demand based on the patterns learned during training. To check whether the forecasted load catches the pattern of the tested load accurately, validation will be performed just by comparing the forecasted load with the actual test data.

In addition, the Recurrent Neural Network model output will be compared with Single Exponential Smoothing, Double Exponential Smoothing, and Holt-Winter's method of forecasting to analyze the result.

The researchers compare the performance of a feed-forward neural network and recurrent neural network [4]. They use the New England-ISO data set from 2007 to 2012. They also show that the RNN has less error than the Feed Forward Neural Network (FFNN) on all domains and error calculations.

Short-term load forecasting of Kathmandu Valley using artificial neural network (ANN) [5] has been presented in this paper, where they concluded that the artificial neural network proved to be the more accurate forecast method.

This paper is focused on generating long-term load forecasting using hourly demand predictions [6]. They proposed a model of an RNN with Long Short-Term Memory (LSTM) cells. They found that LSTM-RNNs are suitable for forecasting.

The researchers presented a thesis paper for the peak load demand [7]. 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.

The researchers mainly focus both on short-term and monthly forecasting, proposing an LSTM-RNN [8]. They found that the LSTM-RNN had fewer forecasting errors in the medium and short term when compared to the best machine learning algorithms.

An ANN model for short-term load forecasting (STLF) with 24 24-hour duration has been done in this paper[9]. They claim that their proposed model gives reasonably accurate results, and is reliable in predicting the electric demand forecasting.

This thesis is related to short-term load forecasting using recurrent neural network (RNN) which has not been carried out in our country till now. The writer of this thesis wants to show the RNN algorithm is the best algorithm to forecast short-term load with less error.

The main objective of this research is the hourly load forecasting of the Gothatar feeder of NEA using the recurrent neural network method (RNN) model. The specific Objective is: To prepare the RNN algorithm, to obtain the hourly forecasting using RNN, SES, DES, and Holt-winter's method and finally compare the results of SES, DES, and Holt-winter's result with the Recurrent neural network (RNN) result to conclude the best model for demand forecasting.

2. Methodology

2.1 Flowchart

The flowchart of the research is shown in Figure 2.

2.2 Data Normalization

The main goal to perform normalization is to convert the input dataset of numeric columns to a common scale, without altering the original data. It normalizes the data within the range 0 to 1.

2.3 Input Features for Model

Six factors are considered as input features for RNN model. They are: Hour of day, Day of month, Month of year, Year, Rainfall, Temperature etc.

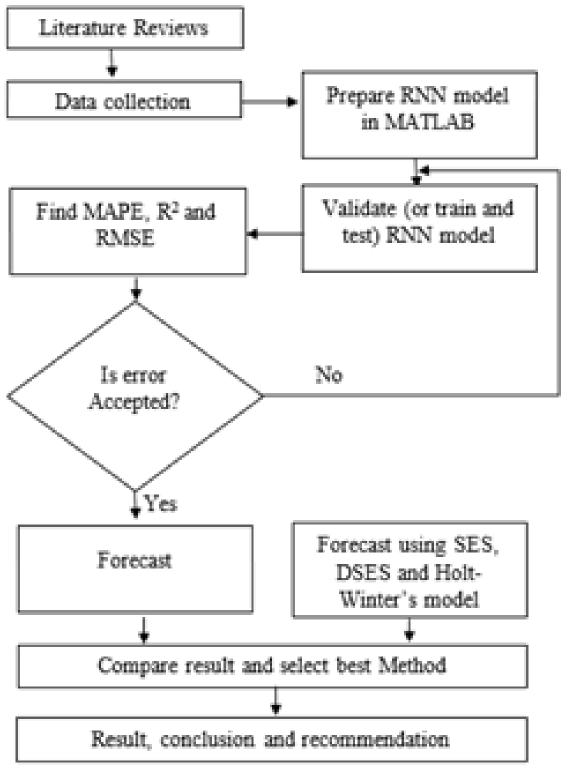

Figure 2: Complete flowchart of research

2.4 Mathematical modeling (Equation) of RNN

The basic form of modeling of the RNN network equation:

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

$Y_t = OutputLayer(h_t)$

The above equation of RNN can be shown in the figure 3:

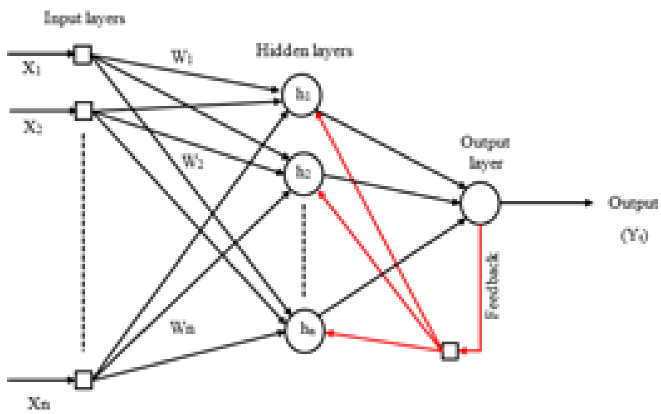

Figure 3: Modeling of recurrent neural network

2.5 Selection of Feeder:

The selection of a feeder depends on the fluctuation of load during seasons, the availability of data, and the type of consumers who use the feeder. the Gothatar feeder perfectly matches these requirements. In previous years, the Baneshwor feeder provided some power in addition to the Goothatar feeder to fulfill customers' demands. So, we decided to choose the Gothatar feeder to study its consumption patterns.

2.6 Forecasting of Gothatar feeder of NEA using RNN modeling:

To forecast the demand using the RNN model, all the data are divided mainly into two parts: The training data (used for training the network) and the Testing data (for validation with real data that is not used in the training process of the RNN model). The training and testing data is split in a 80 : 20 ratio.

Altogether three models are developed and they are trained with past data. six input parameters are used as input data to the input layer of the RNN model. The designed model is then developed and trained using the RNN algorithm which can be done in 'MATLAB 2023'. Adjustments are now made to our RNN model until the best result with fewer errors is achieved. To get the best model, hidden layers, activation functions, no. of neurons optimizer, and so on are adjusted.

2.7 Performance Measure

Different performance measuring parameters like R^2, Root Mean Square Error (RMSE), and Mean Average Percentage Error (MAPE) are used.

2.8 Comparison of Models

The forecasted value obtained with RNN is compared with traditional approaches of forecasting i.e., single exponential smoothing (SES), Double Exponential Smoothing (DES), and Holt-Winter's multiplicative seasonal method for the validation of the best model.

3. Result and Discussion

Data Preparation Data preparation is the first step of the research. The hourly electricity demand data is collected from NEA, Gothatar distribution substation, and rainfall data and temperature data are collected from, the Department of Hydrology and Meteorology

3.1 Data Smoothing

Data smoothing is performed to reduce 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. The hourly demand is smoothed by a simple moving average by taking a smoothing window of 5 which is shown in Figure 4.

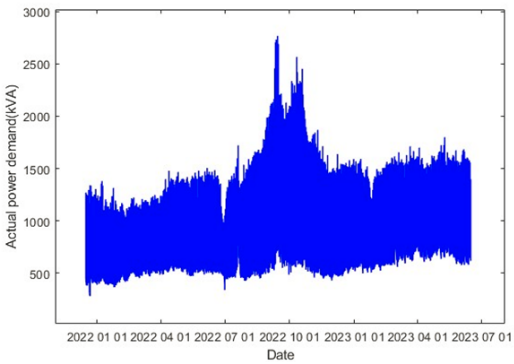

Figure 4: Smoothed diagram of our data

3.2 Results of RNN Model

The coding of the recurrent neural network (RNN) model is performed in the "MATLAB 2023" trial version. The RNN model is trained and then tested to see the forecasted results with performance measures till the best result is achieved. 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 parameters used to obtain the best model are tabulated in Table 1.

Table 1: Selection of activation function, neurons, epoch, R^2 and best mode

Model	AF	NN	Ep	MAPE	R^2
1	tanh logsig tansig purelin	100 50 25 1	500	8.66	0.789
2	tansig logsig tansig logsig trainscg	150 75 50 25 1	2150	7.02	0.81
3	tansig sigmoid tansig sigmoid purelin	30 25 20 15 1	2500	5.34	0.851
4	tanh logsig tanh logsig trainscg	30 30 20 15 1	2600	6.82	0.829
5	tansig logsig tansig logsig purelin	25 25 20 15 1	4800	4.35	0.876
6	tansig logsig tansig maxout	15 15 15 1	4850	5.01	0.84

In Table 1, AF means Activation function, NN means Number of neurons and Ep means no of epochs In Model 5, there are four layers and one output layer. The first layer has an activation function as 'tansig' with 25 neurons. The second layer has an activation function as 'logsig' with 25 neurons. The third layer has an activation function as 'tansig' with 20 neurons. The fourth layer has the activation function 'logsig' which has 15 neurons and the last layer has the activation function 'purelin' which has only 1 neuron and functions as the output layer. Then the model is run and fitted by taking an epoch of 4800 and a learning rate of 0.032. The optimizer selected here is 'Adam as it is the best optimizer used in deep learning forecasting. The training loss for model 5 is shown in the figure 5.

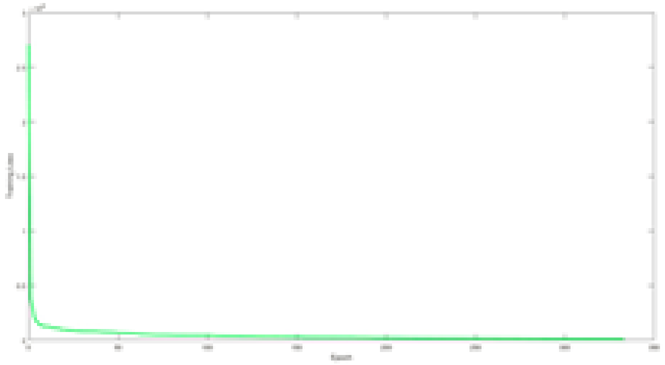

Figure 5: Training loss curve of model 5

From the training loss curve seen in Figure 6, it is clear that loss decreases as epochs increase and finally settles at a constant loss value. So, it is concluded that the model is well-trained. After training the RNN model, it is then tested with the test data.

The model is then used to predict the hourly power demand. Then the performance measures i.e., RMSE and R^2 are calculated using a test and predicted data. The R^2 value obtained for model 5 is 0.876. The trained data and test data curve are then plotted in Figure 6. From the figure, it is clear that the actual and predicted values are close but not very accurate. The predicted values follow almost the same pattern as the actual one.

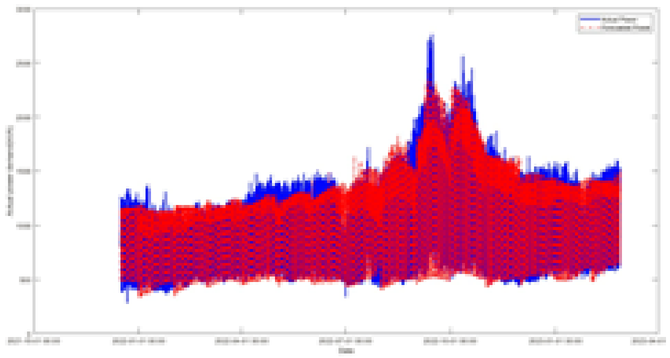

Figure 6: Training graph of our data of model 5

From Figure 6, we can see that the proposed model catches the pattern and is trained very well. The red line represents the predicted data and the blue line represents the actual power demand in Figure 7.

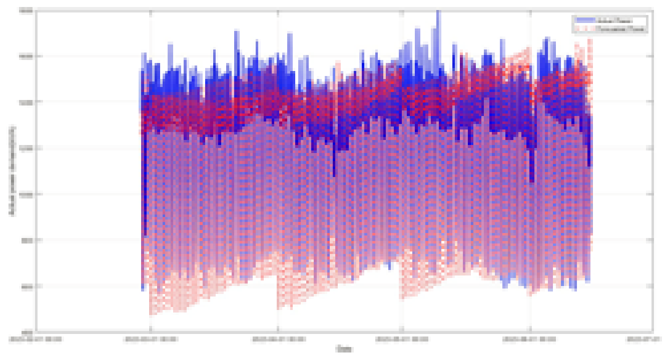

Figure 7: Testing graph of our data of model 5

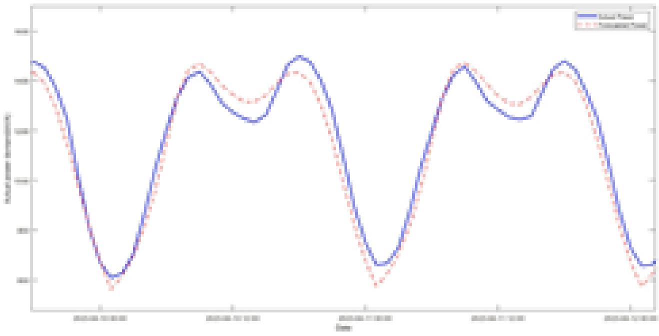

Figure 8: Testing data graph when zoomed

Among all RNN models i.e., model 1, model 2, model 3, model 4, model 5, and model 6, model 5 gives a higher R^2 i.e., 0.876 value. It means the model fits more bitterly than other models. So, the prediction of the model by using model 5 gives the best result with fewer errors. Hence, we chose model 5 to predict the hourly demand of the Gothatar feeder, NEA.

The performance measure i.e., R^2 for all the models is shown in histogram form in Figure 9.

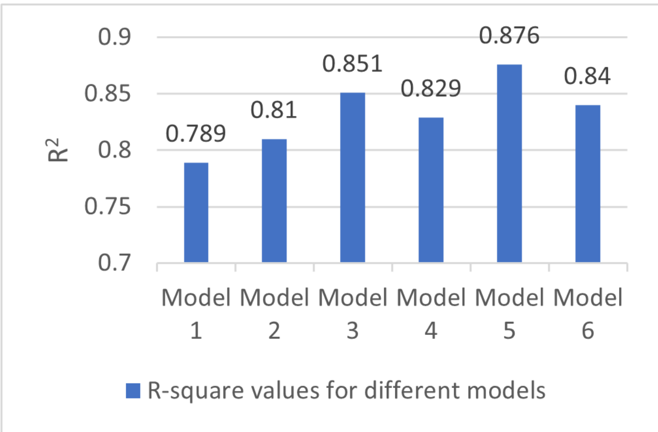

Figure 9: Comparision of all RNN models

Hence, from Figure 9, we can say that Model 5 is the best model for forecasting the demand.

3.3 Results of Traditional Approaches

Apart from the RNN model, forecasting is performed with the help of other time series models to compare their accuracy with the RNN model output.

Following are the time series models that are used to forecast the hourly demand of the Gothatar feeder, NEA:

3.3.1 Single Exponential Smoothing (SES) Method

The single Exponential Smoothing Method is considered a traditional method and is used for time series forecasting. The hourly demand of Gothatar, NEA is predicted using single exponential smoothing.

The hourly demand is predicted using the MS Excel SOLVER tool. The value of the smoothing factor i.e., alpha is optimized using SOLVER by minimizing the mean squared error. The value of alpha obtained after running SOLVER is 1. The actual and predicted demand curve obtained using the SES method is shown in Figure 10.

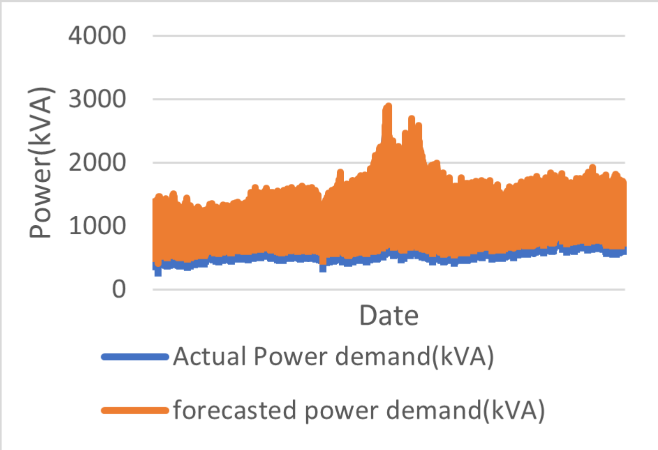

Figure 10: Demand prediction using SES

The R^2 value obtained for the SES method is 0.6098 which symbolizes that the SES method is 60.98 percent accurate for forecasting hourly power demand. The MAPE for the SES method obtained is 15.421 percent. RMSE for the SES method obtained is 188.033 kVA

3.3.2 Double Exponential Smoothing (DES) Method

The double Exponential Smoothing method is considered another traditional method and is used to forecast the series data. The demand is predicted using the MS Excel SOLVER tool.

The actual and predicted demand curve obtained using the DES method is shown in Figure 11.

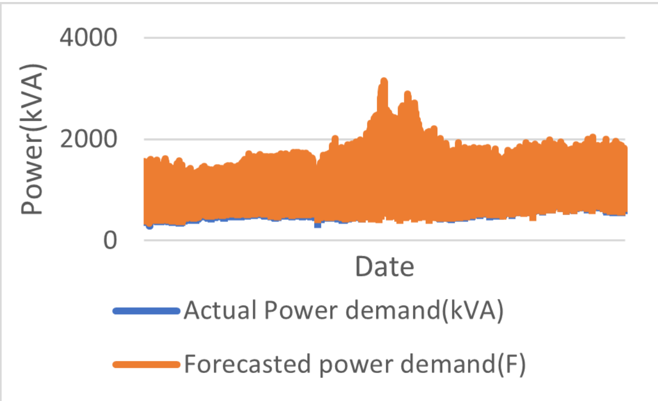

Figure 11: Demand prediction using DES

The R^2 value obtained for the DES method is 0.618 which symbolizes that the DES method is 61.8 percent accurate for forecasting demand. The RMSE for the DES method obtained is 181.06 kVA.

3.3.3 Holt-Winter's Multiplicative Seasonal Effect Model

In Holt-Winter's model, there is an addition of a multiplicative seasonality factor. The hourly demand of the Gothatar feeder, NEA is predicted also using Holt-Winter's multiplicative seasonal. The hourly demand is predicted using the MS Excel SOLVER tool.

The value of smoothing factors i.e., alpha, beta, and gamma are optimized using SOLVER by minimizing the MSE. The value obtained after running SOLVER is 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 12.

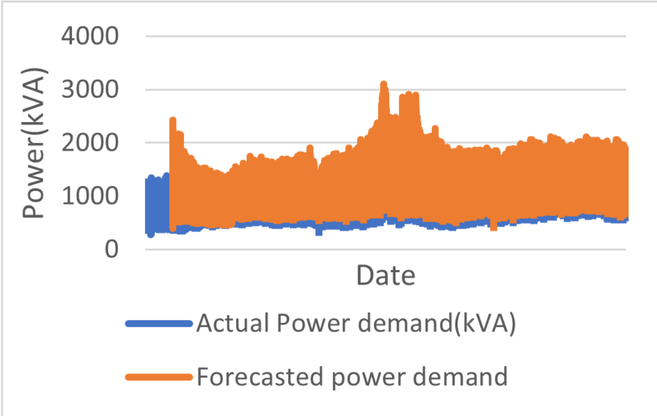

Figure 12: Demand prediction using Holt's winter

The R^2 value obtained for Holt-Winter's Method is 0.634 which symbolizes that Holt-Winter's Method is 63.4 percent accurate for forecasting of hourly demand of the Gothatar feeder, NEA. The RMSE for Holt-Winter's Method obtained is 169.759 kVA.

3.4 Comparison among all models

The performance measures of all methods are calculated and presented in Table 2.

Table 2: Predicted demands of different methods

Date	A.D.	RNN	SES	DES	HW
2023/04/11	1195	1155	1030	1298	1261

Table 3: Comparision between performance measure of all methods

P.M.	RNN	SES	DES	H.W.
R^2	0.876	0.609	0.618	0.634
RMSE (kVA)	69.030	188.0333	181.066	169.759
MAPE (%)	4,350	15.421	13.310	11.502

In Tables 1 and 2, A.D. represents the actual demand of the day, RNN indicates the forecasting of load by using the RNN model, SES indicates the forecasting of load by using Single exponential smoothing, DES indicates the forecasting of load by using Double exponential smoothing and HW indicates the forecasting of load by using Holt's-Winter method.

4. Conclusion and Recommendation

4.1 Conclusion

Thus, the model was formed with RNN, trained with very large data by assuming different features, and selected the best RNN model for forecasting hourly power demand.

By using the selected RNN model, we forecasted the hourly demand of the Gothatar feeder, NEA, and which was validated with the actual demand of the Gothatar feeder, NEA. In addition, the prediction of demand was done with the help of other time series methods i.e., SES, DES, and Holt-Winter's method whose performance measures were compared with the RNN model.

The RNN model is found to be the best forecasting method when the performance was compared in terms of performance measures with an R^2 having 0.876 and an RMSE having 69.03 kVA. While the R^2 and RMSE were 0.609 and 188.033 kVA, 0.618 and 181.066 kVA, and 0.634 and 169.75 kVA respectively for SES, DES, and Holt-Winter's method. The recurrent neural network (RNN) method was found to be the best among all the methods for forecasting hourly demand showing the robustness of the model with non-linear demand data.

4.2 Recommendation

It is recommended that the forecasting using RNN can be carried out by taking humidity, GDP, population growth, etc. as input features in addition to the input features taken in this research.

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

5. Acknowledgment

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