DOI: https://doi.org/10.24113/ijoscience.v4i5.137

Analysis of Electric Load Forecasting using Artificial Intelligence

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Abstract: Electricity demand forecasts are extremely important for energy suppliers and other actors in production, transmission, distribution and energy markets. Accurate models for predicting the load of electricity are critical to the operation and planning of a service company. load forecasts are extremely important for energy suppliers and other actors in production, transmission, distribution and energy markets. short-term load forecasts play an important role in the operation of power systems to ensure an immediate balance between energy production and demand. The accuracy of the prediction generated by the artificial intelligence has several factors, including, but not limited to, what is used to form the network algorithm, how much and which type of data are used in the network's training set. In this research the best combination has been investigated of these factors to decrease performance parameters to give the best forecast possible.
Artificial intelligence techniques have gained importance in reducing estimation errors. Artificial neural network, Extreme Learning Machine and Decision tree such as LSBOOST and RF are among these artificial intelligence techniques. That are used in this research work for performance analysis. In this work, performance evaluation metrics such as MSE, RMSE, MAE and MAPE values are analysed and it is concluded that Random forest decision tree forecasting algorithm gives better performance of forecasting as compared to other artificial intelligence algorithms for 24 hours load forecasting as well as for 7 day load forecasting.

Keywords: Electric load Forecasting, Short Term, Artificial Intelligence, Neural Network, Decision Tree, Performance Parameters.

I. INTRODUCTION

Load forecasting is extremely important in electric energy generation, transmission, distribution and markets. Load forecast has been a central and an integral process in the planning and operation of electric utilities. The Purpose of load forecasting is proper planning and operation of a power utility requires an adequate model for electric power load forecasting [1,2,3]. Load forecasting plays a key role in helping an electric utility to make important decisions on power market, load switching, voltage control, network reconfiguration, and infrastructure development.

There are following types of load forecasting which are [4]:

Long-term electric load forecasting used to supply electric utility company management with prediction of future needs for expansion, equipment purchases or staff hiring. In long-term, among 3-year and 50 year electric load is predicted.

Medium-term forecasting, used for the purpose of scheduling fuel supplies and unit maintenance. This is usually from a week to a year.

Short-term forecasting, it is used to supply necessary information for the system management of day-to-day operations and unit commitment.

Very short-term electric load forecasting which includes few minutes to an hour ahead forecasting of electric loads.

For strategic planning of the development of the electric power systems, both long-term and medium-term forecasts have great significance which includes scheduling of construction of new generation and transmission capacity, maintenance scheduling, as well as long-term demand side measurement and management planning [5,6,7]. However, an accurate STLF technique can alleviate operating costs, keep energy markets efficient, and provide a better understanding of the dynamics of the monitored system. On the contrary, an erroneous prediction might cause either a load overestimation, which leads to the excess of supply and reserve and consequently more costs and contract curtailments for market participants, or a load underestimation resulting in failures in gathering adequate provisions, hence more expensive complementary services [8].

II. RELATE WORK

Hippert et al. [1] designed a STLF system. The design tasks were divided into four stages: data pre-processing, ANN design, implementation, and validation. Although the discussion was in the context of ANN, a significant portion was also applicable to other techniques.

Alfares and Nazeeruddin [2] covered a wide range of techniques classified into nine categories: (1) multiple regression; (2) exponential smoothing; (3) iterative reweighted least-squares; (4) adaptive load forecasting; (5) stochastic time series; (6) autoregressive moving average models with exogenous inputs (ARMAX) based on genetic algorithms; (7) fuzzy logic; (8) ANN; and (9) expert systems. The paper described the methodologies briefly for each category, and discussed their advantages and disadvantages.

Metaxiotis et al. [3] provided a chronological summary of the development of various AI techniques, such as expert systems (ES), ANNs, and genetic algorithms. The advantages of AI techniques in STLF were summarized both conceptually and qualitatively.

Martin Längkvist et al. [4] proposed deep neural networks are applied to time series data with several kernel configurations. However, the usage of deep neural networks in electric forecasting is still limited due to the inability to access large volume of data and powerful computation machines

A. Baliyan et al. [5] proposed a multilayer ANN was to enhance the forecasting performance when the temperature forecast error increases. Recent research work of the ANN model for STLF included taking advantage of several meteorological forecasts. In order to adapt complex real-world data, there are two techniques.

Xiaoqin Wu [6] proposes a new approach for load forecasting in power systems by using trajectory tracking stability theory. And based upon Lyapunov stability theory, the proposed method is essentially model independent and can ensure the prediction error convergence.

Jian Zheng[7] explores Long-Short-Term-Memory (LSTM) based Recurrent Neural Network (RNN) to deal with this challenge. LSTM-based RNN is able to exploit the long term dependencies in the electric load time series for more accurate forecasting. Experiments are conducted to demonstrate that LSTM-based RNN is capable of forecasting accurately the complex electric load time series with a long forecasting horizon.

Tomas Vantuch [8] proposes an innovative algorithm entitled as ensemble of fuzzy linear regression (EFLR) and it bases on fuzzy linear regression combined with boosting mechanism. The fuzzy linear regression is optimized making use of multi objective optimization.

Junran Peng [9] used an adaptive network-based fuzzy inference system (ANFIS) model to construct the short-term load forecasting model based on factors such as weather and date types, etc. Then, the model was trained by the historical electric load data of eastern Czechoslovakia, and the prediction performance of the model is demonstrated.

III. PROPOSED METHODOLOGY

In this paper, an algorithm is proposed which provide a way to predict the electric load forecasting. Figure 1 shows the overall architecture for prediction of load. The proposed work is designed for forecasting the electric load for 24hrs using different algorithm such as Extreme Learning Machine (ELM), Neural Network (NN), Least Square Boosting (LSBOOST) and Random Forest Boosting (RF). Following diagram describes flow of electric load forecasting System.

Proposed Flow Chart

Input: D {Elctric load data};

Output: forecast load for 24 hours

Step1: Normalization of data, D

Step2: For each entity in D, do

Find feature vector (V) from D

Step 3: For each V do

Predict using ELM, NN, LSBOOST and RF

Step 4: Determine the error

Find Performance Parameters i.e. MSE, RMSE, MAE, MAPE

end for

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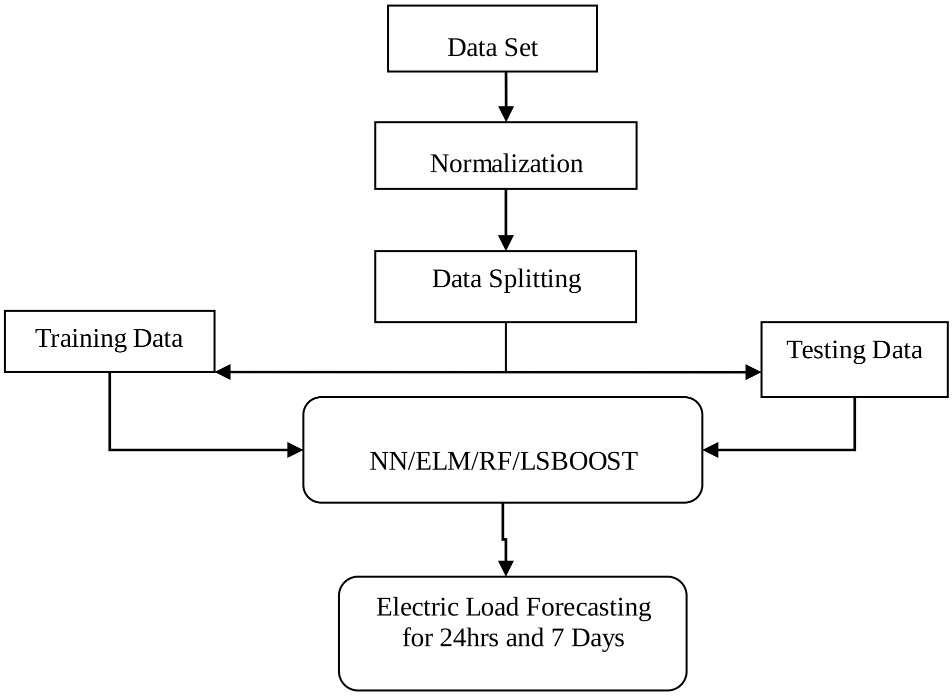

Figure 1: Flow Diagram of Electric Load Forecasting

A. Neural Network Forecasting

Neural networks are a class of nonlinear flexible models that can adaptively recognize models from data. In theory, it has been shown that neural networks can learn from experience in an appropriate number of nonlinear processing units and can estimate any complex functional relationship with great accuracy. Empirically, many successful applications have established their role in pattern recognition and prediction. Although many types of neural network models have been proposed, the most common model for time series prediction is the direct acting network model. Figure 3.3 shows a typical three-layer feedforward model used for prediction purposes [10,11]. The input nodes are the previous delayed observations, while the output provides the forecast for the future value.

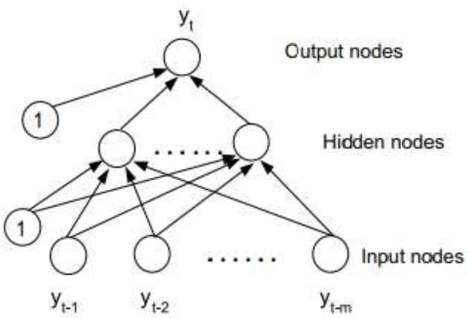

Figure 2: Neural Network

where m is the number of input nodes, n is the number of hidden nodes, f is a sigmoid transfer function, such as logistics:

$$f(x) = \frac{1}{1+\exp(-x)} * \{\alpha_j, j = 0,1,2, \dots \dots, n\} \quad (2)$$

is a vector of weights from the hidden to output nodes and $\{\beta_{ij}, i=0,1, \dots, m; j=1,2,\dots,n\}$ are the weights of the input to the hidden nodes α0 and β0j the weights of the arcs resulting from the polarization terms whose values are always equal to 1. It should be noted that the linear transfer function it is used in the root node as desired for forecasting problems [12].

B. Extreme Learning Machine Forecasting

The single-hidden layer-feed-forward neural network [13]– also termed as ELM – an learn exactly N different observations on almost all non-linear activation functions with at most N hidden nodes. The main difference between ELM and the traditional formation of an electric network is that the hidden ELM layer does not need a setting that randomly selects hidden level parameters. Input weights, hidden neural bias, and hidden layer output weights are randomly assigned to minimize drive failure. ELM transforms the learning problem into a simple linear system in which the initial weights can be determined analytically. For N arbitrary distinct instances $\{(x_i, y_i), i = 1, 2, \dots, N\}$, where x_i and y_i ELM with n inputs, m outputs, k hidden neurons, and an activation function g(x) is modelled as:

$$\sum_{i=1}^{n} \beta_i \, g(w_i^T + b_i) = o_i, i = 1,2, \dots \dots . N \quad (3)$$

Where w_i and β_i represent the weight vectors connecting the input neurons to an ith hidden neurons to the output neurons, respectively, and bi is a threshold of the ith hidden neurons.

The ELM with k = N hidden neurons can reliably approximate these N instances with zero error as

$$\sum_{i=1}^{N} \left|\left|o_i - y_i\right|\right| = 0 \qquad (4)$$

$$\sum_{i=1}^{k} \beta_i g(w_i^T x_i + \beta_i) = y_i \, , i = 1,2,3, \dots \dots . . N \qquad (5)$$

The matrix y is the ELM hidden layer output matrix, in which the i-th column of y is the output of the hidden neuron with respect to the inputs x1, x2. ,,, xN. In the basic ELM, if k << N and Y are a non-square matrix, learning the ELM is equivalent to finding a solution of the least squares β of the linear system Yβ = T.

C. Decision Tree Forecasting

The decision model is based on the actual values of the attributes in the data. The decision interval continues until a prediction decision is made for a given record. It has a default destination variable. Decision trees are trained in the data for classification and regression problems. Decision trees are popular in machine learning because they are often quick and precise. It works for categorical and continuous input and output variables. In this technique, the population or sample is divided into two or more homogeneous subpopulations or more based on the most significant fragment in the input variables.

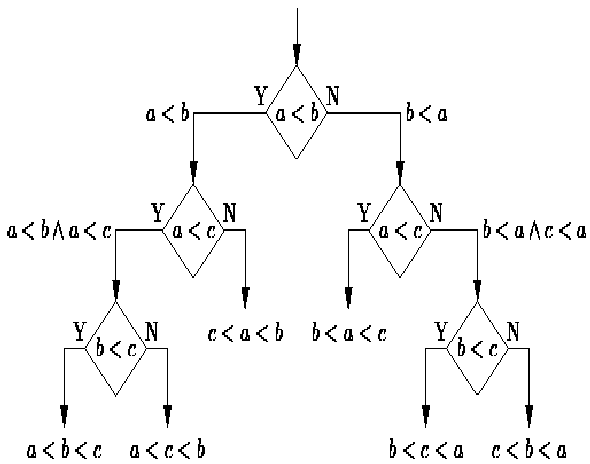

Figure 3: Decision Tree Algorithm

The decision is taken from the tree in the strategic division. This greatly affects the accuracy of the tree. This decision criterion differs for classification and regression trees in Figure 3.4. Decision trees use different algorithms to decide to divide a node into two or more subnodes. The trees break the nodes for all the available variables, then select the division that leads to the most homogeneous sub-nodes. The most popular decision tree algorithms are: Random Forest and least square boosting(LSBoost).

IV. Result Analysis

A. Dataset Description

The load forecast data set comes from the Global Energy Forecasting Competition 2012 (GEFCom2012). This competition is used to predict energy in energy technology education and prepare the sector to overcome prediction problems in the smart grid world. The load forecast trace argument is a problem of forecasting the hierarchical load: yields and hourly forecasts (in kW) for a US public service of 20 zones.

B. Performance Parameters

Mean Square Error (MSE)

MSE of any estimator (classifier) measures the average squares of errors or deviations, i,e. the difference between the estimator and what is estimated. MSE is a risk function corresponding to the expected value of the squared error loss.

$$MSE = \frac{1}{N}(Target_{value} - Obtained_{value}) \qquad (6)$$

Root Mean Square Error (RMSE)

RMSE is a parameter that determines the difference in squares between the output and the input.

$$RMSE = \sqrt{MSE} \qquad (7)$$

Mean Absolute Error (MAE)

MAE measures the average size of errors in a series of forecasts regardless of their direction. This is the average of absolute differences between prediction and actual observation, in which all individual differences are also weighted.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} y_i - \hat{y}_i \qquad (8)$$

Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error (MAPE) is a measure of the predictive accuracy of a forecasting method in statistics, for example in estimating the trend. It usually expresses the precision in percentage and is defined by the formula:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \frac{Target_{value} - Obtained_{value}}{Target_{value}} \qquad (9)$$

.

Scenario I:

In this scenario the electric load dataset is used to predict the 24hr ahead electric load forecasting. This prediction is performed using four different time series forecasting algorithms such as Extreme Learning Machine (ELM), Neural Network (NN), Least Square Boosting (LSBOOST) and Random Forest Boosting (RF). Table I illustrates performance analysis of all the classifiers.

Table I: Performance Analysis of Electric Load Forecasting Algorithms for 24 Hours Forecasting

	MSE (in KWh/hr)	RMSE (in KWh/hr)	MAE (in KWh/hr)	MAPE (in KWh/hr)
Random Forest Decision Tree	1.02E+05	13.3047	65.18	0.07
Least Square Boosting Decision Tree	1.27E+05	14.8326	72.66	0.08
Levenberg-Marquardt Neural Network	2.58E+07	211.7189	916.26	0.98
Extreme Learning Machine	3.66E+08	796.6462	3902.75	4.17

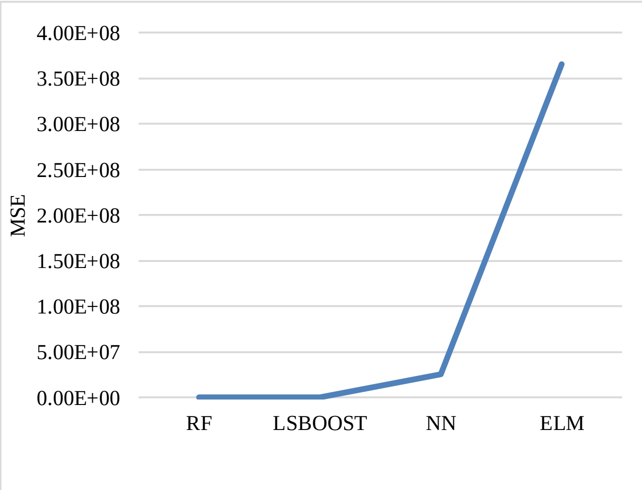

Figure 4: MSE Performance Analysis of 24 Hours Electric Load Forecasting

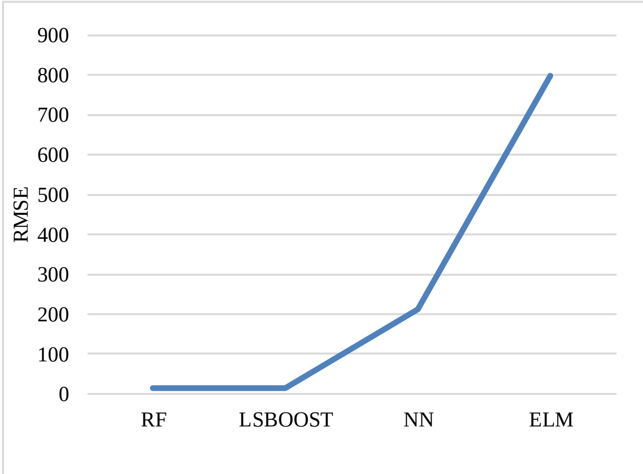

Figure 5: RMSE Performance Analysis of 24 Hours Electric Load Forecasting

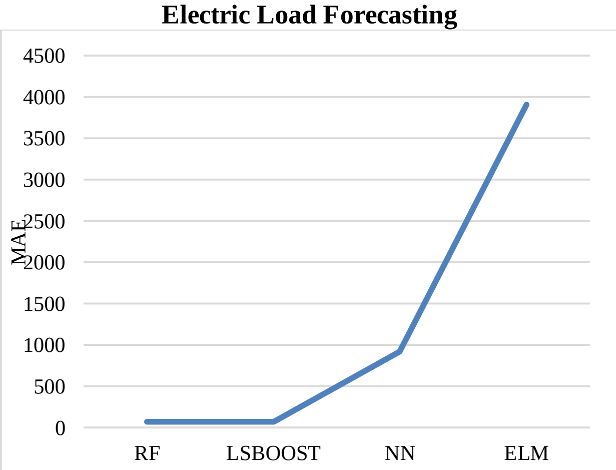

Figure 6: MAE Performance Analysis of 24 Hours Electric Load Forecasting

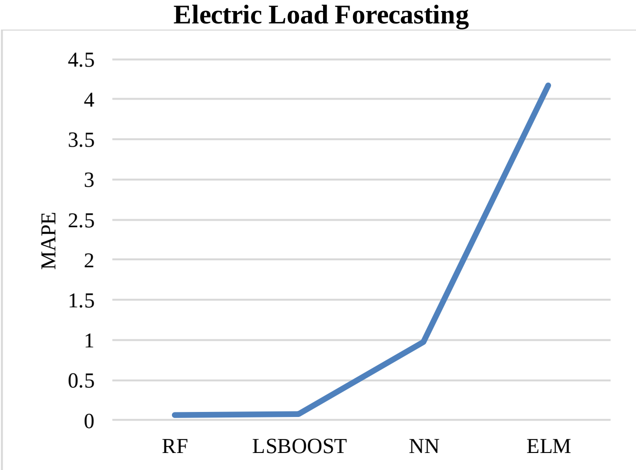

Figure 7: MAPE Performance Analysis of 24 Hours Electric Load Forecasting

Figure 4-7 show the result analysis of Extreme Learning Machine (ELM), Neural Network (NN), Least Square Boosting (LSBOOST) and Random Forest Boosting (RF) for the MSE, RMSE, MAE and MAPE parameter for forecasting electric load testing data values for 24 hours. By comparing the results of the all the forecasting algorithms it has been concluded that Random Forest based decision tree forecasting algorithm outperforms better forecasting than all of the other methodologies.

Scenario II:

In this scenario the electric load dataset is used to predict the 7 day ahead electric load forecasting. This prediction is performed using three different time series forecasting algorithms such as Neural Network (NN), Least Square Boosting (LSBOOST) and Random Forest Boosting (RF). Table II illustrates performance analysis of all the classifiers.

Table II: Performance Analysis of Electric Load Forecasting Algorithms for 7 Days Forecasting

	MSE (in KWh/hr)	RMSE (in KWh/hr)	MAE (in KWh/hr)	MAPE (in KWh/hr)
Random Forest Decision Tree	1.58E+04	5.2446	17.36	0.018
Least Square Boosting Decision Tree	2.96E+04	7.1732	27.11	0.03
Levenberg-Marquardt Neural Network	9.55E+07	407.1784	1975	2.03E+00

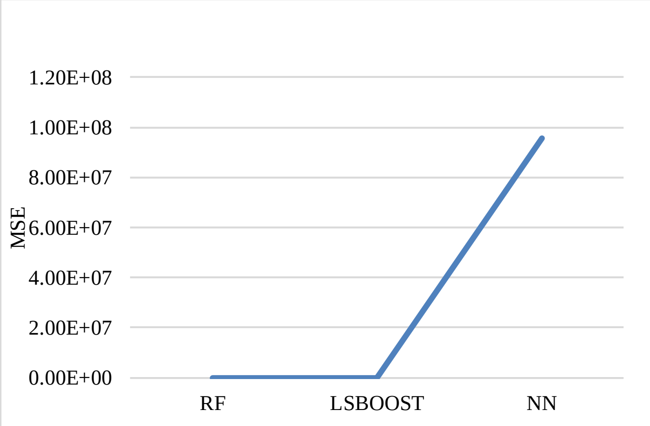

Figure 8: MSE Performance Analysis of 7 Days Electric Load Forecasting

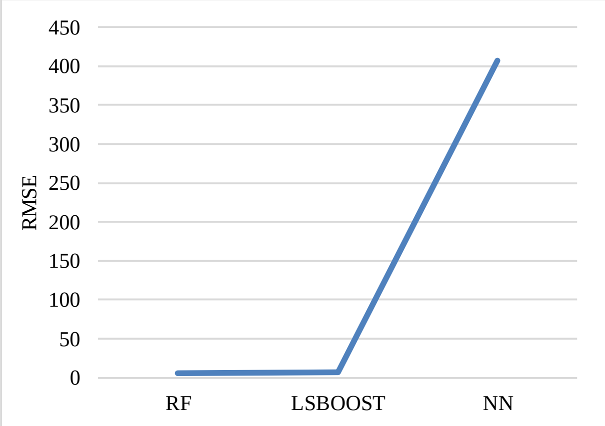

Figure 9: RMSE Performance Analysis of 7 Days Electric Load Forecasting

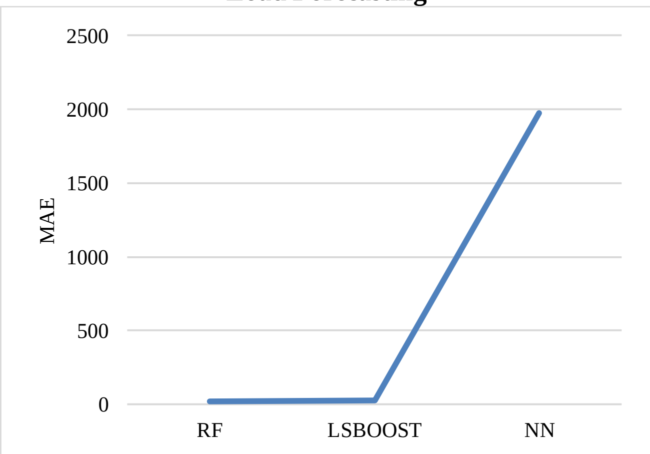

Figure 10: MAE Performance Analysis of 7 Days Electric Load Forecasting

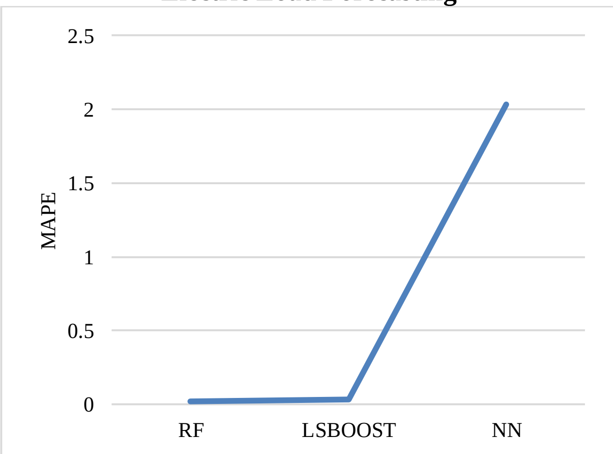

Figure 11: MAPE Performance Analysis of 7 Days Electric Load Forecasting

Figure 8-11 show the result analysis of Neural Network (NN), Least Square Boosting (LSBOOST) and Random Forest Boosting (RF) for the MSE, RMSE, MAE and MAPE parameter for forecasting electric load testing data values for 7 days. By comparing the results of the all the forecasting algorithms it has been concluded that Random Forest based decision tree forecasting algorithm outperforms better forecasting than all of the other methodologies.

V. Conclusion

The new energy market and the smart grid paradigm require both better demand and more reliable forecasts from individual end users to the whole system. However, it is difficult to predict the demand for electricity due to factors such as climatic factors, social activities and seasonal factors. The methods developed for load prediction are roughly analyzed in two categories, namely analytical techniques and artificial intelligence techniques. Analytical methods such as the linear regression method, the Box-Jenkins method and the non-parametric regression method are frequently used in the literature. The methods of analysis work well under normal daily conditions, but they can not give satisfactory results in terms of meteorological, sociological or economic changes and are therefore not updated with time. As a result, artificial intelligence techniques have become more important in order to reduce estimation errors. Artificial neural network, Extreme Learning Machine and Decision tree such as LSBOOST and RF are among these artificial intelligence techniques. That are used in this research work for performance analysis.

In this work, performance evaluation metrics such as MSE, RMSE, MAE and MAPE values are analysed and it is concluded that Random forest decision tree forecasting algorithm gives better performance of forecasting as compared to other artificial intelligence algorithms for 24 hours load forecasting as well as for 7 day load forecasting. Precise forecasts are valuable for operators of independent systems because they are necessary both for efficient production operations and for the constant satisfaction of customer demand. So, the future work will be intended to forecast electric load for long terms such as monthly forecasting as well as seasonal forecasting.

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