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ARTIFICIAL NEURAL NETWORK APPROACH FOR ELECTRIC LOAD FORECASTING IN POWER DISTRIBUTION COMPANY

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Abstract

In recent years, there have been extensive researches seeking the best methods of improving the load forecast accuracy. Many of these methods are statistical based methods which include time series, regression, Box-Jenkins model, exponential smoothing and so on. However, the statistical models offer limpidity in data interpretation and sensible accuracy in load forecasting but characterized by the problems of limited modeling and hefty computational effort which makes them less desirable than the intelligent techniques. Recently, Artificial Intelligence (AI) has been a better substitute. Among the AI methods, artificial neural networks (ANNs) have got some attention from a lot of researchers in this area due to its flexibility in data modeling. In this paper, ANN for electric load forecasting is proposed. The historical data were collected for three months from Yola power transmission company office along Numan road Jimeta/Yola, Adamawa State, Nigeria. Researchers then performed data preprocessing on the data. Afterwards, data mining algorithms were applied in order to forecast electric load. In doing this, two ANN algorithms (MLP and RBF) and SMO algorithm were employed and compared. The results were then interpreted; the obtained models were analyzed to determine the pattern in load forecasting model. The experimental analysis was performed on WEKA version 3.6.10 environment. Also, 10-fold cross validation test option was used to carry out the experiments. Results obtained showed that multilayer-Perceptron model (MLP) gives an accuracy of 86% with Mean Absolute error (MAE) of 0.016, Radial basis function (RBF) had an accuracy of 76% with MAE of 0.030 and Sequential Minimal Optimization (SMO) accuracy of 85% with MAE of 0.090 which indicated a promising level of electric load forecast.

Keywords: ANN; MLP; RBF; SMO; Forecast; Electric load;

1.0 INTRODUCTION

In recent years, Nigeria joined the rest of the world in privatizing the economic sector. As a result, Electric power generation and distribution companies were not left out of the privatization and deregulation. These brought about more attention to the issue of accurate electric load forecasting in regional and national power system. In order to satisfy the consumers, there was the need for suitable assessment of present-day and future electric power load by electric power companies, so as to have optimal scheduling and proper setup of electric power system (Samsher & Unde, 2012; Mohammed & Sanusi, 2012; Olagoke, Ayeni & Hambali, 2016; Hambali, Akinyemi, Oladunjoye & Yusuf, 2016). Load forecasting is vital for energy providers and other stakeholders in electric power generation,

distribution and marketing. Precise and correct electric load forecasting models are crucial for the proper functioning and planning of Utility Company. Every commercial electric power company has several strategic objectives. One of these objectives is to provide end users (market demands) with safe and stable electricity. Accurate forecast yields significant savings in operation and maintenance cost; increases reliability in power supply and distribution system, and provides accurate decision for power development. Errors in load forecasting can result in increase in operating costs (Bunn, 2000; Douglas, Breipohl, Lee & Adapa, 1998; Gross & Galiana, 1987; Hambali, et al., 2016). For instance, over forecast of upcoming electric load may lead to superfluous of load supply, and this is unwelcome practice in the global energy grid. On the other hand, under forecast of load results in failure to provide sufficient reserve, causes blackout in some regions and therefore, increases the peaking unit costs. For individual stakeholder in the global collaboration (Power generation, distribution, Transmission and marketer) in producing adequate electricity, there is the need for each of them to be able to forecast its demands accurately. However, electric power forecast is a complex task since the demand is affected by a number of factors which includes weather conditions, day type, social activities, economic status of consumers, vacations and idiosyncratic of individual consumers' habit (Nahi, René, Maarouf and Semaan, 2006). Weather conditions contribute a lot to the load forecasting. In fact, predicted meteorological conditions are one of the significant concerns in power load forecast. Several climate elements are usually put into consideration in the electric load forecasting which include temperature and humidity. They are considered as load predictors (Olagoke *et. al*., 2016).
In the last few decades, there have been extensive researches seeking the best methods of improving the load forecast accuracy. Many of these methods are statistically based methods among them are time series, Box-Jenkins model, regression, exponential smoothing and so on. The most prominent among these statistically based methods is Box-Jenkins' ARIMA (Box & Jenkins, 1970; Vemuri, Hill, and Balasubramanian,, 1973; Gwo-Chung and Ta-Peng, 2006), which is hypothetically based on univariate time sequences. However, the statistical models give limpidity in the analysis of data and sensible accuracy in load forecasting but concomitant with the problems of limited modeling and hefty computationpower make them less desirable over intelligent techniques (Mohammed & Sanusi, 2012; Olagoke *et. al.,* 2016). Recent researches have converged towards methods that use artificial intelligence (AI) such as fuzzy logic, artificial neural networks and expert system. Among the AI methods, artificial neural networks (ANNs) have gained much consideration from researchers in this area due to its flexibility in data modeling (Mohammed & Sanusi, 2012). The aim of this work is to identify the optimal neural network algorithms for electric load forecasting. Three different algorithms Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), and sequential minimal optimization (SMO) were applied on the data set and their results were compared based on classification accuracy, errors rate and execution time metrics using 10-fold cross validation test options. Then optimal algorithm will be recommended. The remaining part of this paper is structured as follows: Section 2 discusses related work on this study. In section 3, we describe the methodology employed. Section 4 presents discussion of the results. Finally, conclusions and suggestions for future works are presented in section 5.

2.0 LITERATURE REVIEW

For the last few decades now, researchers have devoted a lot of attention to how to improve the accuracy of electric load forecast. The studies in this field have led to the improvement in several forecasting techniques and approaches (Gwo-Chung & Ta- Peng, 2006; Olagoke *et. al.,* 2016; Hambali *et. al*., 2016). These approaches are mostly grouped into two: Classical methods and artificial intelligence (AI) based methods. Classical techniques are statistically based model which include time-series, regression, exponential smoothing, Box-Jenkins model and Kalman filters. AI based methods include ANNs, fuzzy logic and expert systems. Box-Jenkins' ARIMA is one of the classical methods that consider weather as insensitive in modeling approach. It employs past electric load data to forecast the forthcoming load (Box and Jenkins, 1970; Vemuri, et. al., 1973; Chen, Wang & Huang, 1995; Wang & Schulz, 2006) and based on theoretical univariate time sequences. Nevertheless, these classical methods cannot properly handle complex non-linear relations that are present amid the load and several other factors that have impact on it (Samsher and Unde, 2012; Olagoke, et. al., 2016). Since 1990s, different approaches for load forecasting other than the classical approaches have emerged in literatures. The researchers are inclined toward applying various AI techniques for load forecasting (LF). Various AI methods such as fuzzy logic, ANNs and expert systems have been extensively employed to provide wayout to the challenges of non-linearity, large data sets constraint in implementing LF modeling and other difficulties that are associate with classical methods of LF (Olagoke, et. al., 2016; Hambali, et al. 2016).

In the last decade, researchers started embracing AI approaches to increase the performance of load forecasting tasks. ANNs and Knowledge-based expert system (KBES) are the prevailing methods being employed (Rahman and Bhatnagar, 1998). Nowadays, developments of fuzzy inference system and fuzzy theory in electric load forecasting are also getting more considerations. Ying and Pan (2008) develop adaptive network fuzzy inference system (ANFIS) to forecast regional load; the model compares the relationship between the input and output data to evaluate the best distribution of individual functions. Pai (2006) and Pandian, Duraiswamy, Rajan, and Kanagaraj, (2006) also use fuzzy techniques to achieve a better performance in electric load forecasting.

Christopher and Francis (2013) developed a supervised ANN based model for LF and evaluated its performance using the actual load data obtained from Kenya National power grid system. Amera, Lamya and Sozan (2013) examined comprehensive approach of using ANN for LF. Their proposed ANN architectures used datasets of preceding two years' load data acquired from Dohuk Eaton Logic Controllers **(**ELC) in Iraq. They implemented four different ANN algorithms and validated their model with sensible precision on real electric load to generate output data. Mohammed and Sanusi (2012) developed a multilayer feed forward ANN LF model for 132/33KV substation, Kano, Nigeria, using Levenberg- Marquardt optimization technique to train the network. Slobodan, Aleksandar, Srdan, Aleksandar and Filip (2013) presented a STLF method based on ANN technique, designed for large-scale system such as distribution management system (DSM). The system includes pre-processing unit (PPU) and a feed forward ANN arranged in order. Functionality of their approach was evaluated on datasets obtained from Serbian Electrical Utility.

3.0 METHODOLOGY

The methodology used for this work is forecasting a load pattern of Yola Power Transmission Company using ANN algorithms that belongs to the procedure of Knowledge Discovery and Data Mining. The phases involved in carrying out the task include the following:

Data gathering: The historical data was collected for three months from Yola Power Transmission Company's office along Numan road Jimeta/Yola, Adamawa State, Nigeria. These data were for the months of September, October and November 2015. The parameters found in this datasets are as follows: Date, Time (hourly record), Temperature for 24 hours daily, Input voltage and Output voltage. The input voltage is in coming voltage or load into the Transmission Company which is high voltage of 132kv and before it is stepped down into the lower voltage levels of 33kv/11kv/0.415kv, which is the standard used in Nigeria (Input/Output voltage, 132/33kv). The datasets were divided into two: 66% for the training and the rest 44% for the testing of the proposed algorithms. Table 1 shows a sample of a day datasets.

Table 1 Electric Company Datasets

Date	Time (hour)	Temperature (Celsius)	Oil temp.(Celsius)	Wind temp.(Celsius)	Input voltage (kv)	Output voltage (kv)
16/09/2015	1	22	42	44	124	31
16/09/2015	2	22	42	44	124	31
16/09/2015	3	22	42	44	128	32
16/09/2015	4	22	42	44	124	31
16/09/2015	5	22	42	44	128	32
16/09/2015	6	23	42	44	128	32
16/09/2015	7	23	42	44	132	32
16/09/2015	8	23	44	46	136	33
16/09/2015	9	23	47	46	120	34
16/09/2015	10	32	47	48	120	30
16/09/2015	11	32	48	50	124	30
16/09/2015	12	32	48	50	120	31
16/09/2015	13	32	50	52	132	30
16/09/2015	14	32	50	50	132	33
16/09/2015	15	32	50	52	132	30
16/09/2015	16	32	54	60	124	32
16/09/2015	17	32	54	60	124	31
16/09/2015	18	32	54	60	132	31
16/09/2015	19	32	54	58	120	33
16/09/2015	20	32	50	52	120	30
16/09/2015	21	32	40	42	124	31
16/09/2015	22	22	40	42	124	31
16/09/2015	23	22	40	42	128	32
16/09/2015	24	22	40	42	124	31

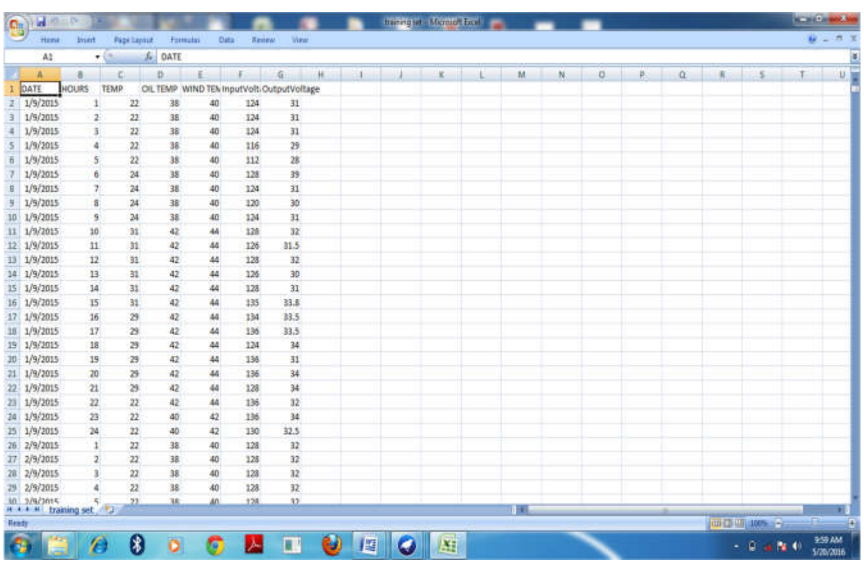

Figure 1 Spreadsheet Interface of the Training Datasets

Pre-processing: This stage involves datasets preparation before applying data mining techniques. At this stage, data cleaning, data transformation and data partitioning were employed as data pre-processing methods.

Data Mining: At this stage, data mining algorithms were applied in order to forecast electric load. In doing this, two ANN algorithms (MLP and RBF) and SMO algorithm are employed and compared.

Interpretation: At this stage, the results of models obtained were analyzed to determine the patterns in the load-forecasting model.

3.1 Experimental Tool Used

The experimental tool used was WEKA. WEKA (Waikato Environment for Knowledge Analysis) is used for forecasting electric load data in this work. WEKA is one of the popular suites machine learning softwares developed at the University of Waikato. It is an open source software available under the GNU General Public License. The Weka environment comprises of a collection of visualization tools and algorithms for data modeling, together with graphical user interfaces for easy interaction with its functionality.

3.2 Data Mining

In this phase, data mining algorithms were applied in order to forecast electric load. To do this, classification algorithms such as MLP, SMO and RBF were employed and compared using WEKA data mining tool. Also, 10-fold cross validation test option was used to carry out the experiments.

3.3 Artificial Neural Networks

Artificial neural networks (ANNs) are mathematical implementation that mimics the thought of human brain design, representing its “learning” and “generalization” capabilities (Gbolagade, Hambali and Akinyemi, 2015). Human brain consists of millions of neurons that are networked together by synapses. ANNs are built up from numerous numbers of simulated neurons, linked to one another in a fashion similar to human brain. Similar to human brain, the forte of neuron interconnections may vary (that is, altered by the training algorithm) in response to motivated stimulus or output result, which permits the network to “learn”.

3.4 Multi-Layer Perceptron

A Multi-Layer Perceptron Feed-Forward Back Propagation Neural Network was one of the famous classifiers employed in the area of science and technology applications. ANN is preferred out of numerous other algorithms due to its ease to use and abilities for supervised learning. Multi-layer refers to the ANN network with three layers: input, hidden and output layers. The feed forward describes the way the network processes the patterns and evokes patterns. When ANN is defined as "feed forward neural network", it indicates that its neurons are connected forward only.

3.5 RBF Neural Network

RBF neural network has features similar to other neural networks (Hambali, and Gbolagade, 2016). The input layer is the first layer; followed by hidden layer that contains several radial basis functions called hidden kernels; and the last layer refered to as output layer.
An RBF neural network can be well-thought-out as mapping of input domain on to the output domain H.

$$g_y(\ddot{h}) = \sum_{i=1}^{x} w_{yi} F(\| \ddot{h} - \ddot{k}_i \|) + p_y; \quad \ldots(1)$$
$i = 1, 2, 3, \ldots, x;$
$y = 1, 2, 3, \ldots, Y.$

where $\|\cdot\|$ stands for the Euclidean norm,
y refers to number of outputs generated,
x is the number of hidden kernels in the network.
$g_y(\ddot{h})$ is output y corresponding to $\ddot{h}$ input.
$\ddot{k}_I$ is the center of kernel i.
w_{yi} is the weight between kernel i and output y.
p_y is the bias on output y.
$F(\| \ddot{h} - \ddot{k}_i \|)$ is the kernel function.

Gaussian kernel function is the most frequently used kernel function for RBF neural networks as shown in equation 2:

$$F(\| \ddot{h} - \ddot{k}_i \|) = \exp\left(-\frac{\|\ddot{h} - \ddot{k}_i\|^2}{2\sigma_i^2}\right) \quad (2)$$

where σ_i is the radius of the kernel i.

The core steps involved in building an RBF neural network include (Hambali and Gbolagade, 2016):
i. Determine the loci of all kernels $\ddot{k}_i$,
ii. For each of the kernel, determine their radius and
iii. Compute the weights between the kernels and the output nodes.

3.6 Sequential Minimal Optimization

Sequential Minimal Optimization (SMO) is an algorithm that offers solution to the quadratic programming (QP) problem of support vector machine (SVM). Its computation process is very fast without any additional matrix storage and without applying numerical QP optimization steps at all. To safeguard convergence, SMO divides overall QP problem into different QP sub-problems, using Osuna's theorem (Platt, 1998).

3.7 Predictor Error Measures

To determine the predictor accuracy, let P^N represent set of test data of the form (t_1, r_1), (t_2, r_2)… (t_p, r_p), such that t_i is n-dimensional test tuples with corresponding values of r_i, for a response value, r, and p is the number of tuples in P^N. Hence, predictors generate a continuous variable instead of categorical variable. It is not easy to determine whether the forecasted value ,$r_i^!$, for t_i is correct. Rather than concentrating on "exact" value of $r_i^!$ match with r_i, we then look at converging of the forecasted value to the real known value. Loss functions measure the error between yi and the predicted value, $r_i^!$. The following error functions were used in this work:

$$\text{Absolute Error} = |r_i - r_i'| \quad (3)$$

$$\text{Squared Error} = (r_i - r_i')^2 \quad (4)$$

From the equation 3, the test error rate or generalization error, is the mean loss over the set of test data. Therefore, we drive another error rates:

$$\text{Mean Absolute Error (MAE)} = \sum_{i=1}^{p} |r_i - r_i'| \quad (5)$$

$$\text{Mean Squared Error (MSE)} = \frac{\sum_{i=1}^{p}(r_i - r_i^{!})^2}{p} \quad (6)$$

The mean squared error overstates the existence of outliers, while the mean absolute error does not cater for outliers. If we compute square root of the MSE, the resulting error measure is termed the root mean squared error (RMSE). This allows the evaluated error to have similar magnitude as the quantity of the value forecasted.

Occasionally, we may express error as relative to the value of predicted r, the average value for r from the training data, P. Thus, we normalize the total loss by dividing the total loss occured by the average predicted value. Relative error measurement include:

$$\text{Relative Absolute Error (RAE)} = \frac{\sum_{i=1}^{p}|r_i - r_i^{!}|}{\sum_{i=1}^{r}|r_i - \bar{r}|} \quad (7)$$

$$\text{Relative Square Error (RSE)} = \frac{\sum_{i=1}^{p}\left(r_{i-r_i^{!}}\right)^2}{\sum_{i=1}^{p}(r_{i-\bar{r}})^2} \quad (8)$$

where $\bar{r}$is the mean value for r_i's of the training data, that is

$$\bar{r} = \frac{\sum_{i=1}^{p} r_i}{p} \quad (9)$$

4.0 RESULT AND DISCUSSION

The implementation of this work was done using WEKA data mining tools. WEKA is a data mining package developed by the University of Waikato, New Zealand for the implementation of difference data mining algorithms. The software is an up-to-date facility for developing machine learning (ML) techniques and their application to real-world data mining problems. It is an assembly of ML algorithms for data mining tasks. WEKA application toolscan be used to implement algorithms for data preprocessing, attribute selection, regression, classification, clustering, and association rules. It also encompasses a visualization tool.

4.1 Evaluation of Classification Algorithms

The performance of classification algorithms are typically determined and measured by estimating the sensitivity, specificity, accuracy and error rates of the classification algorithms.
Sensitivity is the portion of retrieved instances that are significant, that is, rate of correctly classifying instances into the sum of correctly and incorrectly classified instances.
Specificity is the portion of relevant instances that are retrieved.
Accuracy is the overall success rate of the correctly classified instances. These metrics are defined in equation (10) – (12).

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (10)$$

$$\text{Specificity} = \frac{TP}{TP+FP} \quad (11)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \quad (12)$$

All these metrics can be computed based on the following four values: True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN).

4.2 Classifier and Experimental Results

We have predicted electric load using MLP, RBF and SMO on datasets collected from the month of September, 2015 to November, 2015 from Jimeta metropolis,Yola Distribution Company, Adamawa State. The experiments were carried out on the WEKA Version 3.6.10. All the experiments were performed on AMD E2-1800APU with 1.70GHz CPU, 2G RAM and Window 8 OS. The result of the experiments were segregated into sub items for easy analysis and evaluation. The first part is sensitivity (SE), specificity (SP), accuracy (AC), kappa static (KS) and time taken to build model (TTBM) are partitioned in first table (Table 2) while the second part (Table 3), shows the relative mean absolute error (RMAE), root mean squared error (RMSE), relative absolute error (RAE) and root relative squared error (RRSE) for reference and evaluation.
NOTE: Sensitivity is referred to as TP Rate and also specificity is referred to as FP Rate in WEKA.

Table 2 Experimental Results

METRICS	ALGORITHMS		
	MLP	RBF	SMO
SE	0.857	0.760	0.849
SP	0.031	0.053	0.035
AC (%)	86	76	85
KS	0.823	0.70	0.812
TTBM (in Sec.)	691	1197	23

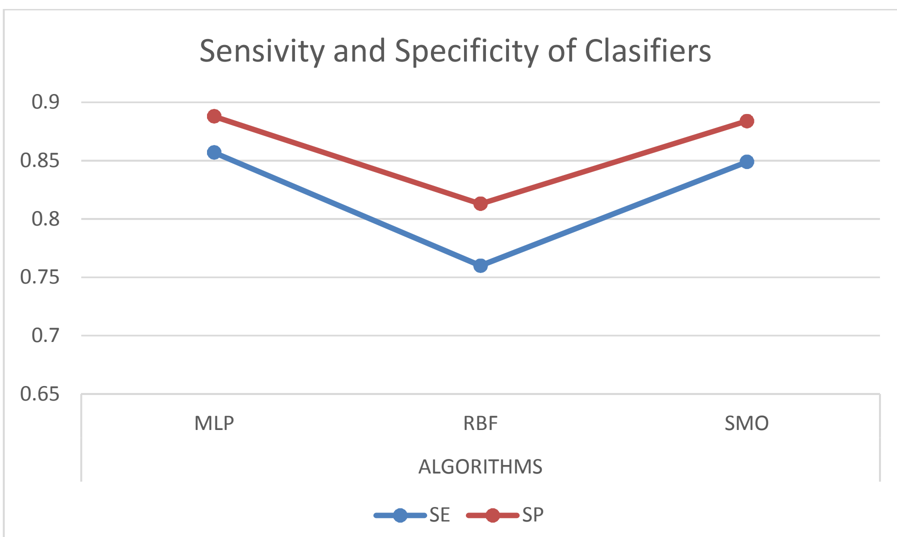

Figure 2 Sensitivity and Specificity of Classifier Algorithms

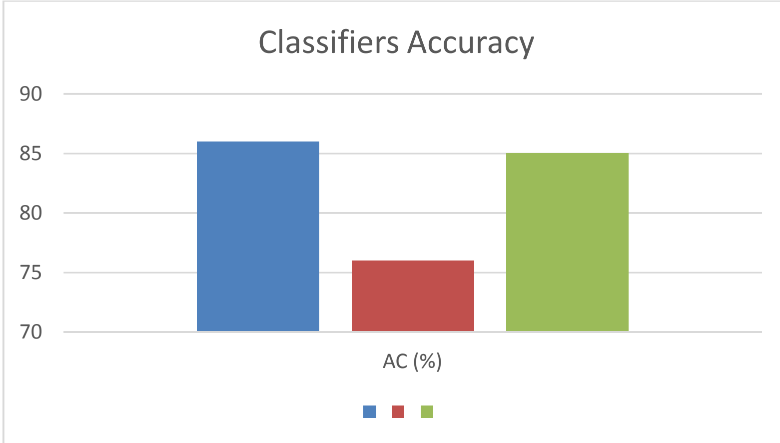

Figure 3 Classifier Accuracy

In the table 2, three Algorithms (MLP, RBF and SMO) were used for the Electric Power load forecasting. It took MLP algorithm 691secs to build the execution model, with correct classification accuracy of 86%, kappa statistic of 0.823, SE of 0.857 and SP of 0.031 while RBF algorithm built its model within 1197secs, with correct classification accuracy of 76%, kappa statistic of 0.70, SE of 0.760 and SP of 0.053. Also, SMO algorithm used 23 sec to build its model, with kappa statistic of 0.812, SE of 0.849 and SP of 0.035. Figure 2 and 3 depict the sensitivity and specificity, and accuracy of classifier algorithms used.

Table 3 Error Rate of Algorithms

ERROR	ALGORITHMS		
	MLP	RBF	SMO
MAE	0.016	0.030	0.090
RMSE	0.114	0.146	0.209
RMAE (%)	19.26	37.46	111.5
RRSE (%)	56.51	72.44	104.0

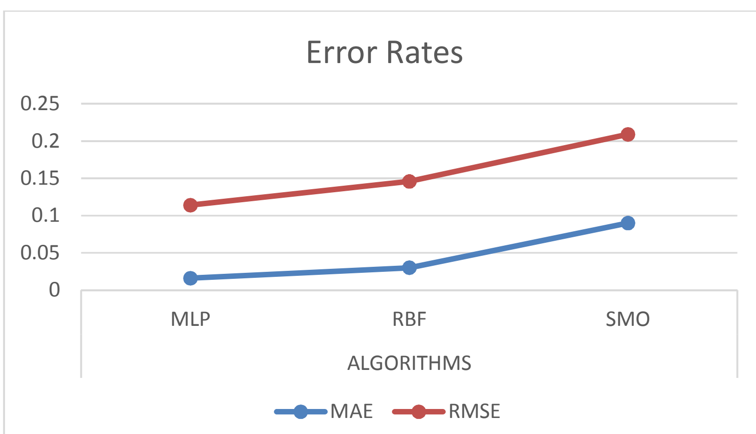

Figure 4 Error Rates

From table 3, the results show that MLP has lowest error rates (MAE, RMSE, RAE and RRSE) of 0.016, 0.114, 19.26% and 56.51% respectively. Figure 4 depicts the error rate of classifier algorithms.This shows that rate of wrongly predicted electric load is minimal and also classification accuracy is more than other algorithms (RBF and SMO). Therefore, the target (actual load) and output (predicted) values are very close. This means that the MLP network predicted output is satisfactory.

5.0 CONCLUSION

This paper presented an improved electric load forecast using Artificial neural network algorithms; Multilayer Perceptron (MLP), Radial basis function (RBF) and sequential minimization optimization (SMO). The metrics used for our results analysis are sensitivity, specificity, accuracy and kappa statistics. The error analysis was also investigated. The datasets used for electric load forecast were obtained for a period of three months from September, 2015 to November, 2015 from Jimeta metropolis, Yola Distribution Company, Adamawa State. The results obtained showed that MLP has the highest classification accuracy and insignificant errors.

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