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HYBRID LEVENBERG-MARQUARDT AND CUCKOO SEARCH ALGORITHM FOR SHORT-TERM LOAD FORECASTING IN ELECTRICAL POWER SYSTEMS

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ABSTRACT: Short Term Load Forecasting (STLF) of electricity supply is important for optimal planning and operation of an electric power system. However, finding an appropriate STLF model for a specific electricity network has become imperative as in-appropriate model yields sub-optimal solution and may cause a huge power loss to electrical power system. This study carry out STLF of electricity supply on Nigerian electric power system using Lavenberg-Marquardt (LM) based Back Propagation (BP) algorithm trained with Cuckoo Search (CS) algorithm. An Artificial Neural Network (ANN) forecasting model that can forecast electricity supply for one day ahead was designed using daily historical hourly load data from Ayede transmission sub-station feeder Ibadan. The initial weight parameter of the designed forecasting model was optimized with CS algorithm. Then, LM based BP algorithm was used to train the forecasting model and simulation was done in MATLAB R2021a. The objective function is to improve the prediction accuracy and minimize the forecasting model error value. The results showed that, the application of CS with LM based BP algorithm for STLF of electricity of Ayede transmission sub-station feeder improved the forecasting accuracy of the feeder, reduced the error value to minimum and provide a reliable tool to optimize the operation of power system. Hence, this study provides a viable solution to the load growth or expansion problem of electric power system.

Keywords: Short Term Load Forecasting, Electricity Supply, Artificial Neural Network, Cuckoo Search algorithm, Lavenberg-Marquardt Back Propagation algorithm, Forecasting Error.

I. INTRODUCTION

The Nigerian power system today is known for its epileptic, inadequate and unreliable nature as a result of continuous addition of load due to the increasing number of consumers [1-2]. In order to improve the performance of the power system, it must be well planned and evaluated so as to ensure adequate and reliable power supply to meet the estimated load demand in both near and distant future. Thus, the need for accurate load forecasting technique, as accuracy in load forecasting has a significant impact on power system operations and planning [3-5]. Load forecasting is the process of predicting future electric load given historical load and sometimes weather information [2]. It is very essential to the entire power sector in order to meet load demands for a given period of time [2, 3]. According to the time span, load forecasting can be classified into Short Term Load Forecasting (STLF); Medium Term Load Forecasting (MTLF) and Long Term Load Forecasting (LTLF) [6]. However, STLF; a forecast needed for a day – to – day economic operations and energy management of power generation plants, is the foundation for efficient power dispatching systems, system planning and maintenance of the generating units. The STLF has therefore been found to be one of the most emerging and challenging fields of research in power system [7- 9]. The techniques use to solve the STLF can be categories into two; Statistical technique and Artificial Intelligent (AI) technique [2, 7]. The Statistical technique such as Autoregressive Integrated Moving Average (ARIMA) model employed by Author [10], Grey Model (GM)) utilized by reference [4] and sample weight assignment method employed by Reference [11] among others. The AI technique such as fuzzy logic utilized by Author [12], expert systems by Reference [10],, Support Vector Methods (SVM) by Author [10] and feed forward Artificial Neural Networks (ANN) which have been reported to have outperformed other forecasting techniques in terms of better accuracy of the forecasting models. The ANN has gained more attention due to its demonstrated capability in non-linear curve fitting [13-14]. However, the success of ANN mostly depends on the training algorithm used in training the ANN. Once the network is trained with a variety of patterns of input and output combinations, the model will be able to predict the correct output when an input pattern is given randomly [5, 8, 9]. The conventional techniques such as Error Back Propagation (EBP) presented by Author [15] on Nigerian power system, Artificial Immune System (AIS) learning algorithm employed by Reference [16], Multi-Layer Perceptron (MLP) Back Propagation Neural Network (BPNN) employed by Reference [17], Lavenberg-Marquardt (LM) based Back Propagation (BP) utilized by Authors [18, 19, 20], Radial Function Network (RBFN) utilized by Author [2] among others have been used in the past for training of ANNs but the algorithm converges slowly and often yields sub- optimal solution [5, 13]. In recent, researchers have employed meta-heuristic optimization algorithm such as, Cuckoo Search (CS) algorithm [21], Whale Optimization Algorithm (WOA), Salp Swarm Algorithm (SSA), Particle Swarm Optimization (PSO) [19], Firefly algorithm (FA), Genetic Algorithm (GA), Moth-Flame Optimization (MFO) among others, were reported to have performed excellently for training of ANN model in terms of quality of solution, computational time and faster convergence [18, 20, 22, 23]. Also these techniques have the advantages of finding set of non-dominated solutions in a single run because of their multi-point search capacity [22, 24]. Thus, in these study accurate forecasts of the electricity load supply for a 24 hour period of the next day in advance has been addressed using LM based BP algorithm trained with CS algorithm for improved convergence speed of the ANN forecasting model. The CS algorithm was employed to optimize the initial weight parameters of the ANN model due to its rapid speed of convergence and strong capability of global search. The LM was then used to continue to train the ANN model due to its efficiency in trading-off between the fast learning speed and guaranteed convergence of the gradient descent in order to improve the prediction accuracy of the ANN forecasting model [25, 26]

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II. PROBLEM FORMULATION

In a bid to efficiently supply electricity energy to the consumers in a secure and economic manner, electric utility companies face numerous economic challenges in their operation. Among these challenges, load forecasting has been found to be the most challenging fields of research as the power demands in a given place do vary with growth in population and economic activities. The accuracy of forecast obtained is however of utmost importance to a system planner. A poor load forecast misleads planners and often results in wrong and expensive expansion plans. Thus, the need for accurate load forecasting technique, as the objective of any forecast is to obtain the forecast with the least error. The lower the forecasting error values, the more accurate are the model. Thus, the objective function is to minimize the forecasting model error value.

Therefore, the objective function is formulated as in (1):

$$\text{Min}\; E_R = \text{Optimize} \sum_{i=1}^{n} (x_i(k) - y_i(k))^2 \qquad (1)$$

Subject to the ANN adjusted weight and fitness function (equality constraint) given in (2) and (3) respectively:

$$\square_{i,j}^{k}(t+1) = \square n^{n} = 1 - \square\square\square\square E\, ik,-j\, R\, 1,k \qquad (2)$$

$$F = \frac{1}{1 + k \sum_{n=1}^{n} E_R} \qquad (3)$$

The inequality constrain is expressed as in (4):

$G_{min} \le G(w,b) \le G_{max}$ (4) where; G is the number of input data; k is a scaling constant; $\square_{i,j}^{k-1,k}$ is the weight between the i^{th} neuron of the layer $k-1$; j^{th} is the neuron of the layer k ; t is the learning time; $\square$ is a proportionality factor known as the learning rate; (w, b) is vector of the weight and bias.

A. System under study and data acquisition

This study presented a STLF of electricity power supply on 32/33 kV feeder of Ayede transmission sub-station Ibadan, Oyo State, Nigeria shown in Figure 1 covering a period of one week from January, 16 - 22, 2023 (dry season) and April, 24 - 30, 2023 (raining season), respectively in order to meet the power requirements of the substation. Daily historical hourly weather data for Month (January and April, 2023) were obtained from the sub-station. The weather (dry and raining season) data were grouped according to the time of the day and the days of the week (Monday to Sunday). Numerical values of 1 to 24 were assigned to time of the day while 1 to 7 was assigned to the day of the week. Four load arrangement; Previous week hourly load, Load of the day (in hours), Load of working days (Monday, Tuesday, Wednesday, Thursday and Friday) and Load of weekend (Saturday and Sunday) were used as input data for the ANN model. The corresponding target is the load of the hour to be predicted. The dataset was used such that 70% employed for the training, 20% for testing and remaining 10% for

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validation. The training data is necessary for obtaining the ANNs weight and bias values. The test data was used in the evaluation of generalization error, while the validation data was used to test the ability of the forecasting model.

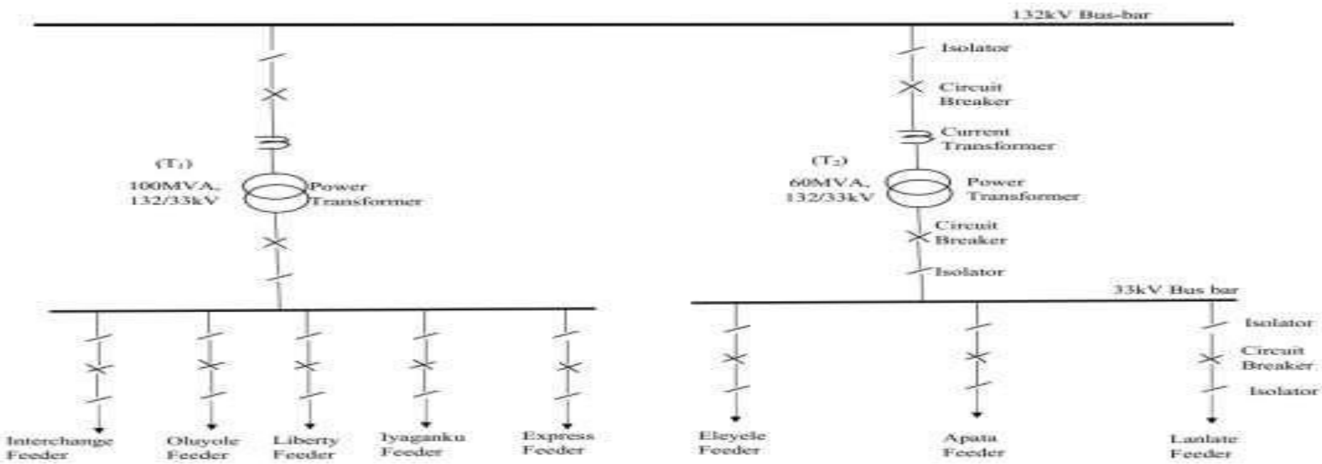

Figure 1: Schematic Diagram of 132/33kV Ayede Transmission Sub-Station

Designing the structure of ANN forecasting model

A feed forward ANN load forecasting model that can forecast electric supply for one day ahead was designed using the pre-processing weather data (dry and raining season) of previous week hourly load, load of the day, load of working days and load of weekend. The coefficients of the ANN weight parameters were identified and used to predict the load of the hour.

In designing the ANN forecasting model, the numbers of output neurons were made to be equaled to the number of outputs. An output neuron was calculated using (5),

$$y_i(k) = f\left(\sum_{i=0}^{d} \square_i x_i(k) + b\right) \quad (5)$$

The ANN logistic sigmoid transfer function was evaluated using (6) and the ANN capability with non-linear equation was estimated using (7), respectively.

$$f(z) = f(\square x + b) = \frac{1}{1 + e^{-(z - z_0)}} \quad (6)$$

$$y_i(x,w) = f\left(\sum_{i=0}^{n} w_{ti}^{(1)} h\left(\sum_{j=0}^{d} w_{tj}^{(2)} x_i + b\right) + b\right) \quad (7)$$

The numbers of neurons in the hidden layer were taken from the empirical formula given in (8) [26]:

$$i = (n + m) + a\sqrt{\;} \quad (8)$$

The error signal at the output neuron of the ANN model was estimated using (9):

$$E_R = \sum^{n} (x_i(k) - y_i(k))^2 \quad (9)$$

i=1

where; i is the number of neurons in hidden layer, n is the number of neurons in input layer, m is the number of neurons in output layer, a is a constant and 1□a□10, y_i (k) is the output value of the neuron in distance time k ; x_i (k) is the basic function

B. ANN with cuckoo search algorithm

The initial weight and bias parameters of the designed ANN forecasting model for STLF was first optimized with CS algorithm to adjust the connection weights and neurons thresholds using training data sets. This was done to determine the optimal or near optimal weight of the ANN model. Then the optimized parameters (weight and bias) were used for the training of the ANN for load forecast. The weights and biases of the network were used as optimization variables while the output forecasting error value was used as the objective fitness function. The CS algorithm parameters were calculated as in (10) to (17):

$$x_i^{t+1} = x_i^t + \square s \square H(p_a - \varepsilon) \otimes (x_j^t - x_k^t) \quad (10)$$

$$x_i^{t+1} = x_i^t + \square\square \text{Lévy}(S,\square) \quad (11)$$

$$\text{Lévy} \sim u = t^{-\lambda} \quad (1 \le \boldsymbol{\lambda} \le 3) \quad (12)$$

$$f(x;\square,c) = \sqrt{\frac{c}{2}} \frac{e^{-\frac{c}{2(x-u)}}}{(x-\square)^{3/2}} \quad (14)$$

$$\text{Step lenght } (\varsigma) = \frac{u}{v^{\frac{1}{\beta}}}; \quad (15)$$

$$u = \text{rand ()} \ ; \ \text{and} \ \ v = \text{rand ()} \quad (16)$$

$$\sigma = \left(\frac{(1+\beta).\sin(\frac{\pi}{2}.\beta)}{\Gamma\left(\frac{1+\beta}{2}\right).\beta.2^{\frac{\beta-1}{2}}}\right)^{\frac{1}{\beta}}; \quad = \frac{3}{2} \quad (17)$$

$$\eta = 0.01\,(X - X_{best}) \quad (18)$$

The connection ANN weights and bias were adjusted and the ANN was trained. The fitness function to be optimized is formulated using Equation (3): Once the initial weight and bias parameters of the network is optimized for each number of setting time, the program executed and the forecasting error value are calculated using Equation (9). where; P_a is the switching parameter, x_i^t and x_j^t are the upper and lower bounds of i^{th} and j^{th} component respectively, H is a standard uniform random number on the open interval (0, 1), s is the number of current generation, α indicates the step size or coefficient of step length, □ is used to indicate the entry wise multiplication, Lévy (λ) represent the step length drown from Lévy distribution, μ and c are the location parameters and scale parameter respectively. Γ is the gamma function, β is the Lévy distribution parameter, u is samples from normal distribution of zero mean, ν is samples from normal distribution of zero deviation, σ is the variance of the normal distribution

D. ANN with CS trained with LM based BP algorithm

In order to improve the prediction accuracy and convergence speed of the ANN forecasting model, the forecasting error value obtained from ANN model trained with CS algorithm was modified via additional training with the LM based BP algorithm. The LM based BP algorithm incorporates the Newton method and gradient descent method as in (19) to (25) to optimize the network weight and biases, for the training of the ANN model:

$e_{p\,m,} = d_{p\,m,} - o_{p\,m,}$ (19)

$w_{k+1} = -w_k \square g_k$ (20)

wk+1 = −wk H gk−1 k (21)

$H = J^T J$ (22)

k+1 =□k −□JT J +□I□−1JTe (23)

□ $H = J^T J + \square I$ (24)

□w =□H +□I□⁻¹g (25)

where, $d_{p.m}$ is the desired output vector and $o_{p.m}$ is the actual output vector, □ is the learning constant (step size) and g is the gradient vector, □ is always positive, called combination coefficient, I is the identity matrix, H is Hessian matrix of the second order function and $g = J^T e$ is the gradient vector of the second order function. I is the identity Jacobian matrix of the same dimensions as H and **λ** is a regularizing or loading parameter that forces the sum matrix H +□I to be positive definite and safely well-conditioned throughout the computation. Once the network is trained for each number of set times, the program is executed. The objective function was evaluated using Equation (1), while MSE and MAPE were determined using (26) and (27) [16]:

1 n 2
MSE = _n □i=1 (l$_a$ −l$_p$) (26)
MAPE =1□=n (la l−a lF)□100 (27)
n i 1

where; l_a is the actual load, l_P is the Predicted load, l_F is the forecasted load;, n is the number of data point

The simulation of all the approaches was carried out in MATLAB R2021a according to the followings algorithm:

Step 1: The system weather data, parameters of CS algorithm were inputed;
Step 2: An initial ANN architecture was created using the pre-processing data set;
Step 3: The error at the output neuron was calculated using (9)
Step 4: Iteration count was set as t = 0;

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Step 5: The fitness function of Cuckoo egg was evaluated using (3);
Step 6: The best value of the fitness value was evaluated;
Step 7: New fitness value was determined;
Step 8: The new fitness value was check for any improved value;
Step 9: The current fitness value gave the optimal ANN weight and the cuckoo egg new nest indicated the network biases;
Step 10: The training was completed by extracting the weights from current nest;
Step 11: The forecasting error signal was calculated using (9);
Step 12: Check, if the error is acceptable, go to step 17, otherwise go to step 13;
Step 13: ANN Jacobian matrix was computed
Step 14: Gradient error was calculated using (9);
Step 15: Optimal weight of ANN using was calculated using (25);
Step 16: ANN weight was updated using (20);
Step 17: The MSE was calculated using updated weights in (26) Step 18: The MAPE was calculate using (29) and then stop.

III. RESULTS AND DISCUSSION

The simulation and performance of the designed ANN forecasting model trained using LM based BP algorithm and CS algorithm under consideration of weather (dry and raining season) condition on of 132/33 kV feeder of Ayede transmission sub-station are hereby presented. Figure 2 showed the designed ANN forecasting network for STLF of the substation. The designed ANN network consists of three (3) layers; the input layer, six (6) hidden layers and the output. There are four parameters that made up the input layer of the network. They are: Previous week hourly load; Load of the day (in hours) ; Load of working days (Monday, Tuesday, Wednesday, Thursday and Friday) and Load of weekend (Saturday and Sunday). .In the network structure the bias nodes were used and the log sigmoid activation function was placed as the activation function for the hidden and output layers nodes.

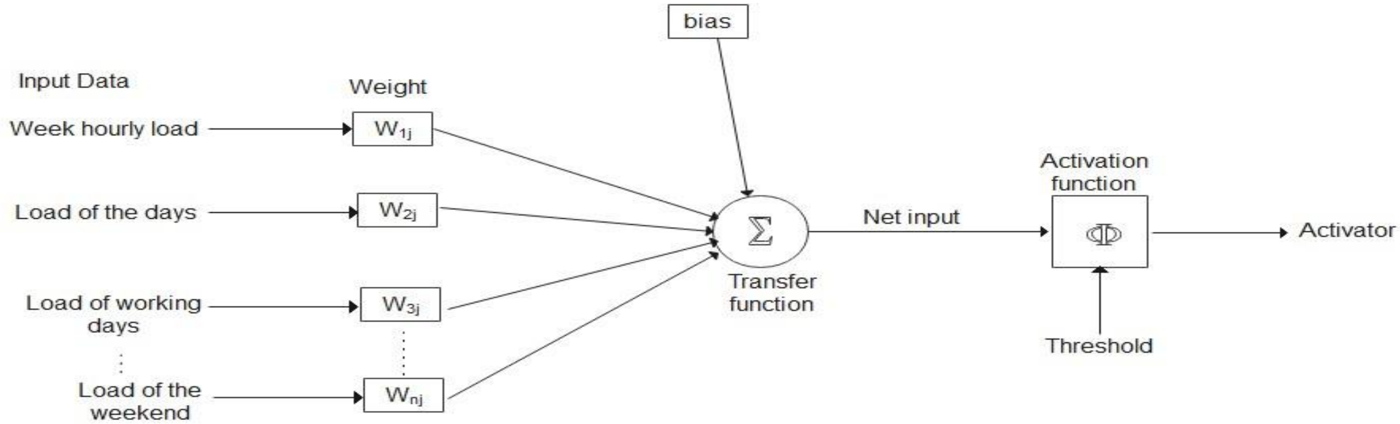

Figure 2: The Designed ANN Forecasting Network

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Figure 3 presented the total hourly predicted load results for the 132/33 kV feeder of Ayede transmission sub-station between 16 to 22 January, 2023 (dry season). The graphs showed the relationship between actual load data and predicted data (MW). It was revealed that the total predicted load for a week (Monday to Sunday) in the sub-station were 48.7, 49.9, 49.51, 49.18, 49.49, 48.62 and 48.64 MW, compared with the actual load data of 48.10, 48.3, 47.9, 48.1, 47.5, 48 and 47.8 MW, respectively. It was observed that the predicted loads were much closer to the actual load values of the sub-station. It could be observed that predicted value agreed with the actual values of the sub-station load data. Also, it was observed that days 6 (Saturday) and 7 (Sunday) during the dry season had relatively high value of predicted loads of 48.62 MW (14.1%) and 48.64 MW (14.2%), respectively, of the total predicted load for the week. These values of predicted load indicated that large amount of energy consumption occurred during the weekends.

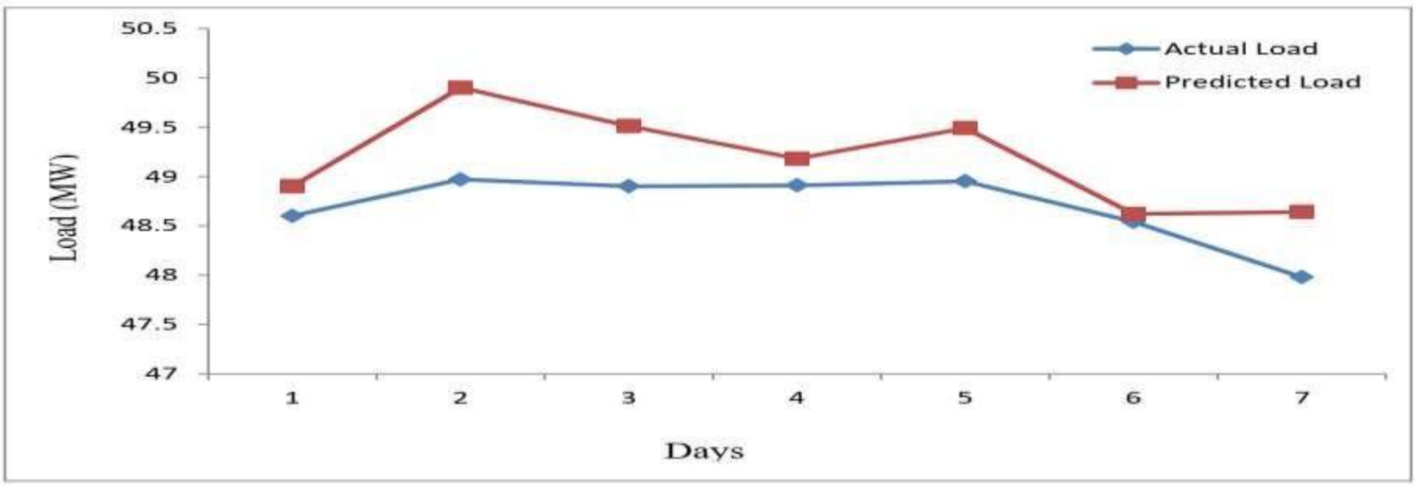

Figure 3: Total Predicted Load between 15 to 22 January, 2023 (dry season)

Table 1 presented the results of daily predicted error of MSE and MAPE for Ayede transmission sub-station feeder between 16 to 22 January, 2023 (dry season). From the Table, it was observed that the total daily MSE and MAPE for the week were; 0.0127, 0.0093, 0.0127, 0.0037, 0.0035 and 0.0053; 3.3861, 5.0229, 5.1885, 2.7770, 2, 4385, 2.0719 and 3.2089 %, respectively

Table 1: MSE and MAPE Results for 16 to 22 January, 2023

	DAYS						
	WEEKDAYS					**WEEKENDS**	
	1	**2**	**3**	**4**	**5**	**6**	**7**
MSE	**0.0127**	**0.0093**	**0.0127**	**0.0047**	**0.0037**	**0.0035**	**0.0053**

MAPE	**3.3861**	**5.0229**	**5.1885**	**2.7770**	**2.4385**	**2.0719**	**3.2089**

Figure 4 presented the total hourly forecasting load results for the 132/33 kV feeder of Ayede transmission sub-station between 23 - 30, January, 2023 during the dry season. From the Table, the total forecasted load for a week (Monday to Sunday) in the sub-station were 47.18, 47, 47.29, 46.13, 46.11, 47.49 and 47.37 MW, respectively. It was observed that the forecasted loads were less than the actual growth rate of the sub-station load. This may due to suppressed demand as many individuals and some commercial customers do not wholly depended on power utility for their energy needs especially during load shedding and irregular supply of electricity.

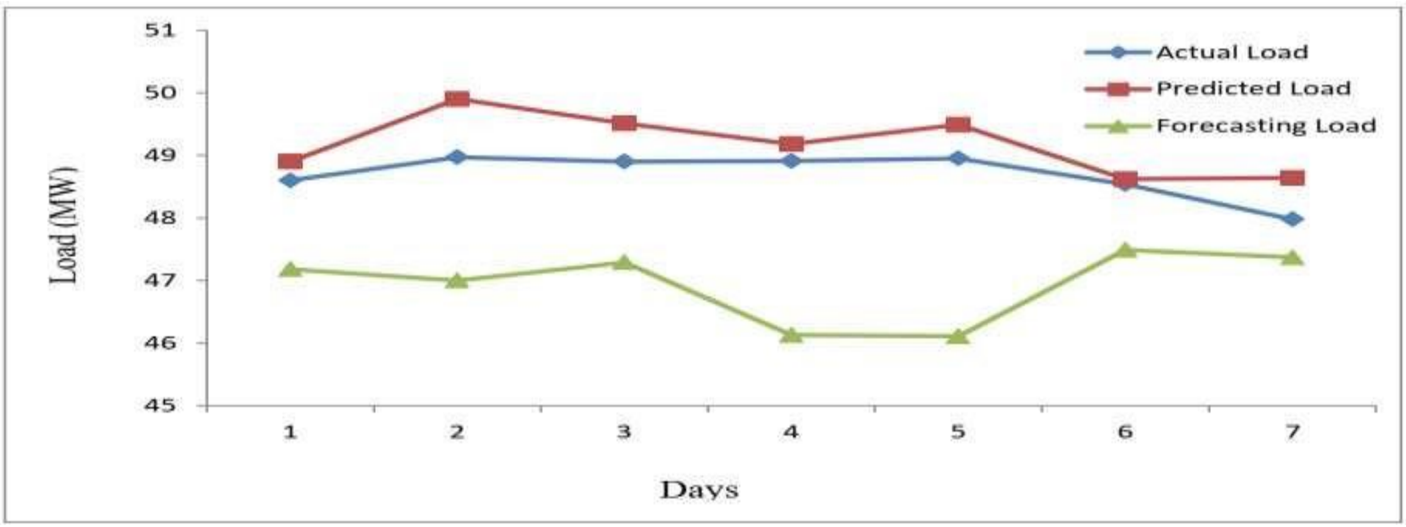

Figure 4: Total Forecasting Load between 23 to 30 , January. 2023 (dry season)

Figure 5 presented the total hourly predicted load results for the Ayede transmission substation feeder between April, 24 – 30, 2023 during raining season. The graphs showed the relationship between actual load data and predicted data (MW). It was observed that the total predicted load in the siub-station were 119.48, 119.7, 118.65, .118.61, 120.13, 117.93 and 120.32 MW, respectively, compared with the actual load data of 119.23, 119.39, 117.99, 118.21, 120.04, 110.08 and 110.58 MW, respectively. It was observed that the predicted loads are much closer to the actual load value of the sub-station. Also, it was observed that day 7 (Sunday) during the raining season had the highest predicted load of 120.32 MW (14.42%) of the total predicted load for the week. This indicated that large amount of energy consumed during the week occurred at the weekend.

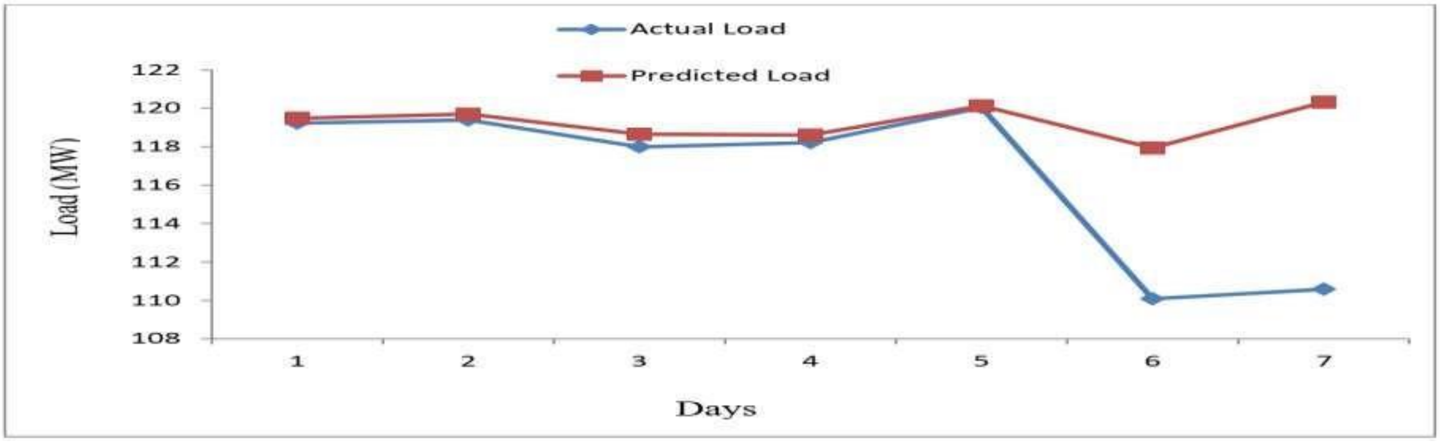

Figure 5: Total Predicted Load between 24 to 30 April,. 2023 (raining season)

Table 2 presented the results of daily predicted error of MSE and MAPE for Ayede transmission sub-station feeder between 24 to 30 April, 2023 (raining season). From the Table, it was observed that the total daily MSE and MAPE for the week were; 0.0054, 0.0026, 0.029, 0.0039, 0.0029, 0.3388 and 0.2130 %; 1.0546, 0.5582, 0.8565, 0.8493, 0.7527, 0.6264 and 0.8957 %, respectively

Table 2: MSE and MAPE Results for 24 to 30 April, 2023

	DAYS						
	WEEKDAYS					WEEKENDS	
	1	2	3	4	5	6	7
MSE	**0.0054**	**0.0026**	**0.0029**	**0.0039**	**0.0029**	**0.3388**	**0.2130**
MAPE	**1.0546**	**0.5582**	**0.8565**	**0.8493**	**0.7527**	**0.6264**	**0.8957**

Figure 6 presented the total hourly forecasting load results for the 132/33 kV feeder of Ayede transmission sub-station between 1 -7, May, 2023 during the raining season. From the Table, the total forecasted loads for a week (Monday to Sunday) in the sub-station were 117.60, 118.21, 117.17, 117.44, 118.03, 118.28 and 118.98 MW, respectively compared with the actual load data of 119.23, 119.39, 117.99, 118.21, 120.04, 110.08 and 110.58 MW, respectively It was observed that the forecasted loads were less than the actual growth rate of the sub-station load. This may due to suppressed demand as many individuals and some commercial customers do not wholly depended on power utility for their energy needs especially during load shedding and irregular supply of electricity.

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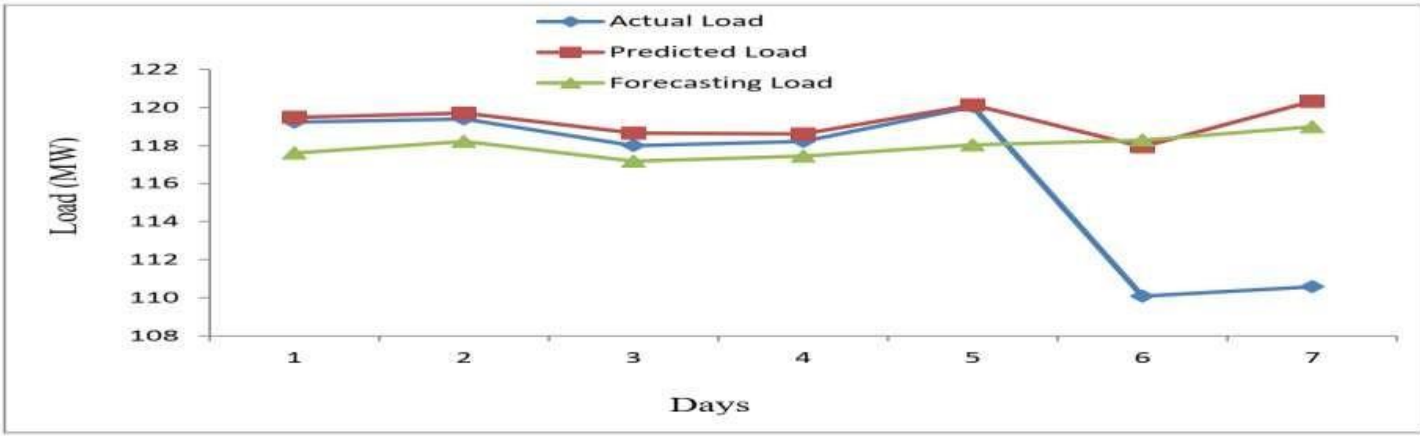

Figure 6: Total Forecasting Load between 1 to 7 , May 2023 (raining season)

IV. CONCLUSION

This study has successfully presented a STLF of electricity supply using LevenberqMarquardt (LM) based BP algorithm trained with Cuckoo Search (CS) to predict and forecast electricity load supply on 32/33 kV feeder of Ayede transmission sub-station covering a period of one week from January, 16 - 22, 2023 (dry season) and April, 24 - 30, 2023 (raining season), respectively in order to meet the power requirements of the sub-station. The initial weight parameter of the ANN forecasting model was optimized with CS algorithm. Then, LM based BP algorithm was used to train the ANN forecasting model with CS and simulation was done in MATLAB R2021a. The simulation revealed that the designed forecasting model can be successfully applied to predict and forecast effective load growth of power system. The predicted load provided more accurate, high quality STLF solution thereby enhanced the capability of the power system. The forecasting model is credible and found to be suitable for STLF of power system. Therefore, application LM based BP algorithm trained with CS for accurate prediction and forecasting of STLF of electricity supply provided an extremely viable approach for expansion of electricity supply growth thereby provides security and stability to the electrical power system planning.

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