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LOAD FORECASTING OF CUMULATIVE ENERGY REQUIREMENTS OF COMERCIAL CLUSTERS FOR YEAR 2035 USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Load forecasting is a key aspect of power system design, operation, and maintenance. To obtain an accurate forecast model which is very vital for the development of any power sector capacity expansion plan be it on generation, transmission and distribution, regression (0.0139) and mean square error (0.99791) were used as criteria for selecting the optimal model for load forecasting. The higher the value of regression, the better the value of the accuracy of the load forecast. In the same vein, the lower the value of the mean square error, the better the accuracy of the load forecast. The load forecast using Backpropagation artificial neural network (BPANN) obtained load forecast in the year 2035 to be 85998MW. This forecast is necessary to provide an increase in generation capacity to meet 85836.99MW of load by 2035. Taking 2021 as base year, the total load demand, which comprises the industrial, commercial, and residential customers were estimated and used to forecast the total load requirements of the customers in year 2035. The ten experimental results obtained by creating ten different topologies of BPANN validated the choice of 30 hidden layer neurons for use in the load forecasting.

1. INTRODUCTION

Energy demand forecasting is an integral process for power system planning, from time-to-time operations and facility expansion in the power utilities. An accurate load forecasting may minimize the future load uncertainty (Resav et al., 2023). It was observed by (Naqash et. al., 2022) that load forecasting is pivotal to the sustainability of electrical energy supply. According to (Aly, 2020), the accuracy of the forecasting models is very important to deal with the new energy generation and consumption. Now, the complexities of

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demand pattern can be found to be within the neighborhood of deregulated energy markets. It then becomes expedient to find an accurate forecasting model for divergent load patterns. Although, there are many developed forecasting models but none of them can be generalized for all demand patterns. Hence, this work presents an optimal topology based back propagation artificial neural network that is applicable for all demand patterns. Real yearly load data obtained from the transmission company of Nigeria's power network are used for the simulation. Load forecasting cannot be written off in the process and planning of electricity industry and the operation of electric power systems (Onah et al., 2015). The more accurate the load forecasting, the more substantial savings in operating costs, maintenance costs, increased reliability of power supply, delivery system, and correct decisions for future development (Quiang et al., 2018).

According to Panda et al., (2017) the results from the comparative analysis carried out by (Panda et al.,2017) show that ANN model is suitable in terms of error minimization for long term electric load forecasting owing to its ability to give satisfactory results in a situation where the availability of data is poor. However, the authors considered one topology model which is unlikely the model to provide the least error minimization for load forecasting.

Rim and Ousama, (2020) carried out load forecasting analysis using three training functions of Artificial neural network (Levenberg–Marquardt, resilient back propagation algorithm and the conjugate gradient algorithm) the results show the superiority of Levenberg–Marquardt over the rest of the algorithm in terms of low error values but the authors did not give attention to the hidden layer neurons of the Artificial neural network exploited in the work.

Samuel et al. (2020) used gradient descent artificial neural network technique for short term load forecasting of Port Harcourt substation. The coefficient of regression obtained is 0.988 with the mean squared error of 0.27. The results show that near accurate values with poor performance of the training algorithm were obtained owing to the fact that the approach gets stuck at local minimum point. Athanasios et.al., (2021) claimed they obtained 100 as the hidden layer neuron of the artificial neural network exploited in their work for load forecasting experimentally but they were silence about the experimental approach exploited to achieve the result.

The study from Yoto et. al., (2023) made an exploit of the annual power grid peak demand data from 2001 to 2020 as inputs to artificial neural network. The performance criteria for the model are mean square error and coefficient of regression. The time and the epoch it took the algorithm to converge were not considered. The results have proved that the data predicted by the Bayesian regulation variant of the Multilayer Perceptron (MLP), is very close to the real data during the training and the learning of these algorithms but it is a very time-consuming approach.

Now, the approach exploited in this study obtained experimentally the optimal hidden layer neuron that will give the best training performance through creation of 10 different topologies of artificial neural network. The study will provide the missing links found in the reviewed literature.

2. MATERIALS AND METHOD

The load demand data of the industrial, commercial, and residential customers from year 2000 to year 2020 was collected from the National Control Center (NCC) of the Transmission Company of Nigeria, Oshogbo. In the MATLAB simulation program, the $feedforwardnet(\,)$ is used to create the neural network. The neural network is trained using the $trainlm$ function owing to its speed and accuracy. The backpropagation artificial neural network (BPANN) is used due to its accuracy and dexterity in data handling.

2.1. Model Formulation

The backpropagation artificial neural network (BPANN) is exploited. BPANN is a Black box model which represents the functional relationship between system inputs and system outputs. By implication, black box models are lumped together with parameter models. The parameters of these functions do not have any physical significance in terms of equivalence to process parameters such as heat or mass transfer coefficients, reaction kinetics, etc. But, if the aim is to represent some trends in process behavior, then the black box modeling approach is very effective. Black box models can be further classified into linear and nonlinear forms. In the linear category, transfer function and time series models predominate. Within the nonlinear category, time-series features are found together with neural-network-based models. The use of neural networks in model building has increased with the availability of cheap computing power and certain powerful theoretical results.

The model comprises the two input vectors year and total load, 10-55 hidden layer neurons, and 1 output vector which are represented as a black box model in Figure 1. It should be noted that the hidden layer has tan sigmoid activation function, and the output layer has purlin function. Both layers have weights, bias, and a summer. To obtain the BPANN model with the optimal hidden layer neurons that will solve the problem of under fitting and over fitting and give the best performance, ten different experimental models were created as shown in Table 1. But 30 hidden layer neurons gave the optimal performance and were selected for the simulation as shown in Figure 2. The forecasting model will have higher accuracy with longer period of historic electricity data. To discuss such a problem in this article, the authors try to assess the BPANN by creating up to ten forecasting model with ten different variation of hidden layer neurons as shown in Table 1.

From the ten different experimental models created in Table 1, it is observed that the selection of 30 hidden layer neurons obtained MSE of 0.0139 and coefficient of regression of 0.99285 at 0.01second using Levenberg–Marquardt or train lm function algorithm of BPANN. These results show that the implicit assumption of randomly selecting any hidden layer neuron for similar simulation do not give optimal solution at all times.

The performance of BPANN is checked by using MSE and regression as shown in Figures 2 and 3 respectively.

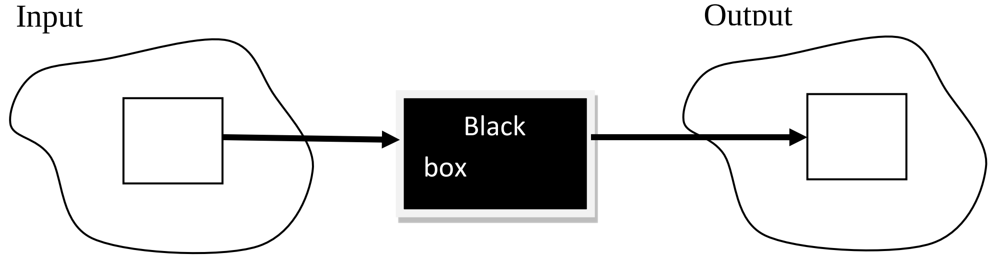

Figure 1: Black box Model

3. RESULTS AND DISCUSSION

Table 1: Models for Back Propagation Artificial Neural Network of the load forecasting

S/No	BPANN Models	MSE	Regression for Validation	Time(s)	Epochs
1	2, 10, 1	0.0631	0.7589	0.14	10
2	2, 15, 1	0.0489	0.8965	0.12	12
3	2, 20, 1	0.0321	0.9582	0.07	16
4	2, 25, 1	0.0208	0.9741	0.06	20
5	2, 30, 1	0.0139	0.99285	0.01	14
6	2, 35, 1	0.0150	0.99381	0.05	16
7	2, 40, 1	0.0356	0.8523	0.35	22
8	2, 45, 1	0.0278	0.9645	0.25	13
9	2,50,1	0.0345	0.8489	0.15	23
10	2,55,1	0.02468	0.9276	0.40	26

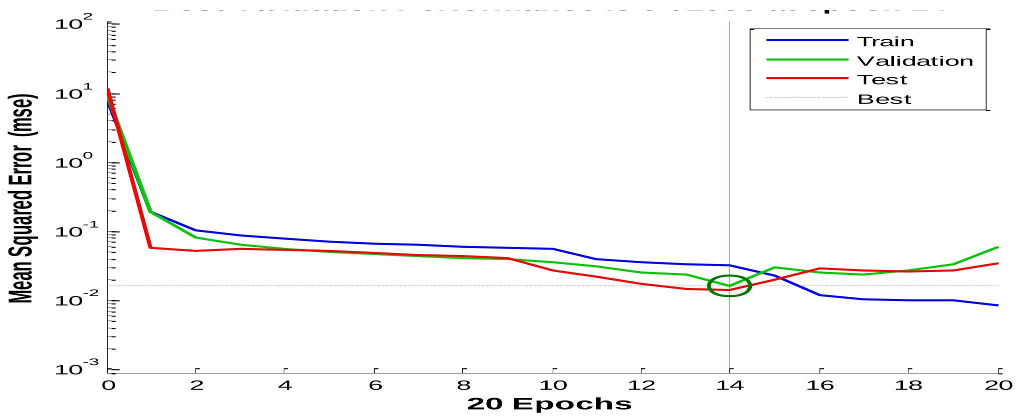

Fig. 2. MSE coefficient

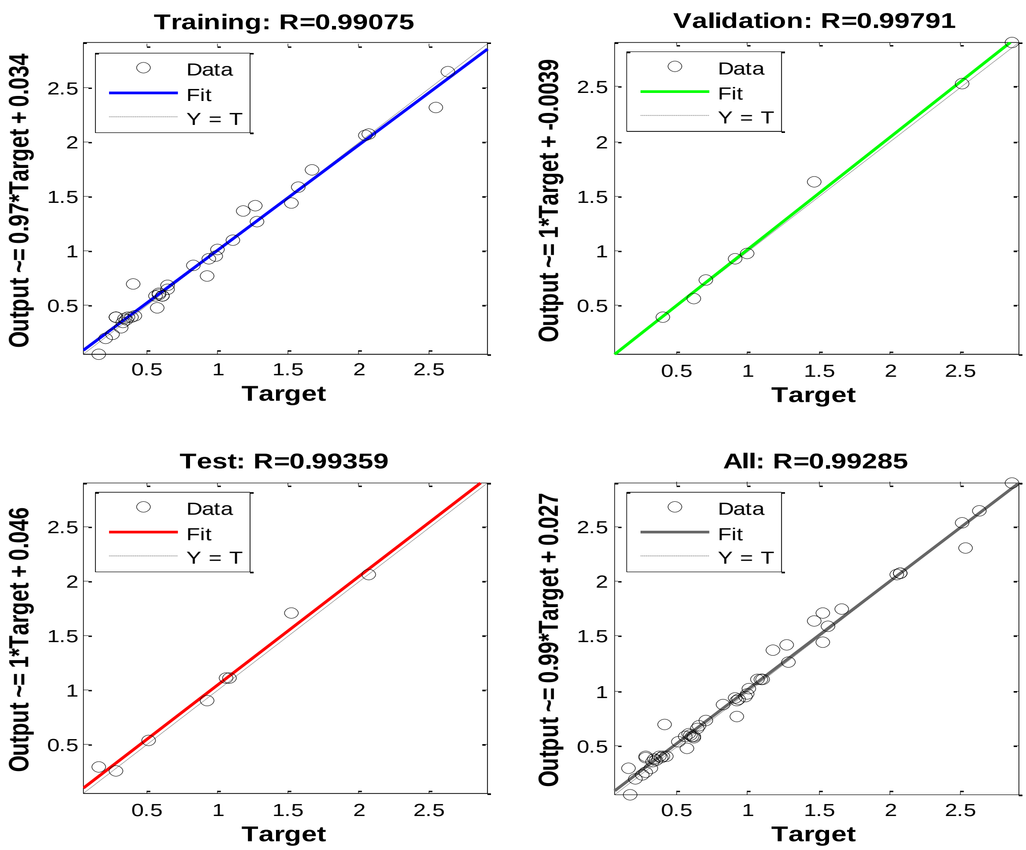

Figure 3 Correlation coefficient

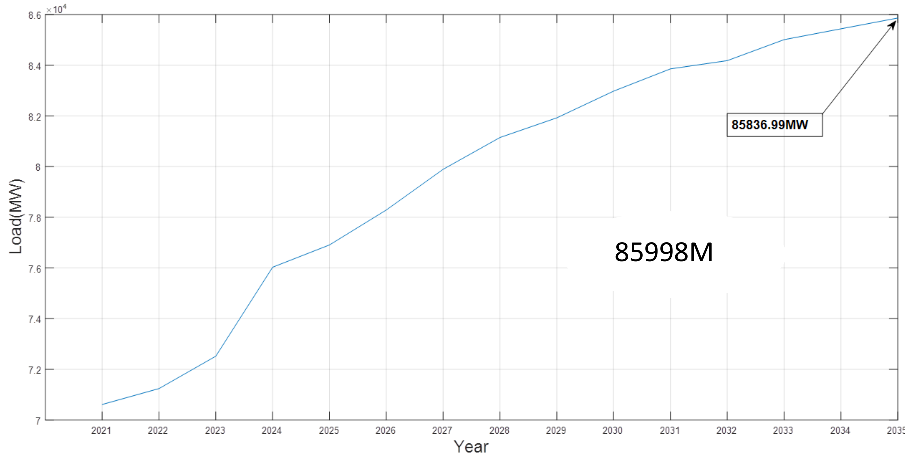

Figure 4: Load forecast for 2035 using BPANN.

From simulations carried out, the output of the neural network model validation forecast is shown in Figure 4. The test forecast horizon is from the historic year 2010-2021. The algorithm computes and outputs predictions that are accurate representations of future loads based on historic load data. The MSE measure is used to give numeric measurement of the level of accuracy of the forecast model.

4. CONCLUSION

This paper presented a practical implementation of long-term load forecasting for real-time application for power systems network. It utilizes a comprehensive load model that can adequately forecast load for a given period of time. The forecasting model will have higher accuracy with longer period of historic electricity load demand data. The BPANN was validated by creating ten forecasting models with ten different variations of hidden layer neurons. Experimental results show that the optimal model for the load forecasting has 30 hidden layer neurons with the highest regression coefficient and the lowest mean square error. The load forecast using backpropagation neural network (BPANN) obtained load forecast in the year 2035 to be 85998MW. The forecast will enable the power sector expansion planners to determine an estimate of additional generation capacity required to meet future load demands. Experimental results obtained by creating ten different topologies of BPANN validated the choice of 30 hidden layer neurons for use in the load forecasting.

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