Modeling and Forecasting of Short-Term Half-Hourly Electric Load at the University of Ibadan, Nigeria.

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ABSTRACT

In this study, the short-term load pattern for the University of Ibadan was investigated and a multi-layered feed-forward artificial neural networks (ANN) model was developed to forecast the time series half-hourly load pattern of the system using the load data for a period of 5 years (2000 to 2004). The study showed that the mean half-hourly load for the period of study ranged between 1.3 and 2.2 MW, and the coefficient of determination (R^2-values) of the ANN predicted and the measured half-hourly load for test dataset decreased from 0.6832 to 0.4835 with increase in the lead time from 0.5 to 10.0 hours.

(Keywords: artificial neural network, electric load, modeling, forecasting, University of Ibadan)

INTRODUCTION

In recent times, the demand for electricity has been on the increase world-wide, due to the increase in population, industrialization, urbanization, and socialization (Mirasgedi et al., 2006). In Nigeria, electricity constitutes one of the major energy resources for household, commercial, and industrial sectors. The share of electricity in the total national energy consumption has been estimated in the year 1989 to be 3.0% (Oladosu and Adegbulugbe, 1994) and in 1999 to be 3.05% (Akinbami, 2001).

At present, Nigeria generates a total of 200-300 MW electricity from the combination of hydro and thermal power stations, which is lower than national demand for electricity. The national generating capacity is accepted to increase to about 10,000 MW in the year 2010. Acute power shortages have led to erratic power supply over the years due in part to the dearth of underlying power generating technology and old facilities of the power stations, and also due to the problems in the transmition/distribution such as overloading of transformers due to inability to forecast the electric energy demand of the system (Waheed et al. 2008). The ability to predict the future demand pattern is crucial in planning, analysis and operation of power systems so as to assure an uninterrupted, reliable, secure and economic supply of electricity.

To address this need for forecasting of electricity demand in different parts of the world, many classic modeling techniques have been proposed and applied to long-term load predictions. The least error squares method with straight line or compound-growth line is one of the most commonly used static state estimation methods by engineers and planners in making long-term load forecasts (EL-Naggar and AL-Rumaih, 2005).

Although the method of least squares is mathematically correct, the accuracy is less reliable in long-term predictions where the dataset is contaminated with bad measurement and trend is projected continually into the future. To overcome this limitation, the use of dynamic state estimation techniques such as Kalman filtering and least absolute value filtering algorithms have been proposed and applied to long-term load forecasting (Temraz et al., 1998). Unlike the static state estimation methods, where the whole dataset is used in the estimation, dynamic filters are recursive algorithms and the estimates are updated using new measurements (EL-Naggar and AL-Rumaih, 2005). But all these proposed methods are not suitable for short-term time series load predictions.

The genetic-based algorithm (GA) technique is another method that has been applied in short-term load forecasting with reasonable accuracy (EL-Naggar and AL-Rumaih, 1998). This class of methods is based on a mechanism of natural selection and genetics, which combines the notion of survival of the fittest, random and yet structured, search and parallel evaluation of the points in the search space (EL-Naggar and AL-Rumaih, 2005). The GA searches for the optimal solution in the search space, and hence gives best solution at a time. The single solution procedure of the GA technique limits its applicability in time series forecasting of electric load.

The artificial neural networks (ANN) approach provides a viable solution to the problem of prediction of time series load pattern because it is based on experience acquired through training on previous data. ANN model can be trained to predict results from examples and once trained can perform predictions at very high speed (Mellit et al., 2006). ANN model is essentially a "black box" approach, in which complex system can be modeled without full understanding of the system mechanisms (Bishop, 1995; Patterson, 1996; Picton, 2000). They have been found to demonstrate excellent self-organization and generalization capabilities, which made them better alternative to other conventional statistical methods such as multiple regression. ANN models are known to be efficient and less time consuming in modeling of complex systems compared to other known mathematical models. They have been widely applied for time series modeling and prediction of complex variables in many engineering systems such as energy systems (Kalogirou, 2000).

In particular, ANN application in electric load modeling and forecasting is gaining much attention, and a great number of studies have reported successful implementations of this model in load modeling and forecasting in many parts of the world. Some recent reports include the works of Ulagammai et al. (2007), Kandil et al. (2006), Mandal et al. (2006a), Topalli et al. (2006), Mandal et al. (2006b), and Gonzalez and Zamarreno (2005). Comprehensive survey of literatures on the application of ANN in modeling and forecasting of load has also been reported by Hippert et al. (2001) and Zhang et al. (1998).

Bakirtzis et al. (1998) has developed an artificial neural network-based model for short-term forecasting of daily load profiles with a lead time of one to seven days for the Energy Control Center of the Greek Public Power Corporation. The results indicated that the developed model provided accurate forecasts. However, all these developed ANN models are based on daily or hourly load forecasts. Since, load patterns are known to be characterized with high variability in time for different energy systems, a micro view of load pattern based on half-hourly variation will be required for more dynamic planning and operation of energy system. Therefore, the aim of this study was to investigate the half-hourly, day-of-the-week, monthly and yearly load variation patterns in the University of Ibadan, Nigeria and to develop a neural network-based model for modelling and forecasting of the short-term half-hourly time series load pattern for the system.

MATERIALS AND METHODS

Data Collection

The data used in this study consisted of the half-hourly time series electric load data for a period of 5 years (2000 to 2004) obtained from the 32 kVA power station of the University of Ibadan (UI), Ibadan, in the Southwestern Nigeria. UI is the first University established in Nigeria in 1948 with current estimated population of over 25,000 students and 15,000 staff. The electricity supply to campus is powered by Power Holding Company of Nigeria (PHCN) through the National grid via two dedicated priority lines from Shasha and Ayede substations.

Design of the ANN Model

Neural Network Toolbox for MATLAB® (Howard and Beale, 2000) was used to design the multi-layer feed-forward back-propagation neural networks. The basic steps involved in designing the network were: Collection/generation of input/output dataset; Pre-processing of data (partitioning of dataset); Design of the neural network objects; Training and testing of the neural network; Simulation and prediction with new input data sets; and Analysis and post-processing of predicted result.

Partitioning of Input/Output Dataset

Prior to the use of the half-hourly time series load data in training of the neural networks, the periods with power outage when there was no power supply from the National grid were recorded as zero load. The load data was then partitioned randomly into three subsets consisting training dataset, 50% of the overall data (29,454 data), validation dataset, 25% (14, 727 data), and the testing dataset, 25% (14,727 data).

Design of the Network Objects

The multi-layer feed-forward back-propagation networks consisted of three layers: input layer; hidden layer; and output layer. There were ten input parameters into the network corresponding past five hours lagged time half-hourly load history *L(t-5.0)*, *L(t-4.5)*, *L(t-4.0), L(t-3.5), L(t-3.0), L(t-2.5), L(t-2.0)*, *L(t-1.5), L(t-1.0), and L(t-0.5)*. The hidden layer consisted of a single layer of neurons, while only one neuron was used in the output layer corresponding to predicted lead time electric load. Networks with ten different lead times prediction from 0.5 to 10 hours: *L(t+0.5)*, *L(t+1.0)*, *L(t+1.5)*, *L(t+2.0)*, *L(t+2.5)*, ………., *L(t+9.5)*, and *L(t+10.0)* were investigated. The schematic of typical network architecture is depicted in Figure 1. Neurons with tan-sigmoid transfer function '*tansig*' was used in the hidden layer, while neurons with linear transfer function '*purelin*' was used in the output layer.

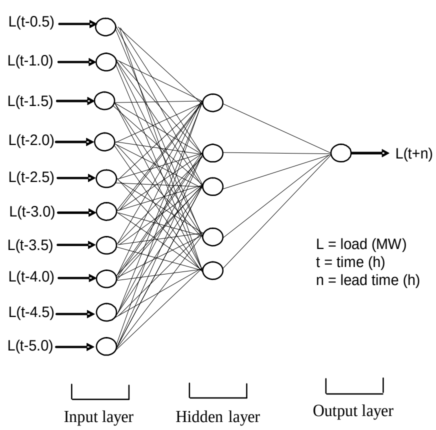


Figure 1: Multilayer Perceptron Network Structure 10-5-1 used for Prediction of Half-Hourly Electric Energy Load.

Training of the Neural Network

The Levenberg-Marquardt '*trainlm*' training algorithms was used in training the different networks The training dataset were fed into networks and the randomly selected initial weights and biases of the networks were updated to minimize the mean square error (MSE) between the network predictions and the targets in the steepest decent direction. The '*early stopping'* technique was used to avoid 'overfitting' (Howard and Beale, 2000).

Testing of the ANN Model

The training process was terminated based on cross-validation or when the threshold of mean square error (MSE) = 0.001 or when the number of iterations was equal to 1000. The mean square error (MSE) and coefficient of determination (R^2-value) of the network predictions and measured values of the half-hourly load were used as the performance criteria for the networks.

RESULTS AND DISCUSSION

Electric Load Pattern of the University of Ibadan

The electric load patterns of the University of Ibadan based on half-hourly, day-of-the-week, monthly and yearly for the study period between 2000 and 2004 are shown in Figures 2 to 5.

Figure 2 shows the pattern of the average electric load on half-hourly basis. The half-hourly electric load was found to range between 1.3 and 2.2 MW. A gradual decline in the average load from 1.6 to 1.3 was observed between the hours of 1.00 to 4.00 am, which corresponded to the period of low academic activities when majority of the university community are expected to be at sleep, and a gradual increase from 1.3 to 2.0 MW was also observed between the hours 5.0 and 10.0 am, when academic activities are expected to resume. The average load peak of 2.2 MW was observed at 11.0 am, which remained almost constant till 16.00 pm. This represented the peak period for academic activities on the campus.

The average electric load pattern based on the day-of-the-week is shown in Figure 3. It can be observed that the average electric load remained fairly constant at about 1.8 MW for every day of the week. No distinctive difference was observed between the load during working days for the week (Monday to Friday) and the weekend (Saturday and Sunday). Other extra curricular activities such as religious services and social activities like wedding ceremonies and other functions which normally take place at the weekends on the campus may account for the non variation in the electric load for the working days of the week and the weekend.

The monthly electric load pattern for the campus is shown in Figure 4. It can be obsvered that, the minimum load of 1.4 MW occurred in the month of June, while the maximum load of 2.2 MW occurred between the months of September and October. The seasonal weather variation from rainy to dry season in Nigeria may account for the monthly load variation observed. The high electric load observed for September (2.2 MW), October (2.2 MW) and November (2.1 MW) corresponded with peak of the rainy season (March to November). The increase in load at this periods may be due to the frequent water heating required for both household and laboratory usage.

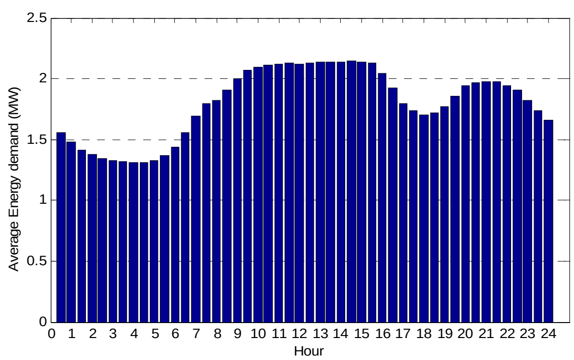


Figure 2: Mean Half-Hourly Electric Load of the University of Ibadan for the Period of 2000 to 2004.

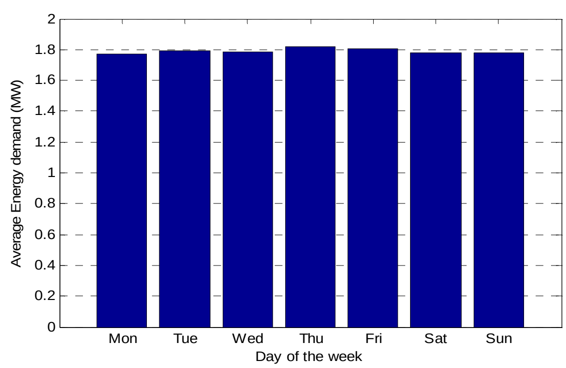


Figure 3: The Day-Of-The-Week Variation in Electric Load of the University of Ibadan for the Period of 2000 to 2004

The yearly average electric load for the period of study 2000 to 2004 is shown in Figure 5. It shows that the yearly electric load varied from 1.0 MW in 2001 to 2.1 MW in 2003 and 2004. The wide variation in the yearly electric load in 2001 compared to other years may be due to numerous industrial actions leading to closure of the University in the year 2001.

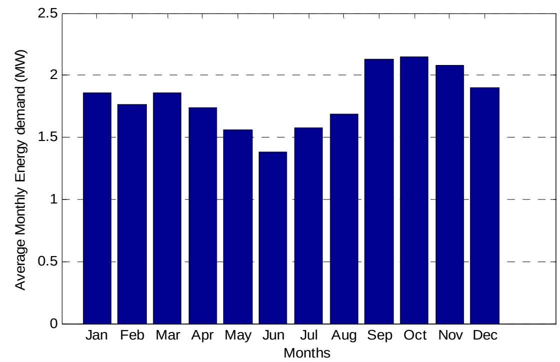


Figure 4: Mean Monthly Electric Load of the University of Ibadan for the Period of 2000 to 2004.

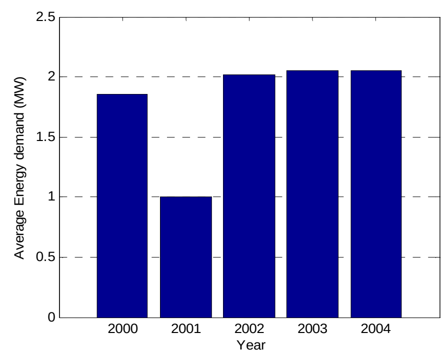


Figure 5: Mean Yearly Electric Load of the University of Ibadan for the Period of 2000 to 2004.

Power Outage Analysis at the University of Ibadan

The power outage corresponding to the periods in which there was no power supply from the National grid was analyzed based on monthly basis. The number of hours in which there was no power supply to the total number of hours available for the month was computed as the power outage percentage.

The monthly power outage percentage for the period of study (2000 to 2004) is shown in Figure 6. The power outage percentage varied from 15%

(July and August) to 49% (May). The erratic power supply in the country which has remained a monster over many decades has been reported to be due in part to the dearth of underlying power generating technology and old facilities of the power stations, and also due to the problems in the transition and distribution such as overloading of transformers (Waheed et al. 2008).

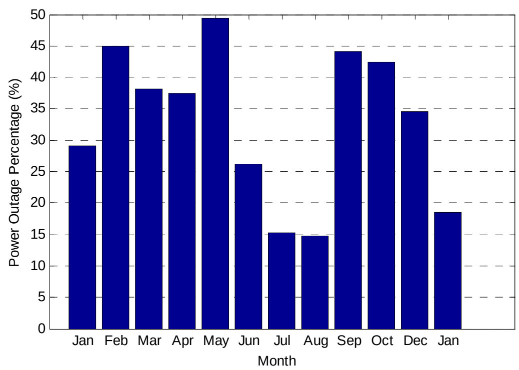


Figure 6: Mean Monthly Power Outage Percentage of the University of Ibadan for the Period of 2000 to 2004.

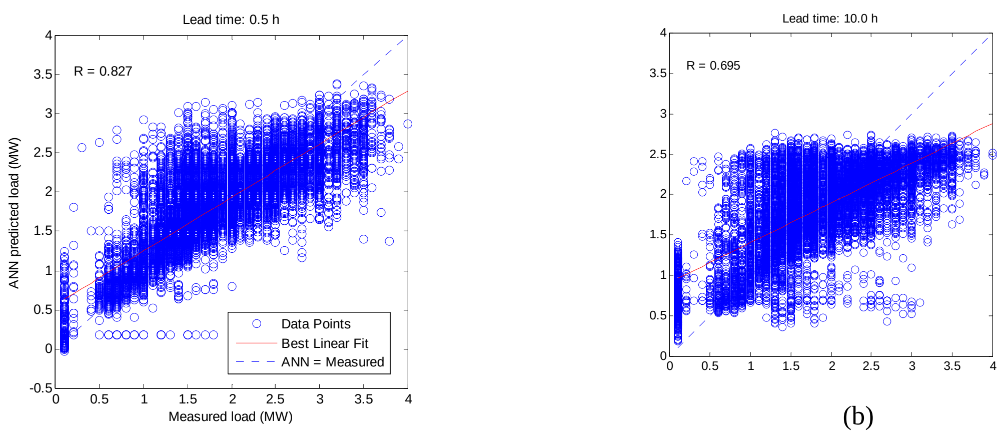
Performance of the Artificial Neural Network Model

The performance of the network in prediction of half-hourly electric energy demand was assessed using the test dataset that was not used during the training process.

The progression in the minimization of mean square error of the training, validation and test datasets during the training process is shown in Figure 7. This shows that the training process was terminated after 65 epochs or iterations due to increase in the validation dataset mean square error.

The coefficient of determination (R^2-value) between the ANN predicted and the measured values using the entire test dataset as shown in Figure 7 is 0.846. The comparison between the measured and the ANN predicated half-hourly energy demand for Dec. 2004 is shown in Figure 8.

The MSE values for lead time of 0.5 and 10.0 h were 0.0813 and 0.1440, respectively. This demonstrated that the model has high predictive accuracy for forecasting the half-hourly electric energy load.



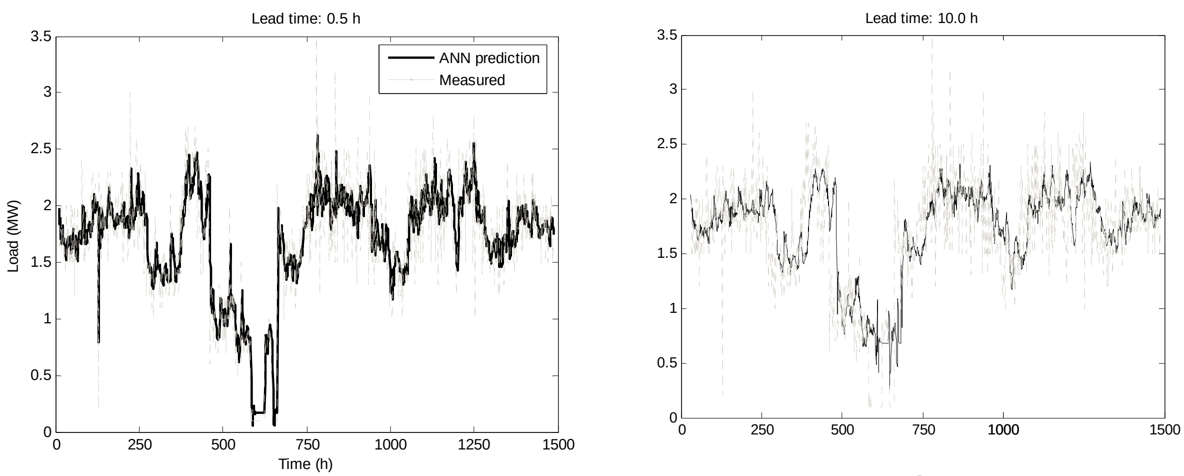
(a)

(b)

Figure 7: Comparison between the ANN Predicted and Measured Values of Load for Test Dataset using Network Structure10-5-1 with Different Lead Times.

Table 1: Performance Characteristics at Different Lead Times for Network Structure 10-5-1.

Lead time (h)	No iteration	Training dataset		Test dataset	
		MSE	R^2-value	MSE	R^2-value
0.5	59	0.1761	0.6816	0.1747	0.6832
1.0	43	0.1873	0.6598	0.1905	0.6555
1.5	24	0.1965	0.6441	0.1997	0.6410
2.0	14	0.2059	0.6288	0.2023	0.6320
4.0	100	0.2340	0.5781	0.2328	0.5765
5.0	24	0.2441	0.5566	0.2495	0.5489
6.0	49	0.2536	0.5428	0.2547	0.5366
7.0	30	0.2611	0.5257	0.2672	0.5169
8.0	43	0.2653	0.5216	0.2646	0.5187
9.0	42	0.2721	0.5057	0.2788	0.4959
10.0	29	0.2830	0.4897	0.2840	0.4835



(a) (b)

Figure 9: Comparison Between the ANN Predicted and Measured Values of Electric Load for December 2004 using Network Structure10-5-1 with Different Lead Times.

CONCLUSIONS

Based on the results obtained in this study, it can be concluded that the half-hourly electric load for University of Ibadan ranged between 1.3 and 2.2 MW, while the power outage percentage varied from 15-49%. The multi-layered, feed-forward, back-propagation artificial neural network with 10-5-1 architecture trained with Livenberg-Margquard algorithm combined with early stopping technique can be used successfully for short-term half-hourly electric load forecasting within acceptable limits.

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