



## DAILY NIGERIAN PEAK LOAD FORECASTING USING ARTIFICIAL NEURAL NETWORK WITH SEASONAL INDICES

S. Y. Musa<sup>1,\*</sup>, E. V. Mbag<sup>2</sup>

<sup>1</sup> DEPT. OF ELECTRICAL AND ELECTRONICS ENGR'G, MODIBBO ADAMA UNIVERSITY OF TECHNOLOGY YOLA, NIGERIA.

<sup>2</sup> DEPT. OF ELECTRICAL TECHNOLOGY EDUCATION, MODIBBO ADAMA UNIVERSITY OF TECHNOLOGY YOLA, NIGERIA.

*E-mail addresses:* <sup>1</sup> [saiduymusa@yahoo.com](mailto:saiduymusa@yahoo.com), <sup>2</sup> [mbagavaandi@hotmail.com](mailto:mbagavaandi@hotmail.com)

### Abstract

*A daily peak load forecasting technique that uses artificial neural network with seasonal indices is presented in this paper. A neural network of relatively smaller size than the main prediction network is used to predict the daily peak load for a period of one year over which the actual daily load data are available using one step ahead prediction. Daily seasonal indices are calculated as a ratio of the predicted load to the actual load. The  $i^{\text{th}}$  index is used as an additional input to a main network that predicts the load for the  $i^{\text{th}}$  day of the year following the one for which the indices were computed. Both neural networks are trained by the back propagation algorithm. The technique is illustrated with data derived from the Nigerian national electric power system. Results obtained are good enough to meet the requirements of practical systems and show appreciable improvement over the normal one step ahead prediction with neural network.*

**Keywords:** load forecasting, neural network, seasonal indices, back propagation, actual load

### 1. Introduction

The anticipated load demand is perhaps the most vital information for the planning and operation of an electric power utility. Accurate models for electric power load forecasting are therefore essential to the operation and planning of a utility company. Basic operating functions such as unit commitment, economic dispatch, fuel scheduling and unit maintenance, can be performed efficiently with an accurate forecast. Load forecasting also helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Load forecasts can be divided into three categories: short-term forecasts which are usually from one hour to one week, medium term forecasts which cover periods from a week to a year, and long-term forecasts which are longer than a year. The forecasts for different time horizons are important for different operations within a utility company. The short term forecast is generally needed for control and scheduling of power system and also as inputs to load flow analysis or contingency analysis [1].

Load forecasting has evolved over the years based on different techniques that include statistical, intelligent systems, neural network and fuzzy. Artificial neural networks(ANN) have lately received much attention, and a great number of papers have reported successful experiments and practical tests. The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990 [2-4]. There have been many attempts to improve the neural network based techniques [4-6]. This work is one of such attempts. This work rallies round the fact that electricity is generally used for powering industrial machinery, comfort heating and cooling, illumination and communication. While the other usages are daily routines, comfort heating and cooling are weather dependent. Major variations in load consumption pattern are therefore primarily due to weather variables and since the weather variables are seasonal in most parts of the world, the load consumption pattern will exhibit some kind of seasonality. In an earlier work to mitigate the effect of seasonality in forecasting with neural network, Alsayeh [7]

\* Corresponding author, Tel: +234-8035134769

suggested training a set of ANN with data for different season. This paper presents an approach whereby daily seasonal indices are first computed for a whole year and the indices are then used to improve the accuracy of another network in predicting the daily loads in the year that will follow. The computation of the indices stems from the fact one step ahead prediction with neural network is more accurate when the predicted variables are in close neighborhood with the data used in training the network. As the variables to be predicted diverge, the accuracy of the prediction drops. The indices are generated based on the separation between the one step ahead predicted value and the actual value in such a way that when an index is inputted into the main prediction network, it will shift the predicted value towards the actual, that is, it reduces the forecast error. Here, simple ratio indices are used. Calculating the indices starts by predicting the daily demand for a whole year that the actual load demand is available. Daily indices are computed as the ratio of the predicted load to the actual load. An index is negative whenever the predicted value is greater than the actual so that inputting it to the ANN with seasonal index

(ANN SI) will make the predicted value to drop. Likewise whenever the predicted value is less than the actual load, the index is positive and inversed. The variations in the indices are in close resemblance to the actual load variations, that is, seasonal. An index computed for a particular date is used as an additional input to the ANNSI when predicting for the same date in the subsequent year. The indices computation scheme is shown in Figure 1 and the load forecasting using the ANNSI is implemented as in Figure 2.

**2 Artificial neural networks**

Artificial Neural networks (ANN), equally called neural networks, are essentially non-linear circuits that have the capability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or nonlinear mathematical function of its inputs. Artificial neural network technology has been reported in many literatures such as [10]. It is basically an attempt to simulate the behaviour of the human neural system. It is composed of non linear computational elements called artificial neurons operating in parallel

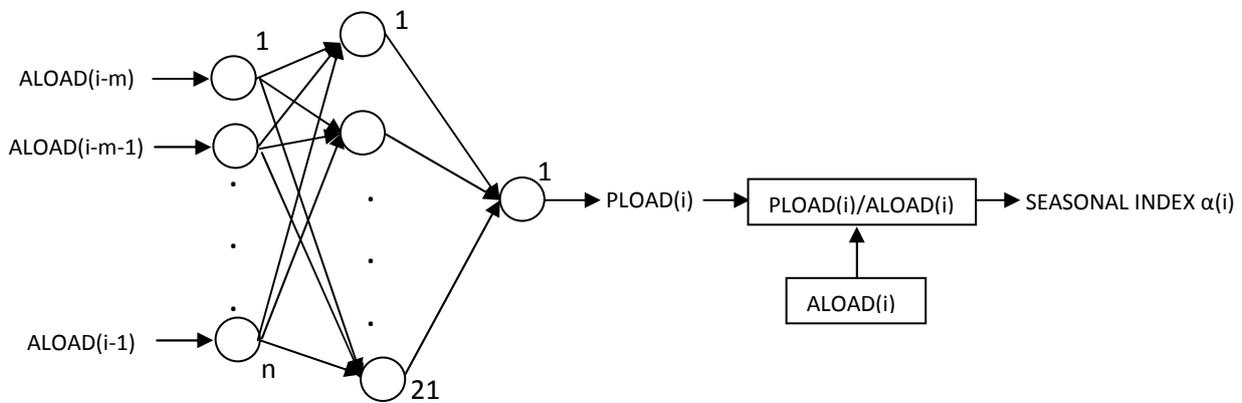


Figure 1 Seasonal indices computing neural network

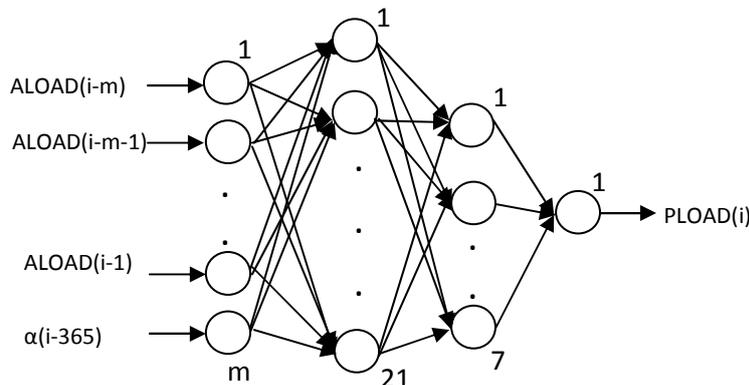


Figure 2 Load forecasting network with seasonal index

In practice network elements are arranged in a relatively small number of connected layers between network inputs and outputs. Feedback paths are sometimes used. In applying a neural network to electric load forecasting, one must select one of a number of architectures. Feed forward networks are most often used. The network elements are interconnected through weightings. The values of the weights are adjusted by training the ANN so that a desired association between the input and output patterns is achieved. For solving pattern recognition related problems such as load forecasting, training by the back propagation algorithm is often employed. The major steps of this algorithm are presented in what follows for a four layer network with input layer  $i$ , with  $n_i$  nodes, first hidden layer  $j$  with  $n_j$  nodes, second hidden layer  $k$  with  $n_k$  nodes and an output layer  $r$  with  $n_r$  nodes. The weights are initially assigned arbitrary values. The output  $Z_j$  of each neuron in the first hidden layer is calculated as;

$$Z_j = f(\sum_{j=1}^{n_i} w_{ji}x_i) \quad \dots \quad (1)$$

The output of the second hidden layer,  $Z_k$ , is

$$Z_k = f(\sum_{k=1}^{n_k} w_{kj}Z_j) \quad \dots \quad (2)$$

And the output of the output layer is

$$Z_r = f(\sum_{r=1}^{n_r} w_{rk}Z_k) \quad \dots \quad (3)$$

$f$  is a limiting threshold function. The error between the output,  $Z_r$ , and the intended or desired output  $Y_r$  is calculated as;

$$\epsilon_r = \frac{1}{2}(Z_r - Y_r) \quad \dots \quad (4)$$

A tolerable limit of this error is usually set before training and until this limit is obtained, the training continues recursively.

The error in the output layer due to any  $r^{\text{th}}$  node  $\delta_r$  is calculated as

$$\delta_r = (Y_r - Z_r)\gamma(1 - Z_r) \quad \dots \quad (5)$$

The errors due to the neurons in the second hidden layer  $\delta_k$  are;

$$\delta_k = f'(Z_k) \sum_{k=1}^{n_k} \delta_r w_{rk} \quad \dots \quad (6)$$

The errors due to the nodes in the first hidden layer  $\delta_j$  is

$$\delta_j = f'(Z_j) \sum_{j=1}^{n_j} \delta_k w_{kj} \quad \dots \quad (7)$$

The changes in the weights between the input layer and the first hidden layer, the first hidden layer and the second hidden layer and the second hidden layer and the output layer are, respectively, given by;

$$\Delta w_{ji} = \delta_j x_i + (w'_{ji} - w''_{ji}) \quad \dots \quad (8)$$

$$\Delta w_{kj} = \delta_k x_j + (w'_{kj} - w''_{kj}) \quad \dots \quad (9)$$

$$\Delta w_{rk} = \delta_r Z_k + (w'_{rk} - w''_{rk}) \quad \dots \quad (10)$$

The weights are then updated in all the layers as;

$$w = w' + \Delta w \quad \dots \quad (11)$$

$w'$  and  $w''$  are the weights obtained one step and two steps respectively before the one being updated. To make the error convergence faster, the change in weights  $\Delta w$  are adjusted by the learning rate ( $\eta$ ) and the momentum term ( $\gamma$ ) as;

$$\Delta w = \eta \delta x + \gamma(w' - w'') \quad \dots \quad (12)$$

### 3. Methodology

This forecast technique is basically two fold. Using daily load data to generate the indices and using the indices to improve the daily load prediction in the following year. Illustrating with the data base of the Nigerian national electric power system, daily peak load data for the entire country (ALOAD) were obtained from the operational records of the Power Holding Company of Nigeria (PHCN) PLC for the year 2008 to generate the indices and for the year 2009 to train the ANNSI and to evaluate the effectiveness of this technique. A one hidden layer neural network with other details as shown in Figure 1 is trained off line using Neural Network Toolbox package in MATLAB with the first thirteen load data as inputs ( $n=13$ ) and the fourteenth load as the desired output. After training, the desired output of the trained net is taken to the input and the other inputs are shifted one step back to start prediction for the fifteenth day of 2008 for the purpose of indices computation. The index for the fifteenth day is calculated as the ratio of the predicted load for the fifteenth day to the actual load for the same day. The inputs are shifted one step back and the sequence is repeated until a complete set of daily indices are generated for the year.

For the purpose of predicting the daily peak load in the following year (2009), a two hidden layer network as shown in Figure 2 is trained, also off line, with the first thirteen load data of 2009 and the index for the fifteenth day of 2008 in the previous year as inputs ( $m=14$  in Figure 2) and the desired output is the actual load for the fourteenth day of 2009. The desired output is shifted to the input and the other inputs are shifted one step back to start prediction for the fifteenth day. To predict for the sixteenth day, the inputs to the trained network are the third to fifteenth actual load data and the sixteenth index. In this manner, the daily load for any length of period is predicted. This is the ANNSI prediction.

For the purpose of comparison, a network with the same structure as the forecasting network is trained with first fourteen load data as inputs and the fifteenth load data as desired output. The desired output is shifted to the input and the other inputs shifted one step back to start prediction for the sixteenth day. This is the normal one step ahead prediction with ANN. All the inputs and the desired outputs to all neural networks are first normalized between 0.2 and 0.8 using the relation

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} (0.8 - 0.2) \dots (13)$$

where x is the raw training set and  $x_{max}$  and  $x_{min}$  are the maximum and minimum inputs in the training set.

To evaluate the effectiveness of this prediction with ANNSI, three extremely distinct seasons in Nigeria are considered. These are the extremely hot period around March to May when the power demand is at its peak, the moist rainy season with its peak in August when the power demand is moderate and the cold dry period around the end of the year when energy consumption is relatively low. The results for one month each in these extreme cases are presented.

**4. Results**

Prediction for one year was carried out but for the brevity of space, only forecast results for three months, selected in extremely different seasons of the year are presented. These are the months of April, August and November. For each month, the maximum forecast errors ( $e_{max}$ ) and the absolute mean error ( $\epsilon$ ) in percentages are calculated for both the ANN with seasonal indices (ANNSI) approach and the one step ahead prediction with ANN (ANN). The errors are calculated as follows,

$$e_{max} = \max \left\{ \frac{100|P_{ai} - P_{fi}|}{P_{ai}} \right\} i = 1, 2, \dots, N_d \quad (14)$$

$$\epsilon = \frac{100}{N_d} \sum_{i=1}^{N_d} \left\{ \frac{|P_{ai} - P_{fi}|}{P_{ai}} \right\} \dots (15)$$

where  $P_{ai}$  and  $P_{fi}$  are the actual and predicted loads respectively for the  $i^{th}$  day and  $N_d$  is the number of days covered by the forecast, that is, 30, 31 and 30 for April, August and November respectively. The summary of forecast errors is given in Table 1.

Table 1: Forecast errors for the three selected months

|          |       | $e_{max}(\%)$ | $\epsilon(\%)$ |
|----------|-------|---------------|----------------|
| April    | ANNSI | 6.60          | 2.75           |
|          | ANN   | 11.32         | 3.46           |
| August   | ANNSI | 6.72          | 2.76           |
|          | ANN   | 9.44          | 3.58           |
| November | ANNSI | 7.16          | 2.47           |
|          | ANN   | 11.31         | 3.47           |

Graphical presentations of forecast results are shown in Figures 3, 4 and 5 for the months of April, August and November respectively.

**5 Conclusion**

An artificial neural network based daily peak load forecasting technique that takes into account seasonality in the load consumption pattern has been presented. Back propagation neural networks have been used to show the effectiveness of this technique over the normal prediction with ANN. This has been shown using the data base of the Nigerian electric power system. Forecast results for three months selected from extremely different seasons show that maximum forecast error drop from 11.32% for the ANN to 7.16% for the ANNSI. Correspondingly the absolute mean error drops from 3.58% for the ANN to 2.76% for the ANNSI. This shows the overall effectiveness of the ANNSI over the normal prediction using ANN.

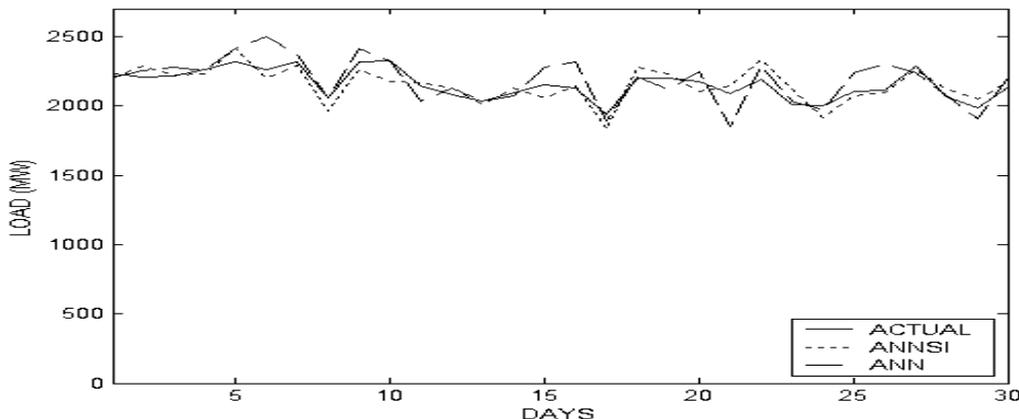


Figure 3: Forecasts for April

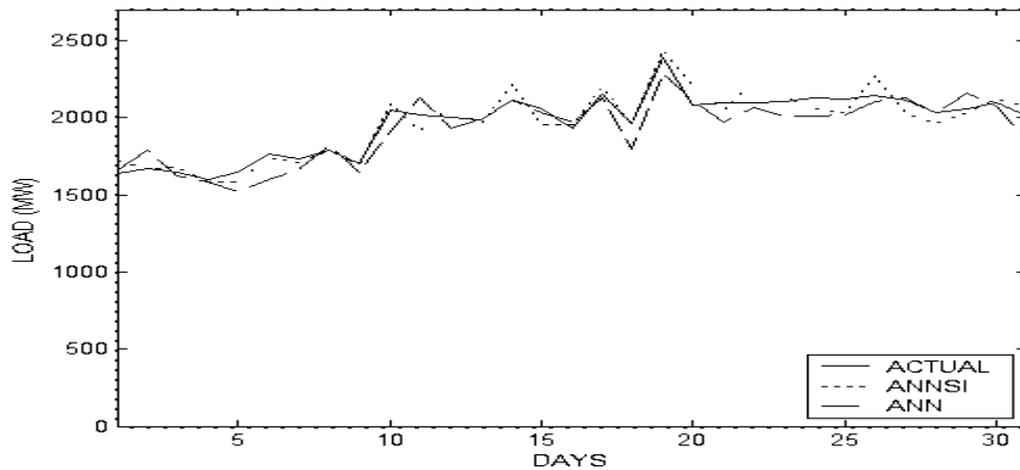


Figure 4: Forecasts for August

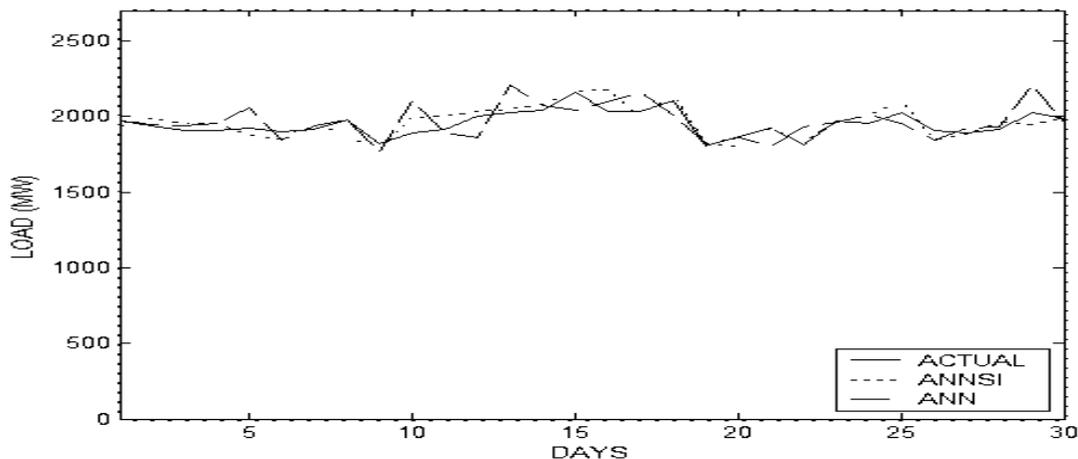


Figure 5: Forecasts for November

## References

- [1] Al-Shareef, A. J., Mohamed, E. A. and AL-Judaibi, E. "One hour ahead load forecasting using artificial neural network for western area of Saudi Arabia". *World Academy of Sciences, Engineering and Technology* 37, 2008, p219-224
- [2] Lee, K. Y., Cha, Y. T. and Park, J. H. "Short term load forecasting using an artificial neural network". *IEEE Transactions on Power Systems* Volume 7, Number 1, 1992, pp124-132
- [3] Lu, C. N. and Vemuri, S. "Neural network based short term load forecasting", *IEEE power Engineer Review* Volume 13, Number 2, 1993, p52
- [4] Al Fuhaid, A. S., El-Sayed, M. A. and Mahmoud, M. S. "Cascaded artificial neural networks for short term load forecasting", *IEEE Transactions PWRS* Volume 12, Number 4, 1997, pp1524-1529
- [5] Chow, T. W. S. and Leung, C. T. "Neural network based short term load forecasting using weather compensation", *IEEE Power Engineer Review*, Volume 16, Number 11, 1996, p49
- [6] Peng, M., Hubele, N. F. and Karady G. G. "Advancement in the Application of Neural Networks for Short-Term Load Forecasting", *IEEE Transactions on Power Systems*, Volume 7, Number 1, 1992, pp250-257.
- [7] Alsayeh, O. A., "Short term load forecasting using seasonal artificial neural networks", *International Journal of Power and Energy Systems* Volume 28, Number 9, 2003, pp 137-143
- [8] Park, D. C., El-Sharkawi, M. A., Marks, R. J., Atlas, L. E. And Damborg, M. J. "Electric load forecasting using an artificial neural network", *IEEE Transactions on Power Systems* Volume 6, Number 2, 1991, pp442-449
- [9] Kalra, P. K., Srivastava, A. and Chaturvedi, D. K. "Possible application of neural nets to power system operation and control", *Electric Power System Research* Volume 25, 1992, pp83-90
- [10] Haykins, S. *Neural Networks - a Comprehensive Foundation*. Prentice Hall, New Jersey, 1999
- [11] Ho, K. L, Hsu, Y. Y, and Yang, C. "Short term load forecasting using a multilayer neural network with an adaptive learning algorithm", *IEEE Transactions on Power Systems* Volume 7, Number 1, 1992, pp141-148.