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

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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^{th} index is used as an additional input to a main network that predicts the load for the i^{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]

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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 (ANNSI) 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

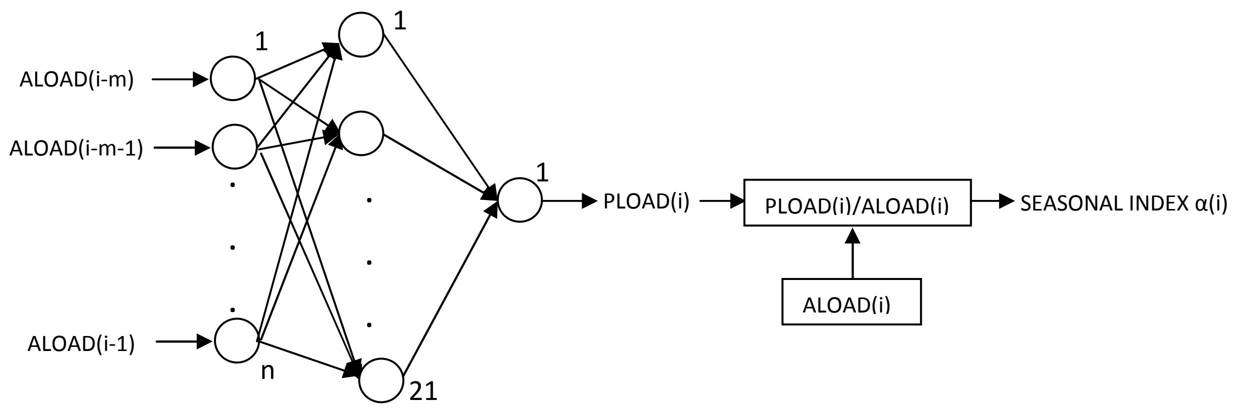

Figure 1 Seasonal indices computing neural network

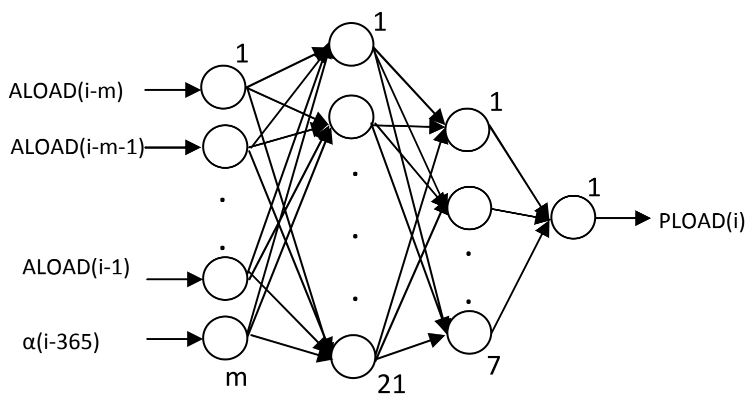

Figure 2 Load forecasting network with seasonal index

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;

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

The output of the second hidden layer, Z_k, is

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

And the output of the output layer is

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

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

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

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^{th} node δ_r is calculated as

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

The errors due to the neurons in the second hidden layer δ_k are;

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

The errors due to the nodes in the first hidden layer δ_j is

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

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;

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

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

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

The weights are then updated in all the layers as;

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

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

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

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

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

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 (ϵ) 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,

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

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

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}(%)	ϵ (%)
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.

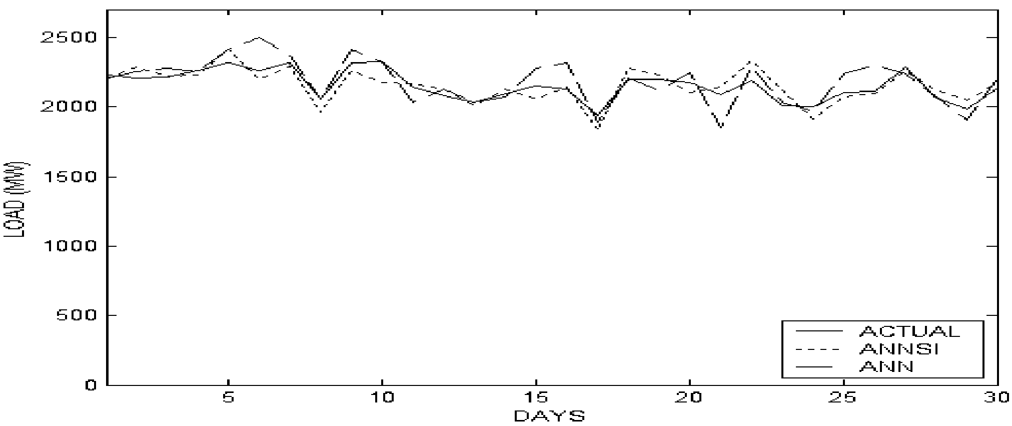

Figure 3: Forecasts for April

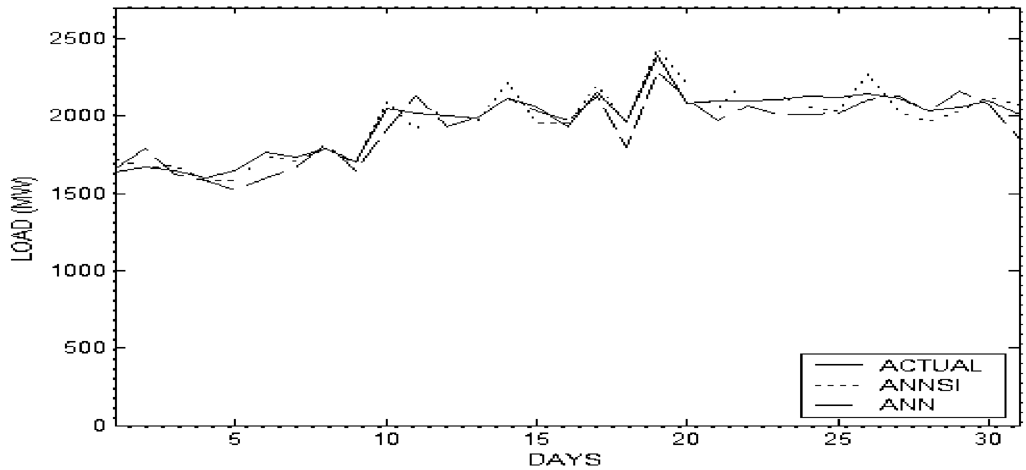

Figure 4: Forecasts for August

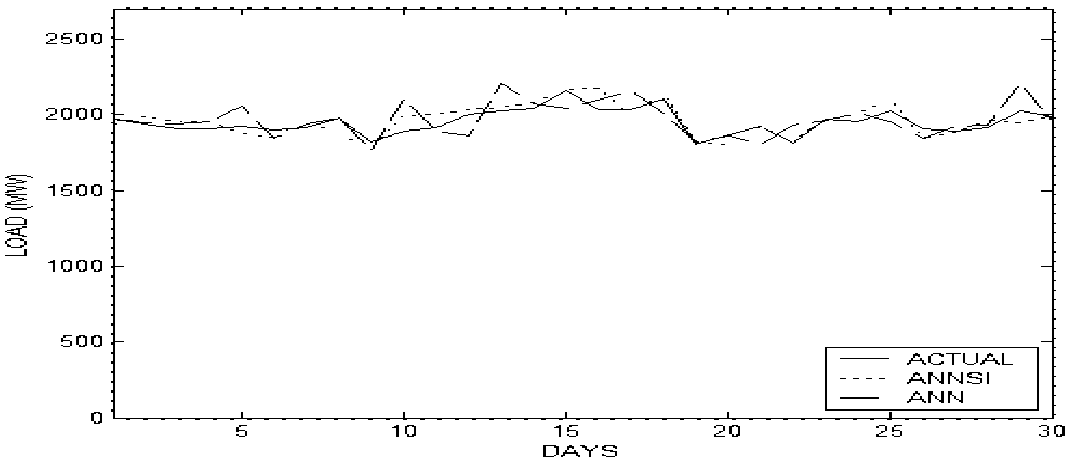

Figure 5: Forecasts for November

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