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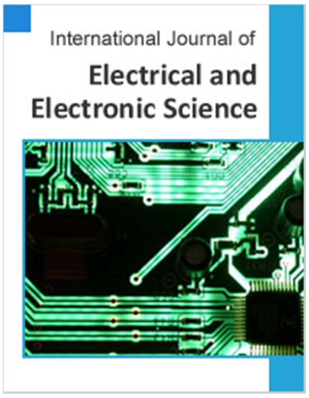

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Artificial Neural Network for Energy Demand Forecast

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Abstract
The importance of forecasting of electricity demand cannot be over emphasized. Load forecasting is needed by utility companies for planning, scheduling, cost management, equipment installation etc. Hence when utility managers do not have accurate estimate of future needs, it becomes difficult to plan. This paper is a study of electric power forecasting in Owerri city (South East Nigeria), using artificial neural network model. MATLAB tool is used in simulating this model. The model, a multilayer time delayed feed-forward artificial neural network trained with error back propagation algorithm, is used to study the pre-historical load pattern of Owerri city power system network in a supervised training manner. After presenting the model with a reasonable number of training samples, which is the historic load demand between 2007 and 2017, the model could forecast correctly the average annual electric power demand in Owerri city for the next ten years (2018 to 2027) as 111.6MW. This means that the present installed capacity will not be able to adequately serve Owerri city in about ten years' time except an expansion in the generation capacity is done annually by about 7%.

1. Introduction

A power system must be well planned adequately so as to meet the estimated electricity demand in both near and distant future. The primary aim of planning is to ensure future demands are met effectively both economically and in terms of engineering. Accurate decision making and planning for owerri city energy future requirement is very important to ensure reliability and confidence. Owerri is a fast developing city, if accurate decisions on future unit commitment, fuel allocation, power wheeling arrangement, load distribution etc can be made, it is only necessary to employ a reliable model for power demand forecasting, therefore, this research is aim at suggesting a solution to the ailing Power demand in Owerri by proposing a model which can perform 24-hours-ahead load forecasting by means of artificial neural network.

1.1. Objectives of the Study

Although the objectives of the study can be inferred from the background to the study outlined in the previous section, it can still be clearly and concisely stated that the objectives of the study are:

To model artificial neural network which can forecast electric power supply for one day in advance (Short Term Load Forecasting);

To train the model (using back propagation algorithm) with pre-historical load data obtained from a sample of the power company so that each input produces a desired output;

To Test the model to get the values of future power supplies; and

In the light of the above, make necessary recommendations and suggestions for further research.

1.2. Problem Statement

Owerri is the state capital of Imo State in Nigeria, a fast developing urban city. It is set in the heart of Igboland, and also the state's largest city. Owerri consists of three Local Government Areas including Owerri Municipal, Owerri North and Owerri West, it has an estimated population of about 1001,873 as of 2016 and is approximately 100 square kilometers (40 sq. meters) in area. About 400 hundred hotels and recreation centers, numerous small and medium scale enterprises scattered around. The only challenge is electric power supply which is grossly inadequate, business owners generate their own power to run their businesses. The consequence of this is very high cost of living. There is no data anywhere to show the actual power demand in Owerri, hence the importance of this study.

1.3. Methodology

Several methods have been used by different authors to forecast energy demand for various cities and nations. The method used for this work is Artificial Neural Network, ANN.

Demand forecast methods should use the past and present available data to project future demands reliably enough so that utility managers can have a working tool for accurate decision making. Accurate demand forecast is needed for engineering and finance planning. In engineering planning, it helps the utility engineers know the amount of power an area will require in a particular time in the future. This will help in scheduling of the downstream networks. The decision makers through accurate demand forecast assist decision makers know the demand estimate for the national grid at a future time so as to be able to pan scheduling adequately. While in finance planning, demand forecast helps the finance team know the generator sizes to purchase or install, cabling and metering systems required and all the cost implications.

Demand forecasting may be applied in long, medium and short –term time scale. There has been various classifications but most conventionally, short-term forecasting is for up to 1 day to 1 week ahead, while medium-term forecasting is for up to 1 week to 1 year. Long-term forecasting is for 1 year and above. Short-term is basically used for real-time controls and security functions while medium term and long-term forecasting is for determining generation, transmission and distribution capacity. Several methods have been used to predict demand, however, the trend now is the use of some Artificial Intelligence Means (AIM). This is because of the complex nature of forecasting. Artificial Neural Network, ANN is one of the methods of AIM. ANN works like the neurons in the human brain, they are able to use historic data to learn patterns and relationships, and then they can predict outputs when a new set of inputs are supplied.

Several techniques are available for forecasting. Matthewman and Nicholson, [1] conducted an early survey of electric load forecasting techniques. Load demand modeling and forecasting was also reviewed in the works of [2], [3], and [4]. Moghram and Rahman, [5] surveyed electric load forecasting techniques and in recent times Alfares and Nazeerudin, [6] conducted a literature survey and classification of methods of electric load forecasting. Also in [7], different types of methods for load estimation were mentioned. Load forecasting methods are many, depending on the number of variables used, these methods are; Extrapolation technique, Scheer's method, End-use method, and Probabilistic extrapolation correlation method. It is noted in [8] that forecasting methods as applied to the electrical industry fall into two broad categories; Estimates based on existing trends and Econometric models. Load forecasting could be carried out either by extrapolation, correlation or a combination of both, [9]. Models based on genetic algorithms; fuzzy logic, knowledge-based expert system, support vector machine, and neural networks techniques that are sometimes used for load forecast, [10].

2. Method and Model Design

The design of the ANN and the procedure for forecasting using the ANN, carried out here in five basic steps, these includes; collection of data, processing of data, building the network, training the network, forecast implementation, and test of performance of the model adopted.

2.1. Research Data Collection

The data that was used in training and testing of the model proposed in this research are the yearly electric power supplied to Owerri city as obtained from Enugu Electricity Distribution Company (EEDC), Egbu, Owerri 132/33kV station. The historic data for 2007 through 2016 is used for the analysis while a ten year forecast from the period of 2007 to 2016 is made. The data to be used is detailed in table 1, which include: Historical electric load demand, Gross Domestic Product, GDP, Population and Industrial Index of Production, IIP. This is the data for Owerri City for the period of investigation.

Table 1. *Owerri City Historic data, 2007-2016.*

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
GDP (Billion Naira)	76	82	76	80	80	83	86	92	98	104
IIP%	26.2	26.8	26.4	27.4	27.9	28.3	28.9	29.3	29.6	32.2
Population (million)	0.45	0.51	0.56	0.64	0.68	0.72	0.78	0.86	0.93	1.14

The above data are needed for the accurate forecasting of future load demand. This is so because population growth, GDP and other natural factors like seasonal changes affect power demand and availability. Weather forecast is not used in this forecast because the forecasted period is long, hence, making it difficult for weather changes to be computed.

2.2. Data Pre-processing and Processing

Neural network training can be made more efficient if certain pre-processing steps are performed on the network inputs and targets [11]. It is convenient to normalize the data before carrying out the training to compensate for the inevitable scaling and variability differences between the variables [12].. Data pre-processing was in two stages: the first action on the load data was to find replacement for missing load values. The case of missing load values arose either due to system collapse, earth fault, feeder opened for the purpose of maintenance operation etc,. In cases like the above, average load information for the preceding month would always be used to refill the missing gap. The second operation on the data was performed to put the input values in the same scale

Table 2. *Monthly peak demand as supplied by EEDC.*

MONTH	Peak Energy Demand (MW)									
	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
January	55	65	71	60	70	78	75	80	85	85
February	64	65	70	50	70	78	75	80	70	80
March	67	70	70	70	75	70	75	75	65	70
April	67	65	70	70	75	70	75	70	60	65
May	71	50	65	65	75	75	80	70	60	80
June	69	50	65	65	70	70	80	75	65	80
July	71	55	65	70	70	60	80	75	75	85
August	72	60	50	70	75	60	60	75	75	80
September	74	65	55	60	61	75	60	80	70	85
October	76	60	55	60	61	60	65	85	75	80
November	78	58	60	65	60	75	60	80	75	75
December	65	63	60	70	69	75	80	85	85	90

2.3. Building the Network

A feed-forward input-delay back propagation using ANN, a toolbox in MATLAB is used for the architecture because of its high level of accuracy. This neural network is used for the implementation of the functional approximation for demand forecasting. One special feature of the input-delayed feed-forward network is that it combines conventional network topology (multi-layer perception) with good handling of time dependencies by means of a gamma memory. This is a versatile mechanism that generalizes the structures of memory, based on delays and recurrences. This scheme allows smaller adjustments without requiring changes in the general network structure. Structure of the network affects the accuracy of the forecast. Network configuration mainly depends on the number of hidden layers, number of neurons in each hidden layer and the selection of activation function.

The data of table 2. is used in implementing demand forecast using this network, hence the data is divided into two sets which are: Input sets and target sets.

The input sets are the Year Index, GDP, IIP and Population. This is a 10 x 4 matrix.

The target or output set is the Annual Peak load Demand.

Table 3. *Peak load, GDP and Population.*

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
GDP (Billion Naira)	76	82	76	80	80	83	86	92	98	104
IIP%	26.2	26.8	26.4	27.4	27.9	28.3	28.9	29.3	29.6	32.2
Population (Million)	0.45	0.51	0.56	0.64	0.68	0.72	0.78	0.86	0.93	1.14
Peak Demand (MW)	70	70	71	75	75	78	80	85	85	90

2.4. Network Training

The feed-forward neural network with tap delay lines (NEWFFTD) used in this work is a dynamic network and was trained using the batch mode style of training. This was implemented using the MATLAB code *train*. This being because *train* has access to more efficient MATLAB training algorithms. The inputs were presented to the network model. The presence of the tap delay lines on the network input ports readily makes the model see the input data as though sequential.

The procedure is to train the ANN with historic data from 2008 to 2017, the ANN is trained to study the relationship between the input data sets and output data set. Basically, the neural architecture consists of three layers, input layer, output layer and hidden layer. The network having learnt the relationship between these data sets can forecast the future peak load for 2018 through 2027.

The neural network mathematical representation of processing element is given by Neurodynamics

Summation function:

n=b*w0+ p1*w1+p2*w2+……+pn*wn (1)

Transfer function:

$$f(x) = (1 + e^{-x})^{-1} \quad (2)$$

Output:

$$y = f(n) \quad (3)$$

The base data of the twelve months of the year 2007 is first considered, it is used to calculate the next year's (2008) data, but 2008 data are available, but are considered as a forecasting data but as a target data. To calculate the forecasting error between the target data of 2008 and the forecasted data of 2009, we will have available in MATLAB coding

Forecasting error,

r = abs (forecast-target) (4)

While the Percentage error,

$$\text{p.e.} = [\frac{(Forcast\ error.r)}{Tangent}] \times 100 \quad (5)$$

From table 3, 2008 data was used as the target data while forecast for 2009 is made, the table shows the error percentage of the network

Let A_t be the actual value

and Ft the forecast value

The error, r is given by difference between A_t and F_t, that is (A_t - Ft)

The difference between A_t and F_t is divided by the Actual value A_t again. That is r/A_t

The absolute value in this calculation is summed for every forecasted point in time and divided by the number of fitted points n. multiplying by 100 makes it a percentage error.

Hence, the formula for MAPE used for our calculation is

$$M = \frac{100}{n}\sum_{t=1}^{n} | \frac{At-Ft}{At} \quad (6)$$

Table 4. *Forecasting for 2009.*

Forecasting of Next Years Load Demand, 2009					
Month	**2007**	**Forecasted Data of 2009**	**Target Data 2008**	**Forecasting Error**	**% Error**
January	55	65.4	65	0.4	0.006
February	64	65.5	65	0.5	0.008
March	67	69.9	70	0.1	0.001
April	67	65.3	65	0.3	0.005
May	71	50.6	50	0.6	0.012
June	69	50.4	50	0.4	0.008
July	71	55.2	55	0.2	0.004
August	72	60.6	60	0.6	0.010
September	74	65.4	65	0.4	0.006
October	70	70.4	60	0.4	0.006
November	70	60.23	58	0.23	0.004
December	65	70.25	63	0.75	0.011
		62.43			0.384

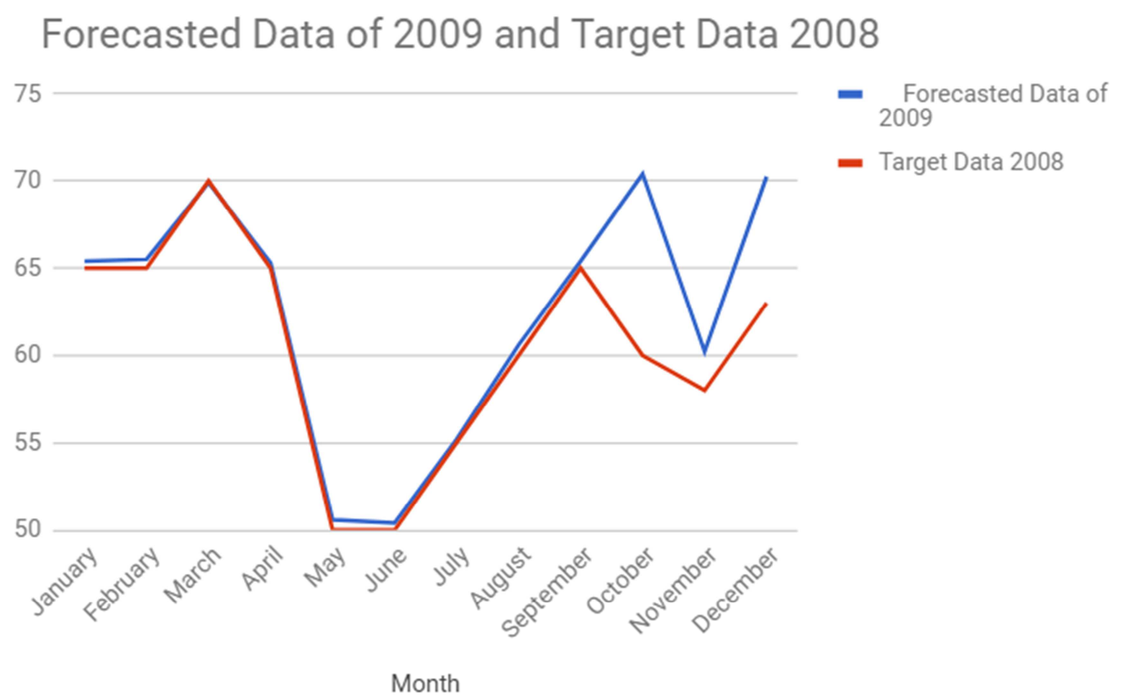

Figure 1. *Graph of Forecasted/Actual Data against Month.*

3. Results and Discussion

Forecast results from the ANN model on the load data from EEDC, Owerri station, are presented and discussed in this chapter. We used known target data sets of 2008-2017, to compare forecasted data set of the same period and duration. In each case, the percentage error is computed. The architecture of the network in each case, is adjusted so as to minimize errors. Tables 4 and 5 shows the results of the controlled forecast because we used known data sets.

In order to ensure that the prediction accuracy is high, we selected the architecture that has the minimum error. The selection is done by using a statistical tool called Mean Absolute Percentage Error, MAPE.

The errors have been calculated separately for the learning and testing data. Here we will present the testing errors related to the data

Table 5. *Forecast of 2010.*

Forecasting of Next Years Demand 2010				
Month	**Forecasted Data of 2010**	**Target Data 2009**	**Forecasting Error**	**% Error**
January	72.3	71	1.3	0.018
February	75.8	70	5.8	0.083
March	70.8	70	0.8	0.011
April	70.6	70	0.6	0.009
May	66.2	65	1.2	0.018
June	65.4	65	0.4	0.006
July	65.1	65	0.1	0.002
August	60.7	50	10.7	0.214
September	55.6	55	0.6	0.011
October	60.3	55	5.3	0.096
November	60.25	60	0.25	0.004
December	61.2	60	1.2	0.020
	65.354			0.493

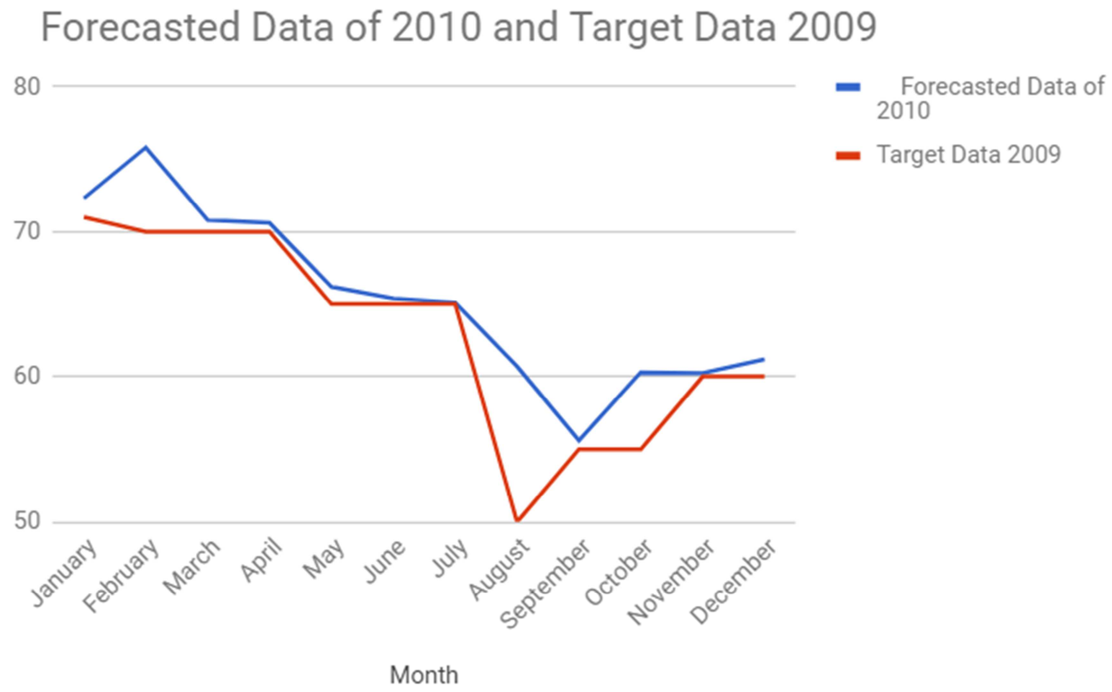

Figure 2. *Graph of forecast data for 2010.*

4. Conclusion

The results show that the ANN method of forecasting via MATLAB has a close relationship between the forecasted data and the target data.

Average energy forecasted from 2009 to 2017 are 62.43MW, 63.52MW, 66.45MW, 74.42MW, 72.65MW, 76.45MW, 79.92MW, 80.99MW and 82.85MW respectively, while the average predicted or forecasted energy from 2018 to 2017 are 89.50MW, 95.40MW, 99.20MW, 103.40MW, 110.20MW, 113.60MW, 119.50MW, 124.20MW, 128.5MW and 132.5MW respectively. Following this growth trend it is clear that the installed capacity of Owerri city will not be able to adequately provide power to the entire area after about 10 years from now, except an adequate system upgrade is carried out to accommodate the increasing demand.

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