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ELECTRICAL LOAD FORECASTING IN NIGERIA USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) TECHNIQUE

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ABSTRACT

Load forecasting is essential to the operations of any power utility company. It allows optimum usage of the available resources. Many load forecasting techniques are available. This research article presents a soft computing technique based on the learning abilities of an adaptive network and the cognitive skills of the fuzzy inference system. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is to be used for this research purpose. ANFIS belongs to a class of adaptive networks and is functionally equivalent to a Fuzzy Inference System.
Selection of significant inputs and identification of a structure that correctly captures the information contained in the system to be modeled, are the two basic steps in developing any model. This model forecasts the load demand by extrapolating the time of the day and the latest load behaviour. The short term historical load data is used as the variable input as well as time for short term load forecast, while the population impact is considered for long term load forecast. In carrying out this research, model is developed on a MATLAB platform for this purpose.
The ANFIS model performed excellently when applied to the Nigerian electrical system obtained quite promising results with the root mean square error evaluated as 0.51%. ANFIS proved to be a valid and promising technique for forecasting electricity consumption.

1.0 INTRODUCTION

Operations planning encompass methodologies and decision processes by which an electric power system is prepared to meet the electric load demand within a set of specified technical as well as economic performance criteria. This results in operating at a lower cost with higher reliability of power systems. Load forecasting, a projection of what the electric load will be at future time intervals of interest is the starting point for operation planning processes. Therefore, establishing high accuracy models of the load forecast is very important.

Many techniques have been developed to obtain accurate load forecast values. They may be classified into two categories (Rafal 2006), Statistical (Conventional) and Artificial Intelligence also referred to as soft Computing. In real practice, the relationship between load and its exogenous factor is complex and non-linear, making it quite difficult to model through conventional techniques, such as time series and linear regression approaches (Asar et al. 2005). The inherent difficulty encountered while using conventional techniques to model complex and non linear relationships is also a major drawback in Fuzzy Logic approach, Artificial Neural Network approach, Neuro Fuzzy approach etc. A major advantage of the AI techniques is the capability to learn non-linear mapping with smaller computational efforts. Artificial Intelligence methods tend to be flexible and can handle complexity and non-linearity as compared to conventional methods.

For this study, a hybrid-fuzzy method, the Adaptive Neuro-Fuzzy Inference system (ANFIS) will be used for the short-term and long-term electrical load forecasting. An Adaptive Neuro-Fuzzy Inference system is a cross-breed between an artificial neural network and a fuzzy inference system. It is a fuzzy Takagi-Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation (Jang 1993).

Fuzzy models possess excellent qualities in representing linguistic and structured knowledge; this is a major limitation of ANN (Asar et al. 2005). Also the behaviour of fuzzy models can be understood easily due to their logical structure and step by step inference procedures. On the other hand, neural network models are particularly good for non-linear mapping. The ANFIS technique is a method for the fuzzy modelling procedure to learn information about the historic data in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the historic data. Hence it combines the advantage of the rule based fuzzy logic system and the learning ability of an adaptive network. The proposed method will be implemented on MATLAB using the Fuzzy Logic Toolbox.

2.0 THE ANFIS MODEL

ANFIS is an adaptive network. An adaptive network is a multilayer feed-forward network (consisting of nodes and directional links through which each node is connected) in which each node performs a particular node function on incoming signals as well as a set of parameters pertaining to the node. The ANFIS is functionally equivalent to Fuzzy Inference Systems (FIS); it belongs to neuro-fuzzy category. A neuro-fuzzy system is defined as a combination of Artificial Neural Networks (ANN) and Fuzzy Inference System (FIS) in such a way that neural network learning algorithm are used to determine the parameters of Sugeno type FIS. It applies a combination of the least-squares method and the back-propagation gradient descent method for training the Fuzzy Inference System (FIS) membership function parameters to emulate a given training data set. This adjustment allows our fuzzy system to learn from the data they are modeling. ANFIS is a network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map. The FIS to be employed makes use of Takagi and Sugeno's fuzzy "if-then" rules. Here the output of each rule is a linear combination of input variables plus a constant term and the final output is the weighted average of each rule's output.

2.1. DEVELOPING THE MODEL

In building any forecast model, there are two basic steps

i. The first step is selection of significant inputs – Input Variable Selection. It is very important that appropriate studies be carried out to know which inputs influence the load consumption the most; either the short term or long term basis. From the study conducted on data gotten from past studies of this subject topic using other methods, it was discovered that for short term load forecasting, several factors should be considered such as day type, hour of the day, previous day load consumption, weather data if possible. The medium and long term forecasts take into consideration the historical load, the economic and demographic data and their forecasts and other factors. For this study, the factors to be considered for short term load forecast are; day type, hour of the day and short term historical data. For the long term forecasting, population data and load data will be used

ii. Identification of a structure that correctly captures the information contained in the system to be modeled. The system load is a random non-stationary process, thus the main difficulty in modeling load demand is to come up with a model that comprises only dominant factors and also minimizes the forecasting error.

2.2. USING THE ANFIS MODEL

ANFIS is available on the MATLAB platform. For the load forecasting problem, the solution to this problem is decomposed into a series of processes to be implemented on the ANFIS application available on MATLAB platform.

To use the ANFIS model, the user defines the number of inputs; the number of membership functions (MFs) and their type, and the number of epochs of training. One of the more unusual aspects of the ANFIS model is that changing even one of these parameters can be the difference between a system that appears not to be working at all and a system that produces almost perfect results. Thus it is paramount to understand the data structure and the major factors affecting data change.

The MATLAB Fuzzy Toolbox comprises 11 in-built membership function types. For this study, Gaussian membership function will be used for both the long term and short term load forecasting.
As with a supervised-learning neural network, the fuzzy system is trained with a set of data called a training data set. This set is represented by several subsets of inputs and one desired output for each subset. Where it differs is in the selection of model parameters. The ANFIS model adjusts the membershfp function parameters using a combination of back propagation algorithm with a least square estimation in order to reduce the error measured between the actual and desired outputs.

3.0. APPLICATION TO LOAD FORECASTING IN NIGERIA

The application procedure involves four steps for load forecasting

- Gathering the data
- Selection of ANFIS structure
- Training the network
- Testing

Step 1 Data Collation
From the National Control Centre of the Power Holding Company of Nigeria (PHCN), historical load data for the year 2003 was obtained.

Step 2 ANFIS Structure

An ANFIS structure specifies the rules and initial parameters of the FIS for learning purposes. The rules are generated by the grid partition method. For the training purpose, membership functions are assigned to each input. Each input has two Gaussian membership functions.

Step 3 Training the network

A. Short Term Load Forecasting

For the short term forecast, the load of the previous day, the hour of the day and the day of the week are selected as training data inputs. These inputs are presented as ANFIS inputs and the load of the day as output. The data for training was selected from January and August 2003, a total of 1008 rows of matrix were generated with four columns (Appendix A). The first three represent the inputs, while the last column is the output. This matrix is presented to ANFIS as its training set.
For the training purpose, membership functions are assigned to each input. Each input has two Gaussian membership functions. The rules are generated by the grid partition method. Since there are three inputs with two membership functions, the rule set contains 2^3, i.e., 8 rules. The ANFIS structure (Fig 3.1) is modified during the training process in such a manner that the desired input/output relationship is learned. The number of rules is fixed therefore; it is the FIS parameters (membership functions) that get adjusted. As expected, the eventual membership function as a result of the training process is quite different from the initial membership function.

B. Long Term Load Forecasting
For the long term forecast, the yearly peak load from 1980 and population data from the same year were presented as the training data for ANFIS. Each input has two Generalized Bell membership functions. The rules are generated by the grid partition method. Since there are two inputs with two membership functions, the rule set contains 2^2, i.e., 4 rules. The ANFIS structure is modified during the training process in such a manner that the desired input/output relationship is learned.

Step 4 Testing

Five hundred and four data sets, comprising of hourly load, hour of the day and day of the week from September 2003 were selected as testing data sets. This data set is fed into ANFIS for evaluation studies. While for the long term forecast purpose, the population data for the corresponding years up to year 2020 was presented to the ANFIS model.

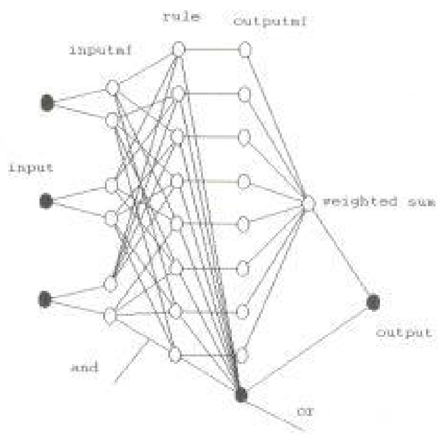


Figure 3.1 ANFIS Structure

4.0 RESULTS

Having utilized the procedures enumerated above, the results obtained are properly analyzed and presented here. The results of testing the trained ANFIS for the STLF were obtained and are presented below in graphical form (Figures 4.1 to 4.7). Tests were carried out on new data for 24 hours of a day over a one-week period. The graphs of each actual and forecast load in Megawatts (MW) for each day were plotted against the time in hours.

It is observed that the ANFIS model's forecast followed the actual load pattern more accurately throughout the forecasted period. In this analysis the model error is evaluated as well. The RMSE[1] is evaluated as 0.51% for the one week period forecast. The Load Forecasting on Long term up till year 2020 was evaluated also and the RMSE error obtained was 2.5%. This was done based on the historical load data and population of Nigeria. The values are presented in Table 4.1.

4.1 Comparison with other Countries.

The power consumption in Nigeria at present is compared with countries such as Brazil, Germany, Japan, South Africa, Russia and United States. The population, and load consumption are presented in Table 4.2 below. Given this scenario, Our ANFIS model is trained based on this information and allowed to forecast from 2012 to 2020 (Table 4.3). This allows us to estimate the minimum power generation required by the country to meet up with the country's desire to be among the top 20 industrialized economies by the year 2020. From the forecast, it is seen that Nigeria requires about 108 GW of electric power by the year 2020 to achieve vision 20:2020.

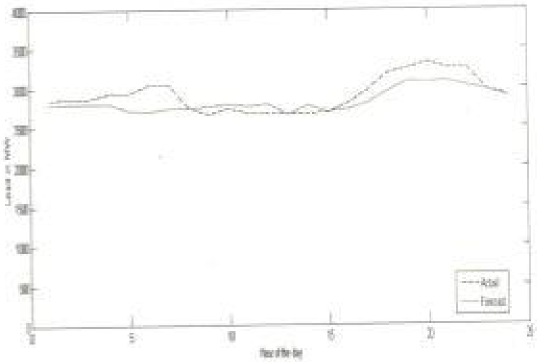


Figure 4.1 Monday Load Forecast

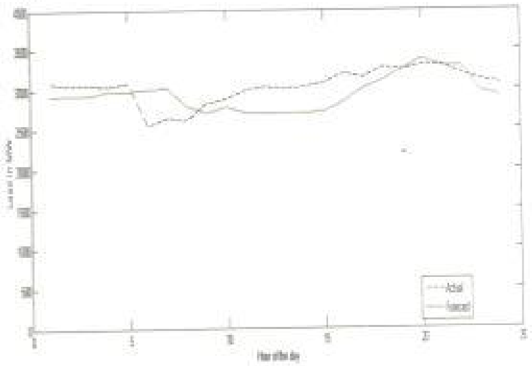


Figure 4.2 Tuesday Load Forecast

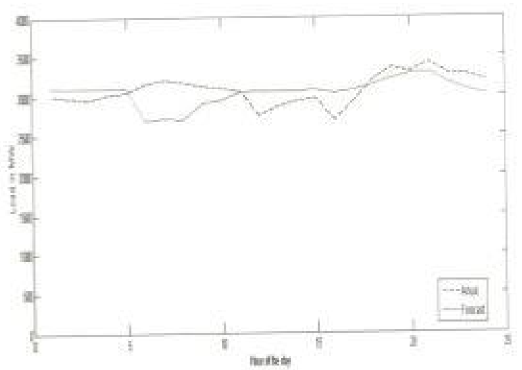
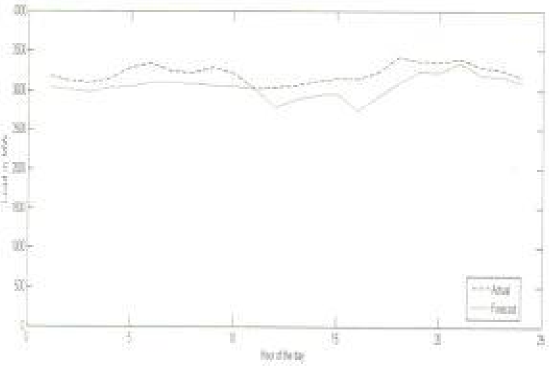


Figure 4.3 Wednesday Load Forecast

[1] RMSE means Root Mean Square Error



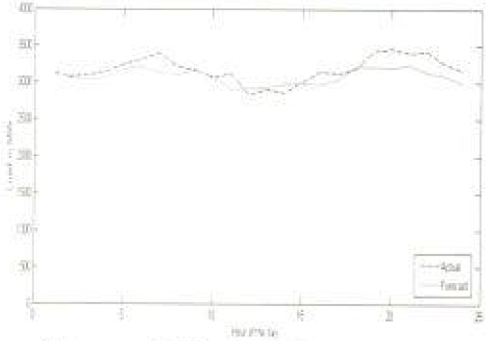


Figure 4.5 **Friday Load Forecast**

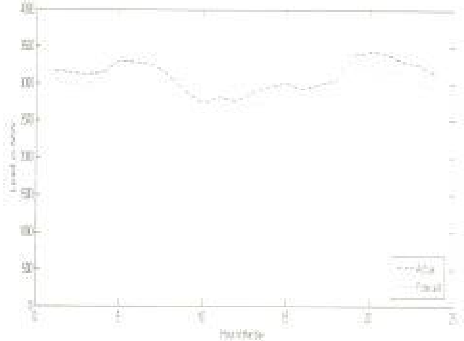


Figure 4.6 **Saturday Load forecast**

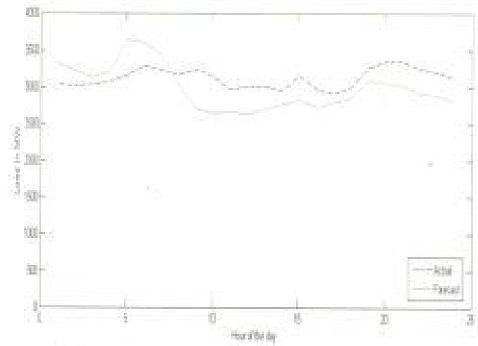


Figure 4.7 **Sunday Load Forecast**
Figure 4.4 **Thursday Load Forecast**

Table 4.1 Long Term Load Forecast

Year	Projected Power Generation in MW
2012	4890.59
2013	5085.16
2014	5286.19
2015	5493.84
2016	5708.32
2017	5929.84
2018	6158.6
2019	6394.84
2020	6638.8

Table 4.2 Estimated Population and Power Generation of some Countries

Country	Estimated Population (Million)	Electricity Generation in GW
Brazil	198.3	111.5
Russia	142.9	221
United States	312.9	1119.67
Germany	91.73	140
South Africa	50.59	52.84
Japan	127.72	280
Nigeria	162.47	3.7

Table 4.3 Electric Power Generation required to achieve Vision 20:2020

Year	Required Power Generation in MW
2012	83803
2013	86556.55
2014	89399.66
2015	92335.21
2016	95366.22
2017	98495.79
2018	101727.12
2019	105063.54
2020	108508.44

5.0 Recommendations and Conclusion

5.1 Conclusion

We have developed on a MATLAB platform, an ANFIS forecasting model that utilizes previous load values, day of the week and hour of the day. This model has been applied to Nigeria's electric power system to forecast on short- term and long term basis using realistic data provided by the country's National Control Centre. When our ANFIS model was tested based on the data, we obtained quite promising results with root mean square error of 0.51%. Thus ANFIS proved to be a valid and promising technique for forecasting electricity consumption.

5.2 Recommendation

The ANFIS model has shown capability to work on the Nigerian power system. It is recommended for adoption by National Control Centre (NCC), PHCN Osogbo, for electrical load forecasting, rather than the primitive regressive or similar day method being utilized. This will ensure the proper coordination of the various generating stations spanned across the country for increased efficiency and effectiveness.

To improve the ANFIS model, two things can be done. First of which is to improve the ANFIS structure and another is to improve the training data set. By incorporating factors such as economic factors, industrial trend, weather and random effects etc, the training data set will be improved which will eventually improve the ANFIS output.

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