Short Term Load Forecasting Using Artificial Neural Networks (Anns) For Umuahia, Nigeria

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Abstract – The electric power industry is currently undergoing an unprecedented reform. One of the most exciting and potentially profitable recent developments is increasing usage of artificial intelligence techniques. This paper presents a study of short-term load forecasting using Artificial Neural Networks (ANNs) for Umuahia, Nigeria. Historical load data obtained from the Enugu Electricity Distribution Company (EEDC) for the month of August 2015 were used. The main stages are the pre-processing of the data sets, network training, and forecasting. The implementation of the network architecture, training of the Neural Network and simulation of test results were all successful with a very high degree of accuracy resulting into 24 hourly load output. The accuracy of the forecasts was verified by comparing the simulated outputs from the network with obtained results from the utility company. The Absolute Mean Error (AME) (%) between the 'forecast' and 'target' loads has been calculated to be 1.73%. This represents a high degree of accuracy in the ability of neural networks to forecast electric load.

Index Terms – Electric, Artificial intelligence, Neural Network, Absolute Mean Error.

1. INTRODUCTION

Peak load reduction is a significant component of energy demand management.

Electric load forecasting can be used to assist in planning how much electricity must be reduced during system peaks to meet the goals of the energy demand management program. The amount of peak reduction may change each day due to the load forecast and facility operations. If the difference between the electric load forecast and the desired maximum peak load is known, facility operators could use this information to schedule when their high electricity operations are to occur [1]. Therefore, it became very imperative for every power system manager to have their power system operate efficiently, securely, and economically. To meet this goal, the behavior of their power system must be understood. Analysis of the system's normal operating bounds, response to customer demands, and reaction to weather events will provide insight on system loading.

In general, the required load forecasts can be categorized into short-term, mid-term, and long-term forecasts.

The short-term forecasts refer to hourly prediction of the load for a lead time ranging from one hour to several days out. Short-term electric load forecasting can provide that insight for the following day to assist in making power system operational decisions.

The mid-term forecasts can either be hourly or peak load forecasts for a forecast horizon of one to several months ahead. Scheduling of fuel purchases, load flow studies or contingency analysis, and planning for energy, while the long-term forecasts refer to forecasts made for one to several years in the future. The quality of short-term hourly load forecasts has a significant impact on the economic operation of the electric utility since decisions such as economic scheduling of generating capacity, transactions such as ATC (Available Transmission Capacity) are based on these forecasts and they have significant economic consequences [2].

Load forecasting can be performed using many techniques such as regression analysis, statistical methods, artificial neural networks, genetic algorithm, fuzzy logic etc.

An artificial neural network (ANN) is a mathematical model that mimics the decision-making processes of the human brain. The fundamental component of the ANN is the neuron [3]. Neurons are programmed to behave similarly to the neurons in the brain by receiving inputs, processing those inputs, and producing an output. The neurons are connected together to form a network that can be used to solve nonlinear problems.

The ANN is well suited for load forecasting because the neurons are designed to receive a number of inputs (historical load information, weather forecast, etc.) and process them through a nonlinear activation function. The neurons of the connected network are trained on system-specific inputs so they can predict trends in the load based on the inputs of other variables. It should not be assumed that an ANN trained with inputs and targets for one power system will produce low error forecasts when used on a different system. The structure and size of the ANN should only be as complex as required to produce acceptable forecast on out-of-sample data.

This work involves the design of an ANNSTLF model for the 132/33KV substation Umuahia in order to obtain accurate

forecasts of the load for a 24 hour period of the next day in advance by training the neural network with previous load data and daily average temperatures to produce a 24 hours load forecast which is necessary for the operational planning of the power system utility company.

2. THE LOAD FORECASTING IN NIGERIA

In Nigeria today, various generation companies, transmission and system operation companies as well as distribution companies are getting ready to take their rightful place in the Nigerian power industry. The government itself is also determined to increase the power generated to 10,000MW by the year 2020.

All the developments highlighted above can only translate to better and efficient services if, among other vital factors, there is a good and accurate system in place for forecasting the load that would be in demand by electricity customers. Such forecasts will be highly useful in proper system planning and operations. In this paper, the study of short-term load forecasting using Artificial Neural Networks (ANNs) for Umuahia, Nigeria in the month of September, 2015 is presented.

2.1. Factors That Influence Electrical Load

Predicting the electric power consumption of an individual piece of equipment in a large facility can be difficult if not impossible without specific metering data for this load. Typically, the usage of a single electrical device in a larger power system is random and usage patterns of other devices may differ from the one under study. There is often a large diversity in individual loads, yet when these individual loads are summed into one larger facility load, patterns emerge which can be statistically predicted [4].

There are four main factors that influence electrical load:

1. Economic
2. Time
3. Weather
4. Random effects

2.1.1. Economic factors

Economic factors consist of investment in the facility's infrastructure through construction of new buildings, labs, and experiments which add load to the electric system. Funding profiles for the site dictate how and when equipment, processes, and experiments can be operated. Utility programs such as demand charges and demand management plans affect the customer's electrical usage patterns during times of system peaking [4]. Economic factors will not influence the STLF as these factors typically change usage patterns over a longer time range than 24 hours; however, economic factors can be the inspiration for studying a system's load pattern and implementing load reduction initiatives.

2.1.2. Time factors

The three time factors that have the most influence on electrical load are:

1. Seasonal effects
2. Weekly-daily cycle
3. Holidays

Seasonal effects account for the long-term changes in the weather patterns.

Hot summer days often create large cooling loads which are more likely to occur during the afternoon and early evening hours. Cold winter nights often create large heating loads which are more likely to occur during the late evening and early morning hours.

Seasonal effects are not only weather patterns, but can include popular vacation dates and changes between Daylight Savings Time (DST) [5]. When DST is in effect, the electrical load profile shifts back one hour relative to the profile under Standard Time. Weekly-daily cycles are electric load patterns that are periodic over the course of a week and during each day.

2.1.3. Weather factors

Weather factors have a significant effect on the short-term electric load profile of a power system [6]. Weather-sensitive loads, such as heating, ventilating, and air-conditioning (HVAC) equipment, will have a greater impact on smaller

Industrial/institutional power systems as these tend to be the larger loads on the system.

HVAC equipment cycling on and off can produce electrical load profiles that appear to have random power swings. As the power system load increases, there will be more load diversity, the effect of load cycling will be dampened, and the electric load profile will be smoother. Other weather factors that can affect the electric hourly load profile are humidity, solar irradiance, wind speed, barometric pressure, and precipitation. High humidity days will make cooling equipment operate for longer duty cycles to remove excess moisture out of the conditioned air. Long durations of high solar irradiance will radiantly heat the interior of buildings forcing the cooling equipment to operate longer and with less diversity. Precipitation has the tendency to reduce the air temperature and thus reduce the cooling load. Wind speed and barometric pressure can also affect the hourly load profile, and often occur in tandem with other factors such as precipitation.

2.1.4. Random Factors

Random factors that influence the electrical load profile consist of all the other random disturbances in the load pattern that cannot be explained by the previous three factors [4]. These disturbances can consist of significant loads that do not have a set operating schedule which makes prediction difficult. Other disturbances such as widespread employee absences (due to sickness, inclement weather, etc.) and planned or unplanned utility system outages can have significant effects on the facility's load profile.

2.2. Short-Term Load Forecasting Methods

A large variety of statistical and artificial intelligence techniques have been developed for short-term load forecasting.

2.2.1. Similar-Day Approach

This approach is based on searching historical data for days within one, two, or three years with similar characteristics to the forecast day. Similar characteristics include weather, day of the week, and the date. The load of a similar day is considered as a forecast. Instead of a single similar day load, the forecast can be a linear combination or regression procedure that can include several similar days. The trend coefficients can be used for similar days in the previous years.

2.2.2. Regression-Methods

Regression is the one of most widely used statistical techniques. For electric load forecasting regression methods are usually used to model the relationship of load consumption and other factors such as weather, day type, and customer class.

Authors in [7] presented several regression models for the next day peak forecasting. Their models incorporate deterministic influences such as holidays, stochastic influences such as average loads, and exogenous influences such as weather.

2.2.3. Time Series

Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend, or seasonal variation. Time series forecasting methods detect and explore such a structure. Time series have been used for decades in such fields as economics, digital signal processing, as well as electric load forecasting. In particular, ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average), ARMAX (autoregressive moving average with exogenous variables), and ARIMAX (autoregressive integrated moving average with exogenous variables) are the most often used classical time series methods [8]. ARMA models are usually used for stationary processes while ARIMA is an extension of ARMA to non-stationary processes. ARMA and ARIMA use the time and load as the only input parameters. Since load generally depends on the weather and time of the day, ARIMAX is the most natural tool for load forecasting among the classical time series models.

2.2.4. Neural-Networks

The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990 [9]. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or nonlinear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs. In practice network elements are arranged in a relatively small number of connected layers of elements 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 (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bi-directional or uni-directional links, and the number format (e.g. binary or continuous) to be used by inputs and outputs, and internally.

The most popular artificial neural network architecture for electric load forecasting is back propagation. Back propagation neural networks use continuously valued functions and supervised learning. That is, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a pre-operational "training session". Artificial neural networks with unsupervised learning do not require pre-operational training.

Author in [10] developed an ANN based short-term load forecasting model for the Energy Control Center of the Greek Public Power Corporation. In the development they used a fully connected three-layer feed forward ANN and back propagation algorithm was used for training.

Input variables include historical hourly load data, temperature, and the day of the week. The model can forecast load profiles from one to seven days. Also authors in [11] developed and implemented a multi-layered feed forward ANN for short-term system load forecasting. In the model three types of variables are used as inputs to the neural network: season related inputs, weather related inputs, and historical loads. Authors in [12] described a load forecasting system known as ANNSTLF. ANNSTLF is based on multiple ANN strategies that capture various trends in the data. In the development they used a multilayer perceptron trained with the error back propagation algorithm. ANNSTLF can consider the effect of temperature and relative humidity on the load. It also contains forecasters that can generate the hourly temperature and relative humidity forecasts needed by the system.

2.2.5. Expert Systems

Rule based forecasting makes use of rules, which are often heuristic in nature, to do accurate forecasting. Expert systems, incorporates rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecasts without human assistance.

Expert system use began in the 1960's for such applications as geological prospecting and computer design. Expert systems work best when a human expert is available to work with software developers for a considerable amount of time in imparting the expert's knowledge to the expert system software. Also, an expert's knowledge must be appropriate for codification into software rules (i.e. the expert must be able to explain his/her decision process to programmers). An expert system may codify up to hundreds or thousands of production rules.

Authors in [13] proposed a knowledge-based expert system for the short term load forecasting of the Taiwan power system. Operator's knowledge and the hourly observations of system load over the past five years were employed to establish eleven day types. Weather parameters were also considered. The developed algorithm performed better compared to the conventional Box-Jenkins method. Authors in [14] developed a site-independent technique for short-term load forecasting. Knowledge about the load and the factors affecting it are extracted and represented in a parameterized rule base. This rule base is complemented by a parameter database that varies from site to site. The technique was tested in several sites in the United States with low forecasting errors. The load model, the rules, and the parameters presented in the paper have been designed using no specific knowledge about any particular site. The results can be improved if operators at a particular site are consulted.

2.2.6. Fuzzy Logic

Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a truth value of "0" or "1". Under fuzzy logic an input has associated with it a certain qualitative ranges. For instance a transformer load may be "low", "medium" and "high". Fuzzy logic allows one to (logically) deduce outputs from fuzzy inputs. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting).

Among the advantages of fuzzy logic are the absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise (or even noise free) inputs. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting. Of course in many situations an exact output (e.g. the precise 12PM load) is needed. After the logical processing of fuzzy inputs, a "defuzzification" process can be used to produce such precise outputs.

2.2.7. Support Vector Machines

Support Vector Machines (SVMs) are a more recent powerful technique for solving classification and regression problems. This approach was originated from Vapnik's [1 5] statistical learning theory. Unlike neural networks, which try to define complex functions of the input feature space, support vector machines perform a nonlinear mapping (by using so-called kernel functions) of the data into a high dimensional (feature) space. Then support vector machines use simple linear functions to create linear decision boundaries in the new space. The problem of choosing architecture for a neural network is replaced here by the problem of choosing a suitable kernel for the support vector machine.

Author in [1, 6] applied the method of support vector machines for short-term electrical load forecasting. The author compares its performance with the autoregressive method. The results indicate that SVMs compare favorably against the autoregressive method.

2.3. Artificial Neural Network (ANN)

An Artificial Neural Network can be described as a mathematical tool that mimics the thought processes of the human brain. ANNs were first applied to load forecasting in the late 1980's [9]. They are described as a multivariate, nonlinear, and nonparametric method which makes the good candidates for modeling complex nonlinear systems. ANNs have good performance in data classification and function fitting.

Neurons are the basic processing components of ANNs. The neurons are programmed to behave similarly to the neurons in the brain by receiving inputs, processing those inputs, and producing an output. The neuron is shown schematically in Figure 1.

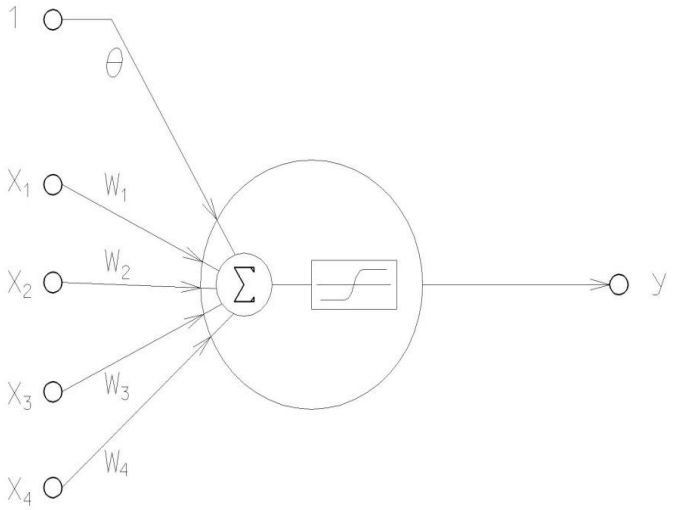

Fig.1: An Artificial Neuron Model

The neuron model consists of the linear combination of one or multiple numerical inputs (represented by Xi in Figure 1) and a constant input term (represented as an input of 1 in Figure 1). Each variable input Xi is adjusted by a unique weight, wi, and the constant input of 1 is adjusted by a variable bias, Θ. The linear combination of these inputs and bias are input to a nonlinear activation function whose output is the output of the neuron. The training of ANNs requires the activation function to be non-decreasing and differentiable. The most common activation functions used in ANNs are the linear function $y = x$, or some variation of the bounded sigmoid function such as the logistic function $y = 1/(1 + e-x)$.

2.4. Back Propagation Algorithm

The objective of supervised training is to adjust the weights so that the difference between the network output *Pred* and the required output *Req* is reduced.

This requires an algorithm that reduces the absolute error, which is the same as reducing the squared error, where

$$\text{Network Error} = Pred - Req = E \quad [1]$$

These outputs are multiplied by the respective weights ($W_{1B}...W_{nB}$), where W_{nB} is the weight connecting neuron n to neuron B. For the purpose of this illustration, let neuron 1 be called neuron A and then consider the weight W_{AB} connecting the two neurons. The approximation used for the weight change is given by the delta rule:

$$W_{AB(new)} = W_{AB(old)} - \eta \frac{\partial E^2}{\partial W_{AB}} \quad [2]$$

Where η is the learning rate parameter, which determines the rate of learning,

$\frac{\partial E^2}{\partial W_{AB}}$ is the sensitivity of the error, E^2, to the weight *WAB* and determines the direction of search in weight space for the new weight *WAB*(*new*).

In order to minimize E^2 the delta rule gives the direction of weight change required. From the chain rule,

$$\frac{\partial E^2}{\partial W_{AB}} = \frac{\partial E^2}{\partial I_B} - \frac{\partial I_B}{\partial W_{AB}} = O_A \quad [3]$$

Since the rest of the inputs to neuron *B* have no dependency on the weight *WAB*.

$$W_{AB(new)} = W_{AB(old)} - \eta \frac{\partial E^2}{\partial I_B} O_A \quad [4]$$

and the weight change of W_{AB} depends on the sensitivity of the squared error, E^2, to the input, I_B, of unit B and on the input signal O_A.

So to summarize the process of back propagation:

a. A pattern is presented to the network (i.e., the input values)

b. The input is propagated through the network to give an output

c. The actual output is compared with the desired output and an error function is defined (that we have to minimize)

d. The errors are propagated back though the network to determine the amount by which to update the weights

e. Update the weights

f. Repeat this process for each pattern (when all patterns have been used we say one epoch has been completed)

g. Continue until for one epoch, all outputs for each pattern are within the tolerance.

h. Then we can say the network is trained and can be tried on test data.

3. DESIGN OF THE NEURAL NETWORK MODEL

MATLAB® (version R2007b) by Mathworks®, Inc., was the computer software used to create and implement the 24-hour load forecast for Umuahia, Nigeria. The Neural Network Toolbox in MATLAB® provides built-in functions and applications to assist in modeling nonlinear systems. It supports ANN training, validation, testing, and simulation with hardcode and graphical user interface (GUI) applications. The MATLAB® code for this research was executed on a 2.10 GHz Intel® Core™2 Duo CPU running Microsoft Corp. Windows® 7 Home Premium (32-bit) Service Pack 1.

3.1. Forecasting Procedure

The STLF procedure for the chosen ANN model is shown in Figure 2.

1. Input Variable Selection: Input variables such as load, day type, temperature and spot prices of the previous day, and day type, temperature and spot prices of the forecasting day are initially chosen.

2. Data Pre-processing: Improperly recorded data and observation error are inevitable. Hence, bad and abnormal data are identified and discarded or adjusted using a statistical method to avoid contamination of the model.

3. Scaling: Since the variables have very different ranges, the direct use of network data may cause convergence problems. Two scaling schemes are used and compared. In the first scheme, all input *Xi* and output *Oi* variables are scaled to be in the [0, 1] range; hence, the input and output variables are scaled as follows:

$$X_i'^{(k)} = X_i^{(k)}/\max\,(X_i^{(k)}) \quad [5]$$

$$O_i'^{(k)} = O_i^{(k)}/\max\,(O_i'^{(k)}) \quad [6]$$

Where k is the index of input and output vectors/patterns.

In the second scheme, the input and output variables are scaled to be in the $[-c, c]$ range, where c is a positive number. The inputs and outputs in this case are scaled as follows:

$$X_i'^{(k)} = X_i^{(k)} - \tilde{X}_i / S_i \quad [7]$$

$$O_i'^{(k)} = O_i^{(k)} - \tilde{X}_i / SO_i \quad [8]$$

Where *Si* and *SOi* are the estimates of the standard deviation of input and output *i*, respectively, and ˜*Xi* and ˜*Oi* are the average values of the corresponding input and output. The error function has different minimum values for the two different scaling schemes.

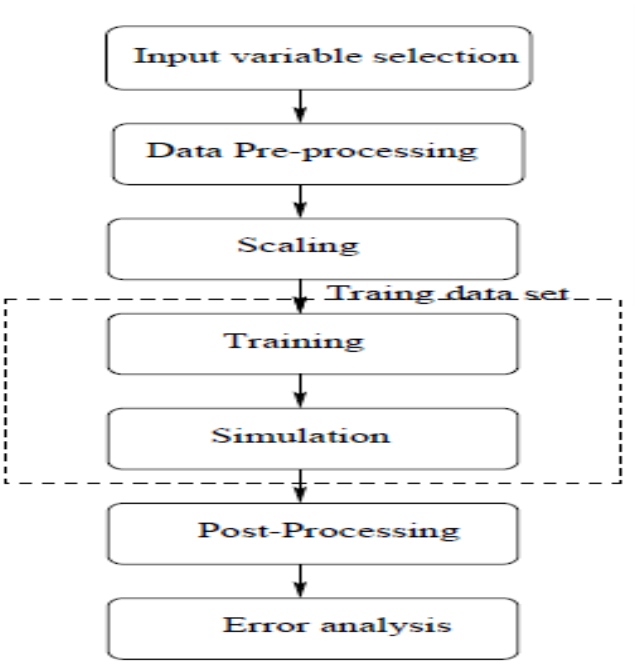

Fig.2: Design flow chart

4. Training: Each layer's weights and biases are initialized when the neural network is set up. The network adjusts the connection strength among the internal network nodes until the proper transformation that links past inputs and outputs from the training cases is learned. Data windows are used for training and moved one day ahead.

5. Simulation: Using the trained neural network, the forecasting output is simulated using the input patterns.

6. Post-Processing: The neural network output need de-scaling to generate the desired forecasted loads. If necessary, special events can be considered at this stage.

7. Error Analysis*:* As characteristics of load vary, error observations are important for the forecasting process.

Hence, the following Mean Absolute Percentage Error (MAPE) ε and Root Mean Square Error (RMSE) σ are used here for after-the-fact error analysis:

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\frac{|X_t - X_f|}{X_t} * 100 \quad [9]$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Xt - Xf)^2} \quad [10]$$

Where *Xt* is the actual load and *Xf* is the forecasted load.

4. RESULT

The results obtained from testing the trained neural network on new data for 24 hours of a day is presented below in graphical form (Figure 3). The graph shows a plot of both the 'target' and 'forecast' load in MW values against the hour of the day. The absolute mean error AME (%) between the 'forecast' and 'target' loads has been calculated to be 1.73%. This represents a high degree of accuracy in the ability of neural networks to forecast electric load, and is obviously negligible and the network can be said to have successfully learned any complex and nonlinear relationship that was presented by the input data.

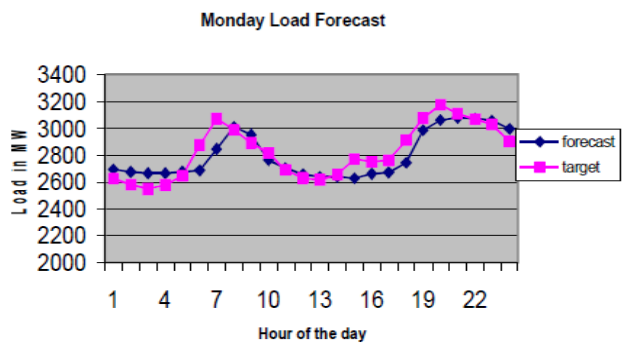

Fig.3: Plots of the 'Target' and 'Forecast' Load in MW Values against the Hour of the Day.

5. CONCLUSION

Electric load demand is a function of weather variables and human social activities, industrial activities as well as community developmental level to mention a few. Statistical techniques and Expert system techniques have failed to adequately address this issue. The daily operation and planning activities of an electric utility requires the prediction of electricity demand of its customers. This paper has presented a study of short-term load forecasting using Artificial Neural Networks (ANNs) for Umuahia, Nigeria. The results obtained in this work confirm the applicability as well as the efficiency of neural networks in short-term load forecasting. The neural network was able to determine the nonlinear relationship that exists between the historical load data supplied to it during the training phase and on that basis, and make a prediction of what the load would be in the next one hour. It must, however, be ensured that the network is not over-trained as this will lead to a loss of its generalizing capability.

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