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Load forecasting using artificial neural networks

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Abstract

This paper presents a study of short-term load forecasting using Artificial Neural Networks (ANNs) and applied it to the Nigeria Electric power system. This gives load forecasts one hour in advance. The inputs used for the neural network are the previous hour load, previous day load, and hour of the day. The neural network used has 3 layers: an input, a hidden, and an output layer. The input layer has 3 neurons, the number of hidden layer neurons can be varied for the different performance of the network, while the output layer has a single neuron. An absolute mean error of 2.84% was achieved when the trained network was tested on one week's data. This represents, on average, a high degree of accuracy in the load forecast.

Keywords: Artificial Neural Networks, Short-term, Load forecasting, Mean Error

1. Introduction

The operation and planning of a power utility company requires an adequate model for electric power load forecasting. Load forecasting plays a key role in helping an electric utility to make important decisions on power, load switching, voltage control, network reconfiguration, and infrastructure development [1].

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 [2]. 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 [3].

A supervised artificial neural network has been used in this work. Here, the neural network is trained on input data as well as the associated target values. The trained network can then make predictions based on the relationships learned during training. A real life case study of the power industry in Nigeria was used in this work.

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.

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 [5]. 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). 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. 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 Artificial Neural Networks

Artificial Neural Networks (ANNs) refer to a class of models inspired by the biological nervous system. The models are composed of many computing elements, usually denoted neurons; each neuron has a number of inputs and one output [7]. It also has a set of nodes called synapses that connect to the inputs, output, or other neurons.
A linear combiner is used to produce a single value from all the inputs [8]. The single value is the weighted sum of the inputs from which the threshold value associated with the neurons is subtracted to compose the activation of the neuron. The activation signal is passed through an activation function to produce the output of the neuron. The chosen activation function is normally a non-linear function (for example, a sigmoid function), a feature that allows the ANN to represent more complex problems [9].
Most ANN models focused in connection with short-term forecasting use multi-layer perceptron (MLP) networks. The attraction of MLP can be explained by the ability of the network to learn complex relationships between input and output patterns, which would be difficult to model with conventional methods [10]. Inputs to the networks are generally present and past load values. The network is trained using actual load data from the past.

3. Load Forecasting Using Neural Networks

The back-propagation algorithm is a supervised learning algorithm used to change or adjust the weights of the neural network. In back-propagation, the gradient vector of the error surface is calculated. This vector points along the direction of steepest descent from the current point, so that a movement over a short distance along it decreases the error. A sequence of such moves will eventually find a minimum error point [11].
The following data were selected as network inputs:
i. The load of the previous hour,
ii. The load of the previous day,
iii. The hour of the day.

This results in a total of 3 ANN input values.
The neural network architecture used has only one hidden layer. Networks with more than one hidden layer are generally more complex and network training is more time-consuming. The number of neurons in the hidden layer must be carefully chosen; too many neurons make the network overspecialized, leading to loss of generalizing capability. If there are not enough hidden layer neurons, the network may find it difficult to learn the behaviour of the series. In this present work, varying number of hidden layer neurons was experimented with, the number ranging from two to eight. Eight neurons were finally utilized because it offered a better model characteristic.

3.1 Pre-Processing

The data employed for training and testing the neural network were obtained from the Enugu Electricity Distribution Company (EEDC) for the month of January 2016 were used.
Due to wrong measurements and other human errors, some out-of- range values were observed in the historical load data as obtained from the EEDC. Corrections were made to such outlier values by replacing them with the average of both the preceding and succeeding values in the series. Principal Component Analysis (PCA) of the data was then carried out using MATLAB® functions "prepca" and "trapca".
After the series had been corrected, the data were normalized so that their values would be between the values 0 and 1, this was achieved by using the sigmoid function and the effect of this is to avoid a saturation of the neural network. The sigmoid function acts as an output gate that can be opened (1)

or closed (0). Since the function is continuous it is possible for the gate to be partially opened (i.e. somewhere between 0 and 1). Models incorporating the sigmoid transfer function show well generalized learning characteristics and yield models with excellent accuracy.

Other transfer functions that can be used include the hyperbolic tangent and the hyperbolic secant functions. These functions exhibit different learning dynamics during training but may not achieve the same accuracy as sigmoid-based models.

4. Results

A back-propagation network with momentum and with an adaptive learning rate was trained and the neural network can forecast future load one hour ahead given the various inputs to the network. A sigmoid transfer function was used in the hidden layer while a linear transfer function was used in the output layer.

The results obtained from testing the trained neural network on new data for 24 hours of a day over three days period are presented below in graphical form (Figure 1, 2 and 3). Each graph shows a plot of both the 'target' and 'forecast' load in MW values against the hour of the day.

The highest absolute mean error AME (%) values were recorded for Tuesday. This is due to the greater deviation about the minimum demand point in addition to errors in the forecast for the peak demand periods.

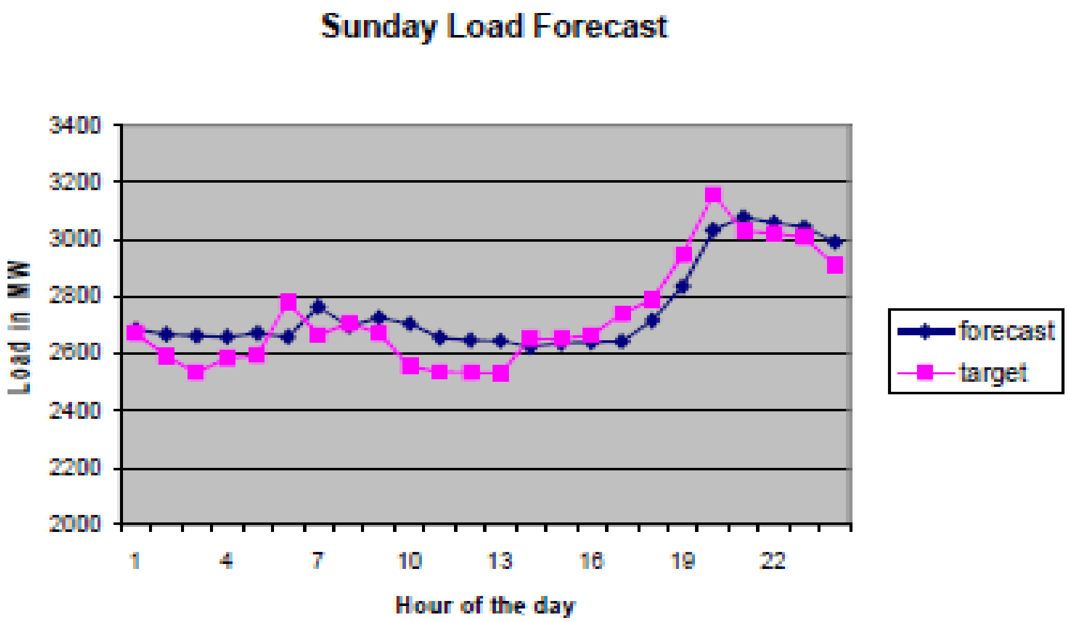

Fig 1: Plots of the 'Target' and 'Forecast' Load in MW Values against the Hour of the Day on Sunday.

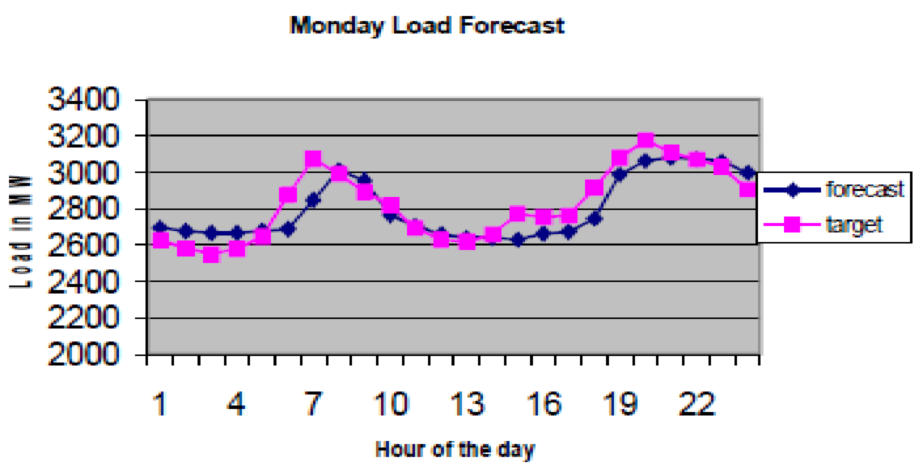

Fig 2: Plots of the 'Target' and 'Forecast' Load in MW Values against the Hour of the Day on Monday.

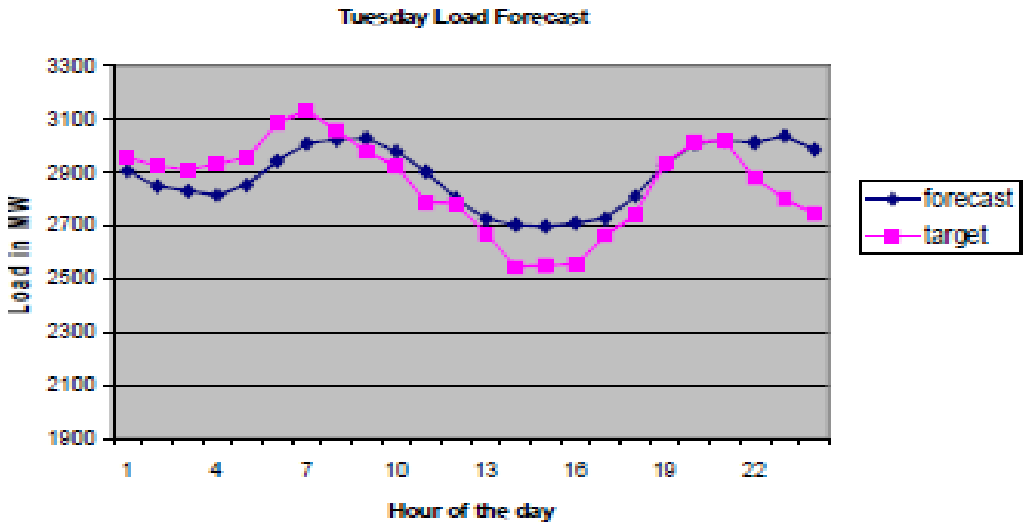

Fig 3: Plots of the 'Target' and 'Forecast' Load in MW Values against the Hour of the Day Tuesday.

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 Enugu, 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.

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