ARTIFICIAL NEURAL NETWORK (ANN) APPROACH TO ELECTRICAL LOAD PATTERN PREDICTION: A CASE STUDY OF OBAFEMI AWOLOWO UNIVERSITY POWER HOUSE

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Abstract

Short-term load prediction is a key component of the daily operation and planning activities of an electric utility. In this paper, the authors utilized the concept of Artificial Neural Networks (ANNs) using the Kohonen's self organizing feature map; which is back-propagating in nature. Historical data were used to train the ANN with learning rate = 0.7 and momentum = 0.4. The proposed methodology enhances the adaptability of the system to sudden changes or special events. The model was tested using two of the seven feeders of the Obafemi Awolowo University electric network. The results of the simulation show empirically that the range of errors observed is still within the tolerance level, as this is expected to improve the decision-making in terms of distribution scheduling.

Keywords: ANN, prediction, short-term, load pattern, training, learning

1. Introduction

The electricity supply industry requires to forecast electricity demand with lead times that range from the short term (a few minutes, hours, or days ahead) to long term (up to 20 years ahead). The quality of short term hourly load forecasts has a significant impact on the economic operation of the electricity supply. Short terms forecast, in particular, have become increasingly vital since the rise of the competitive energy markets. Short term forecasting of electrical load is important for optimum operation planning of power generation facilities as it affects both system reliability and fuel consumption.

This paper examines the applicability of Artificial Neural Networks (ANN) to electrical load pattern prediction and also explore ways of improving the accuracy and reliability of short term electrical load pattern forecasting. Accurate forecasting of electricity and power demand determines the utility to match its generation capabilities to the expected requirements. Electric utility operators for the purpose of scheduling and dispatching generating units need short term forecasts. This is more so as it is very vital for unit commitment, economic dispatch, hydrothermal co-ordination, and load management. According to Ackerman (2000), short run forecast plays an important role in the day to day operations of a utility, and it is typically used for optimizing system operation and scheduling of hydro units and other peaking plants such as gas turbines. The deregulation of the electric power system invariably results in demand elasticity and the need for improved power grid operation and management (Amin, 2001). Researchers have been working on this topic for a long time and have proposed a lot of strategies. Among them, time series, auto-regressive models and various neural network paradigms have found widespread acceptability in load forecasting. However, because of the difficulty in deriving mathematical models that approximate highly non-linear load behaviours under all conditions, heuristic forecasting are most often performed by dispatchers and system operators. In Hippert, Pedriera and Souza (2001), the most popular models are still the linear regression ones and the models that decompose the load, usually into basic and weather dependent components. In electrical engineering, load forecasting have been tried out using most traditional forecasting models and artificial intelligence techniques and have become one of the major research fields (Kher and Joshin, 2003).

(a) Artificial Neural Network and Electrical Load Prediction

Neural network analysis is an Artificial Intelligence (AI) approach to mathematical modeling. Neural Networks are systems that are loosely patterned on the human brain that can learn and discern patterns in real world conditions. According to Basu (1992), Khotanzad et al (1997) and Kodogiannis and Anagnostakis (1999); Artificial Neural Networks (ANN) has caught a lot of attention due to their outstanding ability to simulate arbitrarily linear and non-linear systems. The accuracy for steady state load prediction by ANN has been found satisfactory. However, most of the approaches developed with ANN do not consider highly atypical situation such

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as sudden weather or special events. ANN can be implemented for advanced control, data and sensor validation, pattern recognition, prediction and multivariable quality applications. Some of its benefits are:

· Reduced maintenance costs
· Minimized chances of catastrophic failures
· Early error detection and trend analysis
· Significant reduction in data analysis tasks/time
· Robust, accurate, and operate in real time, etc.

ANNs are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. The biologically inspired methods of computing are thought to be the next major advancement in the computing industry. The fundamental processing element of a neural network is a neuron. The basic units of neural networks, the artificial neurons, simulate the four basic functions of natural neurons. Figure 1 shows the basic components of a typical artificial neuron. The various inputs to the network are represented by the mathematical symbol X[n]. Each of these inputs is multiplied by a connection weight. These weights are represented by W[n]. In the simplest case, these products are simply summed, fed through a transfer function to generate a result. This process lends itself to physical implementation on a large scale in a small package.

According to Hippert, Pedriera and Souza (2001) , qualitative forecasting is based on extracting patterns from observed past events and extrapolating them into the future. The ANNs are very well suited for at least two reasons. First, it has been formally demonstrated that ANNs are able to approximate numerically any continuous function to the desired accuracy. Secondly, ANNs are date-driven methods, in the sense that it is not necessary for the researcher to postulate tentative models and then estimate their parameters. Given a sample of input and output vectors, the ANNs are able to automatically map the relationship between them; they "learn" this relationship and store this learning into their parameters.

The system load is the sum of all individual loads. The two essential components of a system are Base component and Randomly variable component. Generally, the factors that give rise to these can be summarized as:

(i) The meteorological conditions cause large variations in this aggregated load. In addition to the temperature, also wind speed, cloud cover, and humidity have an influenced.

(ii) In the long run, the *economic and demographic factors* play the most important role in determining the evolution of the electricity demand.

(iii) From the point of view of forecasting, the time factors are essential. These are the various seasonal effects and cyclical behaviuors (daily and weekly rhythms), as well as occurrences of legal and religious holidays.

(iv) The other factors causing disturbances can be classified as *random factors*. A large part of the electricity is consumed by industrial activities. Another part is of course used by private people in forms of heating, lighting, cooking, laundry, etc. Also many services offered by society demand electricity, for example street lighting, railway traffic etc.

(v) In the case of residential load, the factors determining the load are much more difficult to define. Each person behaves in his own individual way, and human psychology is involved in each consumption decision. Many social and behavioral factors can be found. For example, big events, holidays, even TV-programs, affect the load.

2. Neural Network Architecture

Artificial neurons may be described as either discrete or continuous. Discrete neurons send an output signal of 1 if the sum of received signals is above a certain critical value called a threshold value; otherwise they send an output signal of 0. Continuous neurons are not restricted to sending output values of only 1's and 0's; instead they send an output value between 1 and 0 depending on the total amount of input they receive – the stronger the received signal, the stronger the signal sent out from the node and vice-versa.

The architecture of a neural network is the specific arrangement and connections of the neurons that make up the network. In general, the most common neural network architectures has three layers. They are:

(i) The first layer, which is called the input layer and is the only layer exposed to external signals. It transmits signal to the neurons in the next layer called the hidden layer.

(ii) The hidden layer, which extracts relevant features or patterns from the received signals. This layer is responsible for processing the input based on the instructions on which the input vector is trained. Many neural networks have more than one hidden layer.

(iii) Output layer, which is the final layer of the network.

Figure 2 shows the architecture of a neural network. Sophisticated neural networks may have several hidden layers, feedback loops and time delay elements; which are designed to make the network as efficient as possible in discriminating relevant features or patterns from the input layer.

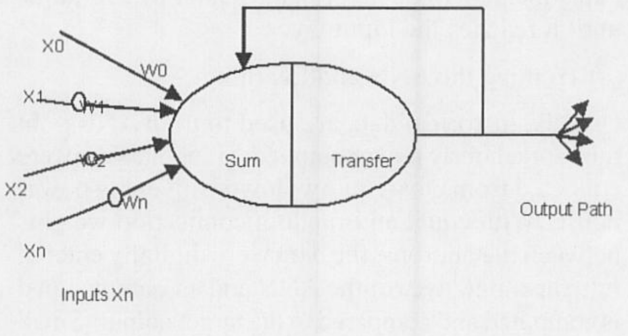

Fig. 1: A Typical Artificial Neuron

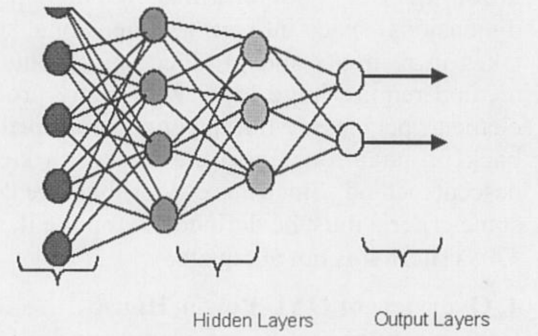

Fig. 2: Neural Network Topology

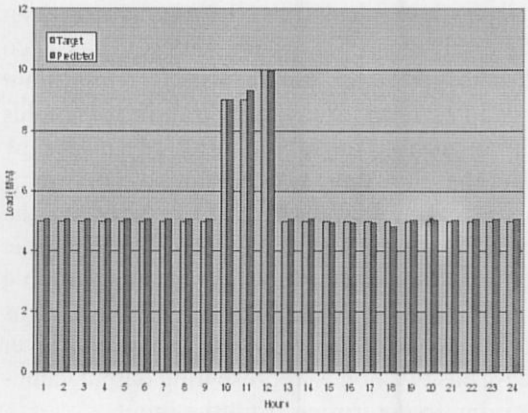

Fig.3: Comparison of target and predicted load for feeder 1

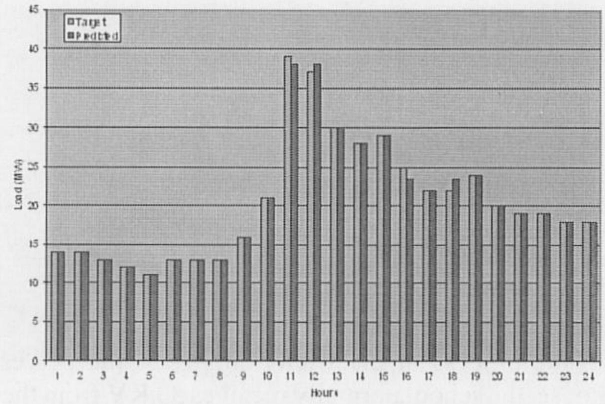

Fig. 4: Comparison of target and predicted load for feeder 4

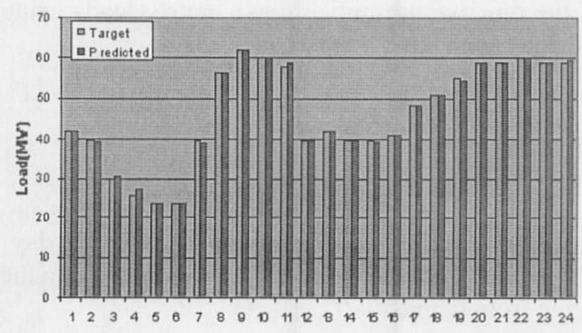

Fig. 5: Comparison of target and predicted load for feeder 5

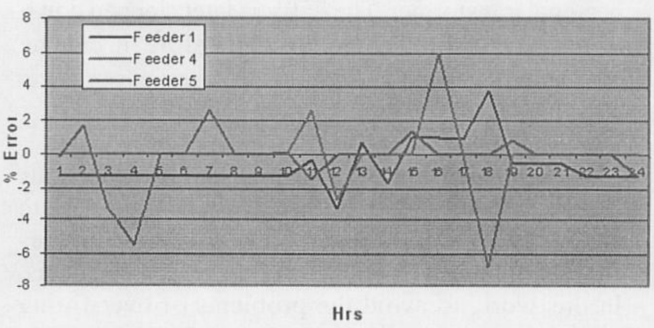

Fig. 6: Percentage errors for feeders 1, 4, and 5

3. Related Works

With power systems growth and the increase in their complexity, many factors have become influential to the electric power generation and consumption. Therefore, the forecasting process has become even more complex, and more accurate forecasts are needed.

Multiple regression is a statistical approach to prediction, though very effective for short term prediction of normal days but it fails to predict correctly those days with special events. Kalman filter resembles that of self-organizing feature map of Kohonen. It is also very good for short term prediction except that it has some shortcomings like failure to predict correctly some special days as in the case of multiple regressions. Exponential smoothing is good for a short term prediction as well but its shortcoming lies in its failure to properly merge and group data of the same type appropriately thereby resulting in a wrong prediction. Learning vector quantization classifies its input data into groupings that it determines i.e. it maps an n-dimensional space into an m-dimensional space. It takes in n inputs and produces m outputs. This method require large layer with many processing elements per class. Multi layer perceptron also uses back propagation algorithm based on steepest–descent method. Since these algorithms are iterative, some criteria must be defined to stop the iterations. This criterion is not adequate.

4. Overview of OAU Power House

For the purpose of efficient and effective management, the present power house was put in place in 1976 with seven feeders named as follows:

Feeder 1	Health Sciences
Feeder 2	Dam
Feeder 3	Secretariat
Feeder 4	Administrative Blocks
Feeder 5	Staff Quarters 1
Feeder 6	Staff Quarters 2
Feeder 7	Students' Hostels

In the process of electricity supply to the power house, the school normally receives 33 KV from the national grid. This is stepped down to 11kV on campus at the power house. This 11kV is further stepped down to 1.8kV at each feeder, which is later stepped down to 750V at each subunit that owns its personal transformer. The 750V is later stepped down to 415V and finally to 240V before it can be consumed by various users.

5. System Model of the ANN

The relationship between the load and its exogenous factors is complex and non-linear making it quite difficult to model through conventional techniques such as time series and linear regression analysis. In this work, to avoid the problems of over-fitting and over-parameterization, the ANN architecture used for prediction of electrical load pattern is Kohonen's self organizing feature map using the Lervenberge Marquard approach of neural network. The algorithm is back-propagating in nature in that it will compare the net output with the target output and calculates an error adjustment for each of the nodes in the network. It maps the N inputs x_1, x_2,……., x_N (N = 24) on the M output nodes y_1, y_2,……., y_M.

It will also adjust the connection weight according to the error value assigned to each node, beginning with the corrections between the last hidden layer and the output layer. After the network has made adjustments to this set of connections, it calculates error values for the next previous and some adjustments will be made again. This will continue until it reaches the input layer.

(a) Training the ANN and Learning

Usually, historical data are used to train ANNs. In this work, hourly power output data for one year were collected from Obafemi Awolowo University power house. With equal and random connection weights between the neurons, the data were digitally entered into the input layer of the ANN and an output signal is computed and compared to the target output. Small adjustments were made to the connection weight to reduce the difference between the actual output and the target output. This process was repeated until the ANN learns to respond in the desired manner. A neural network is said to have learned when it can correctly perform the tasks for which it has been trained. The ANN was able to extract the important features and patterns of a class of training examples and generalize from these to correctly process new input data that they have not encountered before.

As shown in Figure 2, the first layer represents the input layer, in this case with 5 inputs. In the middle is something called the hidden layer, with a variable number of nodes. It is the hidden layer that performs much of the work of the network. The output layer in this case has two nodes, representing output values we are trying to determine from the inputs.

(b) Model Parameters

If for example our 24 hourly loads in a day is given as L[i], i=1,2 …….,24; to get the hourly load pattern of the day, we normalize these hourly loads using the equation:

$$Ln(i) = (L(i) - Lv)/(Lp - Lv) \qquad (1)$$

where $Ln\ (i)$ = normalized load for hour i

$L(i)$ = load for hour i

Lv = Valley load (minimum load) for the day

Lp = Peak load (maximum load) for the day

The normalized hourly load $L_n(i)$ will fall within the range from 0 and 1.

From (1), our load pattern vector is given by

$$X' = [x_i, x_2, \ldots\ldots\ldots\ldots x_{24}]^T \qquad (2)$$

$$[x_n(i), x_n(2), \ldots\ldots\ldots\ldots x_n(24)]^T \qquad (3)$$

The elements of the load pattern vector X'_i, i= 1, ……..,24 always fall within (0, 1) no matter how high or low the daily peak and valley loads are.

The desired hourly load L(i) is given by:

$$L(i) = Lv + (Lp - Lv)Ln(i) \qquad (4)$$

To reach the proper load pattern for the day under study, the 24 hourly load L(i), i = 1, …………..,24; of each day, in one-year period are first compiled. Then these hourly loads are normalized using equation (1) and the resulting load pattern vectors were stored. By analyzing the load pattern vectors over a period of one year, all days in a year can be divided into several groups with each group comprising the days with similar load patterns. These days with similar pattern are called the days of the same day type.

Therefore, the desired load pattern for the given day can be obtained by averaging the load patterns for several recent days of the same type i.e.

$$Load\ Pattern = \left(\frac{Sum\ of\ load\ patterns\ of\ the\ same\ day\ type}{N} \right) \quad (5)$$

where N = number of load pattern of the same day type

The algorithm of the Kohonen maps N inputs x_1, x_2,......, x_{24} on to M outputs nodes y_1, y_2, ..., y_m.

For the vector of load forecasting, the load pattern vector X_i is first normalized to obtain a vector X of unity length before it can be used as input vector to the self-organizing feature map:

$$X = [x_1, x_2, ..., x_{24}]^T \quad (6)$$

$$where,\quad x_1 = \frac{x_i'}{\left(\sum_{i=1}^{24} X'^2 \right)^{\frac{1}{2}}}$$

As shown earlier, each input is connected to an output unit i through connection weight W_{ij}. The continuous–valued input pattern and connector weight will give the output i a continuous–valued activation value a_j defined as:

$$aj = \sum_{i=1}^{N} WijX_i = WjX \quad (7)$$

where X is the input pattern vector in (6)

Finally, we normalize Wj to give unity vector length:

$$Wj = \frac{Wj}{\left(\sum_{j=1}^{24} Wij^2, i = 1 \right)^{\frac{1}{2}}} \quad (8)$$

Usually, errors in the predicted values are calculated using the equation:

$$\%\ Error = \left(\frac{Actual\,Value - Predicted\,Value}{Actual\,Value} \right) x100$$

In a real life situation, a root-mean square error of less than 3 % can always be achieved.

(i) Adaptation of the ANN to Changes

Usually, the ANN exhibit generalization by responding with an output similar to target vectors for input vector close to the previously unseen input vector p. In a situation where we have two inputs and one output and all are binary, the output is:

1 if $WoIo + W_1I_1 + Wb>0$

0 if $WoIo + W_1I_1 + Wb<0$

Otherwise, the ANN will learn or output a 1 if either Io or I_1 is 1.

If the percentage error is large, the network changes the weight of the connection by an amount proportional to the difference between the desired output and the actual output (i.e. the difference between the predicted load and the actual load), as shown in the equation:

$$Wi = n_r * (D - Y)\ I \quad (10)$$

where n_r = learning rate

D = predicted load

Y = actual load

I = variable input

This is called the perceptron learning rule that shows the pattern below:

I_0	I_1	Desired Output
0	0	0
0	1	1
1	0	1
1	1	1

6. Simulation Results and Discussion

In this section, the authors tested the model developed using the MATLAB 6.1 simulation software. For the purpose of this simulation, we will only present the results of the feeders 1, 4 and 5. In this way, the trained ANN predicts the future hourly loads based on new sets of input vector. The results of the simulation (with learning rate = 0.7 and momentum = 0.4) of a period of one day are given in Table 1, Table 2 and Table 3 respectively for feeders 1, 4 and 5.

The target values for the three feeders were compared with the predicted values as shown in Figures 3, 4 and 5. Also, the errors generated at each of the feeders were compared on hourly basis. The results show that the percentage errors recorded for feeder 1 varies between -3.2200 to 3.7140, that of feeder 4 oscillates between -6.8181 and 6.0000 and for feeder 5; it fluctuates between -5.45455 and 2.564366. Figure 6 shows the percentage errors plotted against hours for the three feeders.

7. Conclusion and Future Work

Most existing load forecasting methodologies are severely strained and cannot handle load forecasting very well when sudden changes in weather occur or some special events take place. In the methodology presented in this paper, we have improved the overall forecasting accuracy significantly. The results show improved performance and this is expected to assist the power house to improve their decision–making in terms of distribution scheduling and completion of energy transactions. It will also assist in avoiding unnecessary start-ups of generating units. The range of errors observed is still within the tolerance level and is also suitable for short-term prediction.

In future, efforts will be made to incorporate all the other feeders in order to have a campus-wide view of load forecasting. We will also consider medium-term and long-term forecasting.

REFERENCES

Ackerman, G., 2000. Short Term Load Prediction for Electric-Utility Control of Generating Units. In: D.W. Bunn & E.D. Farmer (Eds.), Comparative Models for Electrical Load Forecasting John Wiley & Sons Ltd, New York, pp. 33-42.

Amin, M., 2001. Towards Self-Healing Energy Infrastructure Systems, IEEE Computer Applications in Power, 14, 1, pp. 220-228.

Basu, N.S., 1992. Short Term Localized Load Prediction, Transactions on Power System, 7, pp. 389-397.

Hippert, H.S. Pedriera, C.E. and Souza, R.C., 2001. Neural Networks for Short-term Load forecasting: A review and evaluation IEEE Transactions on power system, 16, 1.

Kher, V.H. and Joshi, S.K., 2003. Short-Term Electrical Load Pattern Forecasting using Artificial Neural Network, Australasian Universities Power Engineering Conference, Christchurch, New Zealand, October.

Khotanzad, A., Afkhami-Rohani, R., Tsun-Liang, L, Abaye, A., Davis, M. and Maratukulam, D., 1997. ANNSTLF-a neural network-based electric load forecasting system, IEEE Transactions on Neural Networks, 8, pp. 835-846.

Kodogiannis, V.S. and Anagnostakis, E.M., 1999. A study of Advanced Learning Algorithms for short-term load forecasting, Engineering Applications of Artificial Intelligence, 12, pp. 159-173.