FORECASTING DAILY PEAK LOAD OF GHANA USING RADIAL BASIS FUNCTION NEURAL NETWORK AND WAVELET TRANSFORM

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Abstract: *Load forecasting helps electricity utilities make important decisions such as purchasing and generating electric power, load switching and infrastructure development. Energy suppliers, financial institutions and other participants in electric energy generation, transmission, distribution and markets benefit from load forecasts. This paper proposes the combination of wavelet analysis and radial basis function neural network (RBFNN) as tools for short-term load forecasting (STLF). The forecasting model developed predicts peak load one day ahead. The model was developed using a year's load data obtained from the Volta River Authority of Ghana (VRA). The performance of the model was measured using the mean absolute percentage error (MAPE). The overall average MAPE obtained for a testing year was 1.785%.*

Keywords: *Short-term load forecasting, wavelet transform, artificial neural network.*

1. Introduction

Electric power companies have been constantly plagued with technical and economic difficulties as they endeavour to meet customer demand for reliable, quality and safe electric energy in the face of constantly changing load demand. In order to attain optimal performance in the light of these difficulties, it has become necessary for these companies to predict future load demand. Load forecasting basically describes the process of predicting the future load demand of a power system [1].

Load forecasts can be divided into three categories: Short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. [2].

Short-term load forecasting (STLF) which is the focus of this work helps to estimate load flows and to make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. Also, STLF helps to determine the time at which certain load demands are required, it aids in load planning and helps in knowing the various factors which determine power that should be made available at a power station in order to meet load demand. With deregulated power industries, load forecasting is even more important, not only for system operators, but also for market operators, transmission owners and other market participants, so that adequate energy transactions can be scheduled, and appropriate operational plans and bidding strategies established [3].

Most short-term load forecasting methods use statistical techniques such as time series, econometric modeling and statistical learning algorithms, or artificial intelligence algorithms such as neural networks, fuzzy logic, and expert systems. Artificial intelligence algorithms for STLF based on artificial neural networks have however proven more accurate in the prediction of short term load demand than the statistical techniques [2].

This paper presents a daily peak load prediction using Daubechies db3 mother wavelet and Radial basis function neural network.

2. Wavelet Analysis

There are essentially two types of wavelet decomposition: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) [4]. CWT is mainly used for theory research, but DWT is more popular in the field of engineering, because the observed time series are discrete in real world, including short-term load series and as such this has been used in this work [5].

Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, aspects such as trends, breakdown points, discontinuities in higher derivatives, and self – similarity. Wavelet is able to compress and de – noise a signal without appreciable degradation [6].

The process of breaking up a signal into scaled and shifted versions of the mother wavelet using wavelet analysis is called decomposition. The results of the transform are called wavelet coefficients and this can be grouped into two: approximate and detailed coefficients. The approximations are the high-scale, low-frequency components of the signal and the details are the low-scale, high-frequency components [7].

The wavelet expansion of a function $f(x)$ is given as [8]:

$$f(x) = a_0 \phi(x) + \sum_{j=0}^{\infty} \sum_{k=-\infty}^{\infty} a_{2^j+k} W\left(2^j x - k\right) \qquad (1)$$

Where $j = 0,1,2,\ldots,$ and $k = 0,1,2,\ldots,\left(2^j - 1\right)$, and the coefficients are:

$$a_{2^j+k} = 2^j \int_0^1 f(x) W\left(2^j x - k\right) dx \qquad (2)$$

$$a_0 = \int_0^1 f(x) \phi(x) dx \qquad (3)$$

The discrete wavelet transform is an algorithm for computing equations (2) and (3) when $f(x)$ is sampled at equally spaced intervals of $0 \le x < 1$.

Decomposed signals can be assembled back without loss of information using the approximate and detailed coefficients. This process is called reconstruction, or synthesis. The mathematical manipulation that effects wavelet reconstruction is called the inverse discrete wavelet transform(IDWT)[9].

3. Radial basis function

Artificial Neural networks(ANNs), with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques [10].

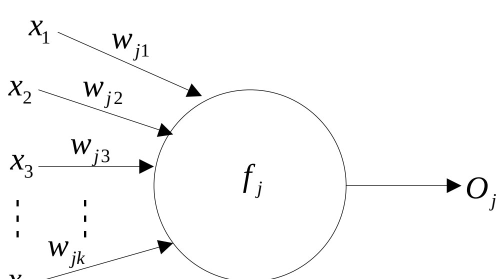

Fig. 1: Mathematical model of an ANN neuron

ANNs are made up of a number of simple and highly interconnected Processing Elements (PE), called neurons, as shown in figure 1. Its mathematical model is expressed as [11]:

$$O_j = f_j \sum_{k}^{N} \left(w_{jk} x_k\right)$$

Where

$j = k = 1, 2, 3, \ldots, N$;

O_j is the output of a neuron;

f_j is a transfer function, which is differentiable and non-decreasing, usually represented using a sigmoid function, such as a logistic sigmoid, a tangent sigmoid, etc.;

w_{jk} is an adjustable weight that represents the connection strength and

x_k is the input of a neuron.

Among the many types of neural networks is the radial basis function (RBF) which is employed in this paper. RBFs are able to model complex mappings which perceptron neural networks can only model by means of multiple layers. They also have non – linear approximation properties. The input to an RBF is nonlinear whilst the output is linear. RBF also has advantages such as interpolation, functional approximation, localization and cluster modeling. These properties lead to quicker learning in comparison to multilayer perceptrons trained by back propagation [12],[13].

4. Development of forecast model

The most important work in building a forecasting model is the selection of the input variables. In selecting inputs for the neural network, normally the near date data have more similarity to the target day than that of distant date data. Therefore the principle employed in selecting inputs is to consider all possible near date data to target.

The inputs selected for training of RBFNN were:

- Previous day's peak load(L1)
- The target day's previous week's peak load(L2)
- The previous day's, previous week's peak load(L3)
- The target day(T)

The same inputs would be required for forecasting. The first three inputs were preprocessed using wavelet decomposition with a db3 mother wavelet and a resolution level of two in MATLAB. This resulted in one approximate coefficient vector(A1) and two detailed coefficient vectors(D1 and D2). Each vector had four elements. The approximate coefficient vector and the two detailed coefficient vectors were then added, $S = A1 + D1 + D2$. The resulting vector, S, was normalized so that the elements ranged between 0 and 1. The forecast days were included in the model by representing them with numbers ranging from one to seven. These numbers were converted to 3 digit binary numbers and concatenated to the corrected coefficients(S) which resulted in a vector with seven elements. The target load was also taken through a similar process as the input load thus resulting in a target vector with four elements.

The radial basis function neural network(RBFNN) therefore had seven input neurons and four output neurons. The RBFNN was trained with a year's data set. The outputs of the trained neural network were then reconstructed to obtained the forecasted load in MW. Figure 2 shows a flow chart for the development of the forecasting model. A flow chart of the proposed load forecasting model is also shown in figure 4.

5. Model Performance

The assessment of the model's prediction performance was by quantifying the predictions obtained against an independent data. The Mean Absolute Percentage Error (MAPE) was used to measure the performance of the developed model. The MAPE between the target day (P_{actual}) and the forecasted day($P_{predicted}$) for each typical day was obtained for all twelve months of the testing year. MATLAB version 7.0.124704 (R14) Service Pack 1, was used for simulation on a Pentium 4, 3.2 GHz 448 RAM platform. MAPE is defined as:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_{actual,i} - P_{predicted,i}}{P_{actual,i}}\right| \times 100$$

The performance of the model was measured against a testing year which is 2005. Sample graphical representations of the model's performance are shown in figures 3, 5 and 6. A MAPE table has been provided showing the average MAPEs for each day of each month of the testing year.

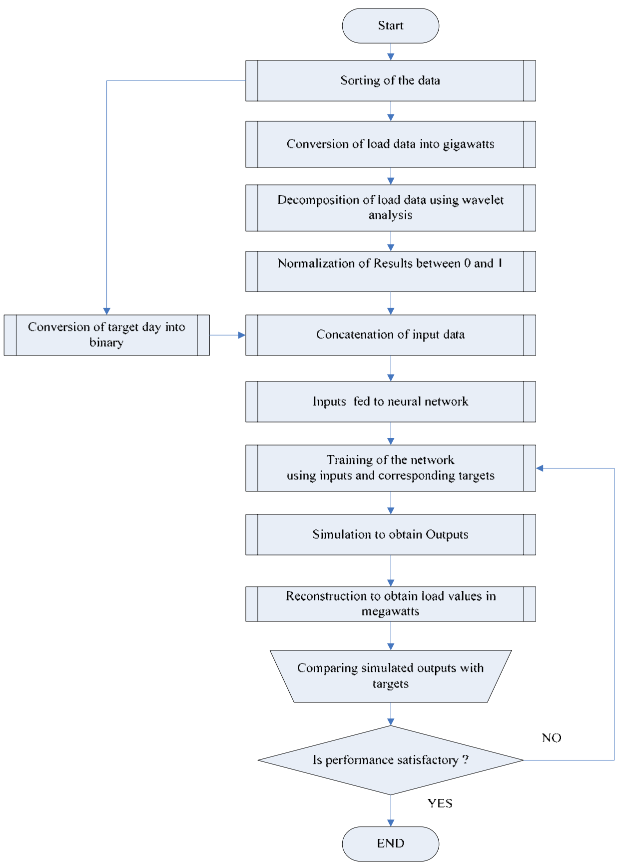

Fig. 2: Flow chart for development of forecast model

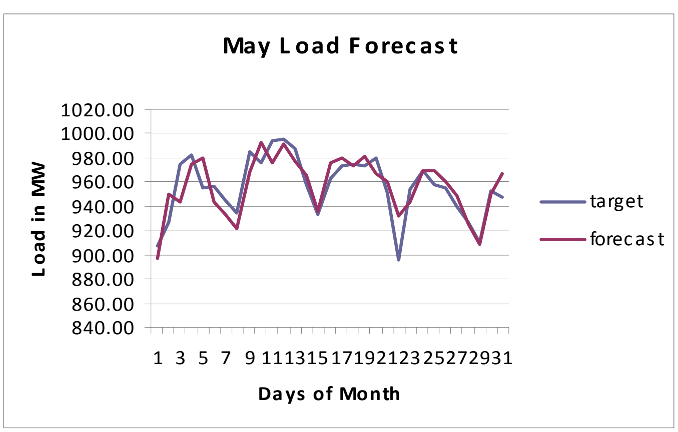

Fig. 3: Predicted and actual daily peak loads for May

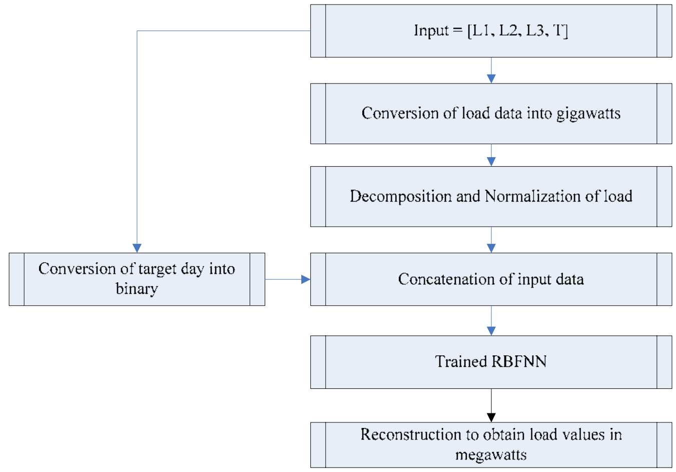

Fig. 4: Flow chart of proposed forecast model

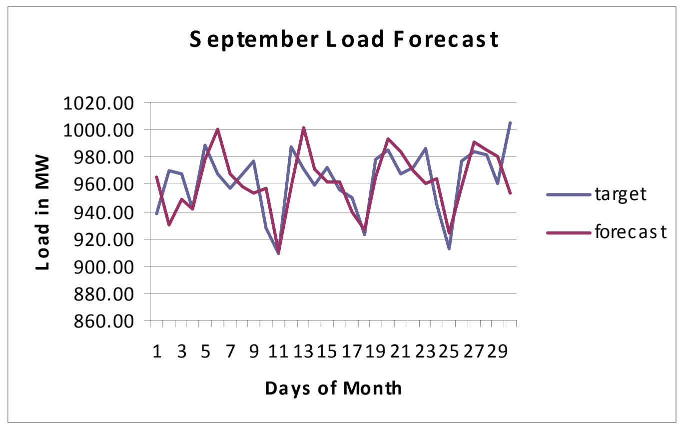

Fig. 5: Predicted and actual daily peak loads for September

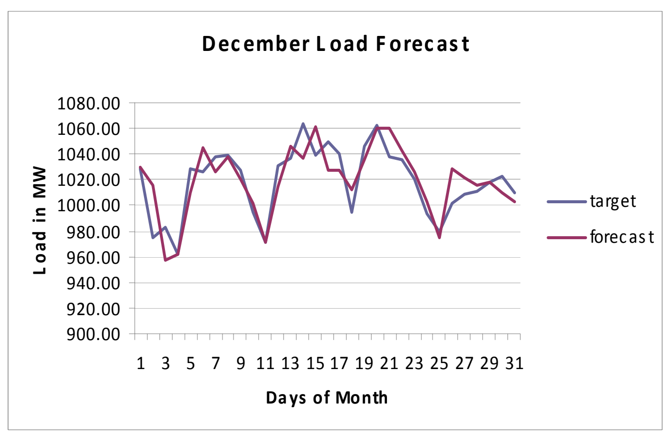

Fig.6: Predicted and actual daily peak loads for December

Table 1: MAPE for each month for the test year 2005

	Percentage MAPEs						
	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Jan	1.90	2.85	1.20	1.27	1.41	2.94	2.22
Feb	2.17	1.35	0.62	0.78	0.75	2.22	2.83
Mar	2.99	1.85	0.90	2.41	2.21	1.5	2.68
Apr	1.49	0.95	0.86	1.03	2.24	2.49	2.96
May	1.41	1.55	0.96	1.07	1.17	0.79	1.35
Jun	3.82	1.58	2.00	1.89	2.89	3.75	0.96
Jul	2.20	1.93	1.73	0.81	2.42	2.11	1.03
Aug	2.95	2.69	0.98	0.78	1.93	2.25	0.64
Sept	1.82	2.05	1.09	1.48	2.96	2	0.46
Oct	3.35	1.04	1.72	0.61	0.97	1.68	1.87
Nov	4.60	3.79	1.42	2.14	2.19	1.32	1.96
Dec	1.73	1.08	1.59	0.61	1.78	1.24	0.59
Avg. daily MAPE	2.54	1.89	1.26	1.24	1.91	2.02	1.63

The network showed good MAPE results. The month of September showed a MAPE as low as 0.46% for Sunday. Thursday showed the overall best average MAPE result of 1.24%, followed closely by Wednesday. The month of May showed the best performance followed by the month of December. Poor predictions were recorded for the month of November. The testing year showed an average daily MAPE of between 1.24 and 2.54 %. The average monthly MAPE was also obtained to be between 1.23% and 2.49%. The overall MAPE obtained for the testing year was 1.785%. This represents a high degree of accuracy.

6. CONCLUSION

This work proposed the combination of wavelet analysis and RBF as tools for STLF. ANNs can extract the implicit nonlinear relationship between past load and forecasted load. They do not rely on explicit function representation of input variables and the load to be forecasted. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques fail to, aspects like trends, breakdown points etc.
The model showed a good performance when tested against the testing year 2005. The overall average MAPE obtained was 1.785%.

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