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Short-Term Load Forecasting Based On Empirical Mode Decomposition and Artificial Neural Network

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Abstract: The Electricity Supply Industry (ESI) across the globe is seeking ways on how to improve its services to its ever increasing teeming customers and one way it hopes to achieve this is to put forward a load forecasting model that will help it meet the effectively the future load needs of its customers so as to serve them better. In this paper a novel method for Short-term load forecasting (STLF) that combines empirical mode decomposition (EMD) and artificial neural network (ANN) that yields a high forecasting accuracy have been put forward. EMD is used to decompose the historical time series data into several intrinsic mode functions (IMFs) and residue components of various frequencies were obtained by this. This is aimed at making the series stationary. For each of these IMFs an appropriate neural network model is built. The predictions from these IMF-ANN models are combined together to obtain the proposed EMD-ANN model. This model is then used for forecasting purposes. To assess the performance of the proposed model, the study adopted real life load data from Power Holding Company of Nigeria (PHCN), Bida, Nigeria. The MAPE of the proposed EMD-ANN model recorded an improvement of 2.44% increase over traditional BPNN model for the whole year and 2.46% over the BPNN model for week day load.
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Keywords: Empirical mode decomposition; Intrinsic Mode Function; Forecasting Accuracy; Model; Decomposition

1. Introduction

Electricity Supply is given major utility companies across the globe a several challenges as population of users of their services keeps on increasing on a daily basis. This situation is not different in the Nigeria Electric Supply Industry (NESI). The industry in Nigeria is characterized by epileptic power supply, incessant outages, improper pricing of power, illegal connections and non-settlement of tariffs. Further, because of the inadequacy of the public supply the cost of doing business in Nigeria is very high, this has forced companies in Nigeria to generate their own Power. As a result of this, many companies have closed down and moved to neighboring countries like Ghana and South Africa. To combat this problem NESI has undergone restructuring since the early 2000s and this has helped NESI tremendously to expand and improve its services and meet up with its ever growing customer demand. For NESI to be able to satisfy its customer and meet its target it needs to plan adequately for this expanding demand of its customers. One such ways it can effectively hope to achieve this is to put forward an efficient and accurate electric load forecasting tool that is adaptive in nature. It is in line with this goal of NESI that we propose in this paper- to put forward a novel short-term load forecasting (STLF) technique for NESI based on Empirical Mode decomposition (EMD) and Artificial Neural Network (ANN),that is adaptive and yields a high degree of accuracy over existing methods

STLF is a very important part of electric load forecasting as it helps in making good load dispatch schedule, as well as, in business and supply planning in the electricity industry. Further, STLF yields the most accurate load forecast results amongst the load forecasting techniques available. Xia, et al. (2011) says STLF need a high precision to a very great extent. With all this, planning for the STLF needs of electricity supply industry across the globe has become very important and requires experts evolving forecasting techniques that will help to combat these teeming challenges.

Empirical Mode Decomposition (EMD) is a data analysis method that is based on time frequency and is proposed by Huang and some of his colleagues in the late 1990's. It overcomes the disadvantage of the wavelength transform, that is, its inability to select the proper wavelength basis function. EMD is a good technique for processing non-stationary and nonlinear data such as electric load and it is at the same time adaptive. Studies where this method have been successfully employed include: Blanco-Velasco et al., 2008; Demir & Ertuk, 2008; Fan & Zhu, 2010; Mahmoud, et al., 2009; Okolobah & Zuhaimy, 2013; Rilling, et al. 2003 and Zhang et al. 2008.

Artificial Neural Network (ANN) is an adaptive system which changes its structure during the learning phase. ANN is inspired by biological neurons. ANN is made up of interconnected group of neurons. The neurons in an ANN are interconnected by information channels which are referred to as interconnections. Each neuron can comprise of several inputs but must have only one output. The inputs to a neuron could be from external sources or from the output of another neuron. There is a connection strength, synapses or weight associated to each connection. To fire a neuron the weighted sum of inputs to the neuron must exceed a given threshold and this produces an output. By tuning or adjusting weights by some learning process, the network recognizes the input patterns. The backpropagation (BP) algorithm is the commonest method for training the feed forward neural network. ANN has been employed in the following studies: Adepoju, et al. 2007; Fadare & Dahunsi, 2009; Phimphachan et al, 2004; Murat & Ceylan, 2005; Zhang & Qi, 2005; Zhang, et al. 1998 and Bunnoon, et al. 2010.

In this paper, a forecasting technique based on EMD and ANN is proposed for effective prediction of STLF in the Electricity Supply Industry (ESI). The remaining sections of this paper are structured as follows: section 2 discusses the methodology of the paper beginning with the EMD algorithm, after which ANN model is discussed. To close this section, the paper discusses the proposed EMD-ANN model. Section 3 discusses the analysis and results of the paper based on real life data that was adopted from an electricity outfit in Nigeria. A brief conclusion of the paper is presented in section 4. Lastly section 6 is the acknowledgement in which we appreciate organizations that has assisted this study in different forms

2. Methodology

This section, discusses extensively the EMD algorithm, then takes a brief look at the ANN forecasting technique and ends by presenting the proposed EMD-ANN model. A schematic picture of the how the proposed model is given highlighting the major steps of implementation.

2.1 EMD Algorithm

Huang, N.E. and his colleagues proposed the signal decomposition technique known as EMD. The essence of the EMD technique is the decomposition of complex signal into several elementary components called intrinsic mode functions (IMFs) which are stationary. In doing this, the EMD technique ensures no loss of information as adding together the IMFs the original load signal will be obtained. For a signal to be considered as an IMF, it must satisfy both of these criteria i) the number of zero crossings and the number of extrema are equal or differ by at most one. ii) the mean value of the upper envelope defined by the local minima must be zero. The algorithm for the extraction of the IMFs is called sifting and it consist of the following steps (Huang et al., 1998) for a given signal $X_{(t)}$.

Step 1: identify all extrema of $X_{(t)}$, all the local extrema can be connected by a cubic spline line. Let the upper and lower envelopes be denote by $e_{max}(t)$ and $e_{min}(t)$ respectively.

Step 2: Obtain the mean of the upper and lower envelopes

$$m(t) = \frac{(e_{max}(t) + e_{min}(t))}{2} \qquad 2.1$$

Step 3: subtract m(t) from the given signal X(t) and call this d(t), that is,

$$d(t) = X(t)$$

Step 4: Examine the properties of d(t):

If d(t) is an IMF it should satisfy the two conditions above for a function to be an IMF

If it does not satisfy the conditions of being an IMF, d(t) replaces X(t).(Zhang et. al. 2008).

Step 5: Repeat steps 1 to 4 until the residue satisfy some pre-determined stopping criterion.

The stopping criterion proposed by Huang et al.(2003) for extracting an IMF is: after iterating pre-determined times and the residue satisfy the requirement that the number of zero crossings and the number of extrema differ by at most one then the sifting process can be stopped by any of the following pre-determined criteria: when the component $C_i(t)$ or the residue r(t) becomes so small that it is less than a pre-determined value of substantial consequence, or when the residue r(t) becomes a monotonic function from which no more IMFs can be extracted. Finally, the original signal can be expressed as:

$$X(t) = \sum_{i=1}^{N} C_i(t) + r(t) \qquad 2.3$$

Where N is the number of extracted IMFs and r(t) is the final residue.

The first component C_1 is the shortest period component of the time series. After extracting all the components C_i denotes the long the long term trend in the data. This implies the IMFs are extracted from the highest frequency to the lowest frequency. The entire process for extracting the IMFs is shown in Figure 1.

2.2 BackPropagation Neural Network (BPNN)

BPNN is a causal model multilayer feedforward network consisting of input, hidden and output layer of neurons. Several connections exist between the upper and lower layers but no known connections between the neurons. The network works from left to right in this manner. Samples are fed to it, the activation of neurons transmits from the input layer through the hidden layer to the output layer. The transfer function of the network usually any of these logarithm of sigmoid type or linear or tangent functions which are differentiable. The output of each node in the BPNN only affects the node next to it.

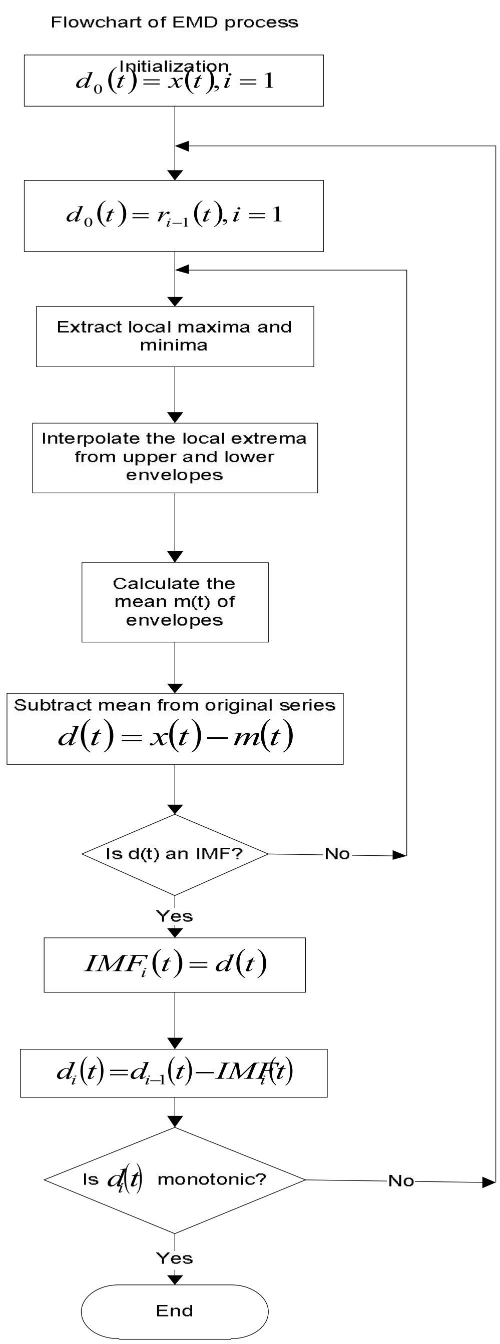

Figure 1 EMD sifting process flowchart.

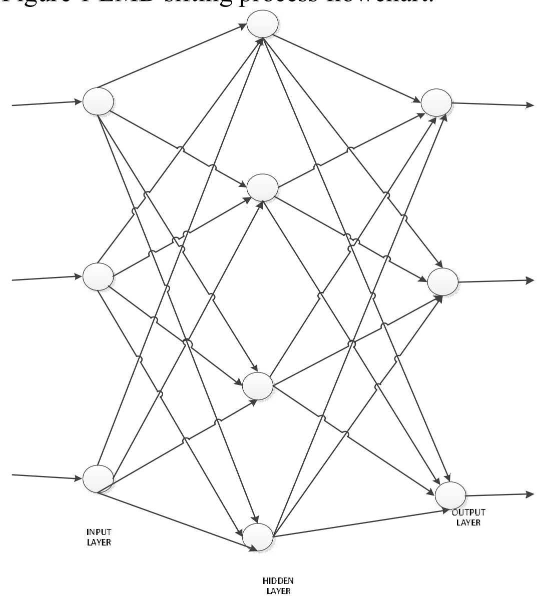

Figure 2 A Schematic 3 layers feed-forward network.

2.3 EMD-ANN Model

The process to achieving this is outlined in the steps below.

Step1: the historical load data is passed through the EMD extraction process described in 2.1 above and by doing this several IMFs is obtained.

Step2: Since the ANN supervised learning algorithm requires feeding the network with target, this too must undergo the EMD extraction process. Here, the maximum and minimum values of the targets must be adjusted severally to ensure that the same number of IMFs is obtained as those in step 1 above. For instance, if step1 has 9IMFs step 2 must be adjusted so that the EMD process yields 9imfs also.

Step3: the IMFs for the load which is the input data for the network is normalized so also those of the target. In this paper all inputs and all targets were normalized to between 0 and 1. This was achieved by means of the following:

$$X_{normalised} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad 2.4$$

Step4: with each IMF from the input and its corresponding IMF from the target EMD-ANN models are developed, that is IMF1 for input is taken alongside IMF1 for target to develop the first model. Likewise IMF2 for input with IMF2 for target are taken for development of second model and so on until all the IMFs for both input and target have been used.

Step 5: Combine all results obtained from step 4 together. Then this result is normalized once again as in step3 above. These normalized results along with the target that is, the original target that has not gone through EMD extraction process are fed into the network as the new input and target and processed through the network.

Step 6: Finally, the results are transformed from their normalized state back to the original form. This is achieved by the following:

$$X = [X_{Normalised} \times (X_{max} - X_{min}) + X_{min}] \qquad 2.5$$

The EMD-ANN model is shown in figure 3

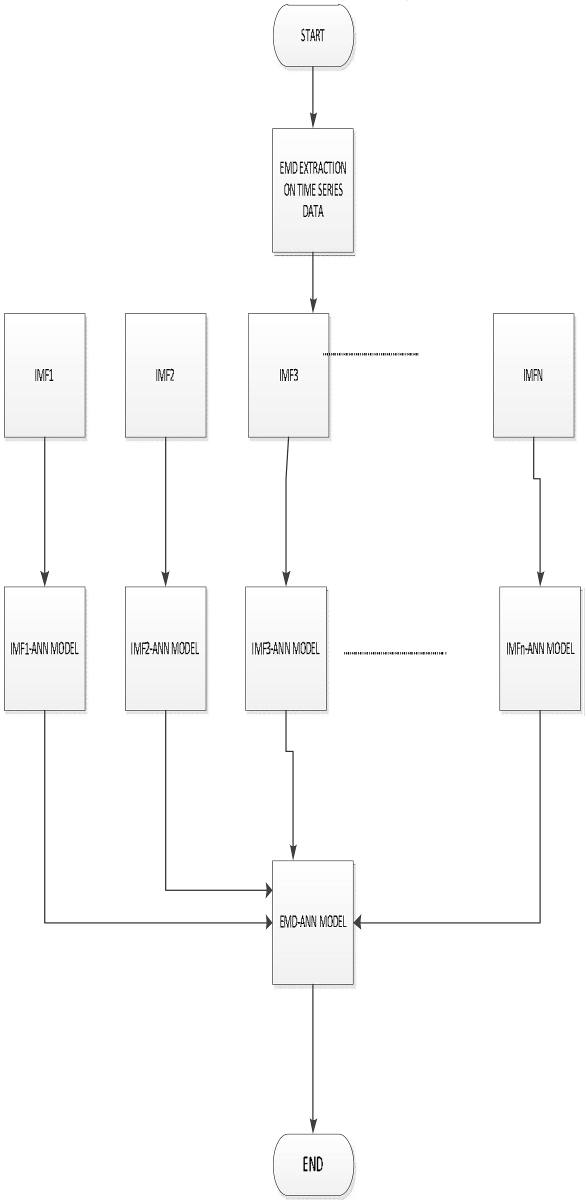

Figure3 EMD-ANN model

3.0 RESULTS AND DISCUSSION

The paper adopts the daily peak load demand (DPLD) of Power Holding Company of Nigeria, Bida Business Area, Bida from January 1st, 2012 to December 12th, 2012 for modeling and testing by applying the methods described above. 70% of the data was used for training the network while 30% was used for testing. All analyses were done using MATLAB. Figure 4 show the 8IMFs and residue components. Figure 5 and 6 are the forecasting results obtained by the EMD-ANN model developed

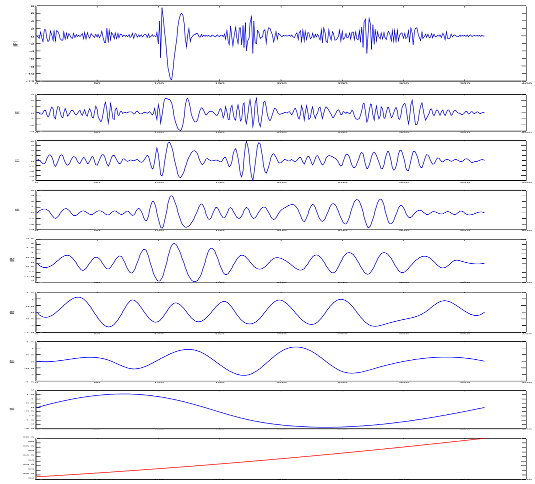

Figure4 Extracted IMFs and residue

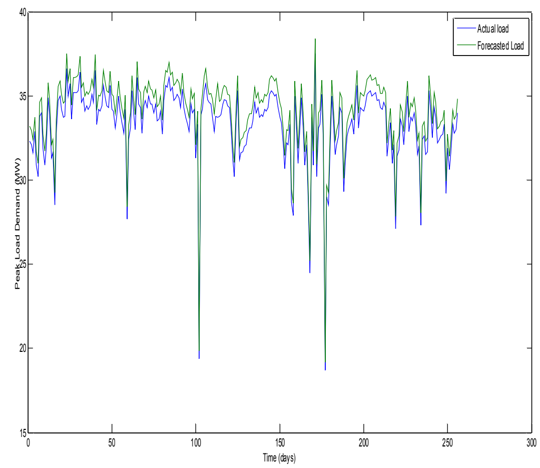

Figure5 Actual and forecasted data for complete year one day ahead forecast

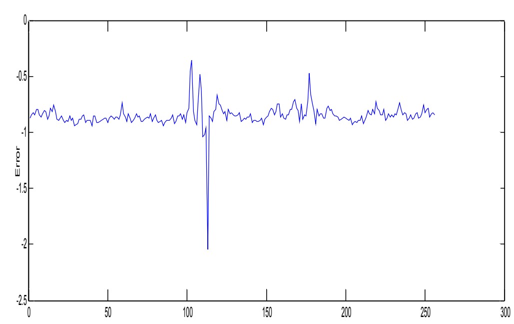

Figure6 Error curve for complete year data (1day ahead forecast)

For evaluating the performance of the model, we adopted the measure mean absolute percentage error (MAPE). The index is presented as follows

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_{i(actual)} - Y_{i(forecast)}}{Y_{i(actual)}}\right| \quad 3.1$$

In the index above, $Y_{i(actual)}$ is the actual time series for period i, $Y_{i(forecast)}$ is the forecast time series for period i, while N is the total number of forecast.

We equally took the weekday values of the time series and equally implemented the EMD-ANN technique on them still considering 70% of this as training data and the other 30% as testing data set and the results in figure 7 and figure 8 are the actual and forecasted results for weekdays load and the corresponding error curve for this respectively. Table 1 is a summary of the comparisons made of the model proposed in this paper that is EMD-ANN and the traditional BPNN in load forecasting abilities.

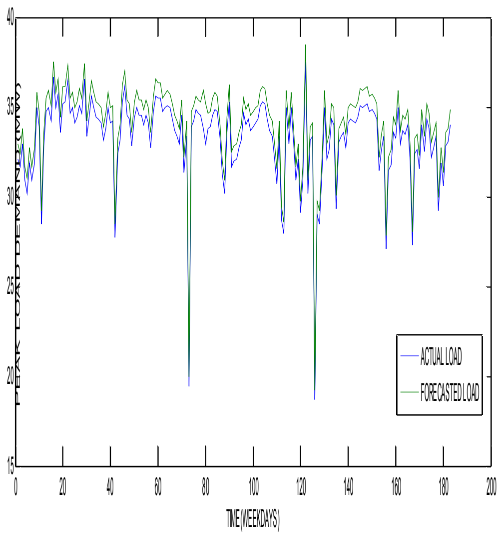

Figure 7: Actual and forecasted data for weekdays (Monday to Friday) load

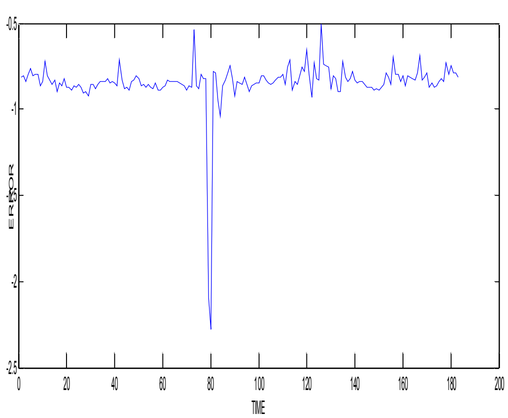

Figure 8: Error curve for traditional BPNN

Table 1: Forecast results for EMD-ANN and traditional BPNN.

Type of model	EMD-ANN	Traditional BPNN	Amount of improvement
WHOLE YEAR	2.56	5.00	2.44
WEEKDAY MODEL	2.55	5.01	2.46

The results in Table 1 reveal that the proposed EMD-ANN model outperform the traditional BPNN model whether for the whole year or weekday models. The reason for this is that the EMD has prepared the data well by making them stable for the forecasting purposes. Further the whole year model recorded a better improvement over the weekday model. This may be due to the presence of larger amount of data in the whole year model compared to the weekday model.

From the results presented in Table 1, we can also observe that the EMD-ANN model yields better forecasting results when compared with the traditional BPNN and we have earlier adduced this to the EMD extraction process that makes the time series data stationary so we can by this, conclude that EMD is a good data pre-processing method for time series modeling and that the EMD-ANN model is an effective method for STLF in ESI.

4.0 Conclusion

In this paper, we use a method based on EMD and ANN to establish a model for STLF. The EMD is used to decompose the load data into 8 stationary IMFs and a residue component. Then appropriate ANN models were developed for each of these IMFS and residue. The predictions from the IMF-ANN models were combined together to obtain the proposed EMD-ANN model. This is then used for forecasting purposes. The results for this model were then compared with that obtained from traditional BPNN method using the same data and the method proposed in this paper yielded better forecasting judging by the MAPE of both methods.

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