Research Inventy: International Journal of Engineering And Science
Vol.13, Issue 3 (March. 2023), PP 03-08
Issn (e): 2278-4721, Issn (p):2319-6483, www.researchinventy.com

Hybrid model using Ensemble Empirical Mode Decomposition for Forecasting Electricity Load Demand

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Abstract:*Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD) is combined in this paper with Artificial Neural Network (ANN) to forecast load demand for Bida a rural community in Niger State Nigeria. The data employed for the study is daily load demand sourced from the Bida office of the Abuja Electricity Distribution Company (A.E.D.C) covering the period 1st January, 2012 to 31st December, 2012. Three major evaluation techniques were used in assessing the performance of the four models measured in this study. The evaluation techniques are: Mean Average Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). From the result posted by the four models measured in this study, it can be observed that for both training and testing datasets the proposed EMD/EEMD-ANN model posted the best forecast accuracy of 4.3635 and 4.3530 for the training and testing datasets respectively judging by the MAPE results of all the four models. The paper then concludes that the proposed EMD/EEMD-ANN model is very promising for electricity load demand forecasting and therefore recommends its use by electricity concerns across the globe. The paper equally suggest the exploration of EMD/EEMD-ANFIS in future studies.*

Keywords:*Decomposition, forecast accuracy, evaluation technique, Performance and Load Demand*

Date of Submission: 08-03-2023 Date of Acceptance: 21-03-2023

I. INTRODUCTION

Electricity load demand forecasting is a major task in managing utility concerns across the globe. Improving the accuracy of load demand forecasting is necessary for utility companies. To this end utility concerns globally seeks ways by which this can be achieved. One of such ways is to find new reliable and accurate forecasting techniques.

An accurate and precise prediction of electricity load is very necessary in forestalling the supply needs of an area. An accurate load prediction can be used to understand the load demand of an area and help in planning, as well as, provision of facilities. This is the reason Bokde, Feyoo, Villanueva & Kulat (2019) says an accurate power prediction is of very necessary benefit for mankind.

Time Series has been used to analyze data for a very long time and this analyses falls under two major categories- univariate and multivariate time series analyses (Xuehang et-al. 2017). Accurate long forecasting can be classed into four types namely: long-term (over one year ahead), medium term (between one month and a year), short term (a day to less than one month) and very short term (minutes to hours ahead) (Koprinska, Rana & Agelidis, 2015).

In the literature, several statistical based linear models have been proposed with the aim of using these linear models to forecast future demands needs (Nadia and Sri Vidya 2021; Mergami & Xu, 2017; Van-Nam, Warut &Van-haw, 2017).

Most recently researches on forecasting models have shifted to using computational intelligence models such as artificial Neural Network (ANN), Neuro-fuzzy and support vector machie. These works are seen in Vaish, Datta & Seethale kshmi, 2020; Khwaja,Anpalagan, Naeem & Venkatesh,2020; Ahmad, Ayub, Ali,Awais, Shiraz & Adam 2020; Tavassoli-Hojati, Ghaderi, Iranmanesh, Hilber, & Shayestch, 2020.

It has been argued that hybrid models which combine two or more prediction methods has raised forecasters of load demand confidence in recent times as they then to give better forecast accuracy results. Such models have been proposed by (Okolobah & Ismail, 2013; Okolobah, 2014; Okolobah, 2022) in the past. In this paper a hybrid model that combines Empirical Mode Decomposition (EMD) / Ensemble Empirical is proposed for electricity load forecasting for the Nigerian Electricity Supply Industry (NESI). The EMD/EEMD is a decomposition technique that decomposes a dataset into finite numbers of sub-series having different components.

The remaining part of this paper is organized as follows: Section 2 reviews some relevant literature such as empirical mode decomposition (EMD) and ensemble empirical mode decomposition (EEMD), Section 3 presents the methodology of the study and discussions in this section closes by presenting the framework of the proposed EMD/EEMD hybrid model, Section 4 presents results of the study using three performance evaluation techniques namely root mean square error (RMSE), Mean Average Percentage Error (MAPE) and Mean Absolute Error (MAE) to evaluate the performance of the proposed model. The final Section is dedicated to concluding the paper along with proffering some recommendations.

II. LITERATURE REVIEW

This Section reviews some of the literature that forms the core of this study such as empirical mode decomposition, ensemble empirical mode decomposition and artificial neural network.

2.1 Review works on Empirical Mode Decomposition

Having et al (2022) says an accurate day-ahead peak load forecasting is crucial not only for power dispatching but is also of immerse interest to investors and energy policy makers likewise government as 1% error drop of forecast can translate to a saving 10 million pounds of operational cost. With this in mind, the authors proposed a novel multivariate Empirical Mode Decomposition (MEMD) and Support Vector Regression (SVR). The model depended on two real life data for its development-the New South Wales and the Victoria in Australia. It was concluded that the proposed model is a promising alternative for day-ahead electricity peak load forecasting.

Liu, M, Ding, L and Bai, Y (2021) employed EMD combined with recurrent Neural Network (RNN) and Auto Regressive Integrated Moving Average (ARIMA) to develop a model for predicting wind speed for Nougolia, China. It was concluded that EMD method can improve the wind speed prediction performance when it is combined after decomposition and that the proposed method lowers the RMSEs when compared with existing models.

Bedi and Toshniwal, (2018) identified electricity of being of great significance for national economic, social and technological activities such as material production, healthcare and education the demand for electricity has grown over the past few decades and argues that with this, efficient electricity demand estimation and management is of great need for planning purposes. It is this need that motivated the development of a new model for load forecasting that combines EMD with long short-term memory network for electricity demand estimation for a season. To demonstrate the applicability of the proposed model, it is applied to the electricity consumption data for the city of Chandigarh. The performance of the proposed model is compared with RNN, LSTM and the results is highly promising.

2.2 Review works on Ensemble Empirical Mode Decomposition

Bokde, Feijoo, Villanueva & Kulat (2019) employed EMD/EEMD method for the prediction pf chaotic, intermittent and stochastic behavior of wind as it is observed that these characteristics poses a lot of challenges in predicting wind speed and wind power. The paper put forward a novel technique for handling intrinsic mode functions (IMFs) generated from EMD/EEMD methods.

Zhang & Hong (2019) combined the complete ensemble empirical decomposition adaptive noise (CEEMDAN) and Support vector regression to forecast for two separate utility concerns-Tokyo Electric Power Company (Japan) and the National Grid (UK). Data preprocessing was done using the complete ensemble empirical mode decomposition adaptive noise (CEEMDAN). The authors say this improves forecasting accuracy. The paper concludes that the propose model outperforms other models.

Lang, Rehman, Zhang, Xie & Su (2020) proposed a median ensemble empirical mode decomposition (MEEMD) aimed at reducing the additional mode splitting problem identified in the original EEMD algorithm. The task was achieved by replacing the mean operator by the median operator during the ensemble process. The result reveal that the proposed MEEMD greatly reduced the problem identified by 50%.

Luuko, Helske & Rasanen (2016) proposed a free software written in C for numerical efficiency that interfaces with Python and R languages. The software that is user friendly can be used to implement EMD, EEMD and CEEMDAN.

III. METHODOLOGY

This Section presents the methodology of the paper. The Section contains three sub-sections beginning with Empirical Mode Decomposition (EMD), then EEMD and ends with artificial neural network which is the method that will be hybrid with EMD/EEMD.

3.1 Empirical Mode Decomposition

i. Empirical Mode Decomposition is one of the breakthroughs in electricity load demand forecasting in the twenty first century as this technique has really helped to improve forecast accuracies of load models in the last two decades. EMD is used in non-linear and non-stationary time series (Huang et al. 1998).The EMD technique decomposes the time series into a number of intrinsic mode functions (IMFs) and a residue. In doing this, it first identifies all the local extrema in the time series and corresponding to each, it forms the upper and lower envelopes respectively using the cubic spline method. Next, the mean of the upper and lower envelopes is subtracted from the time series, which leads to the generation of a local IMF. These steps are repeated until these two conditions are met: The mean of the lower and upper envelopes tends to zero and

ii. The number of extrema and zero crossing differs at most by one.

The entire EMD extraction process is referred to as sifting process.

Five advantages of the EMD technique is outlined below:

a. EMD eliminates noise, randomness and fluctuations inherent in any dataset (Zhang, Qu, Mao, Ma,& Fan, 2017)
b. EMD gives rise to stationary series that are easily modelled (Sun, & Liu, 2016)
c. There are no mathematical/statistical computations involved in the EMD process as it is purely empirical hence easy to learn and understand (Zhang, Wei, Tan, Ke, & Tian, 2017)
d. EMD helps to helps to improve prediction accuracy as the sub-series, that is the IMFs which are the outcomes are stationary (Sun, & Liu, 2016)
e. EMD is a data driven as well as a self-adaptive technique (Hong, Ji, Zhang, Li, Wu, 2016)

3.2 Ensemble Empirical Mode Decomposition

Wu & Huang (2009) proposed the Ensemble Empirical Mode Decomposition (EEMD) technique. It is generally widely accepted as one of the greatest modification to the well-known and employed EMD technique. The EEMD was conceived solely to eradicate the problem of mode mixing that is common in the EMD method.

The EEMD is a repetitive technique and in each repetition, EMD is used to decompose the signal data along with a finite Gaussian white noise. For each repetition, Gaussian white noise of different amplitudes was introduced to the signal data. However, with each repetition, the IMF obtained is noisier but when the mean of the IMFs from the repetitions are obtained, it will be observed that the finite white noise eliminate each other and the final IMF obtained is very meaningful.

3.3 Artificial Neural Network (ANN)

ANN is one of the many forecasting tools that is introduced in the last two decades. It has been employed in solving a wide range of prediction tasks. The areas of its applicability is very wide. It is very efficient and highly reliable tool in the field of forecasting. ANN has the ability of capturing the autocorrelation structure of the time series even if the underlying law is unknown or too complex to describe (Aggarwal *et al.*, 2009). ANN are good candidates for quantitative forecasting which is concerned with extracting patterns from past events and extrapolating them into the future (Haykin, 1994). Some common NN models are: (i) multilayer feed-forward neural network (MFFNN), (ii) RBFNN and (iii) RNN.

This paper adopted the recurrent neural network (RNN) as it is reported in the literature that it is very good for sequential data like time series. RNN suffers from vanishing gradient problem during the backpropagation and for simple RNNs, their memories can only accommodate the last 10 time steps (Bengio et al., 1994).

IV. RESULTS AND MODEL EVALUATION

4.1 The study Area

The study area of this research is one of the historical towns in Nigeria called “Bida”. It is located in Latitude between 9 06’36’’North and Longitude 6 01’39’’East and is a Local Government Area (LGA) in Niger State, Nigeria; refer to Figure 1. The Local Government has an area of 51km^2 with a population of 188,181 by the 2006 census (Wikipedia). Supply of electricity to the area is by one of the unbundled discos in the recent deregulation of the country’s electricity power sub-sector known as the Abuja Electricity Distribution Company (AEDC). Though the population of the area is small power supply is grossly inadequate and is characterize by incessant and epileptic supply with times of no supply almost more than times when there is power supply.

Figure 1: Location of Bida

4.3 Data

The data used for this study was sourced from Abuja Electricity Distribution Company (AEDC) Bida office and it is a record of electricity consumption for the study area collected on hourly basis covering the period from 1st January, 2012 to 31st December, 2012. The data is presented as a timeplot in Figure 2.

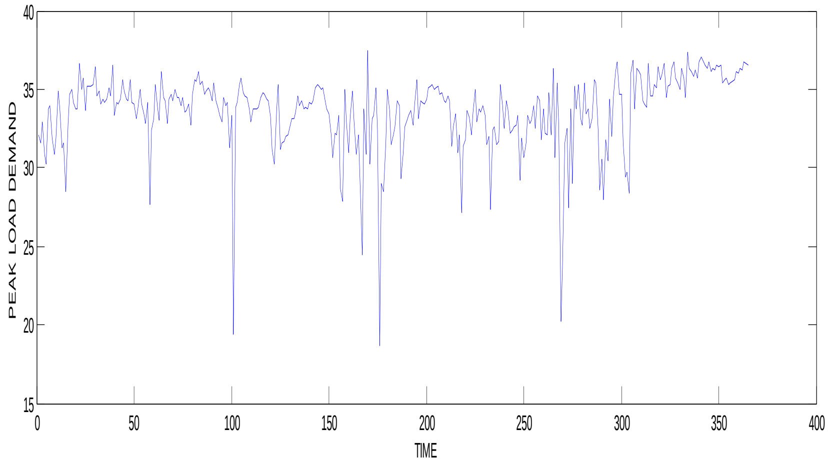

Figure 2: Time plot of the Electric Peak load demand for Bida

4.4 Forecast Accuracy Criteria

The evaluation of the proposed model and other models are compared using three parameters namely Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These parameters are presented in Table 4.1.

Table 4.1: Evaluation Parameters

MEASURES	EXPRESSION
MAPE	$\frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{y_i - f_i}{f_i}\right\rvert x100$
MAE	$\frac{1}{N}\sum_{i=1}^{N}\lvert y_i - f_i\rvert$
RMSE	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - f_i)^2}$

Where N is the total number of results forecasted; y_i is the actual load for the ith item and f_i is the forecast load for the ith item.

Table 4.2: Forecast Accuracies for models compared

	FORECAST ACCURACY EVALUATION					
	TRAINING DATA			TESTING DATA		
MODELS	MAE	RMSE	MAPE	MAE	RMSE	MAPE
ARIMA	23.0120	27.5110	8.0149	23.0311	27.5511	8.0011
EMD-ARIMA	20.1151	24.2156	8.0031	20.1355	24.3015	7.9521
EMD-ANN	14.2115	18.3914	5.1249	14.1368	18.6127	5.1136
EMD/EEMD-ANN	12.1671	14.0178	4.3635	12.1655	14.0168	4.3530

From the results posted in Table 4.2, it can be observed that all the models presented good forecast accuracy results which is an indication that Nigeria Electricity Supply Industry can adopt any of them for its forecast needs but the main principle behind forecasting is to find the model that post the best forecast accuracy. From the above results, judging by the MAPE, it can be seen that for training and testing data sets, the forecast accuracy for the EMD/EEMD-ANN yield 4.3635 and 4.3530. This is the best we therefore posit that the proposed EMD/EEMD-ANN is a very promising model for electricity load forecasting.

V. CONCLUSION AND RECOMMENDATION

The paper proposed a novel model for the Nigeria Electricity Supply Industry (NESI) by combining EMD/EEMD and ANN. The EMD is used to decompose the original load series into its various IMFs and residue. Bearing in mind the drawback of the EMD, which is the additional mode splitting, we therefore pass these IMFs and residue through the EEMD processing. After which the resultant IMFs and residue were used to develop individual prediction models that were aggregated together to obtain the desired EMD/EEMD-ANN model.

We therefore recommend that the EMD/EEMD could be combined with ANFIS for future studies as we believe this would yield a better forecast accuracy.

ACKNOWLEDGEMENT

The authors wish to thank the Tertiary Education Trust Fund (TETFUND) for the award of Institutional Based Research grant that facilitated this work. We are immensely grateful. We equally want to thank the management of the Federal Polytechnic, Bida, Niger State for allowing the use of her facilities and environment for this research work.

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