Comparison Between ARIMA and EEMD+ARIMA Models in Forecasting Electricity Consumption

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Abstract

Accurate forecasting of future electricity consumption is necessary to create a satisfactory design for an electricity distribution system. To enhance forecasting accuracy, autoregressive integrated moving average (ARIMA) was compared with hybrid of ensemble empirical mode decomposition (EEMD) plus autoregressive integrated moving average (ARIMA) denoted by (EEMD+ARIMA), to know which model is better performing a historical US monthly electricity consumption from DEC-2000 to SEP-2022 were used. The data were divided into training set (90%) and testing set (10%) to insure the model accuracy. The mean absolute square error, root mean square error, mean absolute error and mean absolute percentage error measurements were used to test the ARIMA and hybrid EEMD+ARIMA performance, the results show that the hybrid EEMD+ARIMA outperforms ARIMA model with the lowest RMSE, MAE, MPE, MAPE, MASE. For the best model, Akaike Information Criterion and Bayesian Information Criterion were applied to choose the best. The results show that the AIC and BIC of the EEMD+ARIMA were lower than the ARIMA model, which indicates that the EEMD+ARIMA is better than the single ARIMA in forecasting of electricity consumption. The conclusion reveals that the hybrid EEMD+ARIMA provides more accurate forecasting and performs significantly better than the ARIMA in forecasting of electricity.

Keywords: EEMD; SINGLE ARIMA; IMFS; HYBRID EEMD+ARIMA; FORECASTING.

1. Introduction

The electricity demand in the world is steadily increasing due to the increasing population, expanding economy, and climate considerations. The per capita consumption of electricity in the country is one of the largest in the world. Therefore, it is necessary to forecast the consumption of electricity to develop strategies and find solutions that will reduce the consumption of electricity and increase its production as well, to avoid any shortfall in the electric supply in the future. To forecast the electricity consumption data, a complexity problem will occur in the data, because of the non-linearity and non-stationarity of the data, the non-linearity and non-stationarity data structure create some problems such as a high autocorrelation between the lags in time series data, which makes the data more complex compared to data that has a simple autocorrelation, as well as the heteroscedasticity of electricity data, the data with high variations is more complex than the data with small variations. The aforementioned-mentioned problems make the data and the forecasting process more complex. Getting accurate forecasting of electricity consumption is became a very complicated mission, because of the consumption of a high amount of electricity and its causal relationship of the economy and environment, also resulting in the nonstationary and nonlinearity of electricity consumption time series nature, which cannot be predicted accurately by classical predicting methods. With the rise in electricity consumption, countries need to make electricity consumption as stable as possible, as consumption is commensurable to the country's production of electricity, and electricity consumption is correlated to accurate electricity consumption forecasting. Electricity consumption is affected by many concerns, an accurate forecasting models play an important role in optimizing power system management and future planning, the main purpose of forecasting is to help in planning and managing the electricity consumption and power load to achieve the balance between production and consumption of electricity to reduce operating costs and wasted wealth [1]. To create a reasonable and reliable power system, electricity

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companies and platforms are allowed to sell electricity to industrial or residential consumers to enable spatial segmentation of electricity markets and ensure reliable supply [2]. To compare the classical ARIMA and EEMD+ARIMA models, many scholars and experimenters analyzed and investigate different models, A model combining EMD/ARIMA or EEMD/ARIMA for long-term forecasting. [3] [4] used ARIMA and GA-SVR to predict the electricity consumption based on the decomposition techniques based on EEMD. A hybrid EEMD-ARIMA-GA-SVR is used to predict the economy energy consumption, the results show that the proposed framework is feasible, and it is demonstrating better precisions compared to results from other forecasting models. [5] developed a hybrid EMD-FBPROPHET-LSTM electricity consumption forecasting for the short-term, the results showed accurate forecasting compared with traditional methods. [6] proposed a new technique for analyzing nonlinear and non-stationary time series data, the result of which is the power-frequency time distribution, designated as the Hilbert spectrum. [7] add EMD process and filter analysis to improve the performance of the ARIMA model when the series are measurement data, the results approve that the integrating of EMD and filtering processes can help in reducing or removing noise from the original measurement, based on values of MAPE, MAE, and RMSE, the EF-ARIMA forecasts results are reliable and accurate than the forecasts using the classic ARIMA. [8] compared the EMD and EEMD methods in forecasting the price of red chili in Indonesia, the results indicate that the model with EEMD is more accurate than the model with EMD. [9] suggested that residual adjustment models are proposed to improve the accuracy of ARIMA for electricity demand prediction, the results indicate that the modified ARIMA is better than the single ARIMA and the combined one is more satisfactory than others. [10] proposed EMD-MKRVR for wind speed forecasting, the results indicate that the modified model can predict the wind speed more than the other models. [11] used the EEMD+ARIMA to forecast the weekly hotel occupancy of tourism destinations, and the results showed that the EEMD+ARIMA shows more accuracy in forecasting with lower standard deviations than the ARIMA model. [12] forecasted the Corona Virus in Pakistan using EEMD and ARIMA Model, the forecasting results show that the EEMD+ARIMA model is useful for the short-term forecasting of Corona Virus which helps in tracking Corona Virus data in all aspects. [13] used a hybrid EEMD+ARIMA to improve the accuracy of forecasting for daily hotels occupancy, the results indicate that the EEMD+ARIMA model works better than ARIMA in case of short-term predictions, this method can handle the data effectively by dividing the complex hotel's data into a set of different series, the results indicate that the EEMD+ARIMA is suitable and accurate for forecasting daily hotel data. [14] developed a two-stage hybrid framework based on multi-scale optimization, multi-factor, air pollutant forecasting and early warning. The results show that the developed framework can be used as an effective framework. [15] proposed a hybrid ARIMA and GA-SVR framework for prediction based on the EEMD method to predict energy consumption, the results show that the frame demonstrates better accuracy. The final results of all studies compared the traditional models against the hybrid model which shows more accurate in forecasting and outperform the other models.

2. Data and Methodology

The electric power consumption (Thousand ton) data is extracted from the U.S. Energy Information Administration (EIA) [16]. Historical monthly US electricity consumption datasets from DEC-2000 to SEP-2022 are used for the comparison between the performance and accuracy of the ARIMA and hybrid EEMD+ARIMA models. The data were divided into the training set (90%) and testing set (10%) using R software to insure the model accuracy. In electricity consumption series, random and unexpected changes usually happen. The electricity consumption fluctuation appears non-linear and non-stationary features due to its complexity and uncertainty. It is difficult to obtain accurate forecasting. In this paper, we compare a short-term forecasting method of classic ARIMA and hybrid EEMD+ARIMA model in electricity consumption series, to see the difference in the forecasting accuracy using each of them. The description of each model is illustrated below.

2.1 ARIMA

ARIMA is a time series analysis technique, which is an assembly of integrated (I), autoregressive (AR) and moving average (MA) terms, and it is commonly used to forecast future values based on historical data [17]. We define the ARIMA model with different parameters p, d, q where p is the number of autoregressive terms, d represents the number of differences, and q represents the number of moving average terms [18]. The autoregressive moving average (ARMA) model applies to a stationary time series [19]. And it can be expressed as in Equation (1):

$$Z_t = \mu + \Phi_1 Z_{t-1} + \Phi 2\, Z_{t-2} + \ldots + \Phi_p Z_{t-p} - \theta_0 - \theta_1 a_{t-1} - \ldots - \theta_q a_{t-q} \quad (1)$$

Where Z_t is the original time series data, μ is the mean value of sequences $\{Z_t\}$, Φ and θ are unknown parameters, and a_t is a white noise with zero mean and constant variance.

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Many of the simple time series models are special cases of ARIMA(p,d,q) Model such as:

(a) ARIMA(0,d,q) or sometimes called IMA(p,q), because the order of AR is zero.
(b) ARIMA(p,0,0) is called AR(p).
(c) ARIMA(0,0,q) is called MA(q).
(d) ARIMA(0,0,0) is called White noise.
(e) ARIMA(0,1,0) is called random walk, which is stationary after 1st difference.

The forecasting of electricity using the ARIMA model consists of the following steps. [20] [21]:

1. Plot the original electricity consumption data as time series to check the trend and seasonal existence or any unusual observations.
2. If necessary, choose the proper transformation such as differencing the time series data to make data stationary on the mean (detrend), and apply the log transformation on the data to stabilize the variance.
3. Apply the unit roots tests to confirm the stationarity. If it's stationary go to step 4, otherwise repeat step 2 till step 3 is achieved.
4. Compute and examine the ACF and PACF of the transformed series to choose the proper model and order. If the autocorrelation decays slowly and the partial autocorrelation cuts off after lags, this indicates for AR(P) model, if the autocorrelation cuts off after lags and the partial autocorrelation decays slowly, this indicates for MA(P) model, if the decays on both ACF and PACF, this indicates for ARIMA(p,d,q) model.
5. Estimate the parameters for the ARIMA model.
6. Choose the best ARIMA model using the (AIC and BIC) and forecast the time series data using the chosen model.
7. Check if the residuals are a white noise by plotting the ACF and PACF.
8. If the residuals look like white noise, calculate the forecasts. Figure 1 shows the diagram of the ARIMA model process.

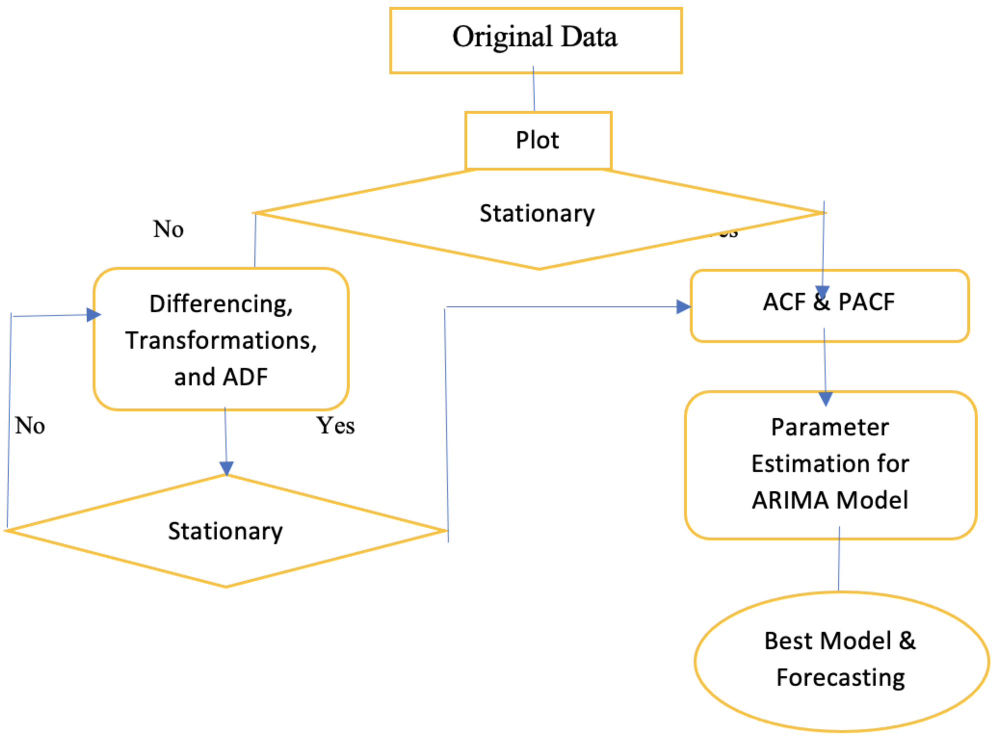

Figure 1: Forecasting using ARIMA model.

2.2 EEMD approach

EEMD technique proposed by [22], The EEMD process steps as follows:

(1) a new time series is generated in the nth trial to a given signal x(t). $Z_n(t) = Y(t) + a_n(t)$.

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(2) Decompose of original series $Z_n(t)$ into a set of IMFs and a residue term using the EEMD as follow: $Z_n(t) = \sum_{m=1}^{M-1} IMF_m^n(t) + r_m^n(t)$, where *M-1* the number of the *IMFs* obtained from each decomposition of $Z_n(t)$, $IMF_m^n(t)$ is the ^{m}th *IMF*, and $r_m^n(t)$ is the residue results in the ^{n}th trial.

(3) Repeat the steps (1) and (2) by adding a white noise $a_n(t)$ to the original series in each trial.

(4) The final IMF resulting from the EEMD (IMF_m^{avg}) is the results of averaging the total IMFs related to N trials and obtained by formula: $IMF_m^{avg}(t) = \frac{1}{N}\sum_{n=1}^{N} IMF_m^n(t)$. The results obtained by EEMD depend on the selection of the (N) ensemble number and the (A) added noise. Interrelation $\delta = \frac{A}{N}$ should be contented [22]. Where δ is the standard error calculated as the difference between the original series and the ensemble IMFs.

2.3 Hybrid EEMD+ARIMA Model

To improve the forecasting accuracy, the original data were decomposed into different components called IMFs using EEMD to obtain sub-sequences stationary series, then forecast each IMF component separately using the ARIMA model. Finally, the sum of the forecasted sub-sequences of IMFs is taken as the final forecast [23]. Figure 2 shows the chart of the EEMD+ARIMA model, the implementation steps are described below:

1. Decompose the original data into a sequence of IMFs and residuals using EEMD.
2. Fit the ARIMA model for every subseries data including the residuals.
3. EEMD+ARIMA is obtained by the sum of the final forecasted from ARIMA models.

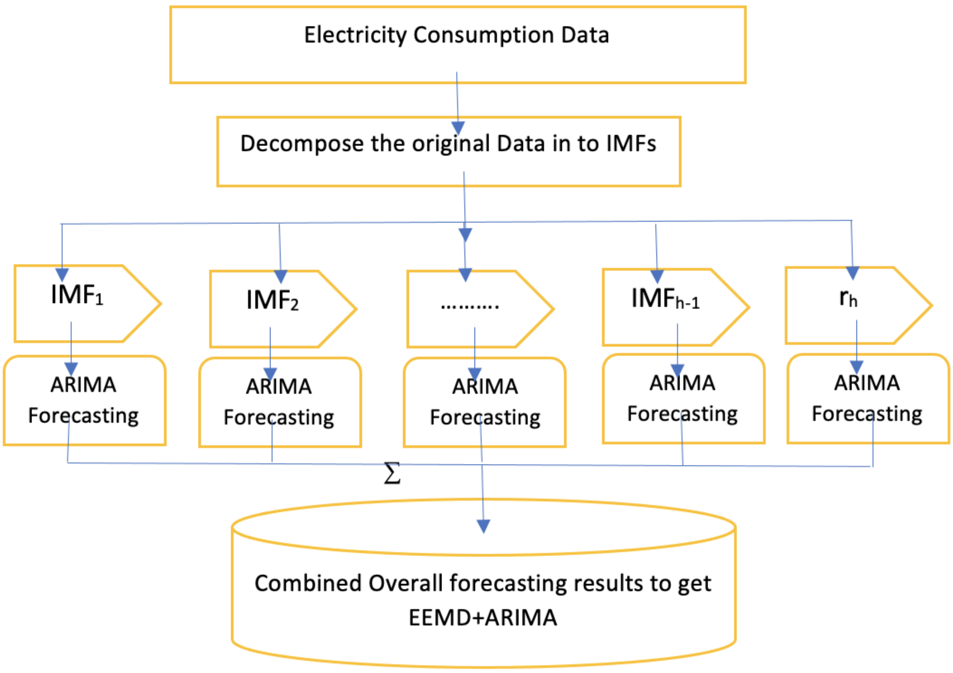

Figure 2: Forecasting using hybrid EEMD+ARIMA model.

3. Mathematical equations, subsections, tables, and figures

3.1 ARIMA Model

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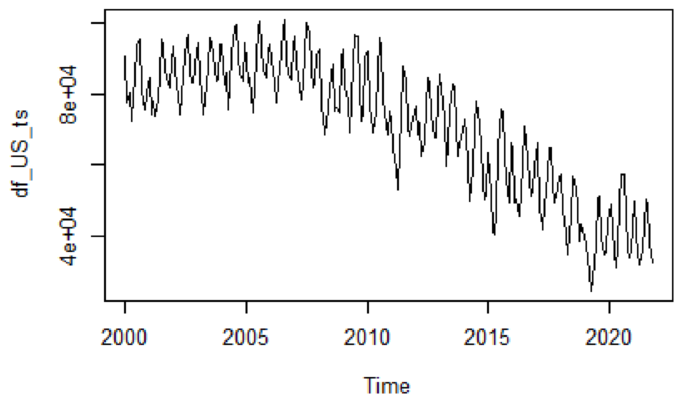

Figure 3: plot of the original electricity consumption data.

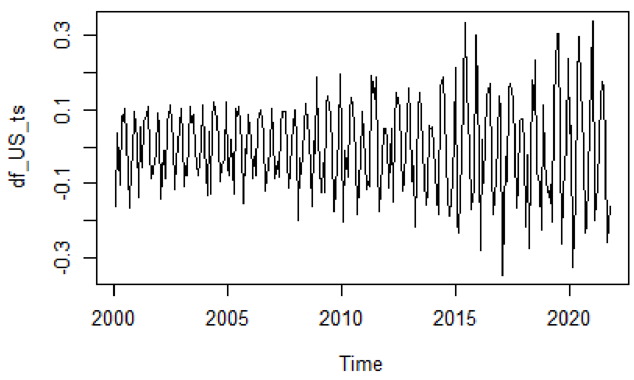

Figure 4: A time series plot of transformed and differenced electricity consumption data.

From Figure 3 and Figure 4 above, it is clear that the electricity consumption series has no-stationarity and non-linearity patterns, because there are a trend and variance fluctuation pattern on the data, which means non-stationarity in the mean and variance, the time plot shows surprising changes, notably the drop-down in the years 2010/2022. This drop is starting from the global economic crisis. furthermore, there is an evidence of variance change, then we will apply a Box-Cox transformation (log-transformation), and for the trend we differenced the time series one time to make sure that the time series is stationary to use the ARIMA model. The time series became stationary after the 1^{nd} difference and log transformation have been applied as shown in Figure 4. The data shows that some heating demand drives energy consumption to its highest levels in different months of the year, with a secondary peak in other months, and the lowest levels in some months of the year, which indicating of seasonality existence.

Table 1: Augmented Dickey-Fuller (ADF) test of differenced data

Augmented Dickey-Fuller Test for differenced data.		
ADF - test value	Lag order	p-value
-7.130	6	0.01

alternative hypothesis: stationary

Table (1): presents the Augmented Dickey-Fuller (ADF) test, it shows that the time series is stationary after the first difference because the p-value =0.01 < 0.05, which implies that the null hypothesis of the unit root is rejected, and the conclusion the series is stationary after the first difference.

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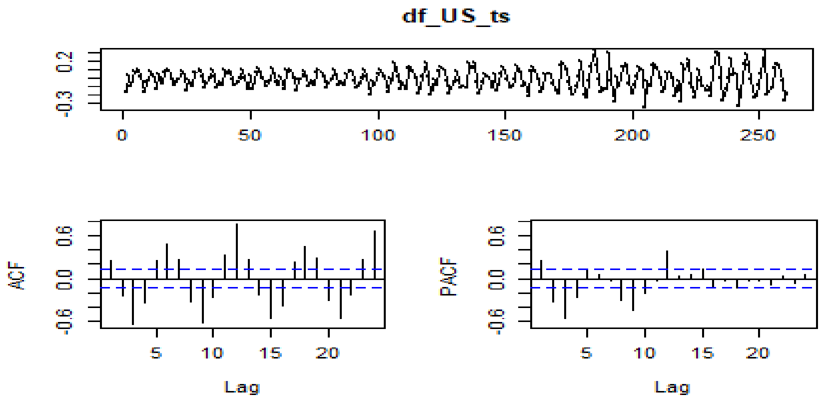

Figure 5: ACF and PACF of the transformed and differenced series.

Figure 5. present the ACF and PACF at lag 20, the decays in both ACF and PACF an indication of the ARIMA process and order of ARIMA (p, p, q) is ARIMA (5,0,0), where p,d,q equals to 5,0,0 respectively.

Table 2: ARIMA model measures accuracy

	RMSE	*MAE*	*MAPE*	*MASE*	*AIC*	*BIC*
ARIMA (5,0,0)	0.086	0.064	1.487	0.561	-469.21	-448.46

Table (2): presents the metrics for the best ARIMA Model was chosen by the lower metrics measurements and lower AIC and BIC and insignificant residuals.

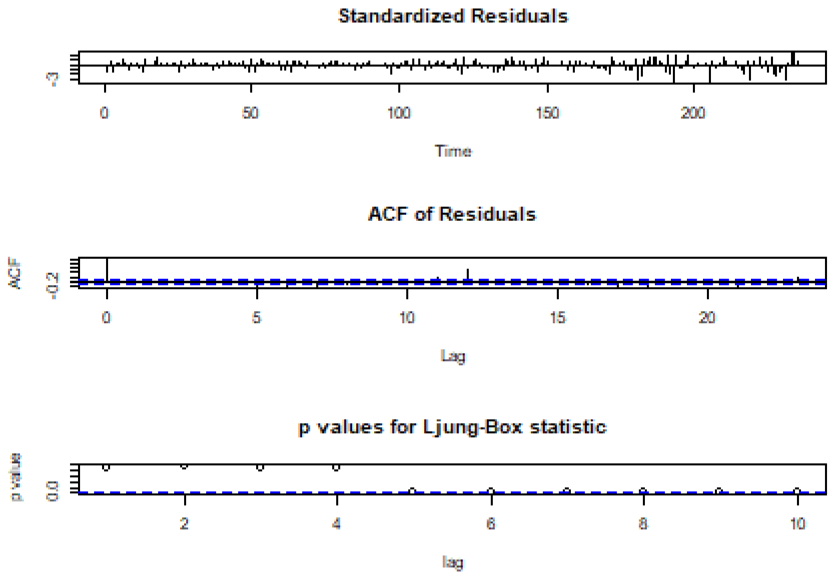

Figure 6: Test of model Adequacy.

Figure 6. the Ljung-Box tests is applied to the residuals obtained from the ARIMA (5,0,0) and the residuals of the model have the following null hypothesis:
H_0: $\rho_1(a)=\rho_2(a)= \cdots =\rho_k(a)=0$ or the residuals are uncorrected.
H_1: $\rho_1(a)\neq\rho_2(a) \neq\cdots \neq\rho_k(a) \neq 0$ or at least one non-zero autocorrelations at specific lags.
The test indicates that there is no autocorrelation at any lag, which means that the null hypothesis of no autocorrelation is rejected because the p-value is high at any lag point. The conclusion is the residuals are white noise. Which indicates the selected ARIMA model is Adequate.

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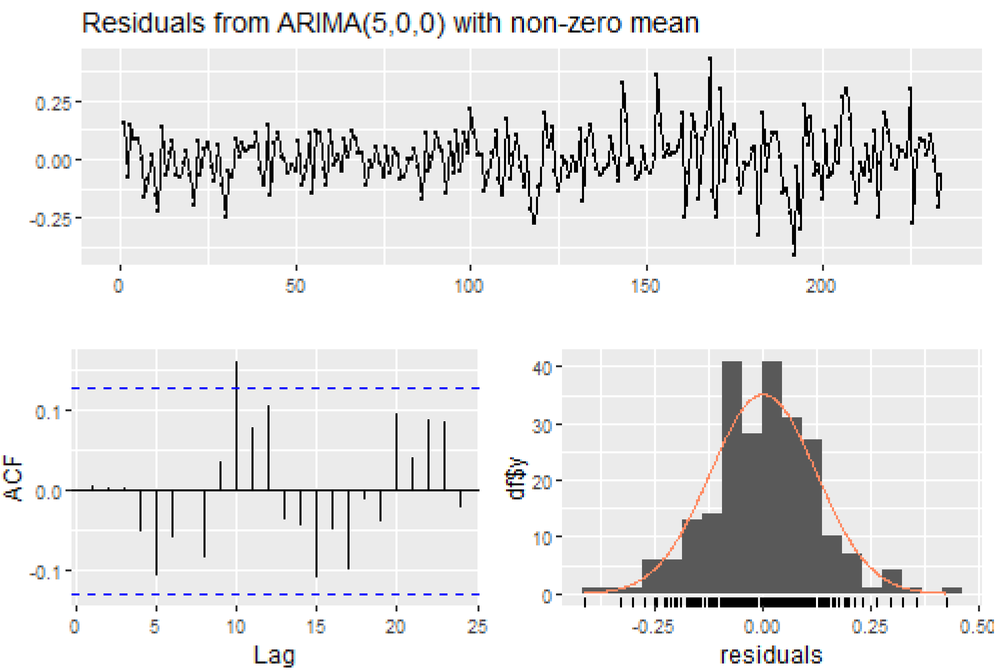

Figure 7: Residual plots for the ARIMA (5,0,0) model.

From Figure 6 and Figure 7, the plot of the ACF for the ARIMA (5,0,0) residuals, which indicates that all sample autocorrelations spikes are insignificant, implies that the residuals are white noise. The plot in Figure 6 returns a large p-value, which means that the residuals are white noise and identically normally distributed with constant variance and zero mean. Thus, we now have a ARIMA model that passes the required checks and is ready for forecasting. Figures. 8 and 9 below, represent the forecasting on training and test sets of the US electricity consumption data.

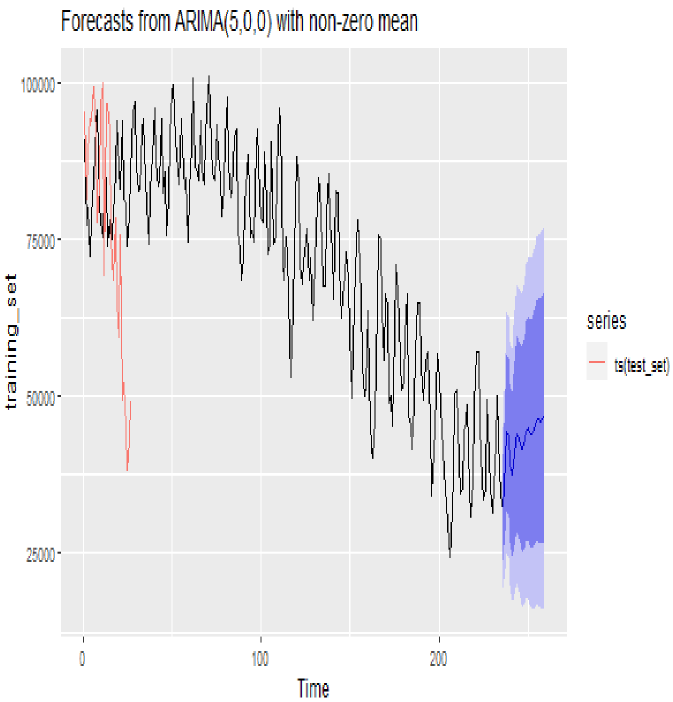

Figure 8: Forecasts from an ARIMA model fitted to U.S Electricity Consumption training data.

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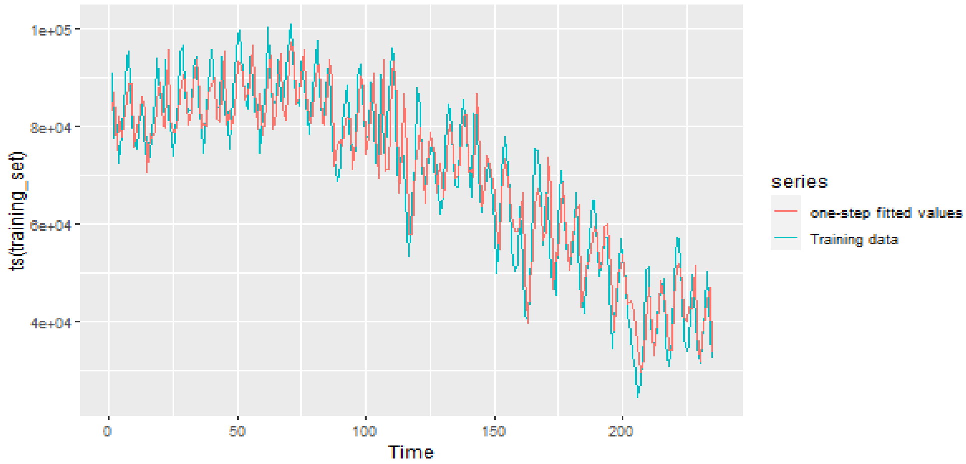

Figure 9: One-step fitted values from an ARIMA model fitted to the US Electricity Consumption training data.

3.2 EEMD+ARIMA

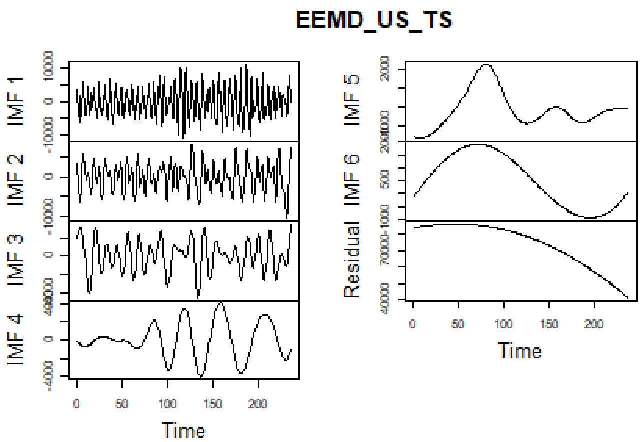

Figure 10: decomposition of time series into IMFs using EEMD technique.

Figure 10. the monthly electricity consumption time series data was decomposed into 7 subseries, statistically independent IMFs, and a residue using the EEMD. The intrinsic mode functions (IMFs) components are named IMF1, IMF2, IMF3, IMF4, IMF5, IMF6, and Residual. Next, the ARIMA model will be used to forecast the components respectively. The forecasting results of EEMD+ARIMA are obtained by summing the forecasting results of each component.

Table 3: ADF test for IMFs obtained from EEMD

Series	ADF - test value	Lag	p-value	Decision
IMF1	-6.321	6	0.01	The null hypothesis is rejected
IMF2	- 9.071	6	0.01	The null hypothesis is rejected
IMF3	- 4.6994	6	0.01	the null hypothesis is rejected
IMF4	-3.363	6	0.05	The null hypothesis is rejected
IMF5	-3.613	6	0.03	The null hypothesis is rejected
IMF6	-1.333	6	0.85	The null hypothesis can’t be rejected

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Residual	0.058	6	0.99	The null hypothesis can't be rejected

alternative hypothesis: the series stationary

Table (3): presents the Augmented Dickey-Fuller (ADF) test for IMFs obtained by EEMD decomposition, the test shows that the IMF1, IMF2, IMF3, IMF4 and IMF5 time series are stationary because the p-value =0.01 < 0.05 which implies that the null hypothesis of the unit root is rejected, while the IMF6 and residual time series are non-stationary because the p-value =0.85 and 0.99 respectively are greater than 0.05 which implies that the unit root hypothesis can't be rejected, the overall conclusion, the IMF1, IMF2, IMF3, IMF4 and IMF5 are stationary, but the IMF6 and residual are non-stationary. Now we will to apply the differencing to make IMF6 and residuals series stationary.

Table 4: ARIMA Model for each IMF obtained from EEMD

IMF	**ARIMA (p, p, q)**	***RMSE***	***MAE***	***MAPE***	***MASE***	***AIC***	***BIC***
IMF1	ARIMA (3,0,2)	0.069	0.052	115.01	0.540	-575.09	-554.33
IMF2	ARIMA (5,0,5)	0.011	0.008	43.607	0.196	-1386.57	-1348.51
IMF3	ARIMA (1,0,0)	0.013	0.010	130.178	0.977	-1345.83	-1338.91
IMF4	ARIMA (0,0,0)	0.010	0.007	151.208	4.773	-1483.62	-1476.7
IMF5	ARIMA (0,0,0)	0.010	0.006	170.001	8.897	- 1452.65	- 1445.73
IMF6	ARIMA (0,2,0)	0.007	0.005	2.060	0.050	-4822.58	-4819.13
Residual	ARIMA (0,2,0)	0.002	0.001	0.095	0.016	- 5400.8	- 5397.35

From the table (4) above, and based on the Akaike information criterion (AIC) and Bayesian Information Criterion (BIC), the best chosen ARIMA models for decomposed series as follows:

- For IMF1, ARIMA (3,0,2) model was chosen.
- For IMF2, ARIMA (5,0,5) model was chosen.
- For IMF3, ARIMA (1,0,0) model was chosen.
- For IMF4, ARIMA (0,0,0) model was chosen.
- For IMF5, ARIMA (0,0,0) model was chosen.
- For IMF6, ARIMA (0,2,0) model was chosen.
- For the residue part, ARIMA (0,2,0) model was chosen.

To measure the performance of our models and make the comparison, we used four metrics to evaluate the errors of the forecasting results, which are calculated as follows.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n-1}} \approx \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \quad (2)$$

$$MAE = \frac{\sum_{t=1}^{n}|(A_t - F_t|}{n} \quad (3)$$

$$MAPE = \frac{\sum_{t=1}^{n}|(A_t - F_t|}{F_t} \quad (4)$$

$$MASE = \frac{1}{n}\sum_{t=1}^{N}\frac{|A_t - F_t|}{\frac{\sum_{t=1}^{n}|(A_t - F_{t-1})|}{n-1}} \quad (5)$$

where A_t is the actual values and F_t is the forecasted values, Forecast error $(F_e) = A_t - F_t$

RMSE is the Root Mean Square Error: measure of how spread out of the residuals.

MAE is the Mean Absolute Error: measure the average magnitude of the errors in a set of predictions, without considering their direction.

MAPE is the Mean Absolute Percentage Error: measure the accuracy as a percentage, which is the average absolute percent error for each time period minus actual values divided by actual values.

MASE is the Mean Absolute Scaled Error: measure for determining the effectiveness of forecasts generated through an algorithm by comparing the predictions with the output of a naïve forecasting approach.

Moreover, we used the AIC and BIC to choose the best ARIMA model, the AIC is calculated by: AIC = -2(LL) + 2K, Where K is the number of variables plus the intercept). LL is the Log-likelihood for measuring the model fit. The model with the lower AIC is the best model [24]. BIC is calculated by BIC = (RSS + log(n) d $\hat{\sigma}^2$) / n. Where

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RSS is the residual sum of squares, d is the number of explanatory variables, $\hat{\sigma}^2$ estimated sample variance of the error, and the model with the lower BIC is the best model [25].

Table 5: Comparison between ARIMA and EEMD+ARIMA

Model\Measure	*RMSE*	*MAE*	*MAPE*	*MASE*	*AIC*	*BIC*
ARIMA	0.086	0.064	1.487	0.561	-469.21	-448.46
EEMD+ARIMA	0.069	0.053	1.264	0.469	-488.15	-462.44

Table (5). show that the EEMD+ARIMA outperform ARIMA model with the lower RMSE, MAE, MPE, MAPE, MASE. The Akaike information criterion (AIC) of the EEMD+ARIMA model is around -488.15 which is less than -469.21 for classic ARIMA model, Bayesian Information Criterion (BIC) of the EEMD+ARIMA model is -462.44 which is less than -448.46 for classic ARIMA model.

4. Conclusion

Forecasting of electricity consumption series remains one of the most difficult areas due to the non-stationary and non-linearity of electricity time series data. In this study, we have presented a comparison between the classic ARIMA and hybrid EEMD+ARIMA approaches. ARIMA and hybrid EEMD+ARIMA were tested on US monthly electricity consumption time series data from DEC-2000 to SEP-2022 based on the comparison of four forecast accuracy measurements named, root mean square error (RMSE), mean absolute error (MAE), mean absolute square error (MASE) and mean percentage absolute error (MAPE). The results indicate that the EEMD+ARIMA outperforms the single ARIMA model with the smallest RMSE, MAE, MPE, MAPE, and MASE. The AIC and BIC were used to choose the best model, the results show that the AIC and BIC of the EMD-ARIMA model are lower than the classic ARIMA model, which indicates that the EEMD+ARIMA is better than the classical ARIMA model. The results showed good accuracy in the ARIMA model, but the hybrid technique with ARIMA is better than the single ARIMA model. ARIMA model is more appropriate for forecasting the future from past values in case of short-term forecasting than the long-term forecasting. the advantage of using hybrid EEMD+ARIMA model is that it has the capability to handle the dominant criteria of the data with heteroskedasticity, no-stationarity and linearity characteristics, since the models are suitable for large number of observations, the models minimize the errors in forecasting by accounting for errors in prior forecasting and enhancing the accuracy of ongoing forecasting, which is good advantages. The overall results show that the EEMD+ARIMA is outperform the classical ARIMA model. Thus, this paper has strengthened the idea that the EEMD+ARIMA forecasting method is suitable for non-stationary and nonlinear time series, and the it is appropriate to forecast the electricity consumption series.

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