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Reverse Effect Of Wavelets On Es And Arima Models Using Usa Electricity Demand Time Series Data

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Abstract: For effective energy management and resource planning, accurate electricity demand forecasts are essential. Time series forecasting methods like Exponential Smoothing (ES) and ARIMA models have grown popular recently because of their capacity to identify complex seasonal trends in data. This study aims to compare the performance of different wavelet families in conjunction with ES and ARIMA models for electricity demand forecasting and we are able to observe the reverse effect of wavelet. The results are compared to assess the accuracy and effectiveness of different wavelets in improving the forecasting performance of ES and ARIMA models. The findings of this study contribute to a better understanding of the applicability of wavelet-based approaches for electricity demand forecasting. However, it's important to note that the choice between ARIMA and Exponential Smoothing ultimately depends on the specific characteristics of the time series data and the forecasting objectives. For complex and noisy data, ARIMA with wavelets emerges as a robust and effective forecasting method, demonstrating superior performance in our analysis.

Index Terms **- Time series analysis, exponential smoothing, ARIMA, wavelet analysis, KPI.**

I. INTRODUCTION

The nation's electricity demand is driven primarily by its population size, economic activities, technological advancements, and changing consumer preferences [18]. The electricity demand in the United States has been shaped by a multitude of factors, resulting in a complex and ever-evolving landscape [19]. With a steadily growing population and continuous economic expansion, the United States experiences an increasing need for electricity to meet the rising demands of households, businesses, and industries [20]. Energy efficiency initiatives have been a key focus area for the United States in recent years [18]. It is important to note that the electricity demand landscape is continually evolving, subject to fluctuations based on technological advancements, government policies, market dynamics, and unexpected events [18].

Accurate electricity demand forecasts help utility companies and power grid operators plan their resources effectively. By knowing the expected demand in advance, they can ensure sufficient power generation, transmission, and distribution capacity to meet the needs of consumers without any shortages or overloads [13]. Forecasting demand allows power providers to optimize their energy mix and schedule generation accordingly, reducing costs and minimizing environmental impact. Sudden spikes or drops in demand can lead to disturbances, blackouts, or grid failures [50]. Forecasts help in planning and implementing load balancing strategies to ensure a consistent and stable power supply. Electricity demand forecasts are vital for policymakers and researchers to understand energy consumption patterns, identify trends, and assess the impact of climate change on electricity usage [12]. This information can influence the formulation of energy policies and environmental regulations.

In order to accurately predict future values, time series analysis and forecasting employ a variety of modeling techniques to examine the historical relationship between the variables. The widely used statistical models in time series analysis, namely the Box-Jenkins based ARIMA (Autoregressive Integrated Moving Average) and ES (Exponential Smoothing) models, cover a wide range of patterns, including stationary, non-stationary, and seasonal (periodic) time series [30,32,52]. That being said, in non-linear situations—that is, when the data is not a linear function of time-the Box-Jenkins approach falls short [2,4,24,30]. Wavelet analysis is a great way to find high-frequency components in time series data for effective forecasting of non-linear data [9,10,14,28,31,33,39]. Using a discrete wavelet, time series of various sizes are split up into separate component series that can be managed separately for forecasting [25,35,37,40,45,47,49,53]. Wavelets provide much more prediction flexibility and refinement than previous methods could [11,16,23,54,62].

In order to forecast the demand for electricity in the United States, the current study focuses on developing hybrid models that account for the dynamic nature of the provided time series data. When managing these types of time series, hybrid modeling can be an effective technique [29,53,63]. The USA electricity demand dataset was used for this, and "demand" was chosen as a variable from among all other provided variables, including coal, gas, hydro, clean, bio-energy, CO_2 intensity, fossil and solar [Data Source: https://ember-climate.org/data-catalogue/monthly-electricity-data/].

II. METHODOLOGY

In this paper, we have used Sigma XL and MATLAB software for our research purpose. We took monthly time series data of USA electricity demand from https://ember-climate.org/data-catalogue/monthly-electricity-data/ over the period of 01-January-2001 to 01-March-2023 which includes 267 observations in total. The dataset is divided into training and testing phase [26]. In the former phase, we made predictive models for each of the decomposed component of the original time series. Following steps are used in the proposed technique (figure 1):

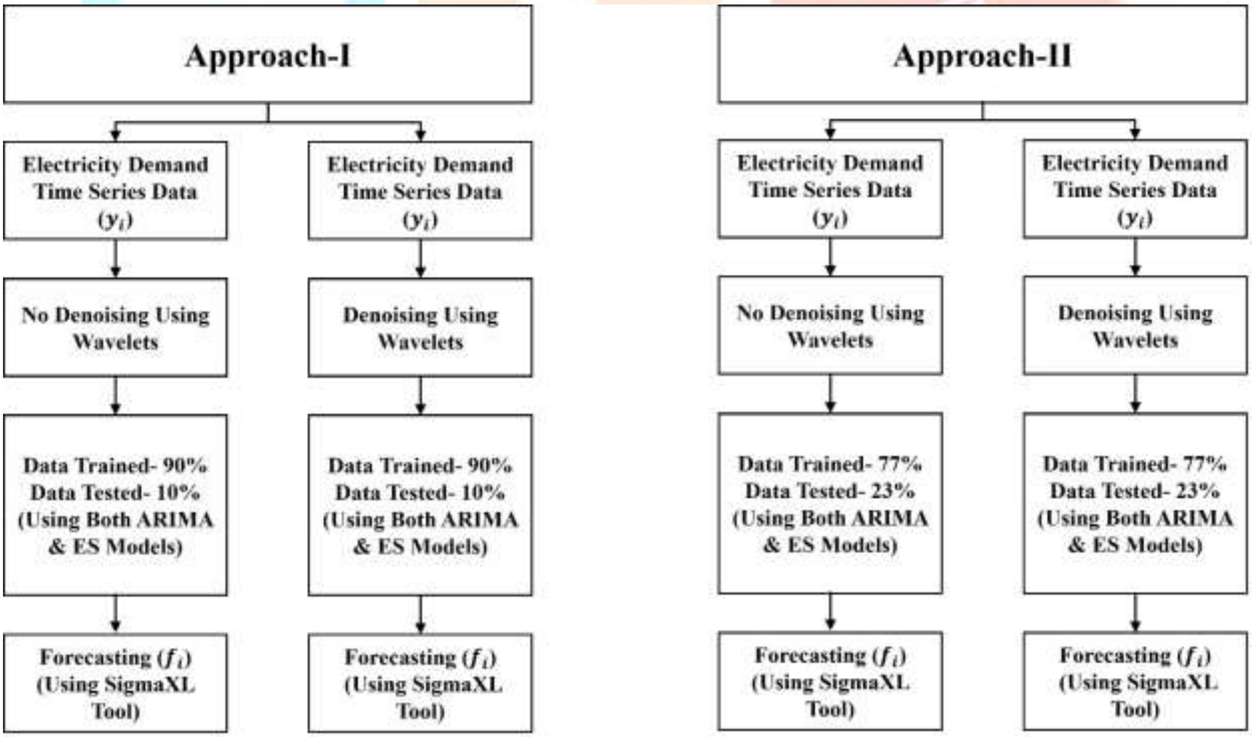


Figure 1: Proposed Technique

Here, two approaches are involved- **First**, out of total 267 readings, 243 are used for training purpose and remaining 24 are used for testing purpose (*which forms 90% & 10% training and testing phase*). **Second,** out of total 267 readings, 207 are used for training purpose and remaining 60 observations are used for testing purpose (*which forms 77% & 23% training and testing phase*). The idea behind these two approaches is to check the variations in the models if any.

2.1 *Wavelet Analysis*

Wavelets are compact support localized functions with zero mean that can analyze transient and non-periodic signals [8,36,41,42].

A function $\Psi(x) \epsilon\, L^2(R)$ is called wavelet if it satisfies the following properties:

$$1)\quad \int_{-\infty}^{\infty} \Psi(x)dx = 0 \qquad \ldots (1)$$

$$2)\quad C_\Psi = \int_{-\infty}^{\infty} \frac{|\widehat{\Psi}(\omega)|^2}{|\omega|} < \infty \qquad \ldots (2)$$

where $\widehat{\Psi}(\omega)$ denotes Fourier transform of $\Psi(\omega)$. Basically, wavelets are a family of functions constructed by dilations and translations of a single function $\Psi(x) \epsilon\, L^2(R)$ known as 'Mother wavelet' (where the scaling function is called 'Father wavelet'). The family of wavelets $\Psi_{a,b}(x)$ are defined as:

$$\Psi_{a,b}(x) = |a|^{-1/2}\, \Psi\left(\frac{x-b}{a}\right) ;\, a, b\, \epsilon R,\ a \neq 0 \qquad \ldots (3)$$

where 'a' is a scaling parameter and 'b' is translation parameter.

For discrete wavelet decomposition of time series $\{f(t): t = 1, 2, 3, \ldots\}$, the mother wavelet function $\Psi_{j,k}$ and the father wavelet function $\varphi_{J,K}$ are defined respectively

$$\Psi_{j,k}(x) = 2^{-j/2}\, \Psi(2^{-j}x - k) \qquad \ldots (4)$$

$$\varphi_{J,k}(x) = 2^{-J/2}\, \Psi(2^{-J}x - k) \qquad \ldots (5)$$

The approximation coefficients $\alpha_{J,K}$ are obtained by convoluting the scaling coefficients $\varphi_{J,K}$ with $f(t)$ and convolution with $f(t)$ of the wavelet function $\Psi_{j,k}$ gives the detailed coefficients which are given as below

$$\alpha_{J,k} = \int_{-\infty}^{\infty} f(t)\varphi_{J,k}dt \qquad \ldots (6)$$

$$\beta_{j,k} = \int_{-\infty}^{\infty} f(t)\Psi_{j,k}dt \qquad \ldots (7)$$

Using above integrals, decomposed series applicable to continuous time series $f(t)$ is given by

$$f(t) = \sum_{k\in Z} \alpha_{J,k}\, \varphi_{J,k}(t) + \sum_{j=1}^{J} \sum_{k\in Z} \beta_{j,k}\, \Psi_{j,k}(t) \qquad \ldots (8)$$

Since the time series data under study is discrete and is of finite length, so the discretized time series $y(t)$ of length $K=2^j$ is given by

$$f(t) = \sum_{k=-\infty}^{2^{J-k}-1} \alpha_{J,k}\, \varphi_{J,k}(t) + \sum_{j=1}^{J} \sum_{k=-\infty}^{2^{J-k}-1} \beta_{j,k}\, \Psi_{j,k}(t) \qquad \ldots (9)$$

The decomposition of $f(t)$ into approximation and detail components is also classified in Figure 2 [48].

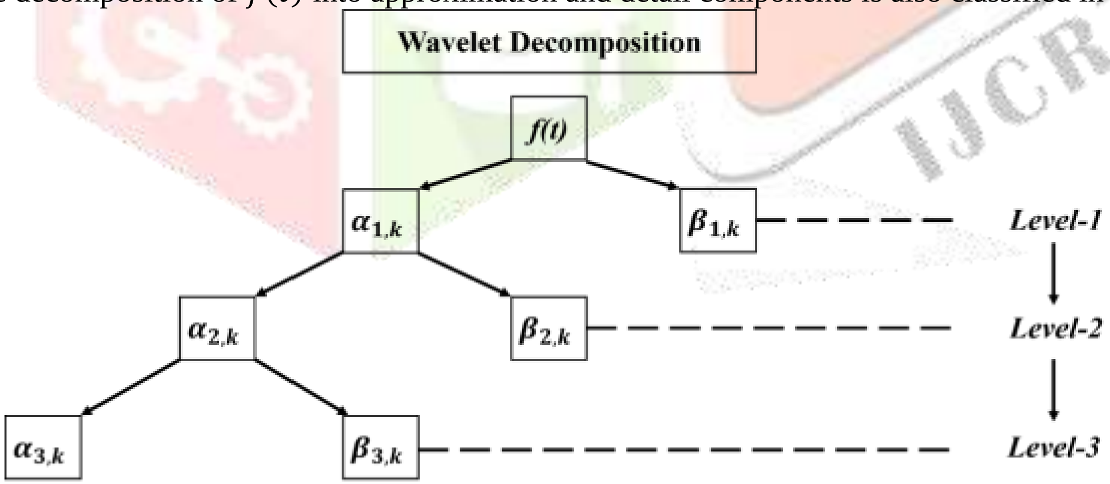


Figure 2

2.2 *Forecasting Time Series Models*

2.2.1 ARIMA Model

The ARIMA model is the best econometric model available; it outperforms the ARMA, MA, and AR models (Autoregressive moving averages, moving averages, and autoregressive respectively). The ARIMA model takes its cues from the 1960 Box-Jenkins Model, which predicts future time series values based on past data. Parameter estimation, model diagnostic checking, and model identification are the three primary phases of the ARIMA modeling approach. Model identification is the step that comes before parameter estimation, when the time series for stationarity and seasonality are modeled. Time series stationarity can be evaluated using an autocorrelation function (ACF) plot. Application of a differencing transformation can yield stationary data in the event that the time series is non-stationary. The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots can be generated using seasonal differencing to model seasonality. Finding the values of the parameters p and q is another benefit of these plots [5,7]. By using maximum likelihood, a widely used evaluation technique, one can estimate the parameters of the suitably chosen model. The model's overall adequacy is lastly confirmed using the Ljung and Box test to make sure that no additional time series modeling is required [38].

An ARIMA (p, d, q) model using lag polynomial L is expressed

$$\left(1 - \sum_{i=1}^{p} \varphi_i L^i\right)(1 - L)^d = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right)\varepsilon_j \qquad \dots (10)$$

where the non-negative integers p and q are the orders of autoregressive and moving average polynomials respectively; d is the non-seasonal differencing required to make data stationary; $f(t)$ is the value of observations and ε t is a random error at time t; φ_i and θ_j are the coefficients.

2.2.2 Exponential Smoothing Model

The simple exponential smoothing (SES) was initially introduced by Muth, who demonstrated that SES offers optimal forecasts for a random walk, with added noise [22]. Afterwards, Pagels divided trends and seasonal patterns into two categories: multiplicative/nonlinear and additive/linear [56]. In general, exponential smoothing techniques are thought of as a collection of techniques for forecasting certain kinds of univariate time series data [56]. Box and Jenkins, Roberts, Abraham, and Ledolter demonstrated that some linear exponential smoothing techniques can be thought of as special cases of ARIMA models, which advanced the development of a statistical framework for exponential smoothing [44,61]. This approach to time series forecasting is basically used when the data show neither a trend nor a seasonal pattern [57,56]. The equation of simple exponential smoothing is given by:

$$S_t = \alpha X_t + (1 - \alpha)S_{t-1} = S_{t-1} + \alpha(X_t - S_{t-1}) \qquad \dots (11)$$

Additionally, the double (Holt's trend corrected method) exponential smoothing model is used when the data exhibits a linear trend and no seasonal pattern [57,27,56]. Adding a term to account for the possibility that a series will exhibit a trend is the main idea behind double exponential smoothing [57,27,56]. The equations are given by:

$S_1 = X_1$, $b_1 = X_1 - X_0$, $For\ t > 1,$

$$S_t = X_t + (1 - \alpha)(S_{t-1} + b_{t-1}) \qquad \dots (12)$$

$$\beta_t = \beta(S_t - S_{t-1}) + (1 - \beta)b_{t-1} \qquad \dots (13)$$

Here, S_t = smoothed statistic (simple weighted average of current observation X_t), S_{t-1}= previous smoothed statistic, α = smoothing factor of data; $0 < \alpha < 1$, t = time period, b_t = best estimate of trend at time t and β = trend smoothing factor; $0 < \beta < 1$ [57,27,56].

The triple (Holt-Winter's exponential) exponential smoothing model is used when the data exhibits both a linear trend and a seasonal pattern [44,21,61,57]. This approach has been employed by us for our research purpose. The equations are given by

$$S_0 = X_0 \qquad \dots (14)$$

$$S_t = \alpha \frac{X_t}{C_{t-1}} + (1 - \alpha)(S_{t-1} + b_{t-1}) \qquad \dots (15)$$

$$b_t = \beta(S_t - S_{t-1}) + (1 - \beta)b_{t-1} \qquad \dots (16)$$

$$c_t = \gamma \frac{X_t}{S_t} + (1 - \gamma)\, c_{t-1} \qquad \dots (17)$$

where, c_t = sequence of seasonal correction factor at time t and γ = seasonal change smoothing factor; $0 < \gamma < 1$ [21,61,57].

2.2.3 *Hybrid Time Series Prediction Model*

Since wavelet decomposition techniques have varying propensities to handle linear and non-linear data features, the coupled models put forth in this work comprise ARIMA and ES models' forecasting on time series data that has been refined by wavelet decomposition techniques. Through the modeling of both linear and non-linear data components, these coupled models can enhance forecasting performance [43]. Time-series data $f(t)$ is first decomposed into approximations (A_j) and detail (D_j) coefficients (Section 5.1) in the wavelet decomposition method. These coefficients can be used as independent series for forecasting, and each of these series is then modeled and forecasted using a suitable ARIMA & ES model. The predicted approximations $(\widehat{A_j})$ and detail $(\widehat{D_j})$ coefficients so obtained are summed to obtain forecasted data $\widehat{f(t)}$, expressed as

$$\widehat{f(t)} = \widehat{A_j} + \widehat{D_j}\ ; j = 1, 2, 3, \ldots \qquad \ldots (18)$$

III. RESULTS AND DISCUSSION

3.1 *Time Series Analysis*

Many time series methods begin with a stationarity check of the data. Autocorrelation function (ACF) and partial autocorrelation function (PACF) plots can be used to assess non-stationarity in time series data, which is indicated by rapid changes. The time series is determined to be non-stationary by a slow decaying ACF plot, which is eliminated by differencing transformation to produce stationary data [7]. After checking stationarity, the next step is to determine the order of the ARIMA model parameter, which can be determined by the ACF plot of differenced time series. Then, an appropriate ARIMA model is fitted to data that generates future values of time series data. So, in both the approaches when wavelets were not used, ARIMA (1,1,1) (Figure 4,Figure 5,Figure 6 and Figure 7) is best fit for our dataset type.

Similarly, our data has both linear trend and seasonal pattern, so we used Holt-Winter's exponential smoothing model with parameter estimates α-level smoothing and γ-seasonal smoothing (Table 1) in both the approaches and models are bases on Akaike information criterion (AIC)

Table 1: Showing the values of parameter estimates in Exponential Smoothing Model (Holt-Winter)

ES-Approach-I	*α- Level Smoothing*	*γ- Seasonal Smoothing*	*ES-Approach-II*	*α- Level Smoothing*	*γ- Seasonal Smoothing*
Without Wavelet	0.362	0.0001	*Without Wavelet*	0.362	0.0001
With Wavelet	0.9999	0.0001	*With Wavelet*	0.9999	0.0001

3.2 *Wavelet Decomposition*

The mother wavelet, its level, and the decomposition order are critical factors to consider when applying wavelet decomposition to time series. Although there are many families of wavelets for decomposition, one of the significant wavelet types with unique benefits is the Coiflet wavelet. The Coiflet wavelet is used to break down time series data on electricity demand in the United States. The approximations consist of details that represent high-frequency components and low-frequency parts that show a trend. To obtain predicted components, an appropriate ARIMA and ES model are separately modeled for the approximation A_3 and details D_1, D_2, and D_3. The predicted outputs $\widehat{A_3}$, $\widehat{D_1}$, $\widehat{D_2}$ $\widehat{D_3}$are finally summed to obtain the forecasts of demand given in Eq.

$$\widehat{f(t)} = \widehat{A_3} + \widehat{D_1} + \widehat{D_2} + \widehat{D_3} \qquad \ldots (12)$$

where capped (^) symbol is used to denote predicted values.

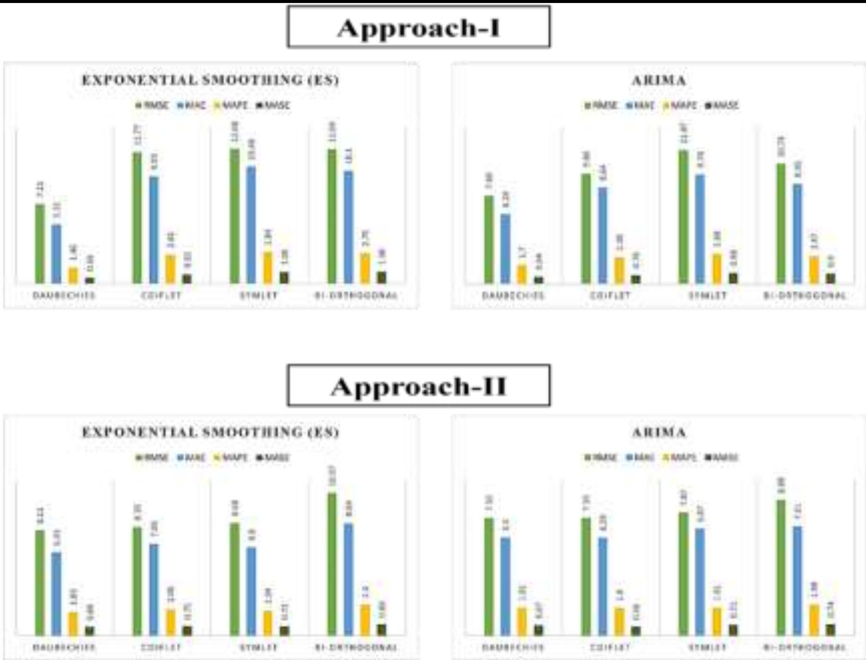


Figure 3: Selection of Best Wavelet for Our Database

So, here we tested approximately all the types of above wavelet available in the MATLAB tool box to denoise the signal then came to the result with full statistical analysis based on Akaike information criterion (AIC) that Coiflet wavelet is best for our research purpose (Figure 3).

3.3 *Hybrid Time Series Model*

Initially, various wavelet functions, such as Daubechies, Symlet, Coiflet, and Biorthogonal are applied to decompose the USA electricity demand dataset into different frequency components. The decomposed series are then reconstructed using selected wavelet coefficients to obtain denoised data. Subsequently, both ES and ARIMA models are applied to the original and denoised time series for forecasting purposes. The Coiflet wavelet comes out to be the best fit for this kind of dataset for both the approaches.

Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ES) are models used for generating values independently or, in conjunction, with Wavelet decomposition [1,3,15,44]. In these models the data is first broken down into series using the Coiflet wavelet. Then both ARIMA and ES models are applied to each constituent series to create a forecast. Finally, the predicted values of the constituent series are added together to obtain the output of the model. In approach-I and approach-II, ARIMA (2,1,1) (See Figure 9) and ARIMA (2,1,5) (See Figure 10) are comes out to be the best models for the denoised dataset and are selected on the bases of Akaike information criterion (AIC) with the significance limit alpha = 0.05. The predictive performance hybrid models and ARIMA & ES models are compared finally to find the best model among them with least forecasting errors.

For the Model evaluation we have used four standard error measures named as Key Performing Indicators (KPIs) and these are defined as:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - f_i)^2}{n}}$$

$$MAE = \frac{\sum_{i=1}^{n} |y_i - f_i|}{n}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - f_i|}{y_i}$$

$$MASE = \frac{MAE}{\frac{1}{n-1} \sum_{i=2}^{n} |y_i - y_{i-1}|}$$

Where y_i's are the actual values, f_i's are the forecasted values and *n* is the total number of observations.

3.3.1 Results and Discussion – Without Wavelet

Table 2: ES on Original Time Series Data without using wavelet with Approach-I

KPIs	*Training Phase (Values)*	*Testing Phase (Values)*
RMSE	8.58	13.62
MAE	6.82	11.22
MAPE	1.99	3.04
MASE	0.67	1.11

Table 3: ARIMA on Original Time Series Data without using wavelet with Approach-I

KPIs	*Training Phase (Values)*	*Testing Phase (Values)*
RMSE	9.26	13.93
MAE	7.42	11.54
MAPE	2.17	3.14
MASE	0.73	1.14

Table 4: ES on Original Time Series Data without using wavelet in Approach-II

KPIs	*Training Phase (Values)*	*Testing Phase (Values)*
RMSE	8.50	10.06
MAE	6.75	8.07
MAPE	1.98	2.40
MASE	0.66	0.860

Table 5: ARIMA on Original Time Series Data without using wavelet in Approach-II

KPIs	*Training Phase (Values)*	*Testing Phase (Values)*
RMSE	9.43	10.14
MAE	7.58	8.35
MAPE	2.22	2.38
MASE	0.74	0.85

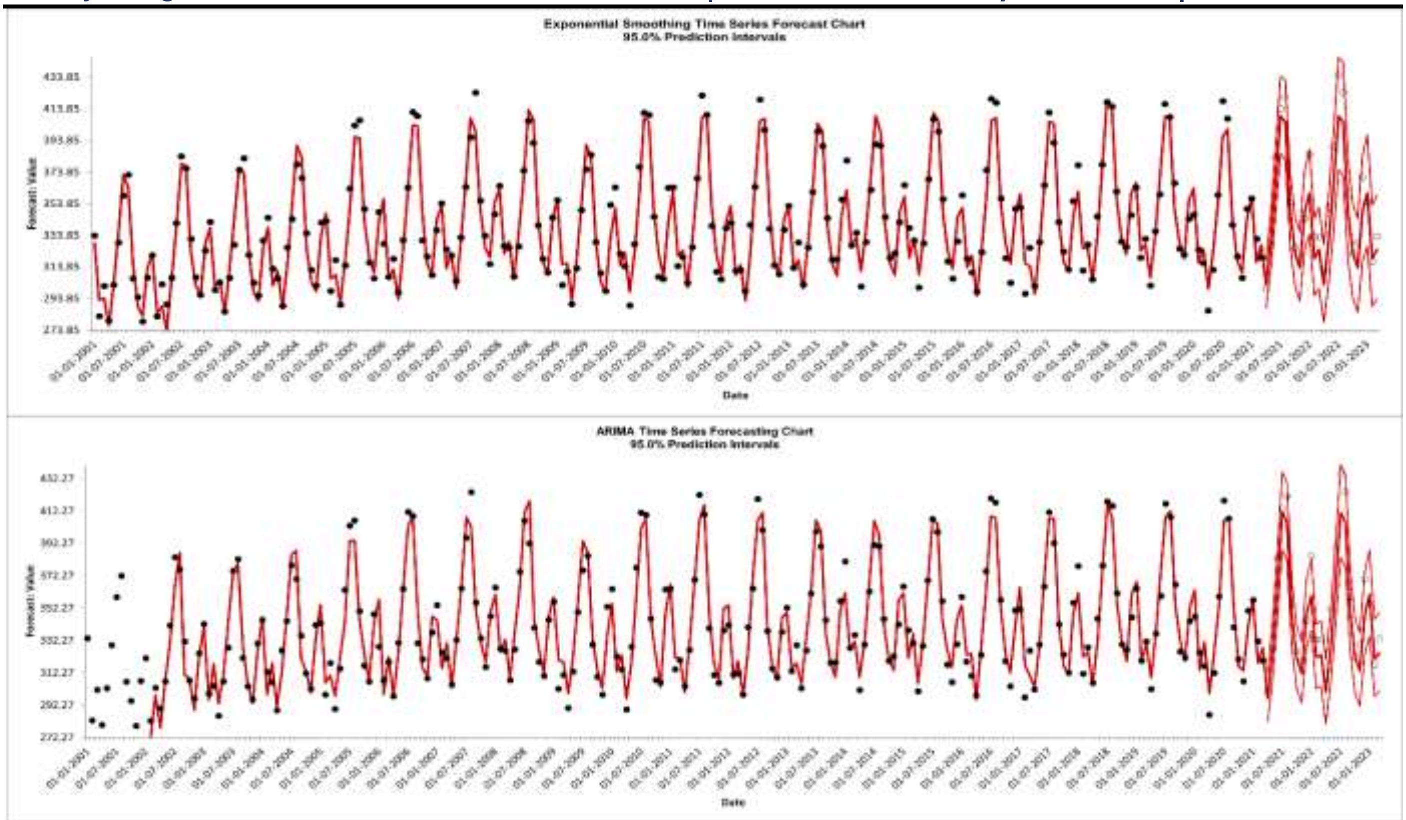
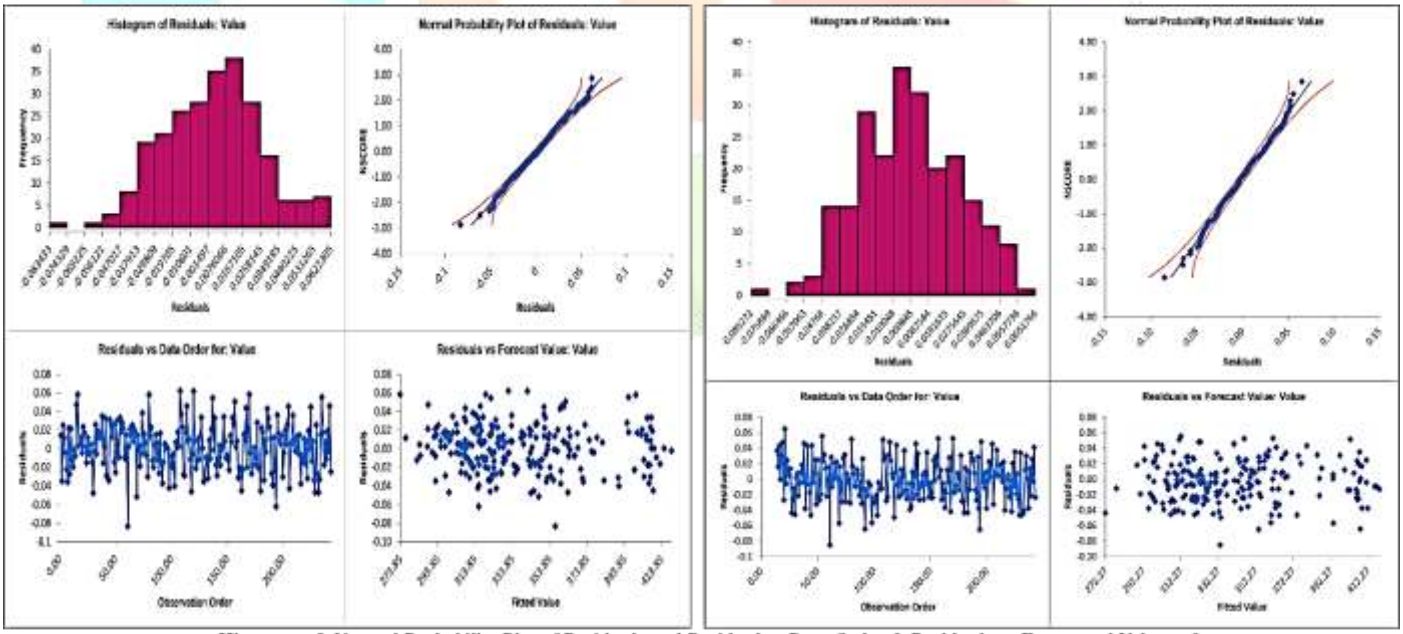


Figure 4: Performance of ES (Holt-Winter Method) and ARIMA (1,1,1) without wavelet in Approach-I



Histogram & Normal Probability Plot of Residuals and Residual vs Data Order & Residuals vs Forecasted Values of ES Model (Left) and ARIMA Model (Right)- Approach-I

Figure 5

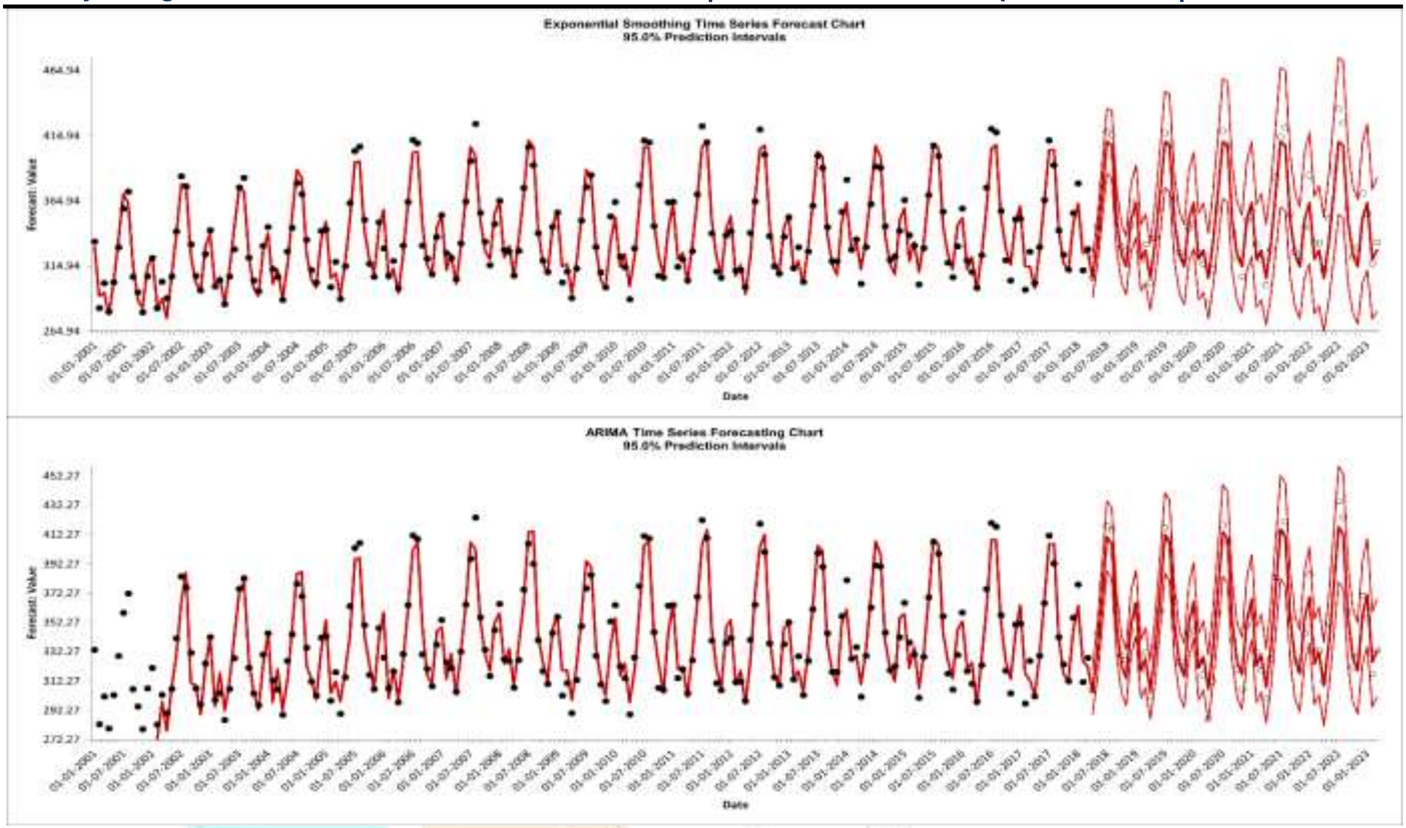
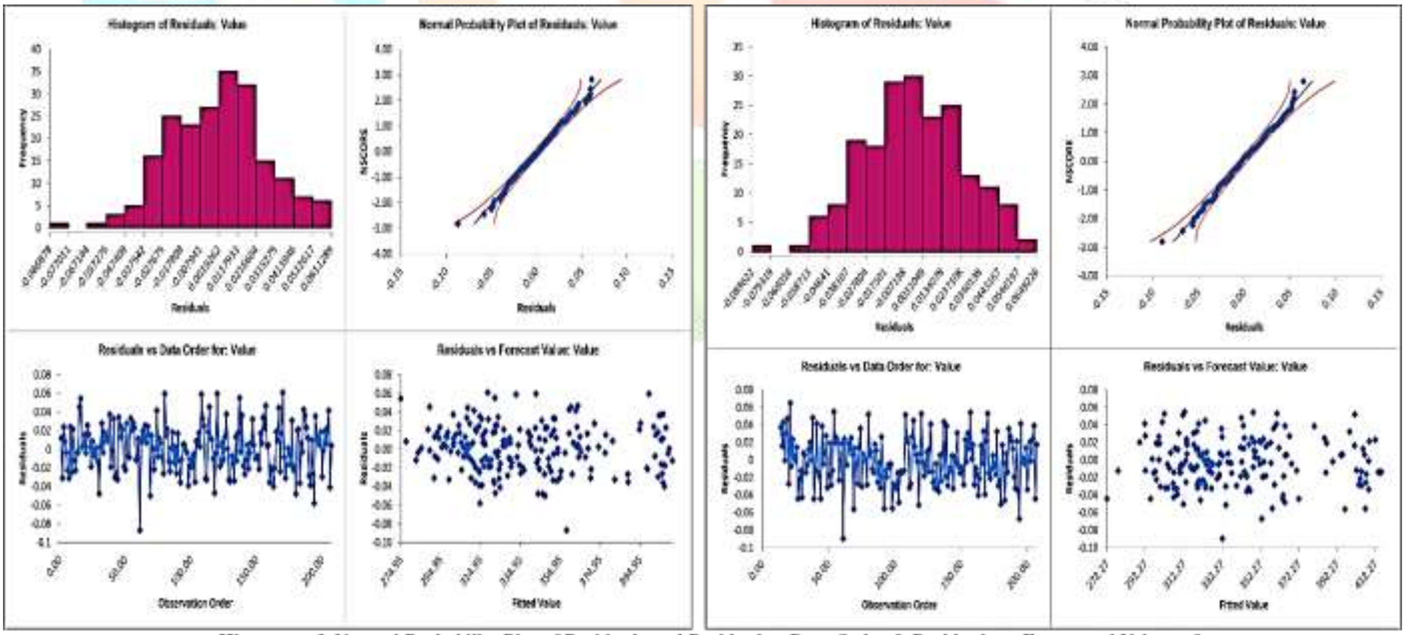
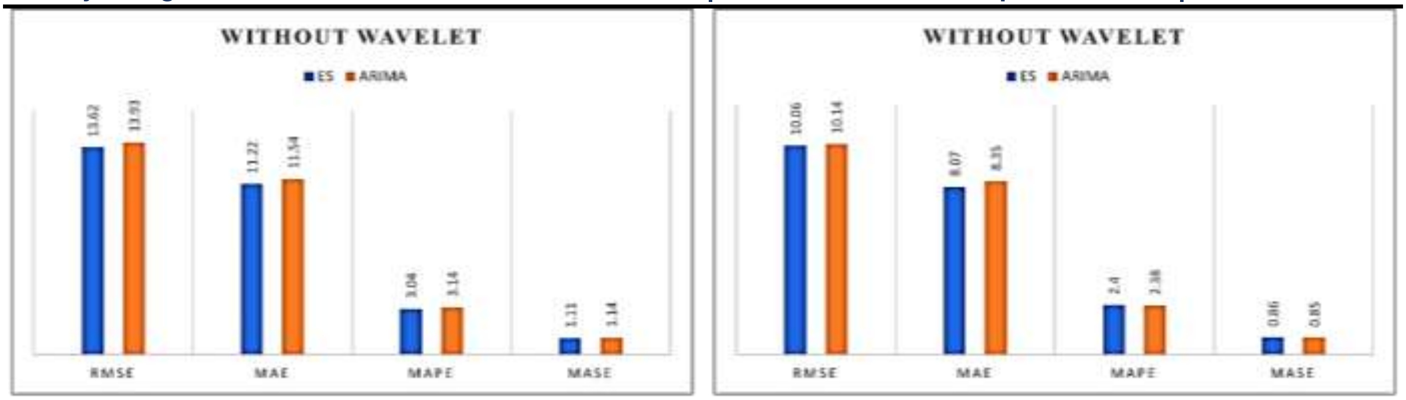


Figure 6: Performance of ES (Holt-Winter Method) and ARIMA (1,1,1) without wavelet in Approach-II



Histogram & Normal Probability Plot of Residuals and Residual vs Data Order & Residuals vs Forecasted Values of ES Model (Left) and ARIMA Model (Right) – Approach-II

Figure 7



Comparison of ES and ARIMA Model without using Wavelet in Approach-I (Left) and Approach-II (Right)

Figure 8

The tables (Table 2, Table 3, Table 4, and Table 5) above, as well as Figure 8, make it abundantly evident that the Exponential Smoothing (ES) model outperforms the ARIMA model in nearly every KPI measure. However, in this case, the data is not denoised using wavelet. Let's now examine the results by applying the wavelet to the original time series data.

3.3.2 Result and Discussion – With Wavelet

Table 6: ES on Denoised Time Series Data using wavelet with Approach-I

KPIs	*Training Phase (Values)*	*Testing Phase (Values)*
RMSE	3.25	11.77
MAE	2.50	9.59
MAPE	0.73	2.61
MASE	0.28	0.82

Table 7: ARIMA on Denoised Time Series Data using wavelet with Approach-I

KPIs	*Training Phase (Values)*	*Testing Phase (Values)*
RMSE	2.74	9.86
MAE	1.96	8.64
MAPE	0.57	2.38
MASE	0.22	0.78

Table 8: ES on Denoised Time Series Data using wavelet with Approach-II

KPIs	*Training Phase (Values)*	*Testing Phase (Values)*
RMSE	3.37	8.35
MAE	2.58	7.06
MAPE	0.76	2.05
MASE	0.29	0.75

Table 9: ARIMA on Denoised Time Series Data using wavelet with Approach-II

KPIs	*Training Phase (Values)*	*Testing Phase (Values)*
RMSE	2.96	7.55
MAE	2.16	6.28
MAPE	0.64	1.80
MASE	0.23	0.58

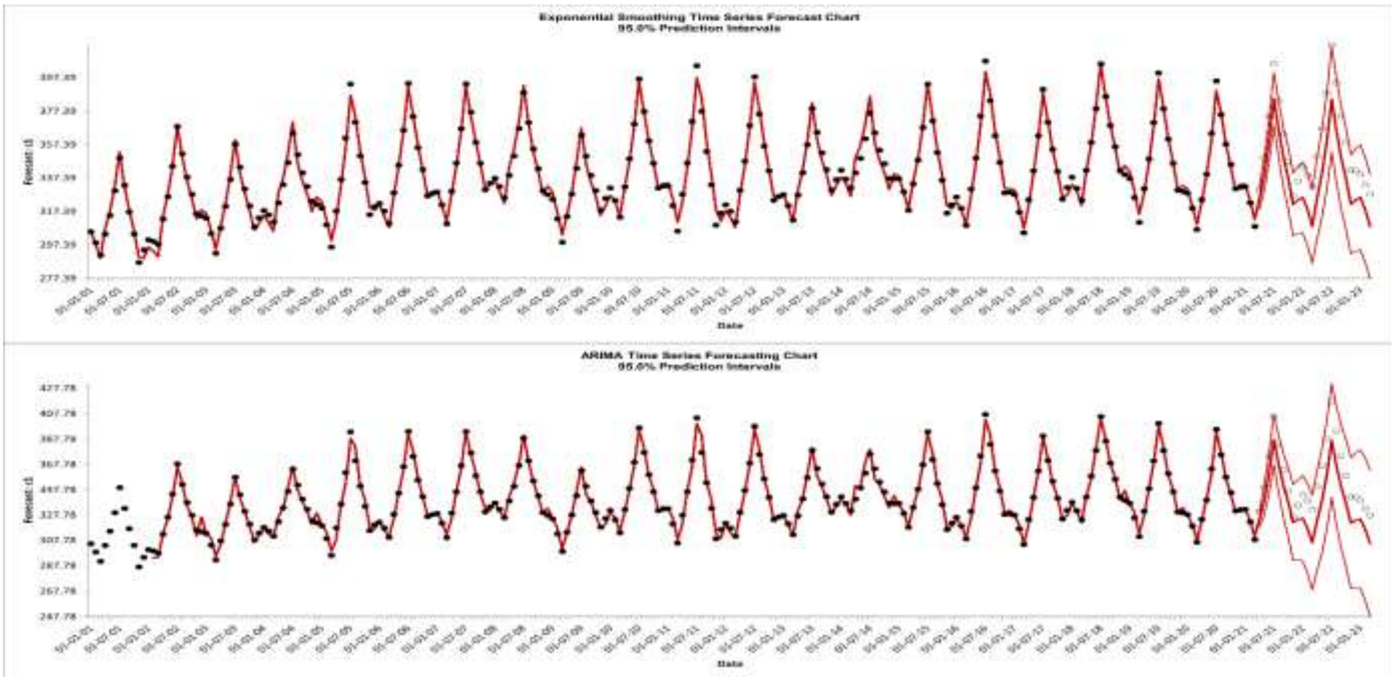


Figure 9: Performance of ES (Holt-Winter Method) and ARIMA (2,1,1) without wavelet in Approach-I

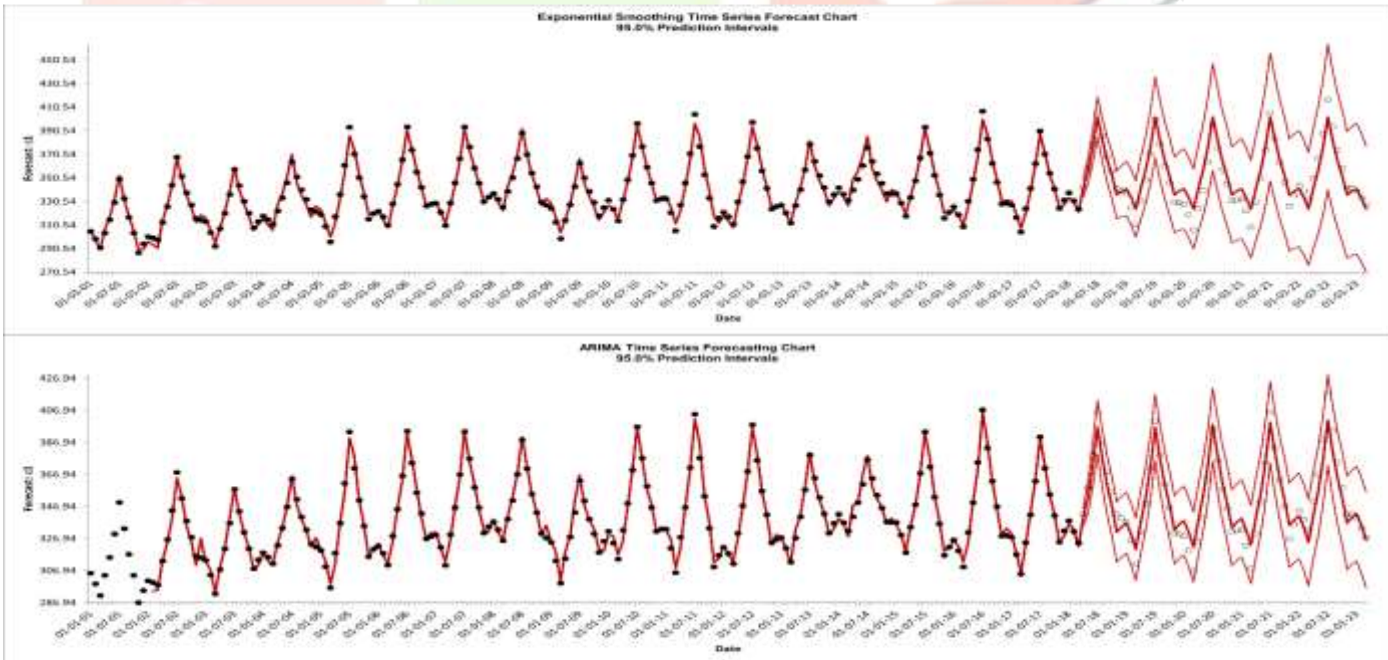
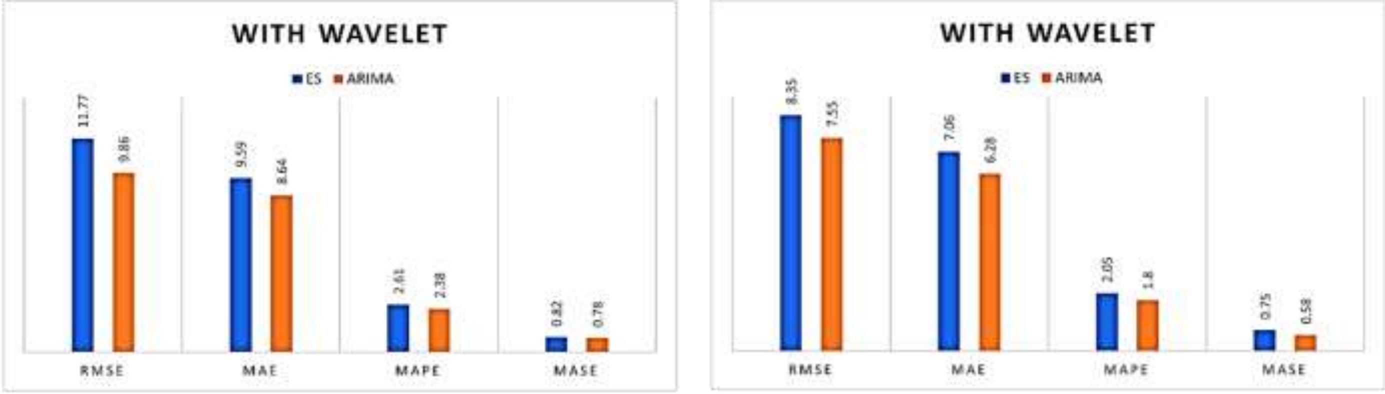


Figure 10: Performance of ES (Holt-Winter Method) and ARIMA (2,1,5) without wavelet in Approach-II



Comparison of ES and ARIMA Model using Wavelet in Approach-I (Left) and Approach-II (Right)

Figure 11

The tables (Table 6, Table 7, Table 8, and Table 9) above, as well as Figure 11, ARIMA model outperforms the ES model in every KPI measure.

3.4 Reverse Effect of Wavelet Over ES and ARIMA Models

Here, we see that in testing phase ARIMA performing better than ES model when wavelets are applied. This is what we called as reverse effect of wavelet over ES and ARIMA model because if we refer to fig. 8, it is clearcut that ES is better than ARIMA but if we refer to figure 11, ARIMA is showing better results than ES which is the scenario of wavelets.

IV. ACKNOWLEDGEMENT

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V. CONCLUSION

Using time series data, we observed the ‘reverse effect’ of wavelet over the Exponential Smoothing (ES) and ARIMA model as when we perform these two models without using wavelets, ES is performing better than the ARIMA model but when the same data is denoised using wavelet, ARIMA comes out to perform better by giving less errors than the ES model. In practical applications where accurate time series forecasting is essential, particularly in domains such as finance, economics, and demand forecasting, our analysis suggests that ARIMA with wavelets may be the preferred choice. The combination of ARIMA's modeling capabilities and wavelet preprocessing enables it to deliver more accurate and reliable forecasts compared to Exponential Smoothing under similar conditions.

VI. DATA AVAILABILITY

The monthly USA electricity demand time series data that is used in this study is available for download from the site of Ember Climate with the given link https://ember-climate.org/data-catalogue/monthly-electricity-data/

VII. CONFLICT OF INTEREST

The author declares that there is no conflict of interest.

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