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Empowering Sustainability: A Consumer-Centric Analysis Based on Advanced Electricity Consumption Predictions

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Abstract: This study addresses the critical challenge of accurately forecasting electricity consumption by utilizing Exponential Smoothing and Seasonal Autoregressive Integrated Moving Average (SARIMA) models. The research aims to enhance the precision of forecasting in the dynamic energy landscape and reveals promising outcomes by employing a robust methodology involving model application to a large amount of consumption data. Exponential Smoothing demonstrates accurate predictions, as evidenced by a low Sum of Squared Errors (SSE) of 0.469. SARIMA, with its seasonal ARIMA structure, outperforms Exponential Smoothing, achieving lower Mean Absolute Percentage Error (MAPE) values on both training (2.21%) and test (2.44%) datasets. This study recommends the adoption of SARIMA models, supported by lower MAPE values, to influence technology adoption and future-proof decision-making. This study highlights the societal implications of informed energy planning, including enhanced sustainability, cost savings, and improved resource allocation for communities and industries. The synthesis of model analysis, technological integration, and consumer-centric approaches marks a significant stride toward a resilient and efficient energy ecosystem. Decision-makers, stakeholders, and researchers may leverage findings for sustainable, adaptive, and consumer-centric energy planning, positioning the sector to address evolving challenges effectively and empowering consumers while maintaining energy efficiency.

Keywords: consumer-centric energy forecasting; exponential smoothing; SARIMA model; energy sector resource planning; consumer engagement; strategic investment; consumption patterns

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1. Introduction

1.1. Background

Sustainable energy management holds absolute importance in the contemporary global view, addressing multifaceted environmental, economic, and social challenges. At its core, sustainable energy management entails the judicious utilization of resources to meet current energy demands without compromising the ability of future generations to meet their own needs. One of its essential aspects lies in mitigating the adverse effects of traditional energy sources, primarily fossil fuels, which have long been fundamental to global energy production but pose significant environmental hazards, including air and water pollution, greenhouse gas emissions, and climate change. By transitioning towards renewable energy sources such as solar, wind, hydroelectric, and geothermal power, sustainable energy management endeavors to curtail these deleterious impacts, building a cleaner, healthier environment for the present and future inhabitants of our planet [1–3].

Sustainable energy management offers a pathway towards energy security and resilience, reducing reliance on finite and geopolitically unstable fossil fuel reserves. Diversification of energy sources through the integration of renewables enhances energy independence, mitigating vulnerabilities associated with supply disruptions and price fluctuations in the global energy market. This bolsters national security and builds economic stability by insulating economies from the volatility inherent in fossil fuel markets. The decentralized nature of renewable energy systems empowers local communities and regions to harness their natural resources, building economic development and job creation in rural and marginalized areas [4–7].

Sustainable energy management plays a vital role in advancing social equity and inclusivity. Access to affordable, reliable, and clean energy is indispensable for human development, underpinning essential services such as healthcare, education, and communication. By extending energy access to underserved populations, particularly in developing countries, sustainable energy initiatives contribute to poverty alleviation, improve living standards, and enhance socio-economic opportunities. Furthermore, by prioritizing community engagement and participatory decision-making processes, sustainable energy projects promote social cohesion and empower marginalized groups, ensuring that the benefits of the energy transition are equitably distributed across society [8–10]. It catalyzes innovation and technological advancement, driving the transition towards a knowledge-based, low-carbon economy. Investments in renewable energy research, development, and deployment stimulate technological innovation, driving down costs and improving efficiency, thereby enhancing the competitiveness of clean energy technologies compared to their conventional counterparts. This builds a virtuous cycle of innovation, job creation, and economic growth, positioning countries at the forefront of the burgeoning green economy. Furthermore, by embracing energy efficiency measures and adopting innovative grid technologies, sustainable energy management optimizes energy usage, reducing waste and increasing productivity across sectors [11–13].

The importance of sustainable energy management cannot be overstated in addressing the complex challenges of the 21st century. Sustainable energy initiatives offer a pathway toward a more prosperous, resilient, and inclusive future for humanity by mitigating environmental degradation, enhancing energy security, building social equity, and driving technological innovation. Embracing sustainability principles in energy management is not merely a choice but a moral imperative, essential for safeguarding the well-being of current and future generations and ensuring the long-term viability of our planet.

Energy forecast analysis is integral to sustainability efforts, supporting informed decision-making and long-term planning in the energy sector [14,15]. It enables stakeholders to anticipate future energy demand, identify trends, and develop strategies for resource allocation and investment decisions [16,17]. Energy forecasting is particularly crucial in integrating renewable energy sources into the grid, addressing challenges related to intermittency, and contributing to the transition towards a low-carbon energy future. Collectively, these measures build a more sustainable and resilient energy system that addresses critical challenges related to resource conservation, environmental protection, and climate change mitigation [18].

ARIMA, SARIMA, and ETS are widely used time series forecasting models in energy consumption estimation. ARIMA, or Autoregressive Integrated Moving Average, is a statistical method designed to capture and forecast patterns in time-series data by incorporating autoregressive and moving average components. The model is characterized by three primary parameters: p, d, and q, representing the autoregressive order, degree of differencing, and moving average order, respectively. SARIMA, or seasonal ARIMA, extends the ARIMA framework to account for seasonal patterns and trends in the data. It incorporates additional parameters to capture seasonal variations, making it particularly suitable for forecasting energy consumption data, which often exhibits recurring patterns over time. ETS, or Error, Trend, and Seasonality, is another widely used forecasting model that decomposes time-series data into components representing error, trend, and seasonality. ETS models are flexible and adaptable, capturing various patterns and dynamics in the data [19–21].

These models play a crucial role in energy consumption estimation and forecasting. Accurate energy consumption forecasts are essential for efficient resource planning, allocation, and management in the public and private sectors. By providing insights into future energy demand, these models enable utilities, energy providers, and policymakers to make informed decisions regarding infrastructure investments, capacity planning, and energy procurement strategies. This, in turn, helps optimize resource utilization, reduce wastage, and minimize the environmental footprint associated with energy production and consumption [22,23].

1.2. Related Literature

Energy efficiency initiatives rely heavily on accurate energy consumption forecasts to identify optimization opportunities and reduce costs [24–26]. Accurate predictions are crucial for promoting sustainability and achieving climate goals by informing strategies to transition to cleaner, renewable energy sources and improve energy efficiency standards [23]. ARIMA, SARIMA, and ETS models are critical in energy consumption estimation and forecasting, facilitating efficient resource planning and supporting sustainability initiatives [27,28]. These models enable utilities to balance load effectively, anticipate peak demand periods, and manage energy storage systems efficiently [29–31]. Predictive models also aid in planning maintenance and infrastructure upgrades, informing government policies, and guiding investments in renewable energy [32–34]. As the energy sector evolves, accurate energy consumption forecasting remains essential for shaping a sustainable energy future.

The literature on electricity consumption predictions offers several merits and demerits that shape the understanding and application of forecasting models in the energy sector. The literature showcases a wide array of methodologies, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) Networks, Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) [35–37]. This diversity allows for exploring various approaches to electricity consumption prediction, catering to different data characteristics and prediction requirements. Studies have demonstrated that advanced prediction models, such as those incorporating deep learning techniques like LSTM with attention mechanisms, can significantly enhance prediction accuracy [36,38]. These models leverage complex patterns in electricity consumption data, leading to more precise forecasts. Some research integrates external factors like climate information, economic indicators, and geodemographic factors to enhance the predictive capabilities of models [39–41]. The literature explores electricity consumption predictions in diverse sectors such as residential buildings, hospitals, universities, and public buildings [42–45]. This broad application scope demonstrates the versatility of prediction models across different domains. On the other hand, one of the challenges highlighted in the literature is the issue of insufficient training data, which can hinder the performance of traditional prediction methods [46]. Limited data availability may restrict the accuracy and generalizability of models, especially in complex prediction scenarios. Some studies highlight the high computational cost of specific prediction models, such as those utilizing deep learning algorithms [46]. This complexity can pose challenges in real-time applications or scenarios requiring rapid decision-making based on forecasts. While advanced models like CNN and LSTM offer improved accuracy, they may lack interpretability compared to traditional regression models [47]. The black-box nature of some complex models can make it challenging to understand the underlying factors driving predictions. Single intelligent algorithmic models, while effective in capturing patterns in data, may lack robustness in predicting electricity consumption under varying conditions [48]. Combining multiple models or developing ensemble approaches may be necessary to enhance prediction stability.

While a substantial body of literature concerning electricity consumption forecasts exists, comprehensive research examining the ramifications of these predictions for the energy sector is scarce. The research gap in the literature regarding the implications of electricity consumption predictions for the energy sector lies in the need for holistic studies that integrate electricity consumption forecasts and the broader impact of their results. The existing literature provides valuable insights into the technical aspects of electricity consumption prediction and its relevance for energy planning. However, understanding the societal implications of these predictions for consumers and industries and the need for continuous monitoring and adaptation strategies to ensure a resilient and sustainable energy future is crucial. Despite advancements in sustainable energy management, a critical need exists for accurate energy consumption forecasts to guide decision-making in the energy sector and facilitate the transition to a more sustainable energy future. Comprehensively evaluating the performance of these models and understanding their broader implications for energy sector planning and societal well-being is crucial. This study aims to address this gap by employing advanced time series analysis techniques to accurately forecast electricity consumption and explore these forecasts' multifaceted implications. By combining technical forecasting with a comprehensive analysis of social consequences, this study aims to create a more resilient, equitable, and sustainable energy future for all stakeholders involved.

1.3. Objectives and Research Questions

As the global energy view continues to evolve, the importance of accurate energy consumption forecasts will only increase, underscoring the significance of these models in shaping a more sustainable and resilient energy future. This study will employ time series analysis to understand the stochastic mechanisms of electricity usage patterns and predict future consumption based on historical data. The benefits of time-series data will be analyzed, and the optimal p, d, and q values in time-series models will be determined. The primary aim of this study is to conduct a comprehensive analysis of electricity consumption forecasting models, with a specific focus on evaluating the performance of the Exponential Smoothing and Seasonal Autoregressive Integrated Moving Average (SARIMA) approaches. By employing these models on electricity consumption data, this study aims to assess their compatibility with historical trends, emphasizing the consideration of multiplicative trends and seasonal effects. The overarching goal is to provide insights into the effectiveness of these models in predicting electricity consumption, thus contributing to the advancement of forecasting methodologies within the energy sector.

The primary objective of this study is to harness the power of advanced time series analysis techniques to forecast electricity consumption patterns accurately. Beyond the technical aspect of prediction, this study explores the multifaceted implications of these forecasts. It aims to explore how these predictions can inform energy sector planning strategies, guiding decisions related to infrastructure development, resource allocation, and policy formulation. Moreover, this study seeks to unravel the societal repercussions of accurate energy consumption forecasts, delving into their impact on community well-being, social equity, and environmental sustainability. By combining technical forecasting with a comprehensive analysis of social implications, this study aspires to create a more resilient, equitable, and sustainable energy future for all stakeholders involved.

This study aims to address several key research questions to fulfill its objectives. These questions will be answered and discussed by interpreting the results of the Exponential Smoothing model and the SARIMA model test for predicting electricity consumption patterns.

RQ.1. *Model Performance and Comparison—How do the Exponential Smoothing and SARIMA models compare in predicting electricity consumption?*

RQ.2. *Implications for Energy Sector Planning—How does accurate electricity consumption forecasting impact the energy sector?*

RQ.3. *Consumer and Industry Impact—How do accurate electricity consumption forecasts empower consumers?*

RQ.4. *Continuous Monitoring and Adaptation—Why are continuous monitoring and forecasting crucial for staying updated on evolving trends in electricity consumption?*

1.4. Practical Implications and Study Outline

The importance of this study is multifaceted, stemming from its unique combination of technical forecasting and social analysis. Firstly, by rigorously evaluating the performance of forecasting models such as ARIMA, SARIMA, and ETS, this study provides energy stakeholders with essential insights. These insights are instrumental in guiding strategic decisions on energy infrastructure development, resource allocation, and policy formulation. Accurate electricity consumption forecasts are crucial for strategic energy infrastructure development, resource allocation, and the effective integration of renewable energy sources. The findings of this study provide valuable insights into the reliability of forecasting models. The emphasis on consumer-centric analysis underscores the practical implications of accurate forecasts for decision-makers, urging the adoption of advanced models like SARIMA. Additionally, the study's exploration of the societal implications of accurate energy consumption predictions fills a crucial gap in existing research. Shining a light on issues of fairness, equity, and sustainability brings attention to the broader societal impacts of energy practices. This holistic approach enhances our understanding of energy dynamics and paves the way for more inclusive and sustainable energy policies and practices.

The following Materials and Methods Section outlines a comprehensive approach to studying electricity usage patterns, employing advanced time series analysis techniques, including Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Error, Trend, Seasonality (ETS) models, with meticulous calibration and dataset preprocessing, to gain nuanced insights into historical trends and fluctuations, providing a foundation for strategic decision-making in the energy sector. The Results Section provides a detailed analysis of the performance of the Exponential Smoothing (ETS) and Seasonal Autoregressive Integrated Moving Average (SARIMA) models in forecasting electricity consumption. A comprehensive discussion provides valuable insights into the strengths, limitations, and future directions of electricity consumption forecasting, emphasizing the need for continuous monitoring, adaptation, and collaboration across sectors and disciplines. This study ends with the Conclusion Section, which summarizes the analysis of electricity consumption forecasting models, underscores the broader implications for energy sector planning, and addresses the challenges and opportunities in the evolving energy sector.

2. Materials and Methods

This research comprehensively explores electricity usage patterns by applying advanced time series analysis techniques, focusing on leveraging data. The overarching objective is to gain a nuanced understanding of historical trends and fluctuations in electricity consumption and to develop robust forecasting models capable of accurately predicting future usage patterns. Forecasting methods are critical in estimating power consumption and its variation in high resolution because, in actuality, the power market interactions are carried out in minutes, 5 min, 15 min, and 30 min [23]. Annual power forecasting is useful for general decisions at a national or international level. The methodology employs the Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Error, Trend, and Seasonality (ETS) models. These models are chosen for their effectiveness in capturing non-seasonal and seasonal patterns in time-series data. Each model is carefully calibrated to align with the characteristics of the electricity consumption dataset spanning from 1973 to 2019 [49]. The research aims to capture long-term trends and cyclical patterns that may influence present and future consumption behaviors by encompassing a broad historical perspective. This section elucidates the step-by-step process, from model selection to dataset preprocessing, validation, and model calibration, underscoring the robustness of our approach in providing reliable insights for strategic decision-making.

2.1. ARIMA and SARIMA Models

The ARIMA (Autoregressive Integrated Moving Average) model is a powerful statistical technique for time series forecasting that effectively captures and predicts patterns and trends. It comprises three main components: Autoregressive (AR), Integrated (I), and Moving Average (MA). The AR component assesses the relationship between observations separated by a fixed time lag (p). The Integrated component makes the data stationary by differencing (d), while the Moving Average component models short-term fluctuations in the data (q) [50–54]. The ARIMA model combines these three components to capture complex patterns in time-series data. By adjusting the parameters (p, d, q), analysts can tailor the model to fit the specific characteristics of the analyzed data. ARIMA models are widely used for forecasting purposes in various fields, such as finance, economics, epidemiology, and climate science. They offer a flexible and versatile framework for modeling and predicting time-series data, making them indispensable tools for decision-making and planning in numerous domains [55,56].

SARIMA, an acronym for Seasonal Autoregressive Integrated Moving Average, is a variation in the ARIMA model specifically designed to capture seasonal patterns in time-series data. It introduces seasonal components (P, D, Q) for seasonal variations. The seasonal autoregressive order (P) captures past observations' influence on the series' current value, while seasonal differencing (D) removes seasonal trends. The seasonal moving average order (Q) models the relationship between an observation and the residual error from a moving average model applied to lagged seasonal observations [57]. Similar to the ARIMA model, SARIMA consists of three main components: Autoregressive (AR), Integrated (I), and Moving Average (MA). However, SARIMA introduces an additional set of parameters to capture seasonal patterns. These parameters are P, D, and Q, representing the seasonal autoregressive order, seasonal differencing, and seasonal moving average order, respectively. The SARIMA model incorporates seasonal components (P, D, Q,s) and non-seasonal components (p,d,q) found in the ARIMA model. The seasonal components include the autoregressive order, the difference order, the moving average order, and the number of periods.

The seasonal autoregressive order (P) captures the relationship between an observation and its seasonal lagged values. Considering the data's seasonality, it accounts for past observations' influence on the series' current value. The seasonal differencing (D) component involves subtracting the observation from its lagged value to remove seasonal trends and make the data stationary. Finally, the seasonal moving average order (Q) models the relationship between an observation and the residual error from a moving average model applied to lagged seasonal observations [58–60]. By incorporating these seasonal components into the ARIMA framework, SARIMA models can effectively capture and forecast time-series data with seasonal patterns. This makes them particularly useful for analyzing and predicting phenomena that exhibit regular seasonal variations, such as monthly sales data, quarterly financial reports, or yearly weather patterns [60,61]. SARIMA models are widely used in various fields, including economics, finance, meteorology, and epidemiology, where understanding and predicting seasonal trends are crucial for decision-making and planning. They offer a powerful tool for analysts and researchers to extract insights from seasonal data and make informed forecasts, facilitating better strategic and operational decisions in diverse domains.

Time series forecasting typically favors using the autoregressive Integrated Moving Average (ARIMA) model. Utilizes the historical data points of the time series. Precise prediction reduces costs and ensures accurate planning and production activities. Univariate time series prediction refers to predicting future values based solely on previous time series values. When the series is not utilized for prediction purposes, it is called multivariate time series forecasting. ARIMA uses historical data to forecast future values. ARIMA consists of three primary components. The elements in question are p, d, and q. The order p represents the autoregressive (AR) term. A time series is given by *it.* p is the number of time lags to regress on, ϵt is the noise at time t, and β is a constant. The linear regression model exhibits both time delays and predictors. For the estimators to be independent, they must have a difference (d), making the series stationary. The value is 0 when the series has already achieved stationarity. The symbol q represents the moving average (MA) series $y_t = \Phi(L)^q \in_t + \in_t$. Φ, which is defined analogously to being absorbed into the constant Θ polynomial. In addition, ARMA(p,q) models are simply a sum of AR(p) and MA(q) models. Displays the count of prediction errors that have been deferred. If p denotes the number of lags of Y, then Y was utilized as the predictor. Then, ARIMA can be represented as a time series forecast t, as shown in Equation (1). To transform ARMA (p,q) to ARIMA (p,d,q) to help tackle non-stationary data, an integration operator Δd and d, where d is the order of differencing, are expressed and used. To clarify this statement, LY is Y delays [extended to P delays], and LYE has lagged prediction errors [extended up to q lag] [62], as shown in Equation (1).

$$Y_t = Const + LY + LYE \tag{1}$$

The combination used here is a linear combination of delays. Thus, the primary purpose is to determine the values of p, d, and q. The minimum difference d must be chosen so that the autocorrelation (AC) reaches zero. The order of AR can determine P. It should equal the lags in partial autocorrelation (PAC), significantly exceeding the specified limit. This is also a conditional correlation. It shows PAC, where y is considered the response variable, and the predictor variables are x_1, x_2, and x_3. The PAC between y and x_3 is shown in Equation (2). It is calculated as the correlation between the regression residuals of y on x_1 and x_2 and the residuals of x_3 on x_1 and x_2 [62].

In regression, this partial correlation could be found by correlating the residuals from two different regressions: the first is the regression in which we predict y from x_1 and x_2. The second is the regression, which predicts x_3 from x_1 and x_2. Basically, it is correlated with the "parts" of y and x_3 that are not predicted by x_1 and x_2. More formally, we can define the sample autocorrelation function as just described as

$$\hat{p}_k = r_k = \frac{\sum\limits_{t=1}^{n-k} (Y_t - \overline{Y})(Y_{t-k} - \overline{Y})}{\sum\limits_{t=1}^{n} (Y_t - \overline{Y})^2}, k = 0, 1, 2, \ldots \tag{2}$$

A plot $\hat{p}_k$ versus k is a sample correlogram. For large sample sizes, $\hat{p}_k$ is normally distributed with mean p_k, and variance is approximated by Bartlett's approximation for processes in which p_k = 0 for k > m. The sample partial autocorrelation function can be represented as Equation (3).

$$\begin{aligned} \hat{\phi}_{11} &= \hat{p}_1 \\ \hat{\phi}_{kk} &= \frac{\hat{p}_k - \sum\limits_{j=1}^{k-1} \hat{\phi}_{k-1,j} \hat{p}_{k-j}}{1 - \sum\limits_{j=1}^{k-1} \hat{\phi}_{k-1,j} \hat{p}_{k-j}} \end{aligned} \tag{3}$$

where $\hat{\phi}_{kj} = \hat{\phi}_{k-1,j} - \hat{\phi}_{kk}\hat{\phi}_{k-1,k-j}, j = 1, 2, \ldots k-1$. For a white noise (WN) process, $Var(\hat{\phi}_{kk}) \approx \frac{1}{n}$. $\pm 2/n^{1/2}$ can be used as critical limits ϕ_{kk} to test the hypothesis of a WN process. It shows the error in the lagged prediction. AC can be calculated using Equation (4). y represents the time series average, k indicates the delay (accepted for k $\geq$ 0), and N represents the full series value.

$$AC = \frac{\sum_{i=1}^{N-K} (y_i - \overline{y})(y_{i+k} - \overline{y})}{\sum_{i=1}^{N} (y_i - \overline{y})^2} \tag{4}$$

If seasonal patterns are needed in the time series, the seasonal term is added to ARIMA and becomes the seasonal ARIMA model (SARIMA). The model can be written as Equation (5) [63].

$$ARIMA(p, d, q)x(P, D, Q)_S \tag{5}$$

(p,d,q) is the non-seasonal part; (P,D,Q)S is the seasonal part of the model, and S is the season's period number. SARIMA is used in this paper because ARIMA does not support time series with a seasonal component, but it is used for univariate data that includes seasonality and trends. Therefore, the following steps have been taken into consideration in SARIMA:

1. The first step is to check whether the series is stationary. If a time series has a trend average that varies over time or seasonality that varies over specific time periods, then it should be converted to a stationary time series.
2. The differencing mechanism is applied. If the time series is not stationary, differencing is applied to make the time series stationary. Take the first difference and check stationarity until it becomes stationary. Seasonal differences should also be controlled.
3. Validation samples are created.
4. AR and MA are included based on AC and PAC.
5. The model becomes ready for prediction.
6. Validate the model by comparing the predicted values.

The parameters (p,d,q) of the SARIMA model are selected. 'p' determines the number of autoregressive terms, 'd' determines the differencing level, and 'q' determines the number of moving average terms. These parameters were manually selected by looking at partial autocorrelation and autocorrelation functions. The p and d parameters are identified according to the behavior of ACF and PCF presented in Table 1 [64].

Table 1. The behavior of ACF and PACF for ARMA models.

Model	ACF	PACF
MA(q)	Cuts off after lag q	Exponential decay and/or damped sinusoid
AR (p)	Exponential decay and/or damped sinusoid	Cuts off after lag p
ARMA (p,q)	Exponential decay and/or damped sinusoid	Exponential decay and/or damped sinusoid

Information criteria such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) were used to evaluate the model's fit. After the model was selected, the prediction and model validation stages were started. The model parameters were chosen as follows in Equation (6):

$$ARIMA\ (p = 1, q = 1, d = 1)\ x\ (P = 1, D = 0, Q = 1, T = 12) \tag{6}$$

These parameters were set as p = 1 (number of autoregressive terms), d = 1 (degree of differencing), and q = 1 (number of moving average terms). While p = 1 and q = 1 indicate that the model is built on the previous value and the previous error term, d = 1 suggests that the data are made stationary by differencing once. In the ARIMA model, seasonal_order = (1,0,1,12) defines the seasonal components of the SARIMA model. Additionally, 1,0,1 indicates the order of the seasonal AR and MA terms, and 12 indicates the length of the seasonal cycle (e.g., 12 months for monthly data). If enforce_invertibility = False, it does not enforce that the model's moving average (MA) polynomial is invertible. This can make the model more stable in some cases. enforce_stationarity = False: It does not require the model's autoregressive (AR) structure to be stationary. This parameter can be helpful when working with non-stationary series [62,65].

Since the SARIMA model has seasonal components (P,D,Q,s) in addition to the non-seasonal components (p,d,q) in the ARIMA model, it has been emphasized in the literature that the SARIMA model should be used for the analysis of such non-seasonal data. When seasonal components (P,D,Q,s) were examined, it was stated that the results gave the necessary prediction results despite the non-seasonal data (p,d,q) without comparison with the ARIMA model.

2.2. ETS Model

The ETS model is an abbreviation for “Error, Trend, Seasonality” components and is a forecasting method used to analyze time-series data. The ETS model predicts future values using the series’ error, trend, and seasonality components. Considering these three components, the model produces a smoothed version of the data, which is used to predict the future behavior of the time series. ETS models are used primarily when seasonality and trends exist in time-series data. This model is an effective tool for analyzing and forecasting time-series data by providing flexibility to different trend and seasonality structures. In this study, an ETS model is defined using the ExponentialSmoothing class, and this model can be explained as follows:

trend = ‘mul’: Indicates that the trend component is modeled as a multiplier. This means the trend changes proportionally, increasing or decreasing over time.

seasonal = ‘mul’: Indicates that the seasonal component is also modeled as a multiplier. This means that the seasonal effect has a rate that varies periodically.

seasonal_periods = 12: Defines the length of the seasonal cycle. It is specified here as 12, a standard period generally used for monthly data. The state space model of the ETS is given below.

$$\begin{aligned} y_t &= w(x_{t-1}) + r(x_{t-1})\varepsilon_t \\ x_t &= f(x_{t-1}) + g(x_{t-1})\varepsilon_t \end{aligned} \tag{7}$$

Here, w, f, and g are coefficients. ε_t represents the Gaussian white noise series. The equation that gives y_t is known as the observation equation. Explains the relationship between x_{t-1} and y_t. The equation that gives x_t is the transition equation that describes the development of situations over time.

Fit (smoothing_level = 0.1, smoothing_trend = 0.2, smoothing_seasonal = 0.5): Trains the model with the specified smoothing parameters. smoothing_level determines the smoothing coefficient of the error component, smoothing_trend determines the trend component’s smoothing coefficient, and smoothing_seasonal determines the smoothing coefficient of the seasonal component. These coefficients affect how “close” or “smooth” the model will be to the data [62,63,65–67].

2.3. Dataset

The World Energy Consumption dataset used in this study, which shows energy consumption by different countries, is a collection of critical metrics maintained by “Our World in Data” and is drawn from “kaggle.com” [49]. The dataset has two primary variables: date (“DATE”) and electricity consumption (“Electricity_Consumption_in_TW”). There are a total of 561 full data points in both areas. The dataset comprises power consumption numbers recorded on specific dates, either annually or monthly. The “DATE” column displays the dates, while the “Electricity_Consumption_in_TW” column indicates the electricity usage on those dates, measured in terawatt hours (TW).

Proper formatting of dates is required. If the dates are not in a standardized format, such as YYYY MM DD, they must be provided for analysis. Code snippets are explicitly created for preprocessing and checking tasks. The Python NumPy and Panda libraries were utilized to preprocess the data by removing missing values, as the initial data obtained were considered sufficient and accurate. In addition, the dataset was examined for any instances of missing or inaccurate data. Below are the data, arranged by month and year.

Table 2 provides data on the world’s electricity use from 1973 to 2019. The data will be analyzed to ascertain the changes in electricity usage throughout the provided period and to forecast future consumption patterns. The dataset includes a graph (Figure 1) that displays electricity usage over the years. This graph allows us to observe the overall patterns and recurring changes in electricity consumption over time. In addition, electricity consumption predictions will be generated after 2019 utilizing time series forecast methods such as ARIMA and SARIMA. These models demonstrate efficacy in forecasting future values by using past data. Figure 1 illustrates the temporal evolution of power use.

Table 2. World electricity consumption between 1973 and 2019 [49].

Electricity_Consumption_in_TW	Month	Year
35.9728	1	1973
36.1334	2	1973
35.0625	3	1973
33.8416	5	1973
33.5107	6	1973
...	...	...

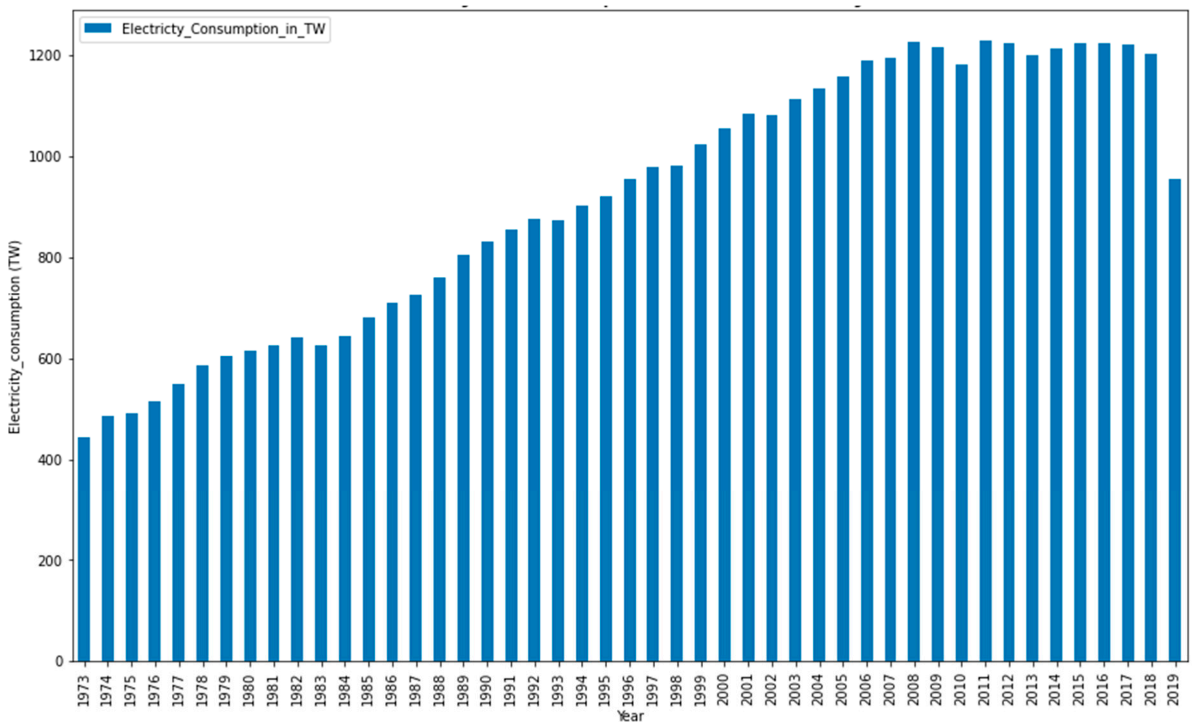

Figure 1. Yearly electricity consumption.

This study examined the spectral distribution of annual electricity usage to draw more precise results. Spectral analysis primarily uncovers concealed periodic patterns, trends, and cyclical elements in time-series data. It displays the frequency components present in the dataset and quantifies the intensity of these frequencies. Figure 2 shows the spectrum analysis graph. The spectral analysis graph is utilized to identify periodic or seasonal components in the data, providing insights into how the data vary over time. Figure 2 displays the time series graph of annual electricity use statistics. The primary axis depicts the progression of consumption over a certain period, while the shaded region indicates the estimated range of uncertainty. This uncertainty is calculated using the following equations in Phyton: Coding was performed on Jupyter using Python. Python, NumPy, Statsmodels, and Pandas libraries were used. Statsmodels were used in the development of the SARIMA and ARIMA models. The shaded area shows the max/min monthly electricity consumption over the year, while the line shows the average consumption. The chart exhibits a prevailing upward trajectory with periodic oscillations over the year. The primary trend depicted in the graph illustrates a progressive rise in power use as time progresses. This scenario is interconnected with the expansion of the population and advancements in industry and technology. The variations observed throughout the year indicate a rise in electricity usage, particularly during the summer, as seen in Figure 3 [49]. Seasonal variations, such as the extensive utilization of air conditioning equipment, cause this circumstance.

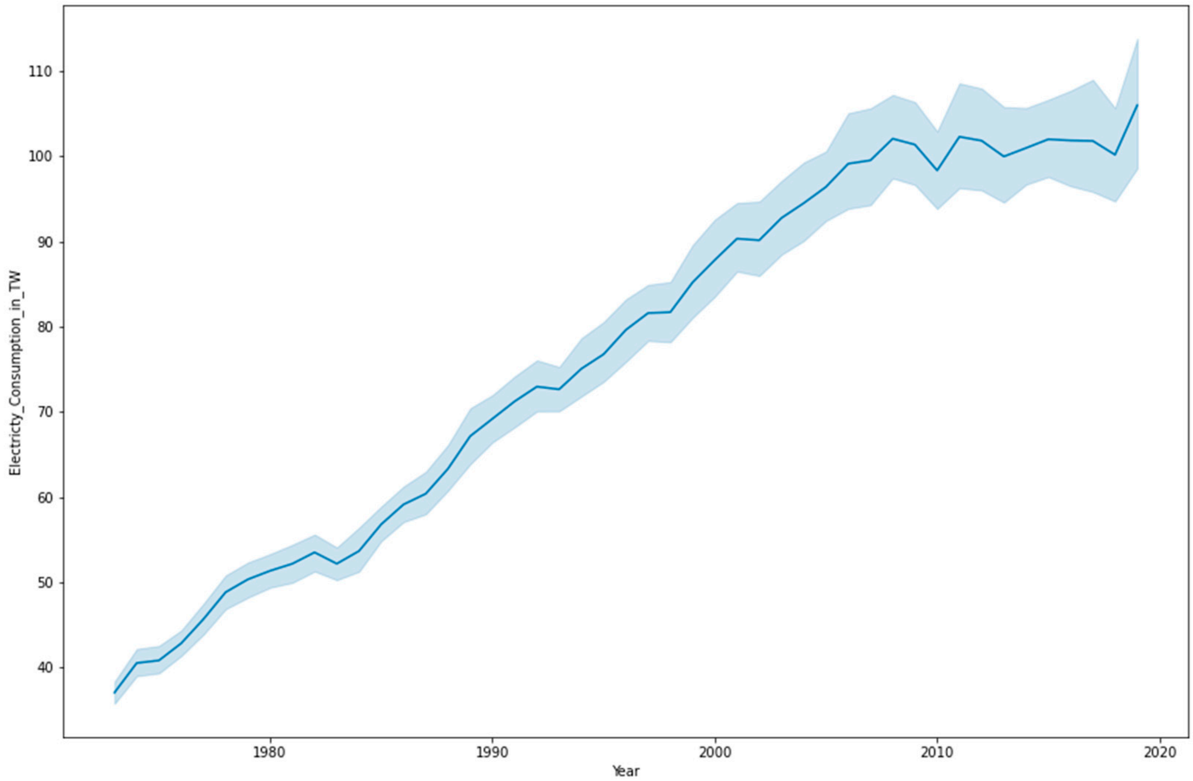

Figure 2. Spectral analysis graph.

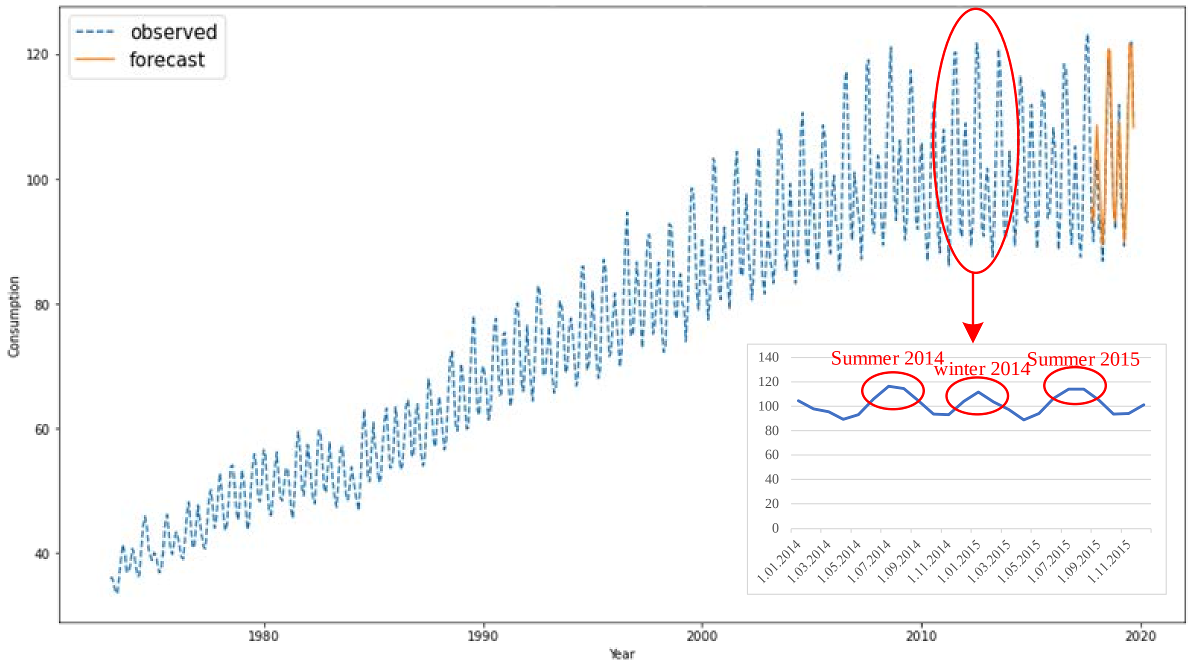

Figure 3. World electricity consumption observed and forecasted values.

3. Results

The Mean Absolute Percentage Error (MAPE) metric will be employed to assess the predictive capabilities of the SARIMA and ETS models. This metric quantifies the percentage difference between the model's predicted and actual values and is commonly used to evaluate the precision of time series forecasts. MAPE is determined by computing the average of the absolute values of all forecast errors and then expressing this average as a percentage concerning the actual values. This metric will assess the effectiveness of the SARIMA model in capturing intricate seasonal and trend patterns and evaluate the ETS model's predictive capability using the smoothed version of the time-series data. This investigation will have a crucial impact in showcasing the efficacy of both models in forecasting electricity consumption data and will offer significant insights for formulating energy management strategies.

3.1. Exponential Smoothing Model Results

Table 3 shows the results of the Exponential Smoothing model applied to an electricity consumption time-series dataset. The figure's components and metrics reveal the model's performance and applicability.

Table 3. Results of the Exponential Smoothing model.

Dependent Variables	Electricity Consumption in TW	Number of Observations	537
Model	Exponential Smoothing	SSE	0.469
Optimized	Yes	AIC	−3749.979
Trend	Multiplicative	BIC	−3681.403
Seasonal period	12 months	AICC	−3748.658

The variable that the "Dependent Variable Model" in Table 3 tries to predict is "Electricty_Consumption_in_TW". There are 537 observations in the dataset on which the "No. Observations" model was trained. It is stated that the model used is "Exponential Smoothing," and the trend is multiplicative. It also indicates that the trend is increasing or decreasing proportionally. The Sum of Square Error (SSE): The sum of squares of the model's prediction errors is 0.469. This seems like a low value and shows that the model fits the data well. The "Akaike Information Criterion (AIC)" and "Bayesian Information Criterion (BIC)" models were selected and used for comparison. The 3749.979 value obtained with AIC and the 3681.403 value obtained with BIC show that the model fits the data well and, with high probability, handle complexity in a balanced manner. Lower AIC and BIC values generally indicated better model fit. Seasonality is also modeled as a multiplier. It states that seasonal effects show variable rates over time [68].

As a result, the model presented a very low SSE and negative AIC/BIC values, indicating that the model fits the dataset well and the predictions are reliable. Furthermore, multiplier trends and seasonality indicate that electricity consumption is increasing or decreasing and has seasonal patterns throughout the year. These results showed that the model effectively models time-series data and can be used to predict future electricity consumption.

Using the available data, electricity consumption for the next 24 months was estimated. The results obtained were evaluated using the MAPE evaluation metric. forecast = np.exp(ets_model.forecast(steps = 24)): Here, the ets_model.forecast(steps = 24) function returns the forecasts for the next 24 time steps using the ETS model. If the model was trained on logarithmically transformed data, the np. exp() function transforms the predictions back to the original scale. This step ensured that the model's predictions were directly comparable to real-world data.

When evaluating the estimated consumption results for the next 24 months, MAPE_Train (0.040432974677989626): This is the average percentage error rate of the ETS model on the training dataset. It can be interpreted as 4.04%. This value indicates how well the model fits the training data and shows a low error rate. MAPE values below 5% suggest that the model reasonably predicts the training data. MAPE_Test (0.024232019088546015): This is the average percentage error rate reflecting the model's performance on the test dataset and can be interpreted as 2.42%. This low MAPE value on the test set indicates that the model can generalize well to the training data and data it has not seen before. Generally, higher error rates are expected on test data because the model is not trained on those data. However, in this case, it was observed that the model performed well with a low error rate in the test data.

3.2. SARIMA Model Results

The developed model was trained on 537 observations. Log Likelihood: the log-likelihood value of the model is 1289.004. This high value shows that the model fits the data well. The AIC value of the model was calculated as 2568.009. AIC is a criterion that measures the model's quality and balances the model's complexity and fit. A low AIC value indicates that the model fits the data well and avoids unnecessary complexity. Table 4 shows the SARIMA model results. The training data are selected at 80%, and the test data are set at 20%.

Table 4. Results of the SARIMA model.

Dependent Variables	Electricity Consumption in TW	Number of Observations	537
Model	SARIMAX (1,1,1) × (1,0,1,12)	Log-likelihood	1289.004
Sample	01-01-1973	AIC	−2568.009
	01-09-2016	BIC	−2546.720
Covariance Type	the outer product of gradients	HQIC	−2559.670

As given in Table 4, the BIC value of the model is 2546.720. BIC is used to evaluate the quality of the model and has generally produced results similar to AIC's. A low BIC value indicates that the model fits and explains the data well enough without overfitting. The Quinn Information Criterion is also used for model selection and is calculated as 2559.670. This indicates that the model captures the dataset well and has an appropriate model complexity. Covariance Type: the covariance type of the model is 'up,' which indicates that the covariance parameter estimates of the model are calculated by the 'outer product of gradients' method.

For the forecast of the next 24 months, the SARIMA model gave the value of MAPE_Train (0.022055772623528584). The average percentage error rate of the model on the training dataset is approximately 2.21%. This value indicates that the model accurately predicts electricity consumption in the training dataset. MAPE_Test (0.02443793308819474) has an average percentage error rate of approximately 2.44%, reflecting the model's performance on the test dataset. This value is significant because the test set generally better reflects the actual world performance of the model. The fact that the model has a low error rate in the test data indicates that the model has a high generalization capacity for unknown data.

Since both MAPE values are low, it is concluded that the predictions for the future 24 months are highly accurate, even though the SARIMA model was trained on historical data. This has shown that the model is reliable for analyzing and forecasting time-series data such as electricity consumption. Accurate energy consumption forecasting is critical for resource planning, demand management, and strategic decision-making processes, particularly in the energy sector. The forecast for the next two years is given in Figure 3.

In Figure 3, the time-series data display the observed power consumption values represented by a blue dashed line, while the anticipated values are shown by an orange line. The graphic displays both empirical data for a given time frame and prognostications made by the model after the conclusion of that data. The recorded data, shown by blue dashed lines, exhibit a progressive pattern over time and evident cyclicality. The upward trajectory signifies an increasing need for electricity usage as time progresses. The orange line represents the model's projections for future power usage values. This line extrapolates from the final point of the observed data and projects into the future. The Model Performance chart demonstrates that the projected values represent the data's overall pattern and cyclical variations. The model accurately captures previous data and accurately predicts present data patterns. However, to assess the long-term precision and dependability of the orange forecast line, it is necessary to have actual test data that can be used to compare the forecasts with the observed values. These test data will enhance our understanding of the model's ability to generalize and reliably predict future values. Figure 4 provides the lag graph of the model for a detailed analysis of existing and future data for a more comprehensive study.

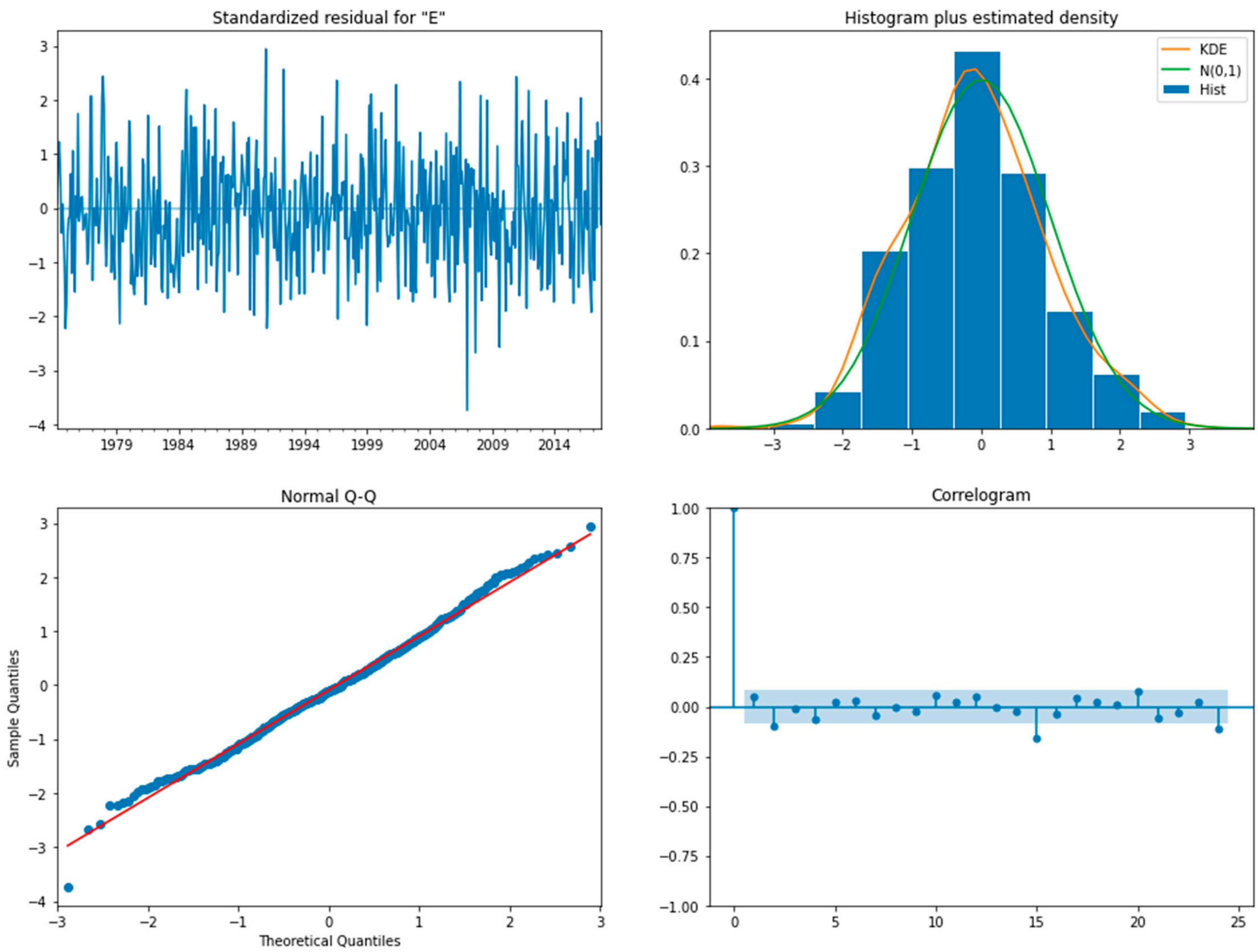

Figure 4. The lag plot graph of the model.

The scatter plot in Figure 4, known as the lag plot, demonstrates that the model's residuals do not exhibit autocorrelation at a lag of 1. This graph illustrates the dispersion of residuals. The histogram indicates that the residuals' distribution closely approximates the standard distribution curve (shown by the green and orange lines). Simultaneously, the standard probability plot (Q–Q plot) can be assessed to determine if the residuals conform to a normal distribution. The graphic displays a time-series plot depicting the temporal evolution of the residuals. If the residuals exhibit homoscedasticity and lack discernible patterns, it suggests that the model reflects the temporal fluctuations of the data well.

When considering the four graphs in the picture collectively, it can be shown that the SARIMA model effectively captures the dataset, and the forecasts are statistically dependable. Thus, the SARIMA model is likely appropriate for forecasting electricity consumption demand for the subsequent two years.

4. Discussion

4.1. Model Analysis

The Exponential Smoothing model demonstrated compatibility with historical trends in electricity consumption. Considering a multiplicative trend and seasonal effects on a yearly cycle, the model provided promising results with a low Sum of Squared Errors (SSE) value (0.469), indicating accurate predictions. Negative Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values affirmed a well-balanced, low-complexity model. The model's forecasting effectiveness was evident with a low Mean Absolute Percentage Error (MAPE) on both the training (4.04%) and test (2.42%) datasets. Similarly, with its seasonal ARIMA structure, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model improved electricity consumption forecasting. High log-likelihood and low AIC and BIC values confirmed an excellent fit with appropriate model complexity. SARIMA slightly outperformed Exponential Smoothing, exhibiting even lower MAPE values on both the training (2.21%) and test (2.44%) datasets. Visualizations (refer to Figures 3 and 4) illustrated SARIMA's ability to capture historical data patterns accurately and maintain statistical reliability in predicting future values.

Enhancing the connection between decision-making and forecast evaluation can improve prediction accuracy, a critical factor for stakeholders such as consumers [69]. Low MAPE values, especially for SARIMA, signify high accuracy and reliability in predicting electricity consumption, ensuring efficient resource planning and demand management for a stable energy ecosystem. Despite the complexity of the models, the low MAPE values indicate practical interpretation by consumers. Accurate forecasting is pivotal for strategic decision-making in resource planning, allowing energy providers to optimize resource allocation sustainably. Decision-makers may consider adopting advanced models like SARIMA, supported by lower MAPE values, influencing technology adoption and future-proofing decisions.

In essence, both Exponential Smoothing and SARIMA models are reliable for forecasting electricity consumption. SARIMA, slightly outperforming Exponential Smoothing, emerges as a more precise forecasting tool. Detailed analysis and visualization offer a comprehensive understanding of the models' performance, marking a significant stride toward a consumer-centric and technologically advanced energy sector.

The results of the Exponential Smoothing (ETS) and SARIMA models, along with associated MAPE metrics, provide insights into the future of electricity consumption. Both models exhibit low MAPE values on training and test datasets, suggesting accurate and reliable predictions. Specifically in SARIMA, the models effectively capture intricate seasonal and trend patterns, which are crucial for understanding cyclical variations in electricity demand. Both models demonstrate a high generalization capacity for unseen data, which is essential for forecasting persisting patterns into the future. The upward trajectory signifies an increasing need for electricity usage, providing valuable insights for energy providers and policymakers. Low MAPE values, coupled with statistical dependability and validation through actual test data, contribute to building trust in the models' ability to predict future electricity consumption reliably. Trust is essential for informed decision-making regarding resource planning and strategic investments.

4.2. Implications for Energy Sector Planning

Accurate electricity consumption forecasts are crucial for guiding strategic infrastructure development within the energy sector [70]. These forecasts assist power plant planners and operators in making informed decisions to balance capacity with anticipated demand. Moreover, implementing energy efficiency measures, demand-side management, and storage technologies in buildings aids in maintaining a balance between energy supply and demand, facilitating sustainable energy transitions [71]. Energy sector planning relies on efficient resource allocation [72]. Forecasts optimize the deployment of resources like fuel, workforce, and equipment, ensuring efficient and cost-effective operations aligned with forecasted consumption patterns. Forecasted trends support the integration of renewable energy sources into the energy mix [73]. Understanding peak demand periods enables strategic deployment of renewables, such as solar and wind, to supplement traditional energy generation during high-consumption periods. Based on consumption forecasts, demand-side management strategies allow energy providers to incentivize consumers to shift energy use to non-peak hours, promote energy efficiency, and deploy smart grid technologies [74]. These initiatives enhance grid stability, reduce the need for excessive peak capacity, and support sustainable energy consumption practices. Grid modernization initiatives, guided by forecasted consumption trends, involve upgrading infrastructure, integrating smart technologies for real-time monitoring, and enhancing overall reliability. These efforts ensure that the energy delivery system is robust and capable of meeting evolving consumer and industrial needs. Long-term policymaking benefits from consumption forecasts, aiding in setting energy efficiency targets, establishing emission reduction goals, and creating incentives for investments in clean energy technologies [75,76]. Investors in the energy sector can use consumption forecasts for informed investment planning [77]. Forecasted trends help identify areas with growing demand, allowing for strategic investments in projects that align with future needs. Understanding consumption patterns also aids in risk mitigation by avoiding overinvestment in areas with stagnant or declining demand. Forecasted energy usage is a baseline for resilience against uncertainties such as economic fluctuations, technological advancements, and geopolitical factors [78,79]. Scenario planning based on different consumption projections enables the development of flexible strategies that can adapt to changing external conditions. Forecasting energy usage aids in setting energy efficiency standards and complying with environmental regulations [80]. Accurate reporting becomes feasible when realistic expectations of future consumption trends inform regulatory frameworks. Engaging communities and stakeholders in energy planning is essential [81]. Consumption forecasts provide a transparent basis for communication, foster a sense of shared responsibility, and garner support for energy initiatives [82]. In conclusion, accurate consumption forecasts are essential for shaping the trajectory of the energy industry, aiding in infrastructure development, renewable energy integration, policy formulation, investment planning, and resilience against uncertainties. The adaptive nature of planning, supported by reliable forecasts, positions the energy sector to sustainably address current and future challenges.

4.3. Consumer and Industry Impact

Accurate electricity consumption forecasts empower consumers to make informed decisions about their energy usage, potentially leading to cost savings [83]. By understanding future consumption trends, individuals can strategically adjust their behavior, shifting activities to off-peak hours and adopting energy-efficient appliances and smart home technologies aligned with forecasted patterns. The forecasted increase in electricity consumption underscores the importance of energy conservation programs [84]. Utilities can educate consumers about energy-efficient practices by incentivizing participation through rewards or discounted rates during non-peak hours to align behavior with sustainability goals [85]. Industries heavily reliant on electricity benefit from accurate consumption forecasts for planning and operational purposes [86]. Anticipating future demand allows them to optimize production schedules, implement load-shifting strategies, and invest in energy-efficient technologies, contributing to cost efficiency and sustainability. Forecasts guide energy providers and businesses in strategically allocating resources to meet anticipated demand [87], supporting uninterrupted service delivery, and fostering a reliable energy supply. Businesses, particularly those in the energy sector, can make informed decisions based on the forecasted consumption trends, which include investment planning, adopting new technologies, and aligning business strategies with the expected market demands. Energy companies can position themselves as reliable providers by staying ahead of the curve and adapting to evolving consumer and industry needs, ultimately enhancing their competitiveness in the market. Forecasted consumption trends influence energy pricing models. Utilities may adjust pricing structures to encourage off-peak consumption, helping to manage peak loads and reduce strain on the grid. Consumers benefit from flexible pricing options that reflect the forecasted variations in demand, allowing them to make cost-conscious decisions and save on energy bills. Accurate forecasts contribute to the resilience of the energy ecosystem by mitigating supply-demand imbalances [88]. This is crucial for maintaining stable and reliable energy services, especially during periods of high demand or unexpected events. Resilience against imbalances enhances overall energy security and minimizes the risk of service disruptions, ensuring a consistent and reliable energy supply for consumers and industries. Transparency in forecasting models builds consumer trust, fostering a positive relationship between consumers and energy providers [89]. Industries benefit from accurate forecasts to ensure compliance with energy efficiency standards and environmental regulations [90]. The impact of accurate electricity consumption forecasts on consumers and industries is multifaceted, shaping behaviors and strategies in the energy sector toward a more sustainable, efficient, and resilient energy ecosystem.

4.4. Continuous Monitoring and Adaptation

Energy consumption patterns are dynamic, influenced by technological advancements, societal changes, and economic fluctuations. Continuous monitoring is crucial to track these trends and maintain the accuracy of forecasting models [91,92]. Emerging technologies such as electric vehicles, smart grids, and decentralized energy sources reshape consumption patterns, necessitating real-time insights to update forecasting models [93]. Climate change and environmental concerns further impact energy usage, highlighting the need for continuous monitoring to adapt to shifts in demand related to weather variations and policy changes [94]. As consumer preferences evolve and global energy consumption rises, particularly in developing nations, forecasting models must incorporate these changes to remain effective [95,96]. Economic fluctuations and geopolitical events can significantly affect energy consumption, emphasizing the importance of continuous monitoring for accurate predictions [97–99]. Regulatory changes also influence consumption patterns, requiring proactive adjustments in forecasting models to ensure compliance [100–103]. Urbanization and infrastructure developments further complicate energy demand patterns, necessitating ongoing monitoring and adaptation of forecasting models to meet future energy requirements [104]. In the integrated global energy market, continuous tracking of international dynamics is essential for reacting to price changes and supply interruptions [105]. Continuous monitoring provides stakeholders with up-to-date insights for informed decision-making, ensuring the ongoing relevance of forecasting models in addressing the increasing electricity demand [106]. The results of this study suggest a future trajectory of increasing electricity consumption, and the accuracy of the forecasting models provides confidence in the reliability of these predictions. Decision-makers in the energy sector can leverage these insights for strategic planning, resource allocation, and meeting the growing demand for electricity. Continuous monitoring and adaptation to changing conditions will ensure the forecasting models' ongoing relevance.

4.5. Limitations

While this study offers valuable insights into electricity consumption forecasting using Exponential Smoothing and SARIMA models, it is important to recognize several limitations that may affect interpretation and generalization.

Model Complexity: Despite their accuracy, the intricate nature of Exponential Smoothing and SARIMA models may hinder understanding and adoption among non-expert stakeholders.

Economic Uncertainties: Predicting consumption patterns amid unpredictable economic fluctuations introduces uncertainty that may affect long-term forecasts and strategic planning in the energy sector.

Technological Advancements: Emerging technologies like electric vehicles and smart grids pose challenges in predicting their specific impacts on consumption patterns, potentially limiting forecasting precision.

Interpretation by Consumers: While low Mean Absolute Percentage Error values suggest practical interpretation, effective communication strategies are necessary to convey forecasted trends to diverse audiences.

Generalization Capacity: The effectiveness of the models may vary across different geographical, socio-economic, and cultural contexts, requiring caution in generalizing findings.

Data Limitations: Data accuracy and reliability, as well as gaps and biases, can influence prediction precision, highlighting the importance of robust data quality and collection processes.

Contextual Factors: Geographical and socio-economic contexts may influence the applicability and generalizability of the models, considering factors such as regulatory environments and consumer behaviors.

Short-Term Focus: While this study examines short-term trends, future research could explore longer forecasting horizons to capture evolving patterns more comprehensively.

Addressing these limitations is crucial for refining forecasting models, enhancing stakeholder acceptance, and ensuring resilience in diverse scenarios. Future research could focus on improving model interpretability, incorporating economic uncertainties more effectively, and examining the impacts of emerging technologies on consumption patterns across various contexts.

4.6. Future Research Directions

Building on this study's findings, future research can advance electricity consumption forecasting by addressing evolving technologies and current limitations. Several research directions are proposed:

Interdisciplinary Model Interpretability: Collaborations between data scientists, social scientists, and communication experts can enhance model interpretability for diverse stakeholders.

Incorporating Economic Indicators: Future research can integrate economic indicators like financial data and market trends to improve forecasting accuracy amid economic uncertainties.

Long-Term Forecasting: Extending forecasting horizons to analyze long-term trends and patterns, considering sustained technological advancements and shifting consumer behaviors.

Enhancing Consumer Engagement: Exploring innovative communication methods and user-friendly interfaces to empower consumers to utilize forecasted information for energy-efficient practices.

Geographical and Socio-economic Variability: Comparative studies across diverse settings can provide insights into contextual factors influencing model effectiveness, guiding the development of adaptable forecasting frameworks.

Dynamic Adaptation to Technology: Developing adaptive forecasting models capable of dynamically incorporating the impacts of emerging technologies through continuous monitoring and real-time adjustments.

Machine Learning and Advanced Analytics: Integrating sophisticated algorithms, including deep learning approaches, to capture intricate patterns in electricity consumption data and improve prediction accuracy.

They are incorporating climate change variables and exploring the inclusion of climate-related variables like temperature variations and extreme weather events to understand their impact on electricity demand.

Cross-Sector Collaboration for Data Quality: Collaborative efforts between the energy sector, regulatory bodies, and technology providers can enhance data quality and the reliability of forecasting models.

Validation in Real-World Settings: Emphasizing comprehensive field testing and verification to validate the real-world effectiveness of forecasting models, contributing to their practical applicability and reliability.

Exploring these directions can enhance the adaptability, accuracy, and societal impact of electricity consumption forecasting models, supporting the sustainable development of the energy sector.

5. Conclusions

This study analyzed electricity consumption forecasting models, focusing on the Exponential Smoothing and Seasonal Autoregressive Integrated Moving Average (SARIMA) approaches. The Exponential Smoothing model and SARIMA model, when applied to electricity consumption data, demonstrated robust compatibility with historical trends. Both models' multiplicative trends and seasonal effects resulted in promising outcomes. Exponential Smoothing showed accurate predictions, as indicated by a low Sum of Squared Errors (SSE) value of 0.469, while SARIMA, with its seasonal ARIMA structure, slightly outperformed Exponential Smoothing, exhibiting even lower Mean Absolute Percentage Error (MAPE) values on both training (2.21%) and test (2.44%) datasets.

The implications of this study extend beyond the realm of Model Performance. Accurate electricity consumption forecasts profoundly impact energy sector planning, resource allocation, and the integration of renewable energy sources. This study underscores the importance of consumer-centric analysis, emphasizing the role of stakeholders and decision-makers in utilizing forecasted information for strategic planning and demand management.

This study highlights the importance of continuous monitoring and adaptation in the face of dynamic technological advancements, economic fluctuations, and changing consumer behaviors. While the models demonstrate high generalization capacity and robustness to unseen data, it is essential to acknowledge several limitations, including the complexity of the models, uncertainties in economic conditions, and the need for enhanced consumer engagement strategies.

Future research directions are proposed to advance electricity consumption forecasting further. These include interdisciplinary approaches to enhance model interpretability, incorporating economic indicators and climate change variables, extending forecasting horizons to analyze long-term trends, and exploring machine learning techniques for improved prediction accuracy.

Providing a roadmap for future research and action in electricity consumption forecasting, this study underscores the significance of forecasting in guiding strategic planning, resource allocation, and meeting the growing demand for electricity. The field of electricity consumption forecasting can evolve to meet the challenges posed by technological advancements, economic uncertainties, and changing consumer behaviors, ultimately contributing to the sustainable development of the energy sector.

The continuous monitoring of evolving trends, interdisciplinary collaboration, and incorporation of innovative technologies stand out as crucial aspects for advancing the field. Decision-makers, stakeholders, and researchers are urged to embrace these findings to foster a sustainable, adaptive, and consumer-centric energy landscape. We stand on the cusp of a transformative energy sector era characterized by increasing demand, technological advancements, and environmental consciousness. Robust forecasting models and proactive decision-making are imperative for shaping an energy ecosystem that not only meets current needs but also anticipates and adapts to future challenges. This study catalyzes informed, strategic, and collaborative efforts toward a resilient, sustainable energy future.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/su16072958/s1, Table S1: Electricty_Consumption.

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