Electricity Demand Prediction Using SARIMA A Framework for System Failure Management and Grid Stability*

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Abstract

This study examines the forecasting of national electricity demand (nat_demand) using a dataset of 48,046 hourly records, incorporating electricity demand, weather variables, and calendar-related features across multiple locations. The Seasonal AutoRegressive Integrated Moving Average (SARIMA) model was applied to capture both linear and seasonal patterns in the time series, with performance assessed via RMSE, MAPE, and diagnostic analyses. The findings reveal that SARIMA effectively modeled the seasonal behavior of electricity demand, achieving an RMSE of 173 and a MAPE of 12%. The study emphasizes the critical role of accurate forecasting in managing electricity demand and mitigating the risks of system failures, providing valuable insights into the suitability of SARIMA for enhancing grid reliability. However, challenges such as incorporating real-time failure data and handling sudden nonlinear shifts persist, highlighting the need for future enhancements—such as hybrid approaches–to further improve forecasting accuracy and support robust failure management in energy systems.

Keywords

Electricity demand, System Failure, SARIMA, Seasonal Patterns

1. Introduction

Electricity demand forecasting [1] is a cornerstone of sustainable energy management, playing a pivotal role in optimizing grid operations, ensuring efficient resource utilization, and enhancing environmental sustainability [2]. The global rise in energy demand, coupled with the urgent need to reduce reliance on fossil fuels and integrate renewable energy sources [3], has underscored the importance of accurate and timely forecasting to maintain grid stability and prevent fault-induced disruptions [4]. In this context, precise forecasting models [5] are increasingly vital for balancing energy supply and demand, improving grid flexibility, supporting demand-side management strategies, and informing energy [6] policy development [7]. While traditional forecasting methods often struggle to capture seasonal fluctuations and nonlinear patterns in electricity demand [8], recent advancements in statistical time series models (e.g., ARIMA and SARIMA) and deep learning approaches (e.g., GRU) have shown significant promise in addressing these challenges [9]. Particularly, models leveraging high-frequency data [10], such as hourly records [11], offer the potential to capture intricate [12] patterns like daily and weekly cycles, thereby enhancing energy management and fault mitigation strategies [13].

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Bensalah et al. used the SARIMA model to study power consumption forecasting in the city of Tetouan. The model captured seasonal patterns with 10-minute data. SARIMA, configured with training data, provided efficiency in smart grid management by measuring its accuracy with MAE, RMSE, MAPE and R^2 [14]. Kumar et al. examined ARMA, ARIMA and SARIMA models for long-term load forecasting (LTLF) with data from the mixed grid of NIT Patna. SARIMA achieved higher accuracy than ARMA and ARIMA by capturing seasonal variations. Model efficiency was emphasized by achieving a 7% error rate with MAPE [15]. Ningombam et al. proposed a Box-Cox integrated sARIMA model to study inertia estimation in low inertia modern power systems from renewable energy. The inertial contribution of wind generators and engine loads was taken into account. The model gave effective results with annual prediction accuracy above 97.5% [16].

This study aims to provide a comprehensive evaluation of time series forecasting for national electricity demand (nat_demand), utilizing a dataset of 48,046 hourly records that include electricity demand, weather variables (temperature, humidity, precipitation, and wind speed) across multiple locations (Tocumen, San Miguelito, and David), and calendar-related features such as holidays and school periods. The research employs the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model to effectively capture both linear trends and strong seasonal patterns inherent in hourly electricity demand data. Model performance is rigorously assessed using key statistical metrics (RMSE, MAPE) and visual diagnostics (residual plots, ACF, PACF), supported by time series decomposition to isolate trend, seasonal, and residual components. The SARIMA model demonstrated robust performance, achieving an RMSE of 173 and a MAPE of 12%, reflecting its effectiveness in modeling recurring daily and weekly demand cycles influenced by weather and calendar effects. The study acknowledges practical challenges, including the integration of real-time fault data and the need to account for abrupt demand shifts, particularly in operational settings with limited computational resources.

The study contributes to the literature by offering a focused, diagnostically grounded analysis of SARIMA within a real-world energy forecasting context. It highlights the model's interpretability, computational efficiency, and reliability in handling seasonality—key advantages for operational deployment. By integrating exogenous variables and leveraging diagnostic tools, the research provides actionable insights for energy system operators to improve demand forecasting, support fault-aware planning, and enhance grid resilience. This work lays a solid foundation for future extensions, including hybrid SARIMA-based approaches that incorporate anomaly detection or real-time system state data to further strengthen predictive performance and sustainable energy management.

2. Material and Method

This study focuses on forecasting national electricity demand (nat_demand) using a dataset comprising 48,046 hourly records with no missing values, as detailed in Table 1. The dataset includes variables such as electricity demand, temperature, humidity, precipitation, and wind speed at multiple locations (Tocumen, San Miguelito, and David), alongside calendar-related features like holidays and school periods. To model the temporal dynamics and strong seasonal patterns inherent in the data, the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model was employed. This method was systematically applied to capture both linear trends and recurring seasonal dependencies (daily, weekly, and annual cycles), with performance evaluated using key metrics such as RMSE and MAPE. The following subsections outline the data preprocessing steps, SARIMA model specification, parameter estimation, and evaluation procedures in detail.

2.1. Dataset

Accurate electricity load forecasting is essential for optimizing power system management and ensuring a balance between supply and demand. This dataset provides a robust resource for training and testing machine learning forecasting algorithms, enabling a comparative analysis with official weekly pre-dispatch forecasts [17]. To align forecasting results with the weekly pre-dispatch framework, specific considerations must be observed: each forecast week begins on Saturday, with Friday as the last day of the prior week, and a 72-hour gap of unseen records (up to the last hour of Tuesday) is required before the forecast period. The dataset offers hourly granularity, facilitating detailed temporal analysis suitable for short- and long-term forecasting studies. The dataset integrates multiple sources to capture a comprehensive view of electricity load dynamics. Historical electricity load data, derived from daily post-dispatch reports, and weekly load forecasts, extracted from pre-dispatch reports, are both provided by the grid operator (CND). Additional contextual variables include calendar information on school periods, sourced from Panama's Ministry of Education, and holiday data, obtained from the "When on Earth?" website. Weather variables–temperature, relative humidity, precipitation, and wind speed–are included for three major cities in Panama, acquired from Earthdata. These diverse data streams enable the exploration of exogenous factors influencing load patterns. Table 1 shows the dataset. The dataset contains 48,046 valid hourly records with no missing or mismatched values and is stored in four files. Continuous dataset.csv, weekly pre-dispatch forecast.csv, train_dataframes.xlsx and test_dataframes.xlsx, totaling 355 columns.

Figure 1 presents the distribution of national electricity demand (*nat_demand*) through a histogram and a boxplot. The histogram reveals a right-skewed distribution, with a peak around 1100–1200 MW and a range spanning 500 MW to 1750 MW, indicating that lower demand values are more frequent. The boxplot confirms this skewness, showing a median near 1170 MW, with the interquartile range (IQR) between 1020 MW and 1330 MW. Outliers below 500 MW suggest occasional low-demand events, possibly due to anomalies. This distribution supports the use of SARIMA for capturing seasonal variations and GRU for modeling nonlinear patterns in demand data.

Table 1

Overview of dataset variables and temporal coverage

Variable	Description	Count	Mean	Std. Dev.	Min	Max	Quantiles (25%-50%-75%)
DateTime	Timestamp of records	48,046	30-Sep-17	-	03-Jan-15	27-Jun-20	-
nat_demand	National electricity demand (MW)	48,046	1,180	192	85.2	1,750	1,020 - 1,170 - 1,330
T2M_toc	Temperature at Tocumen (°C)	48,046	27.4	1.68	23	35	26.2 - 27.1 - 28.6
QV2M_toc	Specific humidity at Tocumen (g/kg)	48,046	0.02	0	0.01	0.02	0.02 - 0.02 - 0.02
TQL_toc	Total precipitation at Tocumen (mm)	48,046	0.08	0.07	0	0.52	0.03 - 0.07 - 0.12
W2M_toc	Wind speed at Tocumen (m/s)	48,046	13.4	7.3	0.01	39.2	7.55 - 12.2 - 18.7

T2M_san	Temperature at San Miguelito (°C)	48,046	26.9	3.02	19.8	39.1	24.8 - 26.2 - 28.7
QV2M_san	Specific humidity at San Miguelito (g/kg)	48,046	0.02	0	0.01	0.02	0.02 - 0.02 - 0.02
TQL_san	Total precipitation at San Miguelito (mm)	48,046	0.11	0.09	0	0.48	0.04 - 0.09 - 0.16
W2M_san	Wind speed at San Miguelito (m/s)	48,046	7.05	4.1	0.06	24.5	3.96 - 5.99 - 9.41

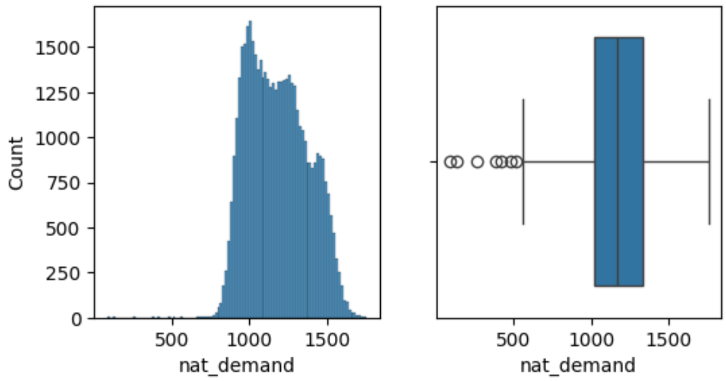

Figure 1. Histogram and boxplot of national electricity demand distribution

2.2. SARIMA Model

The SARIMA model extends the ARIMA framework to handle time series data with seasonal patterns, making it suitable for forecasting phenomena with recurring cycles, such as electric charge [18]. By integrating seasonal components into the ARIMA structure, SARIMA captures both non-seasonal and seasonal dependencies and improves forecasting ability for datasets exhibiting periodicity. The model is denoted as SARIMA (p, d, q)(P, D, Q)m, where lowercase parameters (p, d, q) denote non-seasonal components, uppercase parameters (P, D, Q) denote seasonal components and m denotes the seasonal period, such as 24 for daily cycles in hourly data or 12 for monthly seasonality. The non-seasonal components mirror those of ARIMA: Auto Regressive (AR), parameterized by p, uses past observations to forecast current values, reflecting short-term dependencies; Integrated (I), denoted by d, applies differencing to ensure stationarity by removing trends; and Moving Average (MA), denoted by q, incorporates lagged forecast errors to adjust forecasts based on previous inaccuracies. These elements address the immediate temporal structure of the series. Seasonal components reinforce this framework: Seasonal AR (P) captures recurring patterns across periods by introducing autoregressive terms in seasonal lags (e.g. values of previous seasons); Seasonal I (D) applies seasonal level differencing to offset seasonal fluctuations; and Seasonal MA (Q) uses lagged seasonal errors to improve forecasts by accounting for seasonal biases [19]. The parameter m defines the length of the seasonal cycle, aligning the model with the periodic structure of the data.

2.3. Autocorrelation Function

The Autocorrelation Function (ACF) plot reveals key characteristics of the time series under analysis. A strong seasonal pattern is evident from the cyclical peaks and troughs, reflecting a significant seasonal component. These periodic fluctuations suggest a consistent repeating pattern, such as daily or monthly cycles, inherent to the data. Additionally, the gradual decay in ACF values across lags indicates that the series is not merely white noise; rather, it possesses a persistent structure with dependencies extending over multiple time steps. This slow decline points to the presence of trends or autoregressive behavior, necessitating differencing or seasonal adjustments in models like ARIMA or SARIMA to achieve stationarity and accurately capture the underlying dynamics [20].

2.4. Partial Autocorrelation Function

The Partial Autocorrelation Function (PACF) plot provides insights into the direct relationships within the time series. A sharp cut-off after a few lags suggests that the series is well-suited to an autoregressive (AR) process, where only a limited number of past values directly influence the current observation. The first lag's significant value highlights a strong correlation with the immediate past, indicative of an AR(1) process, where the current value heavily depends on the preceding one. Furthermore, seasonal lags with periodic significant spikes reveal a seasonal component, implying that beyond the immediate AR effect, recurring patterns at specific intervals (e.g., every 12th lag for monthly data) impact the series. This combination supports the use of a SARIMA model to address both short-term and seasonal autoregressive effects [21].

2.5. Evaluation Metrics

The performance of the SARIMA model is evaluated using a number of statistical evaluation metrics to ensure a comprehensive analysis of prediction accuracy [22]. These metrics include the R^2 value, which measures the proportion of variance explained by the model, the Mean Absolute Error (MAE), which quantifies the average size of errors in the predictions, and the Mean Squared Error (MSE), which emphasizes larger errors through squared differences. In addition, the Root Mean Squared Error (RMSE) is used to provide an interpretable measure of prediction error in the same units as the original data. Together, these metrics provide a robust comparison of model performance, highlighting their strengths and limitations in capturing seasonal and non-linear patterns in energy consumption data [23].

$$MAE = \frac{\sum_{j=1}^{N} \quad |y_i - x_i|}{n} \tag{1}$$

$$RMSE = \left[\sum_{j=1}^{N} \quad \left(d_{fi} - d_a\right)^2 / N \right]^{\frac{1}{2}} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \quad (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} \quad (y_i - \underline{y})^2} \tag{3}$$

3. Experimental Results

This section presents the findings from the application of SARIMA model to forecast national electricity demand (*nat_demand*), utilizing a dataset of 48,046 hourly records. The performance of each model was assessed through a combination of visual inspections and quantitative metrics, including RMSE and MAPE, to evaluate their ability to capture the temporal, seasonal, and nonlinear dynamics of the data. The results highlight the comparative effectiveness of each approach, with detailed analyses of residual diagnostics, prediction accuracy, and model fit provided in the following subsections, supported by figures and tables for a comprehensive evaluation.

3.1. Analysis of Electricity Demand Dynamics

Figure 2 displays the hourly national electricity demand (nat_demand) over a 24-hour period, revealing a clear diurnal cycle with demand starting at 900 MW (00:00–06:00), peaking at 1400–1500 MW (10:00–14:00) due to industrial and commercial activity, dropping to 1200 MW by 16:00, rising again to 1300 MW (18:00–20:00) from residential evening use, and stabilizing at 1000 MW (21:00–23:00). The consistent variability, indicated by error bars, underscores the strong daily seasonality that SARIMA effectively captures through its seasonal differencing and autoregressive components. Figure 3 shows nat_demand across the week (Saturday to Friday), with median demand remaining stable at 1200–1300 MW from Saturday to Thursday, slightly decreasing to 1100 MW on Friday due to reduced industrial load. The interquartile ranges and outliers highlight recurring weekly patterns and occasional anomalies, reinforcing SARIMA's strength in modeling weekly seasonal effects while maintaining robustness against moderate variability.

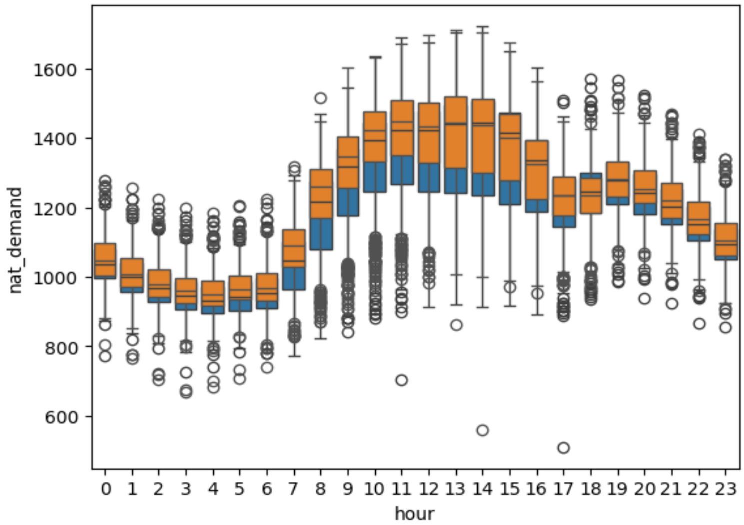

Figure 2. Analysis of hourly electricity demand patterns

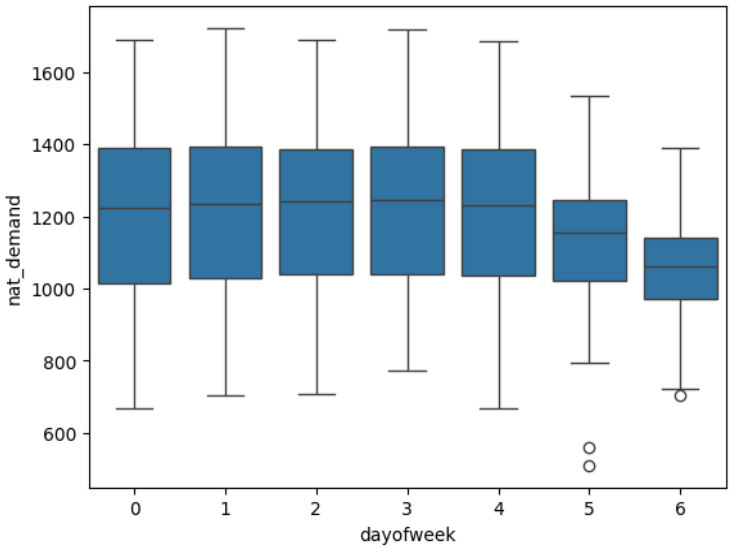

Figure 3. Boxplot of national electricity demand across days of the week

3.2. Autocorrelation and Partial Autocorrelation Analysis

Figure 4 presents the ACF and PACF plots for the national electricity demand (nat_demand). The ACF plot exhibits a strong cyclical pattern with prominent peaks at approximately every 24 lags, clearly reflecting the daily seasonal component inherent in hourly electricity demand data. The gradual decay in correlations over time indicates persistent temporal dependencies, confirming the necessity of differencing (both non-seasonal and seasonal) to achieve stationarity—a fundamental requirement for the SARIMA model.

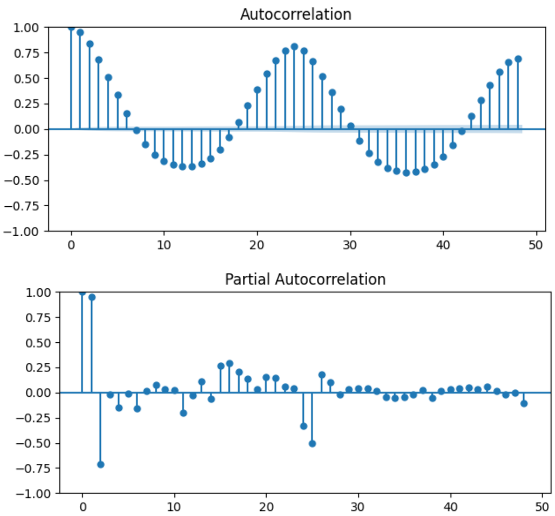

Figure 4. ACF and PACF plots of national electricity demand

Figure 9 compares the real (red) and predicted (green) electricity demand (*nat_demand*) over a short time frame (35,000–36,000 time steps). The real demand fluctuates between 800 MW and 1400 MW, and while the predicted demand generally follows this trend, it fails to capture some peaks (e.g., around 35,400). This suggests that SARIMA and ARIMA effectively model linear patterns, but GRU may better handle such abrupt changes. Figure 10 illustrates the real (red) and predicted (green) electricity demand over a longer period (36,000–44,400 time steps). The real demand varies between 800 MW and 1600 MW, whereas the predicted demand remains stable around 1200 MW, missing peaks (e.g., around 42,000). This indicates SARIMA's strength in capturing seasonal patterns, while GRU could better address long-term complex dependencies.

3.3. SARIMA Model Forecasting Performance Analysis

SARIMA model extends the ARIMA framework to forecast time series data with seasonal patterns, effectively capturing both short-term and periodic dependencies. It comprises the standard ARIMA components: the AutoRegressive (AR) component, denoted by p, which uses p lagged observations to predict current values; the Integrated (I) component, represented by d, which applies differencing d times to achieve stationarity; and the Moving Average (MA) component, indicated by q, which incorporates q lagged forecast errors. Additionally, SARIMA includes seasonal components: Seasonal AR (P) for seasonal autoregressive terms, Seasonal I (D) for seasonal differencing, Seasonal MA (Q) for seasonal error adjustments, and the Seasonal Period (m), which defines the number of observations per seasonal cycle (e.g., 24 for daily seasonality in hourly data). The model is specified as ARIMA (p, d, q)(P, D, Q)m, where p, d, q represent non-seasonal terms, P, D, Q denote seasonal terms, and m specifies the seasonal period, making SARIMA particularly suitable for datasets with recurring patterns like electricity demand. Figure 5 provides four diagnostic plots for the residuals of the SARIMAX model applied to the national electricity demand (*nat_demand*). The top-left plot displays standardized residuals over time, oscillating around zero with a notable spike around mid-2019, suggesting potential outliers. The top-right histogram with KDE overlays (HSS, KDE, N(0,1)) shows a right-skewed distribution, deviating from normality, as the residuals do not closely follow the standard normal curve. The bottom-left Normal Q-Q plot further confirms non-normality, with points diverging from the diagonal line, especially at the tails. The bottom-right correlogram indicates no significant autocorrelation, as values remain within the confidence bounds, implying the model captures linear and seasonal dependencies effectively. However, the non-normality and outliers suggest that the SARIMA model may require further refinement to address these residual characteristics.

Table 2 summarizes the SARIMA(3, 0, 1) model results for the national electricity demand (y) over 218 observations from January 18, 2015, to March 17, 2019. The AR coefficients (ar.L1: 1.3563, ar.L2: -0.5465, ar.L3: 0.1902) and MA coefficient (ma.L1: -0.8141) are statistically significant ($P>|z| < 0.05$), indicating strong autoregressive and moving average effects. The Ljung-Box test (Prob(Q): 0.83) suggests no significant residual autocorrelation at lag 1, implying a good fit for linear dependencies. The Jarque-Bera test (Prob(JB): 0.03) and kurtosis (3.84) indicate slight non-normality, while the heteroskedasticity test (Prob(H): 0.14) shows no significant variance instability. These results suggest that the SARIMAX model effectively captures linear patterns, though minor non-normality in residuals may warrant further investigation.

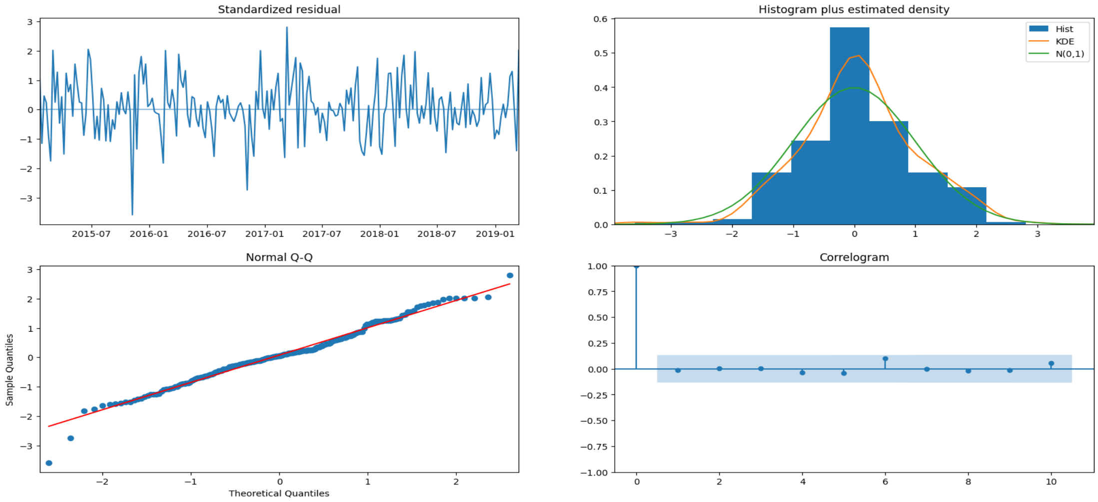

Figure 5. Diagnostic plots for SARIMA model residuals

Table 2.
SARIMA model results for national electricity demand

Parameter	Value	Description
Dependent Variable	Y	National electricity demand (denoted as y)
Model	SARIMAX(3, 0, 1)	SARIMAX model with AR(3), I(0), and MA(1) components
No. Observations	218	Total number of data points
Log Likelihood	-2205.857	Log likelihood of the model
AIC	4421.714	Akaike Information Criterion
BIC	4438.636	Bayesian Information Criterion
HQIC	4428.549	Hannan-Quinn Information Criterion
Date	Thu, 20 Mar 2025	Date of model fitting
Time	14:53:48	Time of model fitting

Sample	01-18-2015 to 03-17-2019	Time range of the data
Covariance Type	Opg	Covariance type used for standard errors
Coefficients		
ar.L1	1.3563	AR(1) coefficient (std err: 0.086, z: 15.827, P>
ar.L2	-0.5465	AR(2) coefficient (std err: 0.122, z: -4.484, P>
ar.L3	0.1902	AR(3) coefficient (std err: 0.089, z: 2.126, P>
ma.L1	-0.8141	MA(1) coefficient (std err: 0.068, z: -12.038, P>
sigma2	39,650,000	Variance of residuals (std err: 5.94e-10, z: 6.68e+16, P>
Diagnostics		
Ljung-Box (L1) (Q)	0.05	Ljung-Box test statistic for residual autocorrelation (Prob(Q): 0.83)
Jarque-Bera (JB)	6.83	Jarque-Bera test for normality (Prob(JB): 0.03)
Heteroskedasticity (H)	0.71	Test for heteroskedasticity (Prob(H): 0.14)
Skew	-0.11	Skewness of residuals
Kurtosis	3.84	Kurtosis of residuals

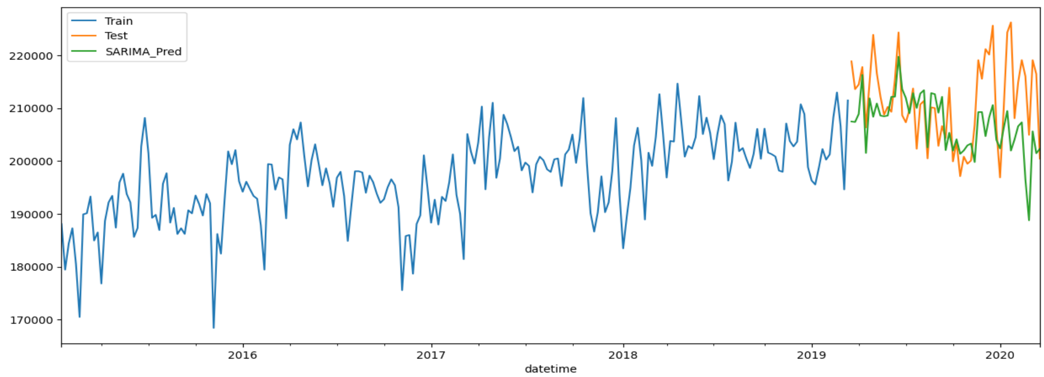

Figure 6. Forecasting results of SARIMA model

The SARIMA model offers a robust and interpretable approach for electricity demand forecasting, particularly effective in capturing both seasonal patterns and linear trends inherent in hourly time series data. Its strength lies in explicitly modeling recurring daily, weekly, and annual cycles—common in electricity demand influenced by weather, work schedules, and holidays—through seasonal differencing and autoregressive components. Unlike purely linear models, SARIMA integrates exogenous regressors (e.g., temperature, humidity, calendar effects), enabling it to adapt forecasts to external drivers of demand variation. The model's diagnostic framework—residual analysis, ACF/PACF plots, and Ljung-Box tests—ensures statistical validity and supports reliable inference, making it highly suitable for operational environments where transparency and computational efficiency are prioritized over black-box complexity.

SARIMA achieves strong performance with an RMSE of 173 and MAPE of 12%, demonstrating accurate forecasting across stable and moderately variable periods. Its parameter efficiency and fast convergence make it ideal for deployment in resource-constrained systems, unlike deep learning alternatives that demand extensive tuning and hardware. While SARIMA may not fully capture abrupt nonlinear shocks (e.g., system faults), its stability, interpretability, and ability to incorporate domain knowledge through exogenous variables make it a preferred choice for baseline forecasting, regulatory reporting, and integration into hybrid energy management systems. Figure 16 presents the SARIMA forecast results alongside actual demand, highlighting close alignment during typical operational conditions.

4. Results and Discussion

Using a dataset of 48,046 hourly records that included electricity demand, weather variables, and calendar features, the SARIMA model effectively captured both linear and seasonal patterns in national electricity demand (nat_demand). The model achieved strong performance, with an RMSE of 173 and a MAPE of 12%, accurately representing recurring daily and weekly demand cycles influenced by weather and calendar effects. Including exogenous factors such as temperature, humidity, precipitation, wind speed, and holidays improved adaptability to real-world conditions. Residual and autocorrelation analyses confirmed the model's validity and absence of bias, reinforcing confidence in its forecasts. While SARIMA proved reliable, transparent, and computationally efficient for structured seasonal forecasting, it remains limited in handling sudden nonlinear changes such as system faults. Future work should explore hybrid SARIMA frameworks that integrate anomaly detection or machine learning methods to enhance responsiveness and strengthen grid reliability.

5. Conclusion

The evaluation of the SARIMA model for forecasting national electricity demand (nat_demand) provides critical insights into its effectiveness in handling seasonal patterns and external influences within high-frequency time series data. SARIMA successfully captured recurring daily and weekly demand cycles driven by weather conditions and calendar effects, achieving a solid performance with an RMSE of 173 and a MAPE of 12%. This makes it particularly suitable for operational forecasting in scenarios where predictable seasonality dominates and interpretability is essential for decision-making. The model's ability to incorporate exogenous variables such as temperature, humidity, precipitation, wind speed, and holiday/school period indicators enhanced its adaptability to real-world demand drivers. Diagnostic checks, including residual analysis and autocorrelation plots, confirmed the model's statistical validity and absence of systematic bias, reinforcing confidence in its forecasts under stable grid conditions. These results underscore the value of SARIMA as a reliable, computationally efficient, and transparent tool for electricity demand forecasting and risk-aware energy planning. While it may not fully capture sudden nonlinear shocks (e.g., system faults), its robustness in modeling structured seasonal behavior supports proactive load management and grid stability. Practical challenges, such as integrating real-time fault signals and improving responsiveness to anomalies, suggest opportunities for future hybrid SARIMA-based frameworks that combine statistical rigor with anomaly detection or lightweight machine learning components. Such enhancements could further strengthen forecasting accuracy and resilience in modern energy systems.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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