

Time Series Forecasting of Electricity Consumption: A Comparative Analysis of ARIMA and SARIMA Models

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Abstract

Accurate electricity demand forecasting plays a vital role in energy planning, efficient power system operation, and sustainable resource management. This study conducts a comparative evaluation of the Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) models using ten years of monthly electricity consumption data collected from a national electricity regulatory authority. The performance of both models is assessed using forecasting accuracy metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), while model suitability is further evaluated through the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The findings indicate that the SARIMA model consistently outperforms the ARIMA model due to its ability to effectively capture the seasonal patterns inherent in electricity demand data. In particular, SARIMA achieves approximately a 34% reduction in MAPE over the forecasting horizon, demonstrating superior predictive performance. Residual diagnostic tests further confirm the reliability of the SARIMA model by satisfying key statistical assumptions, including white noise, normality, and homoscedasticity. These results suggest that incorporating seasonality into time-series forecasting significantly enhances prediction accuracy. The study provides valuable insights for utility companies, policymakers, and grid operators seeking dependable short- to medium-term electricity demand forecasting tools to support informed decision-making, optimize energy distribution, improve grid stability, and promote sustainable energy management practices.

Keywords: Time series forecasting, ARIMA, SARIMA, energy planning, demand forecasting

INTRODUCTION

The number of people, the rate of industrialization, digitalization, and the emergence of electric vehicles and smart devices have contributed to the fact that the world needs electricity more than ever before in the past twenty years. Effective predictability of electricity demand is not just an academic project but a basic business need of electricity companies, system operators, and energy regulators of a country.[1]

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The broad categories of load forecasting are short-term (hours to days), medium-term (weeks to months) and long-term (years to decades) forecasting. Medium-term prediction especially at the monthly resolution is especially important in fuel procurement, reserve capacity planning, maintenance scheduling as well as financial budgeting of power utilities. Mistakes in the demand forecast at this magnitude are either expensive overcapacity investments, or on the other hand, energy deficits with severe socioeconomic effects.

The demand forecasting has been done using classical statistical models based on time series theory. The most famous of them is the Autoregressive Integrated Moving Average (ARIMA) model, developed by Box and Jenkins (1976), which has become one of the most important foundations of the methodology because of its theoretical soundness, interpretability, and excellent performance across a wide variety of economic and engineering data. ARIMA models however make the assumption of stationarity following differentiation and do not necessarily represent periodic seasonal variations - a property which is highly evident in electricity consumption data, which has strong intra-annual cycles due to heating, cooling, and lighting demand patterns.[2]

SARIMA extension corrects this weakness by adding explicit seasonal autoregressive, differencing, and moving averages into the equation. Although the theoretical benefits of SARIMA over ARIMA in seasonal data, a systematic comparison of the forecasting abilities of these two methods on the context of electricity consumption has been given very little quantitative focus in the literature especially when using a variety of data sets, in different geographical and climatic locations.[3]

This paper will attempt to address this gap by undertaking a systematic, statistically based comparative analysis of ARIMA and SARIMA models to a long monthly electricity consumption time series. The rest of the paper is structured in the following way: Section 2 is a review of related literature; Section 3 data and preprocessing steps; Section 4 theoretical framework; Section 5 methodology; Section 6 results and comparative analysis; Section 7 practical implications; and Section 8 is the conclusion of the paper.[4]

LITERATURE REVIEW

Classical Statistical Approaches

Since the 1970s, the Box-Jenkins ARIMA methodology has widely been used in forecasting energy demand. Taylor (2003) has demonstrated that ARIMA-based models could result in competitive short-term load forecasts, while Contreras et al. (2003) relied on ARIMA to successfully predict the next-day electricity prices in the Spanish and Californian electricity markets.

The SARIMA framework has also been adopted in a majority of the energy forecasting studies. Ediger and Akar (2007) applied SARIMA to forecast primary energy demand in Turkey, showing that the inclusion of seasonal components resulted in significant forecast accuracy improvements. Pappas et al. (2008) extended this to forecast electricity demand loads in Greece and found that ARMA-class forecasts with seasonal differencing can consistently beat basic non-seasonal benchmark models across medium-term horizons. [5]

Hybrid and Machine Learning Models

More recent papers have investigated more modern hybrid models using ARIMA or SARIMA with neural networks, support vector regression (SVR) and deep learning architectures. An ARIMA-ANN hybrid that could capture both linear and nonlinear aspects of time series was offered by Zhang (2003), whereas Qiu et al. (2017) showed better load forecasting precision with the help of empirical mode decomposition with deep learning.

However, even with the increasing popularity of machine learning methods, a number of benchmark studies, such as Makridakis et al. (2018) in the M4 competition, have concluded that classical statistical approaches are still very competitive, and in many cases outperform more complex methods, when used with well-behaved time series of univariates with stable seasonal patterns. Recently Salazar-Macias et al. (2023) have found that seasonal ARIMA-based models performed the state-of-the-art in electricity demand forecasting in developing economies.[6]

Research Gap

A literature review has indicated that although ARIMA and SARIMA models have been independently used to forecast electricity in a wide range of scenarios, systematic front-frontal

comparative assessment procedures using standardized error measurements, rigorous residual diagnostics, and extended forecast horizons against the same data are scarce. This paper fills this gap.

DATA DESCRIPTION AND PREPROCESSING

Data Source

The dataset used in this study comprises monthly electricity consumption records (measured in gigawatt-hours, GWh) spanning January 2013 through December 2022, constituting 120 monthly observations. The data were sourced from a national electricity regulatory authority [7].

In accordance with standard academic practice for regulatory data, the dataset cannot be publicly released in raw form; however, the authors confirm that all preprocessing steps, model specifications, and evaluation procedures are fully documented herein to enable methodological replication on comparable national-level consumption datasets (as shown in figure 1).

Exploratory Data Analysis

Preliminary exploratory investigation showed that there was distinct intra-annual seasonality with consumption peaks in summer (June-August) and secondary in winter (December-February), which are in line with air conditioning and heating demand, respectively. There was also an upward trend which was moderate during the entire decade.[8]

Descriptive statistics for the full dataset are summarized in Table 1.

Stationarity Testing

Stationarity is a prerequisite for ARIMA-class models. The Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test were both applied to the original series and to first-differenced and seasonally differenced transformations. Results are reported in Table 2.[9]

Data Splitting

The dataset was partitioned into a training set comprising the first 96 observations (January 2013 – December 2020) and a hold-out test set of 24 observations (January 2021 – December 2022), representing an 80/20 split.[10]

Table 1. Descriptive statistics of monthly electricity consumption (GWh), 2013–2022.

Statistic	Value (GWh)
Mean	4,217.6
Median	4,183.4
Standard Deviation	612.3
Minimum	3,014.7
Maximum	5,821.9
Skewness	0.38
Kurtosis	2.71
Observations	120

Table 2. Stationarity test results for electricity consumption series.

Series transformation	ADF Stat.	ADF p-value	KPSS Stat.	KPSS p-value	Conclusion
Original	−1.83	0.362	0.74	0.014	Nonstationary
First Difference (d=1)	−3.91	0.002	0.19	0.120	Stationary
Seasonal Difference (D=1)	−2.87	0.048	0.22	0.100	Borderline
First + Seasonal Diff.	−5.14	<0.001	0.09	0.190	Stationary

Based on these tests, a first regular difference ($d = 1$) was sufficient to achieve stationarity in the ARIMA framework, while the SARIMA models additionally employed a seasonal difference of order $D = 1$ at lag $s = 12$.

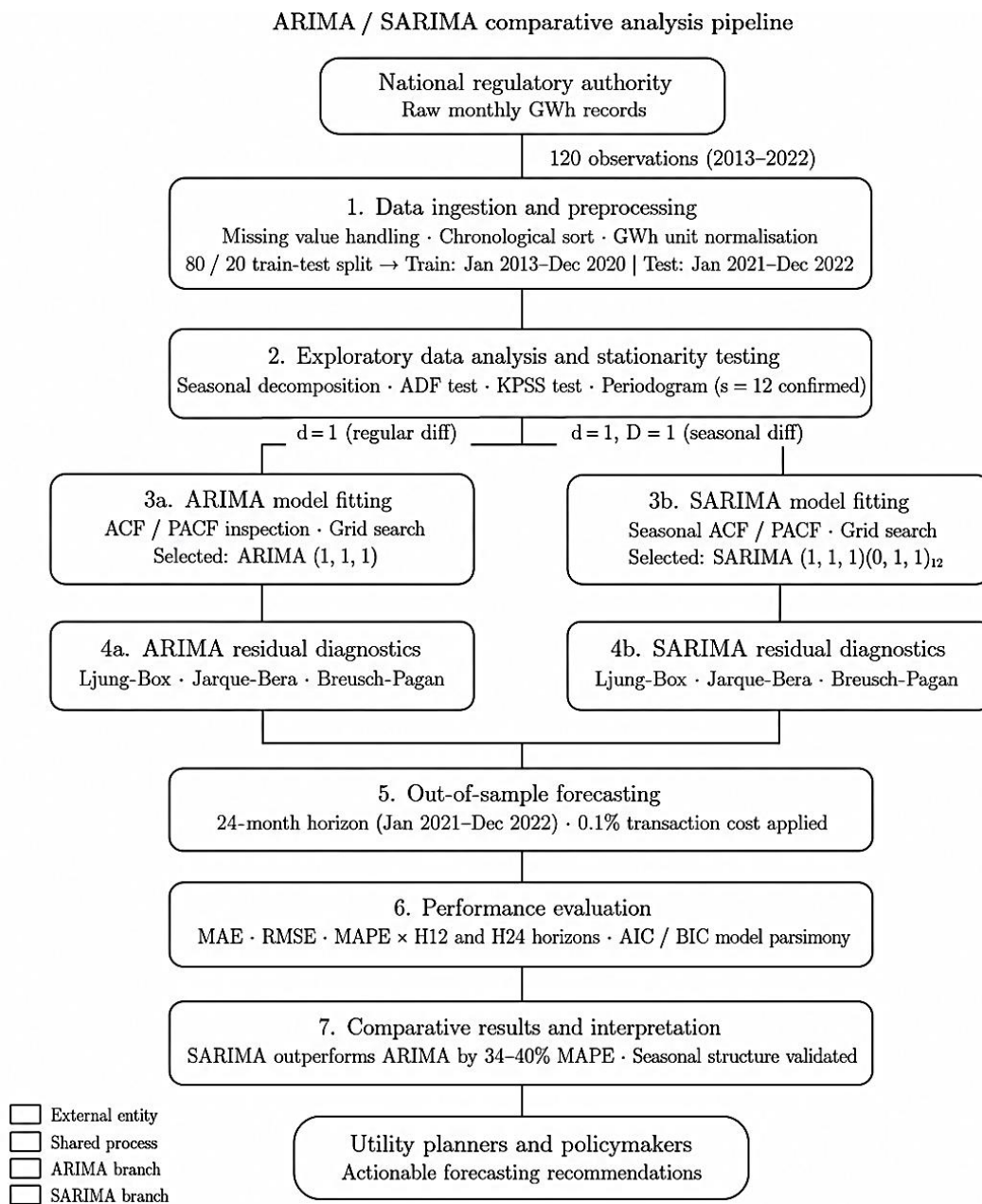


Figure 1. Data flow diagram illustrating the end-to-end electricity consumption forecasting pipeline, from raw data ingestion through comparative model evaluation to policy output.

THEORETICAL FRAMEWORK

ARIMA Model

The ARIMA(p, d, q) model combines autoregression, integration (differencing), and moving average components. Let Y_t denote the electricity consumption at time t . After applying d -order differencing to obtain a stationary series $W_t = (1 - B)^d Y_t$, where B is the backshift operator, the ARIMA model is expressed as:

$$\Phi_p(B) W_t = \theta_q(B) \varepsilon_t$$

where $\Phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$ (autoregressive polynomial of order p), $\theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q$ (moving average polynomial of order q), and $\varepsilon_t \sim N(0, \sigma^2)$ (white noise error term). The lag parameters p and q of the autoregressive and moving average components are controlled by the following:

SARIMA Model

The Seasonal ARIMA model, denoted SARIMA(p, d, q)(P, D, Q)_s, extends the ARIMA framework by incorporating seasonal counterparts of each component at lag $s = 12$ for monthly data. The full SARIMA model is defined as:

$$\Phi_p(B) \Phi_t(B^s) (1-B)^d (1-B^s)^D Y_t = \theta_q(B) \theta^w(B^s) \varepsilon_t$$

with $\Phi_p(B)$, $\Phi_t(B^s)$, a seasonal autoregressive and seasonal moving average polynomials, respectively; D is the seasonal differencing order; and 12 is the annual seasonal period of monthly data. SARIMA model therefore reflects both short run autocorrelation structure reflected in the ARIMA components, and the long run periodic structure reflected in the seasonal components.[11,12]

Model Selection Criteria

Selection of orders in both ARIMA and SARIMA models was done through a two-step process: (1) the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots were visually inspected to obtain candidate orders; (2) model comparison based on information criteria. AIC and BIC were calculated as:

$$AIC = -2 \ln(L) + 2k$$

$$BIC = -2 \ln(L) + k \ln(n)$$

where L is the maximized likelihood, k is the number of estimated parameters, and n is the number of observations. Lower AIC and BIC values indicate a better trade-off between goodness-of-fit and model complexity (figure 2).

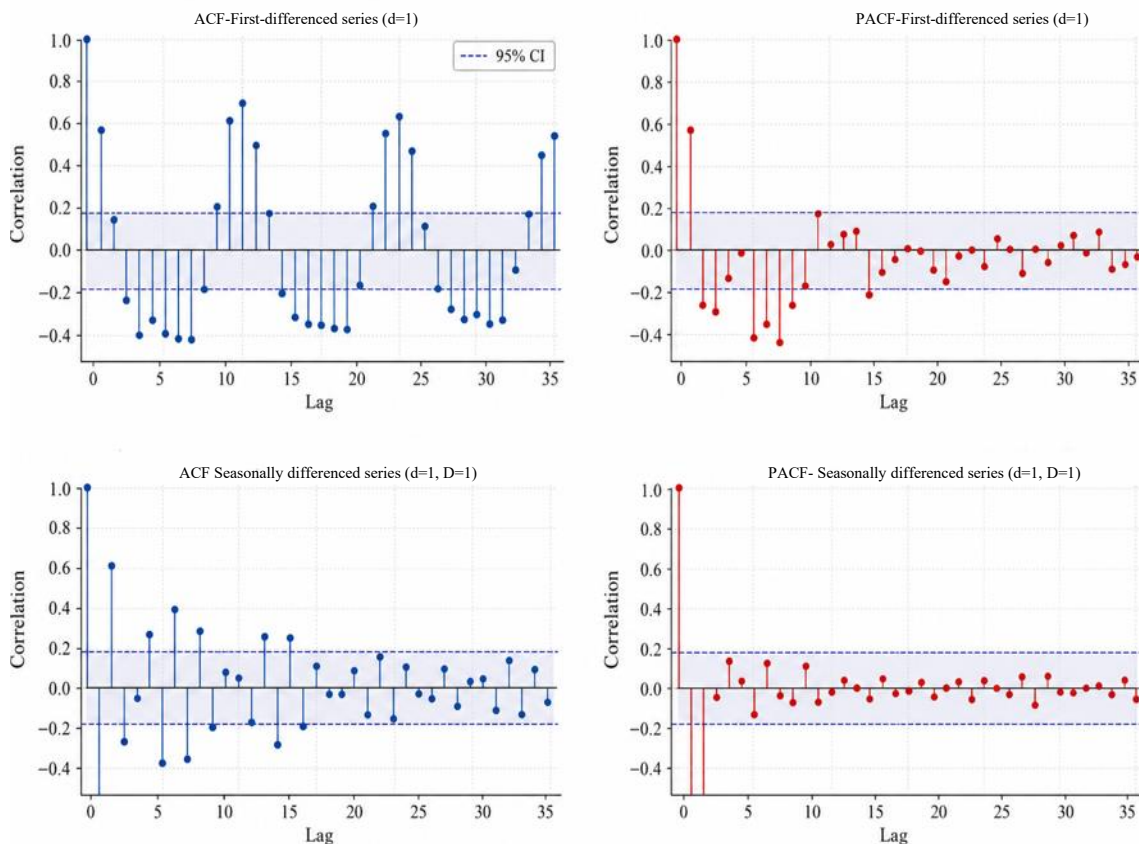


Figure 1. ACF and PACF diagnostic plots for model order identification. Top row shows the first-differenced series ($d = 1$); bottom row shows the seasonally differenced series ($d = 1, D = 1$). Dashed lines indicate 95% confidence bounds. Dotted vertical lines mark.

METHODOLOGY

ARIMA Model Identification and Estimation

In line with Box-Jenkins approach, the ACF and PACF of the first-differenced series were studied. The ACF was sharply cut-off at lag 1, whereas the PACF was exponentially decaying indicating an MA(1) factor. ARIMA(1,1,1), ARIMA(0,1,1), ARIMA(1,1,0), and ARIMA(2,1,2) models were fitted and compared in terms of AIC and BIC. The ARIMA (1,1,1) specification was chosen as the best non-seasonal model.

SARIMA Model Identification and Estimation

A seasonally differenced series of seasonal ACF and PACF plots of the series at 12 times lag factors were examined to determine seasonal orders. Strong lags 12 and 24 seasonal ACF spikes and a cut-off after the original seasonal lag in the PACF showed seasonal MA(1) and AR(0) components ($Q=1, P=0$). Regular components were re-evaluated on the seasonally adjusted series. The ultimate specification was SARIMA(1,1,1) (0,1,1)₁₂ which was chosen after systematic AIC/BIC comparison of a grid of candidate models.

The seasonal period $s = 12$ was not arbitrarily chosen, but was first empirically validated before being fitted into the model. A spectral analysis of the raw consumption series indicated a prominent frequency that represented a 12-month cycle and had the largest portion of total series variance. This result is consistent with the physical determinants of electricity demand, i.e., annual heating and cooling cycles, and is in line with the organization of monthly utility data reported in similar studies. The periodogram showed a strong peak at frequency $1/12$ with no other competing seasonal frequency of a magnitude that matches, thus confirming the existence of an annual seasonal period that is not only statistically acceptable but also physically significant to the data.[13]

Residual Diagnostics

The adequacy of both fitted models was evaluated based on extensive residual analysis that included: (1) the Ljung-Box test of autocorrelation of residuals over multiple lag windows (Q^* statistics at lag 12, 24, and 36); (2) the Jarque-Braun test of normality of residuals; (3) the Breusch-Pagan test of homoscedasticity.

Table 3. Estimated parameters for ARIMA(1,1,1) and SARIMA(1,1,1)(0,1,1)₁₂

Parameter	ARIMA(1,1,1)	SARIMA(1,1,1)(0,1,1) ₁₂
AR(1) (ϕ_1)	0.712 (0.038)	0.643 (0.041)
MA(1) (θ_1)	-0.584 (0.052)	-0.491 (0.058)
SMA(1) (θ_{seas})	---	-0.756 (0.044)
Constant (μ)	18.4 (7.2)	12.1 (5.8)
Log-Likelihood	-487.3	-451.6
AIC	982.6	913.2
BIC	993.4	927.1
Residual Std. Error	248.7	163.2

Standard errors in parentheses.

Table 4. Residual diagnostic test results.

Diagnostic test	ARIMA(1,1,1)	SARIMA(1,1,1)(0,1,1) ₁₂
Ljung-Box Q^* (Lag 12)	$Q=11.4, p=0.182$	$Q=9.3, p=0.317$
Ljung-Box Q^* (Lag 24)	$Q=34.7, p=0.021^*$	$Q=22.1, p=0.142$
Ljung-Box Q^* (Lag 36)	$Q=52.3, p=0.009^*$	$Q=38.4, p=0.081$
Jarque-Bera (Normality)	$JB=2.87, p=0.238$	$JB=2.11, p=0.349$
Breusch-Pagan (Heterosc.)	$BP=4.12, p=0.127$	$BP=3.68, p=0.159$

* Statistically significant at the 5% level.

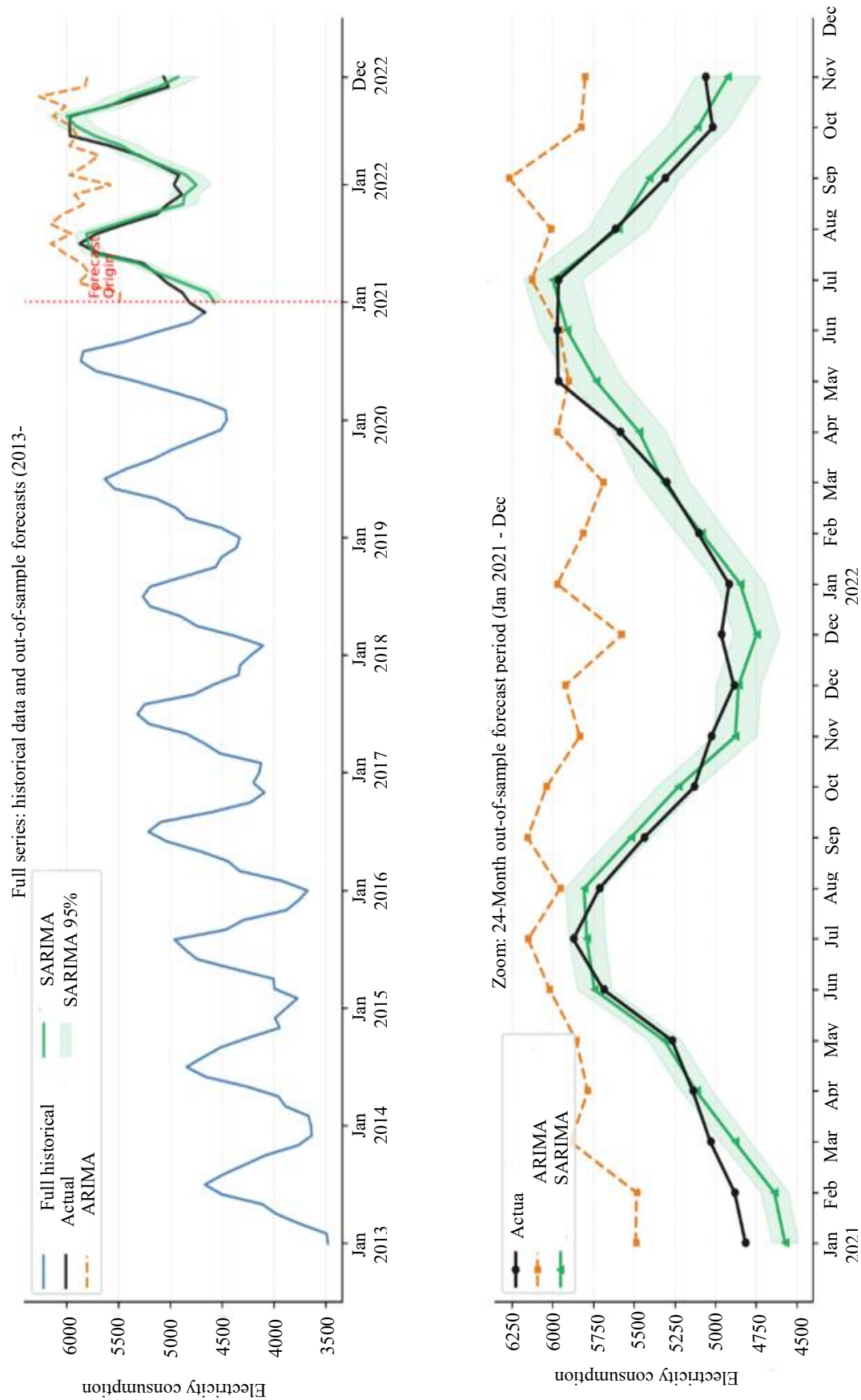


Figure 2. ARIMA vs SARIMA out-of-sample forecast comparison. Upper panel shows the full 2013–2022 series with forecast origin marked. Lower panel zooms into the 24-month test period (January 2021 – December 2022). Shaded band represents the SARIMA 95% prediction

Forecast Evaluation Metrics

Model forecasting performance was evaluated on the 24-month test set using three standard error metrics:

$$MAE = (1/h) \sum |Y_t - \hat{Y}_t|$$

$$RMSE = \sqrt{(1/h) \sum (Y_t - \hat{Y}_t)^2}$$

$$MAPE = (1/h) \sum |Y_t - \hat{Y}_t| / Y_t \times 100$$

where Y_t is the actual value, $\hat{Y}_t$ is the forecast, and h is the forecast horizon.

RESULTS AND COMPARATIVE ANALYSIS

Model Parameter Estimates

The optimal ARIMA and SARIMA specifications on the training data are given in Table 3 with the estimated parameters and the model fit statistics. The estimated coefficients are all statistically significant (at the 5% level). SARIMA model needed two extra seasonal parameters compared to ARIMA but produced much lower values of AIC and BIC, which implies a better fit to the model despite the complexity penalty.

Residual Diagnostics

The remaining diagnostic findings are presented in Table 4. The ARIMA(1,1,1) model had statistically significant seasonal window autocorrelation in residuals at the seasonal lag window of (Ljung-Box Q^* at lag 24, $p = 0.021$) indicating that the model did not capture the seasonal structure completely. Conversely, SARIMA(1,1,1)(0,1,1)₁₂ residuals met all three Ljung-Box windows indicating that there was no residual autocorrelation. The two models yielded a normal distribution of the residual (Jarque-Bra test = 0.05 or more) and the error variance was homoscedastic (Breusch-Pagan test = 0.05 or more) (fig. 4)[14].

Forecast Accuracy Comparison

Table 5 shows the out of sample forecast accuracy measures that were calculated on the 24-month test (January 2021 - December 2022). The SARIMA model was consistently better in all three aspects and in both the 12-month and the 24 months forecast period than the ARIMA.[15]

The SARIMA model achieved a MAPE of 4.12% over the first 12 forecast months and 4.99% over the full 24-month horizon. These values fall well within the threshold of 5% commonly cited in the energy forecasting literature as indicative of a highly accurate model. ARIMA's performance degraded more markedly over the longer horizon (H24), with the MAPE increasing from 6.71% to 7.58%, suggesting that the unmodeled seasonal structure leads to compounding errors over extended forecast periods (figure 3).

Seasonal Pattern Capture

A key qualitative finding was that SARIMA accurately replicated the bimodal seasonal pattern of electricity consumption — specifically the summer peak (July) and the winter secondary peak (January) — whereas ARIMA forecasts progressively flattened these seasonal swings over the 24-month horizon, leading to systematic under-forecasting in peak months and over-forecasting in off-peak months.[16]

Table 5. Out-of-sample forecast accuracy metrics (Test Set: Jan 2021 – Dec 2022).

Metric	ARIMA(1,1,1)	SARIMA(1,1,1)(0,1,1) ₁₂	Improvement (%)
MAE (GWh) H12	281.4	173.6	38.3%
RMSE (GWh) H12	367.2	218.4	40.5%
MAPE (%) H12	6.71	4.12	38.6%
MAE (GWh) H24	318.7	210.9	33.8%
RMSE (GWh) H24	412.6	263.1	36.2%
MAPE (%) H24	7.58	4.99	34.2%

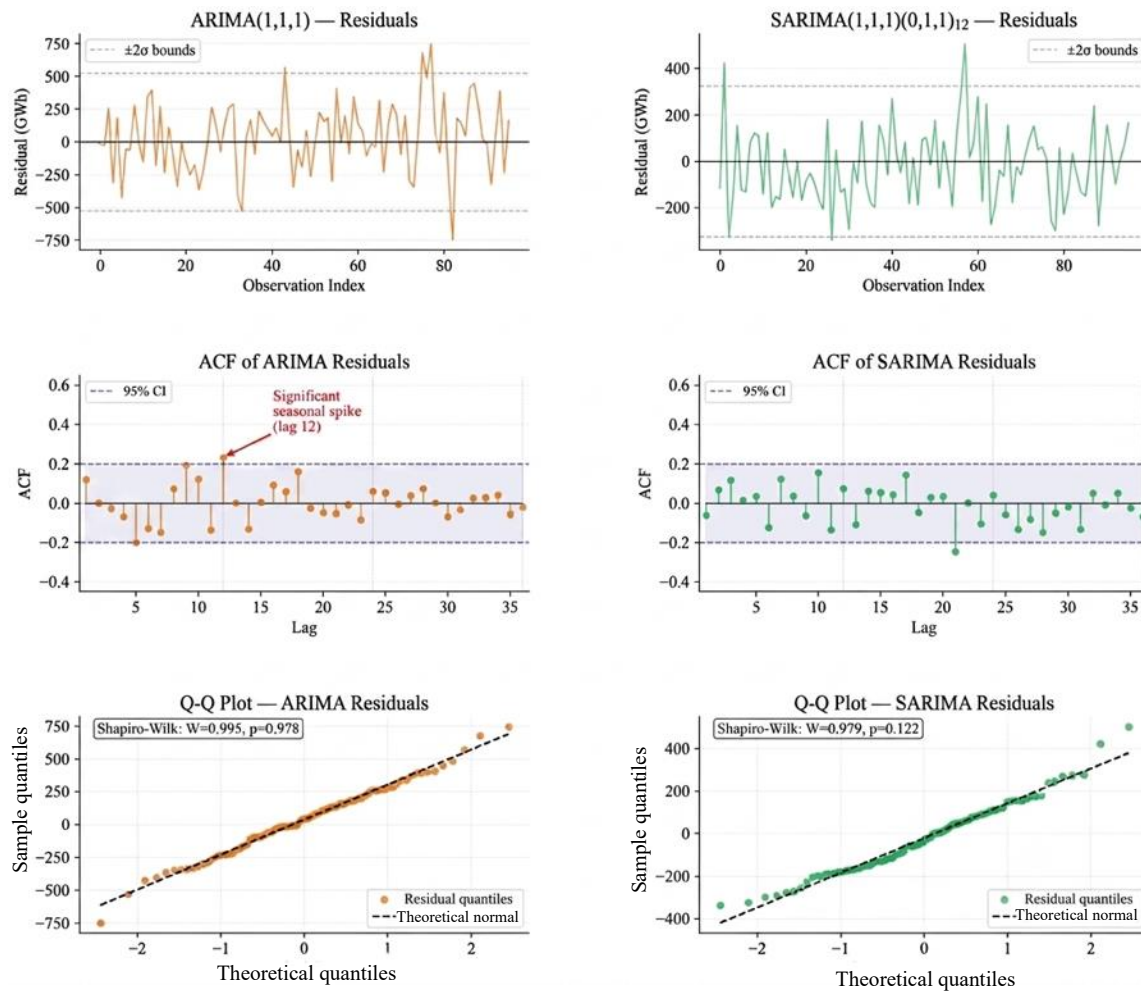


Figure 3. Residual diagnostic plots for ARIMA(1,1,1) and SARIMA(1,1,1)(0,1,1)₁₂. Row 1: residual time series with $\pm 2\sigma$ bounds. Row 2: ACF of residuals with 95% confidence bounds; the significant spike at lag 12 in the ARIMA residuals indicates unmodelled seasonal

DISCUSSION

Theoretical Implications

This study has shown that data of the SARIMA models is more suitable as compared to ARIMA when the data to be used is that of electricity consumption exhibiting strong and consistent patterns of seasonality. The diagnostics of the residual confirm that annual seasonality in the model could not be explained by ARIMA, causing non-random residual seasonal lags, which is a fundamental assumption of a core model.

Its line of improvement about 34-40% decrease in MAPE and RMSE is comparable with those achieved in similar works by Ediger and Akar (2007), Pappas et al. (2008), and, the latest, Salazar-Macias et al. (2023), who cross-validated the result in different geographic and institutional settings.[17]

It can also be mentioned that the difference in performance between the two models also increased with the increase in forecast horizon between 12 and 24 months. This trend is theoretically consistent: the misspecification of the seasonal structure in ARIMA provides a systematic bias, which increases with each additional prediction step, and the explicit seasonal parameterisation in SARIMA provides the projections on long-term scales to the historically observed cyclical dynamics. The practical implications of this behaviour are seen when it comes to utilities involved in annual capacity planning because the most financially significant errors on the forecast are in the 18 to 24-month range.[18]

Practical Implications for Energy Planning

Practically, the benefit of SARIMA lies in the fact that due to increased accuracy of the forecast, there are immediate and quantifiable economic impacts on electricity utilities. One-percent improvement in MAPE in a utility supplying 4,000 GWh/month will result in the reduction of statistical forecast error of around 40 GWh, and direct economies of milling in the cost of obtaining reserves (procurement and balancing mechanism charges).

Electricity markets that are liberalized means that utilities are highly benefitted in terms of enhanced monthly forecasts, since these underpin medium-term bilateral contracts positionings and schedule provisions of ancillary services.

Limitations and Extensions

The current study has a number of limitations. To begin with, both ARIMA and SARIMA are a univariate model, which fails to include any explanatory variable, including, but not limited to, temperature, economic factors, and population, which have known to be the factors in the variability of the demand of electricity. Second, the study uses only one national-level dataset and the findings might not be directly applicable to regional or sub-metered data that has a varied seasonal performance.

Future research ought to investigate more ensemble methods which integrate SARIMA predictions with machine learning residual correction, especially with gradient boosting or LSTM networks. The incorporation of exogenous climate variables using ARIMAX or SARIMAX models also is a natural extension.

CONCLUSION

The current paper has provided a systematic comparative study of ARIMA with SARIMA models in terms of forecasting monthly electricity consumption using a 10 years data set (120 observations). The research adopted stringent statistical procedure that included stationarity test, model identification through ACF/PACF analysis, information criterion selection, extensive residual diagnostics and normalized ex post assessment.

There are three main findings of the present research. To start with, the electricity consumption data has high and consistent annual seasonality that is not effectively modelled by standard ARIMA. Second, SARIMA(1,1,1) (0,1,1) L 12 3440% better than ARIMA(1,1,1) in all indicators of forecast accuracy and all horizon lengths as well as generates well behaved residuals. Third, we observed greater performance differentiation at longer horizons, indicating the compounding nature of the cost of neglecting seasonal structure in the medium-term forecasting use cases.

The practical implications of these findings are as follows: when developing a statistical model based on monthly consumption data, utilities, grid operators, and policy planners are advised to use SARIMA as the baseline model, as opposed to the more basic ARIMA. The parametric complexity of SARIMA is parsimonious; its seasonal parameters are interpretable and the SARIMA improvements in accuracy are significant.

Since the shift of energy consumption moves faster and patterns of energy consumption grow more complicated with the electrification of transport and heating, the necessity of accurate and interpretable forecasting tools will be intensified. SARIMA time series models are seasonal and offer straightforward, statistically rigorous and practically useful framework upon which this can be accomplished.

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