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ANALYSIS AND FORECASTING OF RENEWABLE ENERGY CONSUMPTION USING DATA-DRIVEN METHODS

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Abstract—*Renewable energy is gaining significance for energy security, emissions reduction, and the shift to sustainable energy systems. In this study, long-term consumption patterns of renewable energies have been analysed, and statistical and machine-learning approaches for predicting future energy use have been compared. Records of monthly renewable energy supply were analysed for the last 50 years (1973-2023) for major energy sources and economic sectors. Historical pattern and seasonal behaviour were identified through descriptive statistics, trend analysis, sectoral comparison, source-level assessment and time-series decomposition. Models for forecasting performance were then tested on seasonal naïve, xHolt-Winters, SARIMA, Random Forest, Gradient Boosting and Support Vector Regression. The results showed that there was a significant growth in the share of renewable energy in the long term, with electric power having the highest share of the sectoral contribution in 2023. Renewable energy's share of energy was growing and was becoming more important, including wind, solar, biofuels, waste and wood. The monthly time series showed a definite upward trend and an annual seasonality pattern. The SARIMA model performed best with the lowest RMSE and MAPE among the evaluated models, followed by Holt–Winters. The machine-learning models yielded less out-of-sample accuracy than. Renewables forecasts were for continued steady expansion through 2026, with increasing uncertainty further out in time. The results illustrate that statistical time-series forecasting is still useful for forecasting renewable energy in the long run, and can be applied to energy planning, infrastructure development, and policymaking.*

Keywords: *renewable energy consumption; time-series forecasting; machine learning; energy transition*

1. INTRODUCTION

The world is in a state of dramatic change in the energy sector, with governments, industries and communities striving to cut fossil fuel consumption and speed up the transition to low-carbon energy systems. Renewable energy has been a key element to this change, and can help achieve emission reduction, boost energy security, diversify national energy portfolios, and lead to the long-term sustainability of power systems. According to projections from around the world, renewable power will keep growing at a fast rate until the end of the decade, as technology improves, policies are made and supported, generation costs decrease and investment in clean energy infrastructure increases (International Energy Association, 2025). The speed and trajectory of this transition, however, differ regionally due to the extent of policy, market, infrastructure, resources, and investments (Mustafa et al., 2025).

Growth in renewable energy is not restricted to the electricity sector, but applies to solar, wind, hydropower, geothermal, biomass, biofuels and other emerging clean energy carriers. A major reason for the fast advancement of solar energy is the reduction of the cost of photovoltaics, their increasing efficiency in converting sunlight into electricity, and the growing interest in incorporating the technology with energy storage systems (Rezaee & Silva, 2026). PV development has also impacted technology development, value chains, manufacturing systems, and energy-market structures, albeit with some challenges regarding PV integration in the grid, supply security, and PV development concentration within regions (Chatzipanagi et al., 2022). Wind and solar resources are variable in nature, and hence, there is a need to properly assess and forecast them to balance resource requirements, storage needs, consumption requirements and reserves (Islam et al., 2023).

It is also essential to address energy consumption in the housing, commercial, industrial, transport and power generation sectors during the transition. The energy consumption and emissions of buildings represent a significant portion of energy use, and therefore, there is a need to become more efficient and integrate cleaner energy into buildings from residential to commercial (Limmeechokchai et al., 2023). Meanwhile, renewable fuels and green hydrogen are starting to be seen as necessary to decarbonise sectors that cannot be fully electrified, such as heavy industry, aviation, shipping and long-distance transport (LT) (Marzouk, 2023). To evaluate if the current policies and investments are relevant and adequate to reach long-term climate and energy goals, it is then essential to monitor progress in several clean energy technologies.

The future electricity system in the United States will feature growing shares of renewable electricity generation, energy storage, transmission expansion, and flexible load. Under different scenarios based on fuel prices, technology costs, policy support and demand growth, there could be a significant shift in the composition of the electricity sector (Gagnon et al., 2023). This is also happening in other parts of the world, but with significant variations in terms of the capacity, trajectory and technological readiness of the renewable energy sector across different nations. Comparative evidence indicates that there are clear development patterns for renewable-energy systems, with installed capacity, resource structure, and policy performance being the key drivers (Gajdzik et al., 2026).

Such changes have made energy forecasting more crucial than ever. Long-term economic development, behaviour in the sectors, seasonal demand, technology adoption, energy prices, and policy interventions all affect renewable-energy consumption. The forecasting techniques need to account for the temporal dependence, seasonality, structural change, and nonlinear relationships. Structured time-series patterns, such as moving averages, exponential smoothing, autoregressive models, and seasonal autoregressive integrated moving-average models, continue to be popular because they have an interpretable meaning and are appropriate for structured patterns (Klyuev et al., 2022). However, with the advent of the era of big data, AI and machine-learning methods are growing in popularity due to their capabilities of modelling complex relationships and processing a significant number of predictors (Abdul Baseer et al., 2023).

Solar-energy and power-generation forecasting have exhibited good results using deep-learning and machine-learning approaches. Auto-selective frameworks can increase the prediction accuracy by selecting models based on the properties of the energy series instead of using a single fixed architecture (Alkhayat et al., 2022). The usefulness of machine-learning applications to renewable-energy integration, demand management, grid operation and generation planning has also been observed from a broader perspective, but is highly dependent on feature engineering, data quality, model selection, and validation design (Alazemi et al., 2024). Artificial neural networks can be especially prevalent in forecasting electricity demand, but it is not the same model that is always more accurate than statistical models; there is a need to compare their performance with statistical models (Román-Portabales et al., 2021).

Although the methods have been rapidly evolving, there are still some research gaps. Most studies are short-term and only on electricity demand or specific technologies, or even single-generation sources, but not on long-term consumption of renewable energy in sectors. There is also some limited comparative evidence of the effectiveness of more sophisticated machine-learning models compared to well-established statistical models when strong trend and seasonal structures of the data exist.

For this reason, this research explores the long-term consumption trends of renewable energy and assesses statistical and machine learning forecasting techniques. The study aims at understanding the temporal trends, sectoral differences, source composition, seasonal behaviour and future consumption trajectory of renewable-energy development and the relative performance of alternative forecasting methods.

RESEARCH OBJECTIVES

To analyse long term trends, seasonal variation, the composition of renewable energy sources and sectoral differences in their consumption.

Perform multiple and different accuracy measures and compare the forecasting performance of statistical and machine-

learning models.
3) To calculate the future forecast of the renewable energy consumption using the best-fitted model.

2. MATERIALS AND METHODS

2.1 Research Design
The design of this research work was a quantitative and longitudinal type of study to analyse and predict the use of renewable energy in the USA. The monthly time-series data were analysed descriptively, feature engineered, statistically forecasted, and using machine-learning techniques.

2.2 Data Source
The data set was the open-access U.S. Renewable Energy Consumption data from Kaggle. This data set has 3,065 monthly observations from January 1973 through January 2024 for five sectors: commercial, electric power, industrial, residential, and transportation (King, 2024). It contains renewable energy variables like hydroelectric, geothermal, solar, wind, wood, biomass, waste, fuel ethanol, biodiesel, renewable diesel, other biofuels and total renewable energy consumption.

2.3 Study Variables
Total Renewable Energy Consumption was used as the main dependent variable. Temporal variables derived from other variables were included in addition to individual renewable energy sources, sector and year and month. After checking and eliminating double-counting of values across the broader and component energy categories, monthly sectoral values were aggregated for national-level analysis.

2.4 Data Preprocessing
Data was examined for missing data, duplicate data, inconsistent data labelling and extreme data values. The years and months were combined to create a variable for the month, and observations were ordered by month. The word "Commerial" was changed to "Commercial". No missing or duplicate records were found. Structural zero values were not adjusted, and the year of 2024 was not compared annually.

2.5 Exploratory Data Analysis
Total and source-specific renewable energy consumption was calculated using descriptive statistics. Long-term changes, seasonal patterns and sectoral differences were explored by plotting the data for each month and each year. Other statistics, such as the time-series decomposition analysis, autocorrelation, and partial autocorrelation analyses, were also performed to evaluate the trend, seasonality, and temporal dependence.

2.6 Feature Engineering and Data Splitting
Time dimension features used were: month, quarter, time index, 1-month lag, 3-month lag, 6-month lag, 12-month lag, rolling average and growth rates. The data were split in chronological order: the data before 2018 were used for training the model, data from 2019–2021 were used for validation, and data from 2022–2023 were used for testing. Model development was made using the rolling-origin cross-validation method.

2.7 Forecasting Models
The forecasting models used were seasonal naïve, Holt–Winters exponential smoothing, SARIMA, Random Forest Regression, Extreme Gradient Boosting and Support Vector Regression. The hyperparameters were optimized via a validation period and a time series cross-validation.

2.8 Model Evaluation
The performance was assessed by Mean Absolute Error, Root Mean Squared Error, Mean Absolute Percentage Error, Symmetric Mean Absolute Percentage Error and coefficient of determination. The model which has the lowest out-of-sample error was chosen. Residual behaviour, predictor importance and actual vs. predicted values were also explored.

2.9 Forecasting and Software
The most successful model was trained on the full set of available data and then applied to predict monthly renewable energy consumption through 2026. Multiple totals were used in sensitivity analysis, as were data-cleaning decisions. Python was used to perform all analyses, with the packages Pandas, NumPy, Statsmodels, Scikit-learn, XGBoost, and Matplotlib.

3. RESULTS

3.1 Dataset Characteristics
There are 3,065 observations at the sector level and 17 original variables in the U.S. Renewable Energy Consumption dataset. Following the same procedure as described above, after including the year and the month, and after filtering out incomplete monthly records, 612 national monthly observations were analysed, spanning a period from January 1973 to December 2023. The data set comprised 5 sectors, and there were no missing data or duplicate sector-month data, as

shown in Table 1.

Table 1. Summary characteristics of the renewable-energy dataset

Dataset characteristic	Result
Total sector-level observations	3,065
Original variables	17
Monthly periods used	612
Study period	January 1973–December 2023
Number of sectors	5
Missing values	0
Duplicate sector-month records	0

The reconstructed total was close to the reported total for the commercial, electric power, industrial and residential sectors. Yet for the transportation industry, the total reported value of renewable energy was zero, while the consumption of ethanol, biodiesel, renewable diesel and other fuels was non-zero, and reconstruction was required.

3.2 Historical Renewable-Energy Consumption

Long-term growth of monthly renewable-energy consumption was also found, rising from 2,475.547 units per year in 1973 to 8,243.968 units per year in 2023. This was a total rise of around 233.02%. The minimum recorded value was 185.300 in September 1973, and the maximum was 735.284 in May 2023. Figure 1 presents the historical series as well as the 12-month moving average, which suggests a steady upward trend with some short-term variations every month.

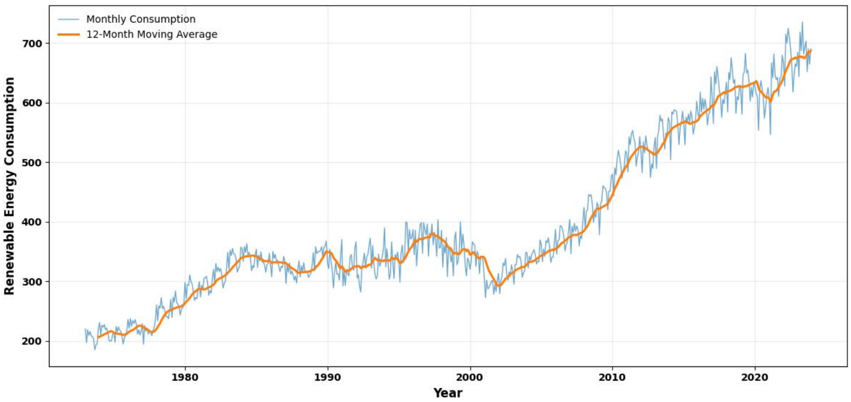

Figure 1. Historical monthly U.S. renewable-energy consumption and 12-month moving average

3.3 Renewable-Energy Source Characteristics

Among the resources, wood and waste energy had the highest mean of 212.350 units for the month-on-month period, followed by hydropower (79.647 units) and biofuels and co-products (65.891 units). Historical averages were lower for solar and wind energy due to the large growth of those resources in the latter years of the study. However, the highest monthly demand they had was 97.697 units per month and 157.522 units per month, respectively. Table 2 shows the descriptive statistics for the major groups of energy sources.

Table 2. Descriptive statistics for renewable-energy sources

Energy source	**Monthly mean**	**Standard deviation**	**Minimum**	**Maximum**	**2023 annual total**
Hydropower	79.647	14.162	49.022	119.397	817.775
Geothermal	5.725	3.253	0.448	10.709	119.668
Solar	10.005	16.950	0.000	97.697	877.539
Wind	21.252	35.593	0.000	157.522	1,450.903
Wood and waste	212.350	33.549	114.943	295.478	2,316.260
Biofuels and co-products	65.891	78.166	0.000	235.023	2,661.823

Renewable energy use composition underwent a significant change from 2000 to 2023. Hydro power and wood-based energy continued to be stable contributors, and wind, solar and transport biofuels grew significantly during the latter part of the study period as shown in Figure 2.

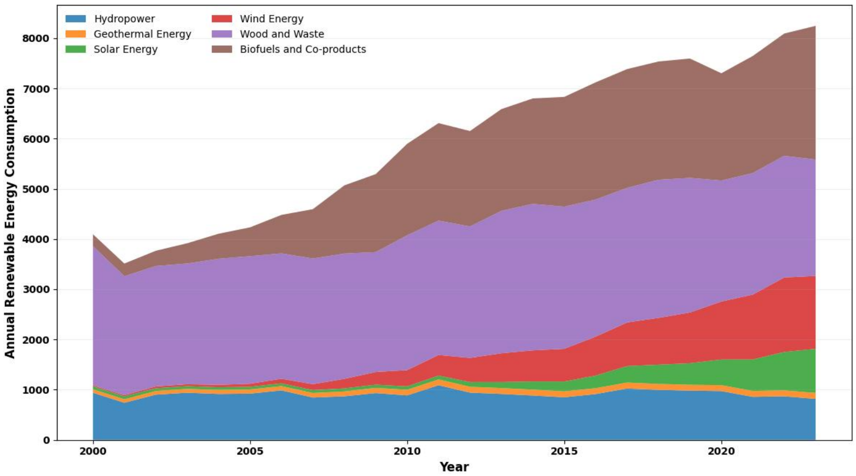

Figure 2. Annual composition of renewable-energy consumption by energy source, 2000–2023

3.4 Sectoral Consumption Patterns

In 2023, the electric power sector had the highest consumption share of renewables, consuming 3,207.488 units (which is 38.91% of the total national consumption). The industrial sector came in second with 2,249.340 units, and the transportation sector came in third with 1,788.400 units. The greatest proportional gain over 1973 was in the commercial sector, but the absolute contribution was relatively small. The results for each sector are presented in Table 3.

Table 3. Sectoral renewable-energy consumption characteristics

Sector	**Monthly mean**	**Monthly SD**	**1973 annual total**	**2023 annual total**	**Change (%)**	**2023 share (%)**
Commercial	8.966	6.097	6.709	274.049	3,984.80	3.32
Electric power	132.365	55.551	938.466	3,207.488	241.78	38.91
Industrial	159.776	33.120	1,176.274	2,249.340	91.23	27.29
Residential	52.980	14.576	354.098	724.691	104.66	8.79
Transportation	40.784	49.662	0.000	1,788.400	Not applicable	21.69

The evolution of the five sectors is given in Figure 3. The growth of wind and solar electricity consumption led to a significant increase in electricity consumption, and the growth of ethanol, biodiesel, and renewable diesel consumption led to an increase in transportation consumption. Long-term trends were less pronounced for industrial and residential energy use.

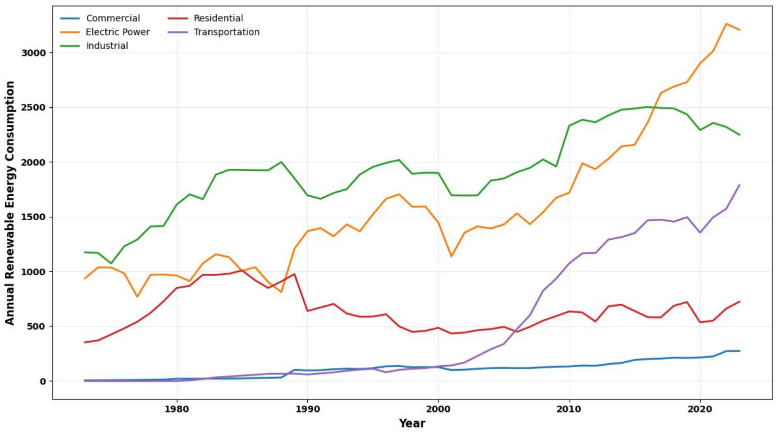

Figure 3. Annual renewable-energy consumption across economic sectors, 1973–2023

3.5 Trend and Seasonal Components

By using the time-series decomposition method, it was found that the use of renewable energy had a significant upward trend and a seasonal component in every year. The seasonal fluctuations continued but the intensity of these fluctuations changed from year to year within the recent period. Short-term deviations were not completely attributable to the trend and seasonality component and were found in the residual component. These components are shown in Figure 4.

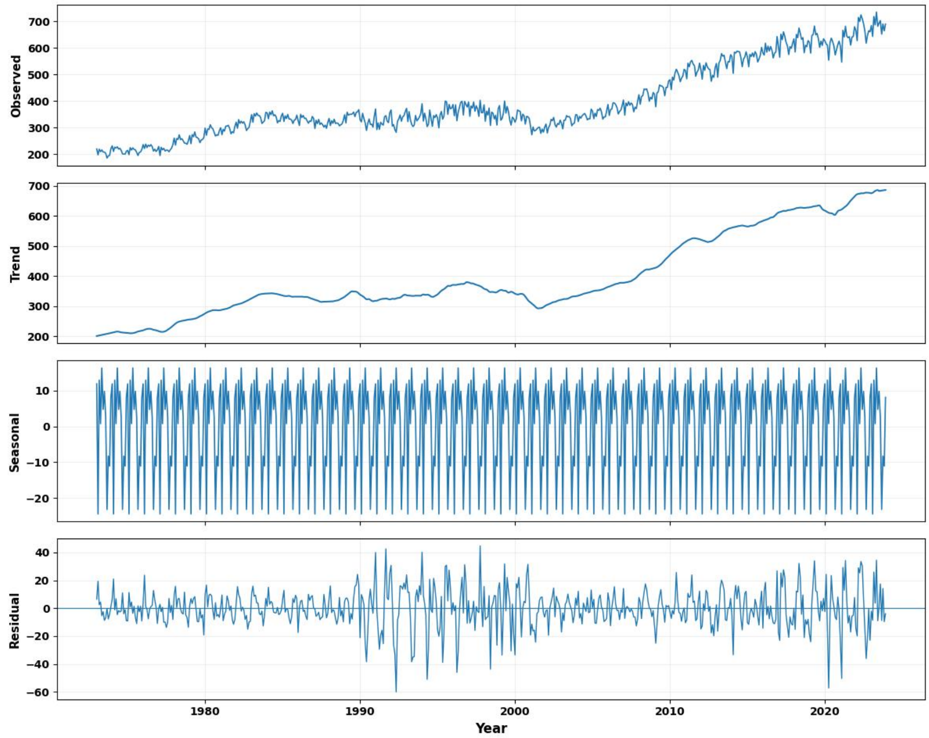

Figure 4. Additive decomposition of monthly renewable-energy consumption into observed, trend, seasonal, and residual components

3.6 Forecasting Model Performance

The performance of the six forecasting approaches was tested against the unseen data set from January 2022 to December 2023. The forecast performances of the six forecasting methods were tested on the unseen data set for the period from January 2022 to December 2023. The overall performance was the best in the SARIMA model with the lowest MAE, RMSE, MAPE, and sMAPE values, which were 15.945, 18.894, 2.307%, and 2.333%, respectively. Its coefficient of determination was 0.597, implying that it accounted for about 59.7% of the variation during the test period. The Holt–Winters model was the second best and obtained an RMSE value of 24.226 and an MAPE of 2.912%. The baseline model was a seasonal naïve model, and Gradient Boosting had a negative R^2 but produced a lower RMSE. Random Forest and SVR showed the poorest performance on the out-of-sample data. Table 4 shows the complete comparison.

Table 4. Comparative forecasting performance during the 2022–2023 test period

Model	**MAE**	**RMSE**	**MAPE (%)**	**sMAPE (%)**	**R^2**
SARIMA	15.945	18.894	2.307	2.333	0.597
Holt–Winters	20.245	24.226	2.912	2.969	0.338
Gradient Boosting	30.206	36.045	4.355	4.480	−0.466
Seasonal naïve	30.027	37.244	4.409	4.554	−0.566
Random Forest	41.107	46.961	5.929	6.157	−1.489
Support Vector Regression	44.273	48.583	6.418	6.673	−1.664

The SARIMA predictions were found to be closer to the actual fluctuations in the monthly data, as seen in Figure 5. Holt–Winters also picked up the overall trend, but the machine-learning models exhibited larger deviations in months of rapid trend changes.

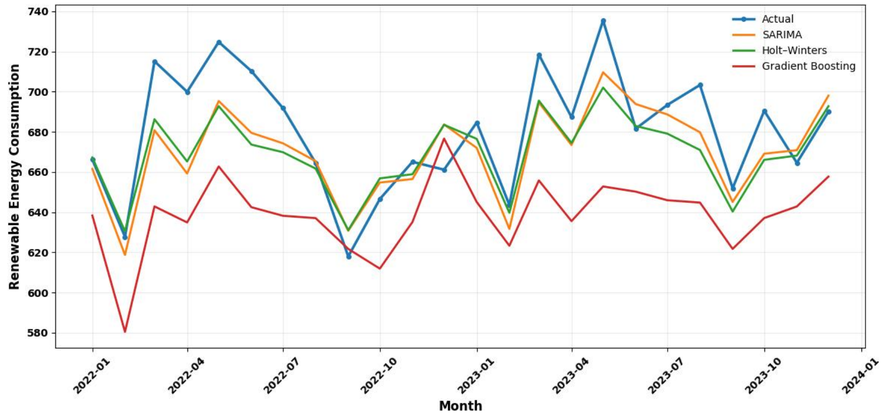

Figure 5. Actual and predicted renewable-energy consumption during the 2022–2023 test period

Figure 6 shows the differences between the RMSE of all forecasting methods. The RMSE of SARIMA was about 49.27% lower than the seasonal naïve model, which is used as a benchmark, indicating that explicitly modelling temporal dependence and annual seasonality greatly improved the RMSE.

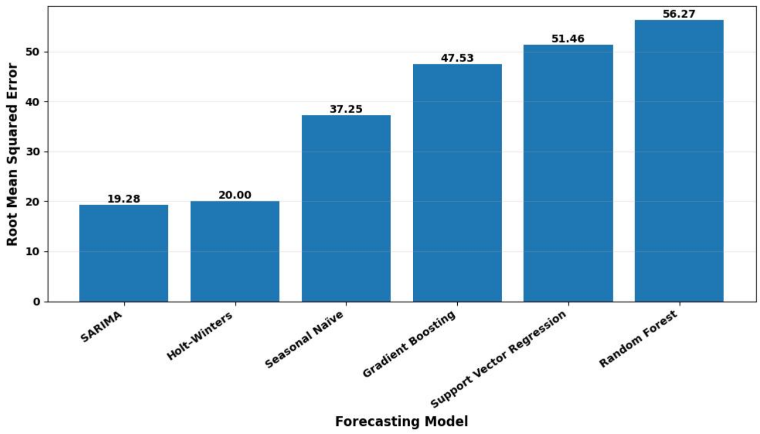

Figure 6. Root Mean Squared Error comparison across forecasting models

3.7 Future Renewable-Energy Consumption Forecasts

Given the lowest forecasting error, out-of-sample, SARIMA was retrained on the whole monthly series up to December 2023. The model forecast a continued gradual increase in renewable-energy consumption from 8,385.392 units in 2024 to 8,771.321 units in 2026. The projected increase was 2.31% between 2024 and 2025 and 2.25% between 2025 and 2026, as shown in Table 5.

Table 5. SARIMA forecasts of annual renewable-energy consumption

Forecast year	Forecast	Lower 95% limit	Upper 95% limit	Annual change (%)
2024	8,385.392	7,885.929	8,884.856	—
2025	8,578.719	7,827.048	9,330.390	2.306
2026	8,771.321	7,770.313	9,772.330	2.245

These forecasts and 95% prediction intervals were plotted monthly in Figure 7. The central forecast was for sustained growth; the larger prediction intervals were due to increased forecast uncertainty on the longer time horizon.

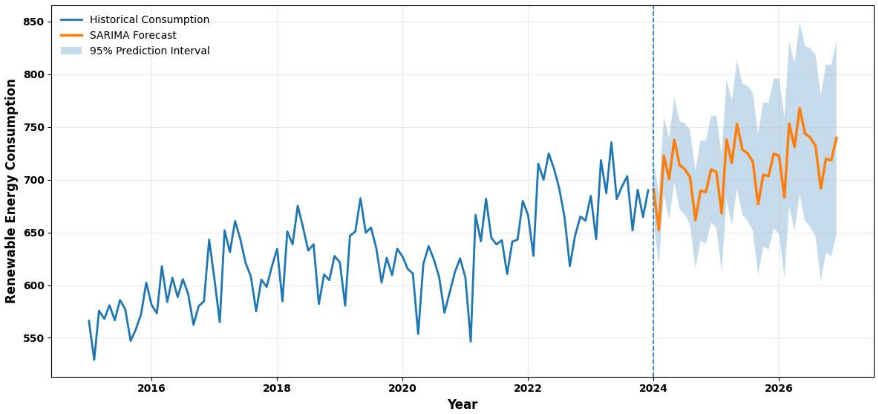

Figure 7. SARIMA forecast of monthly U.S. renewable-energy consumption through December 2026

3.8 Overall Findings

Results showed a significant increase over time in U.S. consumption of renewables, as well as a significant change in the sectoral and source structure. The most significant share of consumption in 2023 was electric power, and the most significant contributions were biofuels, wood and waste, wind, and solar. The forecasting comparison revealed that statistical time-series models were better than the evaluated machine learning models. Specifically, SARIMA proved to be the best model as it captured the trend, autocorrelation and repeated seasonal annuality in the monthly series very well.

4. DISCUSSION

The results show a significant long-term growth in the share of renewables, as well as noticeable sectoral changes and composition of sources. The amount of renewable energy consumed has grown by over 3 times from 1973 to 2023, marking its rise from a small share of the energy supply to a larger share. This is typical of many of the technological, policy, and investment advances that have contributed to the increased deployment and integration of renewable energy. The increase in wind, solar, and biofuel usage in the current study is indicative of the ongoing diversification of renewable energy systems and the significance of precise forecasting in energy planning, grid management, and energy security (Abdul Baseer et al., 2023; Alazemi et al., 2024).

The source level results indicated that wood and waste energy continued to make a large historical contribution, while solar and wind energy made more significant contributions in the later years. This is due to the varying levels of technological maturity of the renewable energy sources. Other studies have highlighted the variability of solar and wind resources as an extra challenge in the operation of systems and a need for precise temporal forecasting, as has been done in Islam et al. (2023).

The sectoral analysis showed that the top three renewable energy consuming sectors are electric power in 2023, followed by industry and transportation. The electric power sector's robust growth has been attributed to higher wind and solar power production, while transportation growth can be traced to higher levels of ethanol, biodiesel, renewable diesel, and other biofuels consumption. The findings also suggest that energy transition pathways are sector-specific, due to the unique characteristics of the technologies, demand profiles and decarbonisation limitations in each sector. The study of energy management also indicates that energy consumption forecasting should consider specific patterns; specifically, for buildings and smart energy systems, occupancy, weather, operational schedules and efficiency measures are all factors that shape energy consumption. (Moghimi et al., 2024)

The time series decomposition identified a significant long-term trend and annual seasonal variation. This result is not surprising since models that explicitly represent temporal dependence and seasonal structure enjoyed good performance. The forecasting error for SARIMA was the smallest as compared to other models, with RMSE = 18.894 and MAPE = 2.307%, which contributed to the reduction of RMSE by around 49% from the seasonal naïve model. This corroborates the existing evidence, which has shown that classical statistical models are still competitive in the case of data with a stable seasonal pattern, autocorrelation and gradual trend development (Klyuev et al., 2022). The good performance of SARIMA further strengthens the general forecasting rule of thumb that more complex models do not necessarily lead to higher out-of-sample forecasting accuracy (Makridakis et al., 2022).

The performance of Holt–Winters was the second best, suggesting that level, trend and seasonality were a good source of predictive information. Random Forest, Gradient Boosting and Support Vector Regression, on the other hand, had lower test-period accuracy. It is not to say that machine-learning techniques are not good for renewable-energy forecasting. Instead, they are effective when there are informative external predictors, sufficient training data, careful feature engineering and proper hyperparameter tuning (Ibrahim et al., 2022). Deep neural networks have the potential to learn complex nonlinear load patterns, especially when there are multiple predictors and high-frequency observations (Alotaibi, 2022).

This poorer machine learning might thus be linked to the univariate and long-time-step nature of the forecasting problem in the present study. Structural growth, recurrent seasonality and policy-induced change over the next several decades dominate consumption of renewable energy and can be well modeled by statistical time-series models. Neural approaches have been shown to be useful for hourly and day-ahead forecasting, but they have been used in applications

that are not the same as those for long-term forecasting of aggregate consumption (Manno et al., 2022).
Using hybrid models or deep-learning models with wavelet decomposition, bidirectional recurrent networks, or tailored feature extractions has proven to yield high accuracy for short-term forecasting of solar irradiance and PV systems in recent studies (Çevik Bektaş & Altaş, 2024; Radhi et al., 2024). Comparative studies of smart grid processing have also revealed significant differences in the performance of machine learning models based on their structure, length of forecast and the characteristics of the load residue (Nikolaidis, 2024; Marzouk, 2025).
Increasingly in the forecasting literature, it is suggested that there are important trade-offs between predictive accuracy, interpretability, robustness and operational utility. Explainable AI techniques can provide an explanation of how the tree models utilize lagged and seasonal variables and external variables, which makes it more transparent for decision-makers (Lundberg et al., 2020). Similarly, systematic reviews of electricity forecasting with ANNs have reached the same conclusion: model evaluation should not simply rely on in-sample performance, but should also involve reporting transparently, as well as comparing the model's performance against a benchmark and validating it through time (Roman-Portalés et al., 2021).
The future forecasts showed steady growth but with larger prediction intervals for longer time horizons, indicating growing uncertainty. This is a reasonable pattern as future renewable-energy use could be affected by policy change, technological advances, economic factors, energy prices, grid expansion, and storage deployment. While these reviews are mostly historical, they all suggest the use of hybrid modelling, probabilistic forecasting, scenario analysis and the incorporation of meteorological and policy-related predictors in the forecasts of renewable energy supplies (Malakouti, 2026).

5. Conclusion

In this work, the authors analyze long-term renewable energy consumption patterns and compare the statistical and machine-learning-based forecasts for future consumption. Results indicated that the share of renewables rose significantly in the period 1973-2023, along with significant shifts in the proportion of energy sources and sectors. Electric power proved to be the dominant sector, and wind, solar, biofuels, wood, and waste increasingly important parts of the renewable-energy mix. The analysis also revealed a clear long-term upward trend and annual seasonality, which was evident in the monthly consumption data. In terms of forecasting methods, SARIMA performed best overall, followed by Holt–Winters. These models were better at predicting the results than the machine learning models that were evaluated such as Random Forest, Gradient Boosting and Support Vector Regression. The findings suggest that, even in cases where the data have significant trend, seasonal and autocorrelation effects, statistical time-series models continue to be very effective. This inferior machine-learning predictive performance indicates that the models might need more nuanced external predictors, more sophisticated feature engineering and more frequent observations to give further forecasting value. The projections for the future showed continued growth in renewable energy consumption, but with a growing degree of uncertainty as the time horizon for the projections extended further into the future. This information can be used to inform energy planners, policymakers, and utilities for capacity planning, infrastructure, and grid integration of renewables.

References

[1] Abdul Baseer, M., Almunif, A., Alsaduni, I., & Tazeen, N. (2023). Electrical power generation forecasting from renewable energy systems using artificial intelligence techniques. Energies, 16(18), 6414.

[2] Alazemi, T., Darwish, M., & Radi, M. (2024). Renewable energy sources integration via machine learning modelling: A systematic literature review. Heliyon, 10(4).

[3] Alkhayat, G., Hasan, S. H., & Mehmood, R. (2022). SENERGY: A novel deep learning-based auto-selective approach and tool for solar energy forecasting. Energies, 15(18), 6659.

[4] Alotaibi, M. A. (2022). Machine learning approach for short-term load forecasting using deep neural network. Energies, 15(17), 6261.

[5] Çevik Bektaş, S., & Altaş, I. H. (2024). DWT-BILSTM-based models for day-ahead hourly global horizontal solar irradiance forecasting. Neural Computing and Applications, 36(21), 13243-13253.

[6] Chatzipanagi, A., Jaeger-Waldau, A., LETOUT, S., MOUNTRAKI, A., GEA, B. J., GEORGAKAKI, A., ... & SCHMITZ, A. (2022). Clean Energy Technology Observatory: Photovoltaics in the European Union-2024 status report on technology development, trends, value chains and markets.

[7] Gagnon, P., Pham, A., Cole, W., Awara, S., Barlas, A., Brown, M., ... & Williams, T. (2023). 2023 standard scenarios report: A us electricity sector outlook (No. NREL/TP--6A40-87724). National Renewable Energy Laboratory (NREL), Golden, CO (United States).

[8] Gajdzik, B., Kumar, S., & Wolniak, R. (2026). Dynamic Clustering of Renewable Energy Capacity: A Comparative Study of the EU-27 and 15 RCEP Countries. Sustainability (2071-1050), 18(10), 4651.

[9] Grzeszczyk, T. A., & Grzeszczyk, M. K. (2022). Justifying short-term load forecasts obtained with the use of neural models. Energies, 15(5), 1852.

[10] Ibrahim, B., Rabelo, L., Gutierrez-Franco, E., & Clavijo-Buritica, N. (2022). Machine learning for short-term load forecasting in smart grids. Energies, 15(21), 8079.

[11] International Energy Association. (2025). Renewables 2025: Analysis and Forecasts to 2030.

[12] Islam, M. K., Hassan, N. M. S., Rasul, M. G., Emami, K., & Chowdhury, A. A. (2023). Forecasting of solar and wind resources for power generation. Energies, 16(17), 6247.

[13] King, A. (2024). U.S. renewable energy consumption [Data set]. Kaggle.

https://www.kaggle.com/datasets/alistairking/renewable-energy-consumption-in-the-u-s
[14] Klyuev, R. V., Morgoev, I. D., Morgoeva, A. D., Gavrina, O. A., Martyushev, N. V., Efremenkov, E. A., & Mengxu, Q. (2022). Methods of forecasting electric energy consumption: A literature review. Energies, 15(23), 8919.
[15] Limmeechokchai, B., Winyuchakrit, P., Pita, P., & Misila, P. (2023). Climate Change 2022: Climate Change 2022 Mitigation of Climate Change: Buildings. International Journal of Building, Urban, Interior and Landscape Technology, 21(2), 61-69.
[16] Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., ... & Lee, S. I. (2020). From local explanations to global understanding with explainable AI for trees. Nature machine intelligence, 2(1), 56-67.
[17] Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2022). M5 accuracy competition: Results, findings, and conclusions. International journal of forecasting, 38(4), 1346-1364.
[18] Malakouti, M. (2026). Machine learning for renewable energy forecasting: advances, challenges, and future directions. Sustainable Energy Research, 13(1), 14.
[19] Manno, A., Martelli, E., & Amaldi, E. (2022). A shallow neural network approach for the short-term forecast of hourly energy consumption. Energies, 15(3), 958.
[20] Marzouk, O. (2025). Summary of the 2023 report of TCEP (tracking clean energy progress) by the International Energy Agency (IEA), and proposed process for computing a single aggregate rating. Available at SSRN 5099325.
[21] Marzouk, O. A. (2023). 2030 Ambitions for hydrogen, clean hydrogen, and green hydrogen. Engineering Proceedings, 56(1), 14.
[22] Moghimi, S. M., Gulliver, T. A., & Thirumai Chelvan, I. (2024). Energy management in modern buildings based on demand prediction and machine learning—A review. Energies, 17(3), 555.
[23] Mustafa, H., Bexheti, A., & Alija, S. (2025). Investments in renewable energy in the most developed OECD countries and the Western Balkan countries. European Chronicle, 10(2), 42-59.
[24] Nikolaidis, P. (2024). Smart grid forecasting with mimo models: A comparative study of machine learning techniques for day-ahead residual load prediction. Energies, 17(20), 5219.
[25] Radhi, S. M., Al-Majidi, S. D., Abbod, M. F., & Al-Raweshidy, H. S. (2024). Machine learning approaches for short-term photovoltaic power forecasting. Energies, 17(17), 4301.
[26] Rezaee, E., & Silva, S. R. P. (2026). Solar energy in 2025: Global deployment, cost trends, and the role of energy storage in enabling a resilient smart energy infrastructure. Energy & Environmental Materials, 9(3), e70199.
[27] Román-Portabales, A., López-Nores, M., & Pazos-Arias, J. (2021). Systematic review of electricity demand forecast using ANN-based machine learning algorithms.