Advanced International Journal for Research (AIJFR)

E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

Powering a Sustainable Future: Decadal Trends, Seasonality, and Predictive Forecasting of Wind Energy in Rajasthan

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Abstract
This study analyses the temporal dynamics and forecasting behaviour of wind energy generation in Rajasthan using monthly data from April 2015 to January 2026. A comprehensive time-series framework is employed, combining decomposition techniques, trend estimation, stationarity testing, and comparative model evaluation. The results reveal a statistically significant upward trend alongside a strong and stable seasonal pattern driven by monsoon wind regimes. Multiple forecasting models, including ARIMA, ETS, Holt–Winters, TBATS, STLM, STL+RWD, and NNETAR, are evaluated using RMSE, MAE, and MAPE. The findings indicate that the STLM model achieves superior performance in minimizing absolute forecast errors while effectively capturing the underlying seasonal structure. DM test results further show that differences in predictive accuracy across leading models are not statistically significant, suggesting convergence in performance when seasonality is adequately modelled. The 24-month forecasts highlight a consistent intra-annual cycle, with peak generation during monsoon months and lower output during winter. These results underscore the importance of decomposition-based approaches in renewable energy forecasting and provide practical insights for improving seasonal planning, resource allocation, and grid management. By enhancing the predictability of wind energy availability, the study contributes to sustainability-oriented energy planning by supporting more efficient integration of renewable resources, reducing reliance on fossil-fuel-based balancing, and enabling more informed decision-making in the transition toward a low-carbon and resilient energy system.

Keywords: Wind Energy Forecasting; STLM; Seasonal Decomposition; Time-Series Analysis; Renewable Energy Planning; Rajasthan; Forecast Accuracy; Sustainability.

1. Introduction

The global energy system is undergoing a profound transformation driven by climate change imperatives, energy security concerns, and the rapid growth of electricity demand. Renewable energy has emerged as the cornerstone of this transition, with wind energy playing a particularly central role due to its scalability, declining costs, and low carbon footprint [33, 17]. Over the past two decades, global wind power capacity has expanded significantly, reflecting both technological maturity and strong policy support across regions. This expansion is not merely a technological shift but part of a broader sustainability transition aimed at reducing greenhouse gas emissions and achieving long-term environmental resilience. Wind energy contributes directly to decarbonization by replacing fossil-fuel-based generation and indirectly supports sustainable development goals related to clean energy access and climate action [16, 17].

Within this global transition, India has positioned itself as a key actor through ambitious renewable energy targets, and Rajasthan has emerged as one of the most strategically important states in this transformation. Characterized by vast open landscapes, favorable wind corridors, and strong policy backing, Rajasthan offers substantial potential for wind energy expansion. However, integrating large-scale wind capacity is not simply a matter of installation; it requires systematic planning, reliable forecasting, and robust grid management. As Giroh et al. (2024) emphasize, effective wind integration in Rajasthan involves "collecting and processing data, assessing resource potential, forecasting power generation, evaluating grid integration and stability" [10]. This highlights that forecasting is not a peripheral activity but a central pillar of sustainable energy system planning.

Small changes in wind speed can lead to disproportionately large variations in power output, introducing operational and planning challenges for electricity systems [2]. Forecasting therefore plays a critical role in mitigating these uncertainties. It enables system operators to optimize dispatch decisions, reduce balancing costs, and improve coordination between renewable and conventional energy sources [9]. More importantly, accurate forecasting contributes to sustainability by enhancing the reliability of renewable integration, reducing dependence on fossil-based backup generation, and enabling efficient utilization of clean energy resources [16, 28]. In this sense, forecasting is not only a technical requirement but also a sustainability enabler.

Over time, wind forecasting methodologies have evolved from simple statistical models to advanced machine learning (ML) and hybrid frameworks. Contemporary approaches span deterministic, probabilistic, and ensemble-based methods designed to capture the nonlinear and stochastic nature of wind behavior [32]. Many models now incorporate multi-scale temporal structures to account for daily, monthly, and seasonal variations [17]. However, despite these advances, a significant limitation persists. Much of the literature focuses on short-term forecasting aimed at operational efficiency, while comparatively less attention is given to long-term trends and seasonal dynamics that are critical for policy planning and sustainability-oriented decision-making. This imbalance is important because sustainable energy transitions require not only accurate short-term forecasts but also reliable long-term insights that guide infrastructure investment, resource allocation, and policy design [28, 30].

Rajasthan provides a particularly relevant context for addressing this gap. Unlike mature energy systems where growth has stabilized, Rajasthan is experiencing continuous expansion in renewable capacity, supported by government policies and investment initiatives [6, 7]. The state's renewable trajectory is closely aligned with national sustainability goals, making it an ideal case for examining how forecasting can support long-term energy planning. In such emerging systems, the ability to anticipate seasonal variability and long-term trends is essential for ensuring that renewable growth translates into actual sustainability gains rather than operational inefficiencies or grid instability.

Ideally, forecasting models would provide seamless integration between historical data, meteorological inputs, and future projections, enabling policymakers to make informed decisions regarding capacity expansion, reserve allocation, and infrastructure development. In practice, however, forecasting frameworks often fall short of this ideal. Even studies that recognize the importance of forecasting for policy tend to prioritize short-term accuracy rather than long-term reliability [23]. As forecasting horizons extend, uncertainty increases and predictive accuracy declines, posing challenges for medium- and long-term planning [5, 30]. This limitation is particularly critical in sustainability contexts, where planning decisions must account for long-term environmental and economic outcomes rather than short-term operational gains.

To address the complexity of wind time series, many studies adopt decomposition-based approaches that separate the data into trend, seasonal, and residual components [24]. These methods improve forecasting accuracy by isolating structural patterns and reducing noise in the data. Recent advancements extend this principle through hybrid and deep learning models that capture multi-frequency behavior and nonlinear dependencies [12]. However, important challenges remain. Data quality issues, such as outliers and structural breaks, are often under-addressed despite their impact on long-term forecasting performance [18]. Additionally, inappropriate temporal aggregation can distort seasonal patterns, particularly in systems undergoing rapid structural change [22].

Another critical issue relates to the evolving nature of energy systems. Wind capacity, regulatory frameworks, and climatic conditions are not static; they change over time, making it difficult for conventional models to maintain accuracy over extended horizons [14]. This has led to the development of adaptive and hybrid forecasting approaches that adjust to changing conditions [2]. At the same time, there is growing recognition that traditional accuracy metrics such as root mean square error (RMSE) and mean absolute error (MAE) may not fully capture the robustness required for policy-oriented forecasting [20, 11]. In sustainability-focused planning, forecast reliability and stability are often more important than marginal improvements in statistical accuracy, as decisions involve long-term investments and environmental commitments.

Despite these methodological advancements, empirical evidence from Rajasthan remains limited and fragmented. Existing studies have primarily focused on short-term forecasting at specific locations, such as Jaisalmer and Jodhpur, using techniques like nonlinear autoregressive with exogenous inputs (NARX) and wavelet-based models [3, 26]. While these studies provide valuable insights into local wind behavior, they do not address the broader challenges of long-term trend analysis, seasonal dynamics, and policy-oriented forecasting at the state level. This creates a significant gap in the literature, particularly in the context of sustainability-driven energy planning.

The present study examines wind energy generation in Rajasthan over the period 2015–2025, with a focus on long-term structural trends, seasonal dynamics, and forecasting performance. The analysis is grounded in time-series theory, where trend and seasonality are recognized as key determinants of forecasting accuracy [21]. By integrating decomposition techniques with forecasting models, the study captures both deterministic and stochastic components of wind generation. Beyond methodological considerations, the research situates forecasting within a sustainability context, emphasizing its role in improving renewable integration, reducing planning uncertainty, and supporting long-term energy transition objectives.

Despite growing interest in renewable energy forecasting, existing studies are largely oriented toward short-term operational accuracy, with limited attention to long-term structural behaviour and seasonal variability at the regional level. This limitation is particularly relevant for Rajasthan, where rapid renewable expansion necessitates a deeper understanding of temporal dynamics for effective planning. Moreover, the integration of forecasting into sustainability-oriented policy frameworks remains fragmented, with few studies offering a unified approach that combines trend analysis, seasonal decomposition, and medium-term forecasting.

To address this gap, the study develops a comprehensive analytical framework that integrates decadal trend analysis, seasonal decomposition, and predictive modelling. This approach enables a systematic examination of how long-term growth and seasonal variability jointly shape wind energy generation, while also providing forecasts that are directly relevant for planning and policy.

The primary objective of this research is to analyse and forecast wind energy generation in Rajasthan using historical data from 2015–2025 and to generate projections for the subsequent two years (2026–2027). Specifically, the study aims to:

- Analyse long-term trends in wind energy generation to understand the structural growth trajectory of renewable energy in Rajasthan.
- Identify and interpret seasonal patterns associated with climatic cycles and their impact on energy availability.
- Develop and validate a forecasting framework that incorporates both trend and seasonal components.
- Evaluate the performance of decomposition-based and seasonal models relative to conventional approaches.
- Generate forecasts that support energy planning, including capacity management, reserve allocation, and grid integration.

This study contributes to the literature by integrating long-term trend analysis, seasonal dynamics, and forecasting within a single framework, thereby extending existing work that typically addresses these elements in isolation. By shifting the focus from short-term prediction to medium-term planning relevance, the research provides insights that are applicable to policymakers, grid operators, and energy planners.

Following the CARS logic, the paper first establishes the territory by framing why wind forecasting matters for renewable-dominant power systems and climate-aligned energy planning. It then identifies the niche by showing that seasonal, state-level wind forecasting that directly speaks to policy planning remains limited—particularly for Rajasthan using decade-long evidence. Finally, it occupies the niche by developing and validating a seasonal forecasting framework for Rajasthan (2015–2025) and extending forecasts for the next two years to support planning and governance needs. The remainder of the paper is organized as follows: Section 2 reviews relevant theory and forecasting literature; Section 3 describes data and methods; Section 4 presents results and validation; Section 5 discusses Final Forecasting, planning, and policy implications; and Section 6 concludes with limitations and future research directions.

2. Review of Literature

Wind power has become a central pillar of decarbonization strategies, but its integration into modern grids remains technically demanding because generation is governed by meteorological variability rather than controllable fuel inputs [30, 9]. In high-renewable systems, forecasting is not merely a support function; it is a core instrument for reliability and economic efficiency because wind uncertainty affects dispatch, reserve requirements, and market outcomes [28, 25]. Accordingly, the forecasting literature has expanded rapidly, yet it remains uneven in how it addresses long-horizon planning needs, especially when the research objective is to extract trend and seasonality and then deliver a next-24-month forecast for a specific region such as Rajasthan.

A consistent starting point across forecasting studies is that wind generation is non-stationary, driven by interacting atmospheric variables (wind speed, direction, temperature, air density, pressure), and shaped by local terrain effects [30]. This physical complexity causes discontinuity and volatility in wind output, which directly complicates grid scheduling and energy market decisions [30, 20]. Yet, a critical weakness in a large portion of forecasting studies is the tendency to treat wind time series as a pure prediction problem, sometimes under emphasizing structural diagnosis (trend and seasonality) even though time-series theory treats decomposition as foundational for robust forecasting [21, 32]. For Rajasthan, this matters because any 2015–2025 series will plausibly mix meteorological seasonality with structural change (capacity growth, grid curtailment, policy shifts), and ignoring these components risks unstable forecasts.

In the traditional methodological stream, statistical models such as autoregressive (AR)/ autoregressive moving average (ARMA)/ and autoregressive integrated moving average (ARIMA) have been widely applied because they capture temporal dependence and provide interpretability [34, 15].
These models remain valuable as benchmarks, particularly when the aim includes identifying persistent patterns. However, the literature also highlights those linear statistical frameworks struggle with nonlinear dynamics and highly volatile wind behavior, which can produce systematic errors when wind regimes shift [16, 8]. This is a major limitation for long-horizon applications because deviations accumulate as the forecasting horizon increases and uncertainty compounds [18, 27]. Therefore, while ARIMA-type models may be useful to diagnose trends/seasonality (especially in a decomposition framework), they can become insufficient alone when the target is a 24-month forecast under regime variability.

Responding to these shortcomings, ML and AI models have been proposed to better represent nonlinear relationships and interactions between predictors and wind output [19, 25]. Tree-based models (random forests, boosting) are attractive because they can handle nonlinearity and heterogeneous feature spaces while offering some interpretability compared to deep neural models [25, 1]. In long-horizon contexts, this becomes particularly relevant because structural change can be partially absorbed via flexible nonlinear mapping. Yet the literature also reveals a central constraint: model performance depends heavily on data resolution, feature quality, and stationarity of the learned relationships across time and context, meaning out-of-sample drift is an enduring risk [1, 18]. For Rajasthan, where both climate variability and capacity expansion may co-evolve during 2015–2025, a model that performs well in one regime may degrade in another unless trend/seasonality are explicitly modeled first.

Deep learning represents another wave of forecasting innovation, motivated by its ability to learn complex temporal dependencies. Gated Recurrent Unit/Long Short-Term Memory (GRU/LSTM) type architectures are designed to capture longer-term relationships in sequential data and have shown improved accuracy compared to some classical approaches [16, 31]. However, deep learning research is also criticized for high data and compute requirements, limited interpretability, and the risk that performance improvements in benchmark datasets do not always translate into robust operational gains in new contexts [31, 20]. These limitations are especially significant for long-horizon regional forecasting, where the practical value is not only accuracy but also transparency and stability under changing conditions.

To reduce noise sensitivity and improve predictability, many studies have adopted hybrid pipelines that combine decomposition/denoising with statistical or ML predictors. Decomposition-based hybrid models are justified by the claim that wind power series can be transformed into subcomponents with clearer frequency structure, allowing models to learn on more stable signals [24, 18]. Evidence across studies suggests hybrids often outperform standalone predictors because they simultaneously reduce noise and improve feature extraction [8, 24]. Yet, a critical observation is that many hybrid studies emphasize short-term or medium-term performance improvements rather than validating seasonal-to-annual forecasting robustness. This creates a mismatch between the dominant forecasting literature (short-term operational focus) and planning needs such as a two-year horizon.

A parallel development concerns uncertainty representation. Short-horizon point forecasts can be operationally useful, but as horizons extend, decision-makers need quantified uncertainty because risk grows with time [28, 30]. Probabilistic or interval forecasting addresses this by providing prediction intervals or distributions rather than single values, thus supporting risk-aware planning [20]. However, evaluation is itself a major methodological bottleneck. The literature emphasizes that error metrics like MAE/RMSE are convenient but may not reflect the true loss function of forecast users, and metric choice can change conclusions about “best” models [20]. This critique is strengthened by newer work arguing for consistency in interval metrics (e.g., coverage- and width-based measures) and standardization of evaluation practice [4]. Therefore, studies aiming at multi-month planning should not only forecast but also justify evaluation design aligned with planning decisions.

Regionally, Rajasthan is a high-value context because wind development has strategic importance within India’s renewable transition, yet empirical forecasting work remains limited and often concentrated on short-term, site-specific prediction rather than long-series structural analysis [26]. At the national/state level, evidence indicates substantial wind capacity presence in India and Rajasthan, supporting the need for generation forecasting as renewables become less controllable than conventional plants [23]. The key gap is therefore not the absence of forecasting methods, but the absence of an integrated framework that (i) first diagnoses trend and seasonality in a decade-long regional series, (ii) selects a forecasting model consistent with those structural properties, and (iii) delivers a robust 24-month forecast with evaluation aligned to long-horizon planning.

In summary, existing literature provides rich methods—statistical, ML, deep learning, hybrid, and probabilistic—but remains fragmented in relation to the combined objectives of trend/seasonality extraction plus 24-month regional forecasting. The present research responds by treating structural time-series analysis as a necessary first step, followed by model selection grounded n both predictive performance and planning-relevant evaluation, applied to Rajasthan wind generation (2015–2025) as a policy-relevant case.

3. Methodology

This study adopts a quantitative time–series approach to analyse long-term trends, seasonal patterns, and medium-term forecasting of wind energy generation in Rajasthan. Monthly wind energy generation data from April 2015 to Jan 2026 were obtained from the Central Electricity Authority (CEA), Government of India. The dataset contains complete monthly observations without missing values, making it suitable for long-horizon time-series analysis. Monthly aggregation is appropriate as it captures seasonal variations in wind energy generation while smoothing short-term fluctuations.

All analyses were conducted using the R statistical computing environment. The wind generation data were converted into a time-series object and examined for structural characteristics before model estimation.

To identify the temporal structure of the series, classical multiplicative decomposition and Seasonal-Trend decomposition using Loess (STL) were applied. These methods separate the series into trend, seasonal, and irregular components, allowing clearer identification of long-term growth patterns and recurring seasonal fluctuations in wind generation.

Following structural analysis, multiple forecasting models were estimated, including ARIMA, Holt–Winters exponential smoothing, ETS (Error–Trend–Seasonal), TBATS, and decomposition-based models such as STLM. Forecast accuracy was evaluated using RMSE, MAE, and mean absolute percentage error (MAPE).

To determine whether differences in forecasting performance were statistically significant, the Diebold–Mariano (DM) test was applied. The best-performing model was selected based on both forecast accuracy and statistical testing. The final model was then re-estimated using the full dataset and used to generate wind energy forecasts for Rajasthan for the period February 2026 to December 2027.

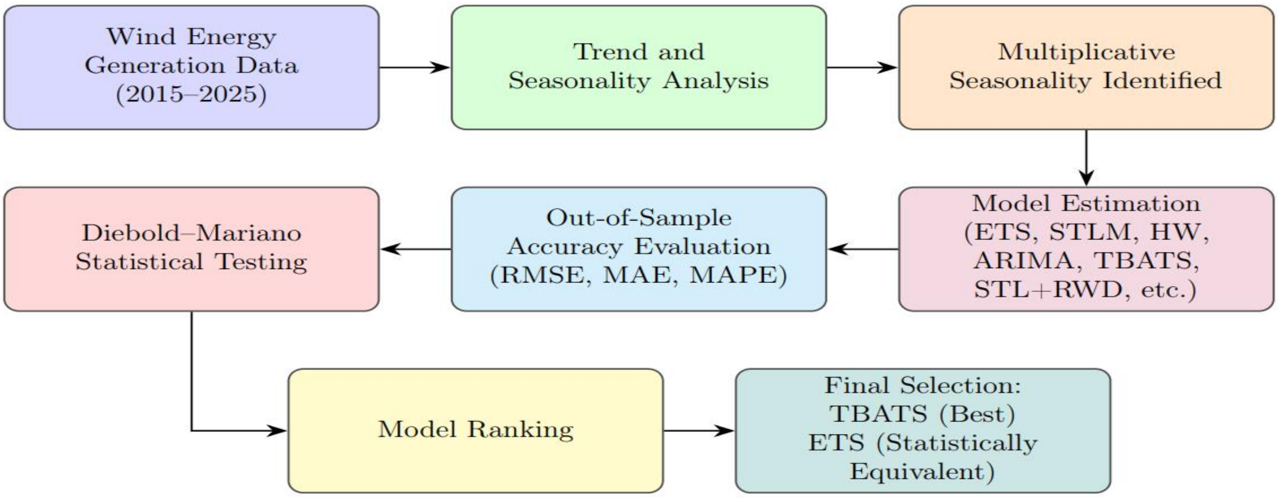


Figure 1: Structured framework for forecasting model evaluation and selection.

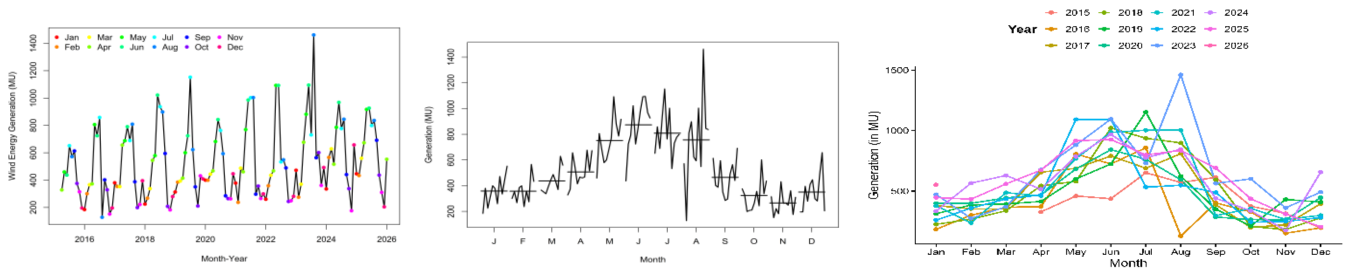
4. Results and Discussion

This section presents the empirical findings related to structural behaviour, trend dynamics, stationarity characteristics, and forecasting performance of the Wind energy generation time series.

4.1 *Structural Dynamics of Wind Generation*

This subsection investigates the structural evolution of Wind energy generation through visual inspection of the time series and decomposition-based analysis, enabling identification of long-term growth patterns and seasonal characteristics.

Visual Behaviour of the time Series: Figures 2a, 2b, and 2c collectively illustrate the temporal dynamics of wind energy generation in Rajasthan over the period 2015–2025. The series exhibits a clear upward trajectory, with generation levels increasing substantially over time, reflecting structural expansion in installed wind capacity and improved resource utilization. Earlier years generally record lower peaks, whereas later years show significantly higher generation levels, in some instances exceeding 1400 MU, indicating sustained growth in wind power production. In addition to this long-term trend, a strong and consistent seasonal pattern is evident across all three figures.



(a) Monthly wind energy generation
(b) Month plot
(c) Seasonal plot

Figure 2. Temporal structure of wind energy generation in Rajasthan

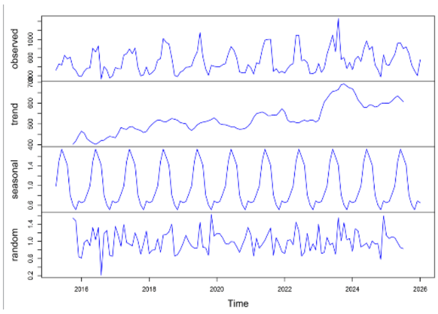
Wind generation remains relatively low during winter months (November–February), begins to rise from March onwards, and reaches its peak during the monsoon period (May–August), particularly in June and July when wind speeds are highest. This recurring annual cycle demonstrates a stable 12-month periodicity driven by climatic conditions.

Importantly, while the shape of the seasonal pattern remains consistent across years, the magnitude of seasonal peaks increases over time. This scaling behaviour suggests the presence of multiplicative seasonality, where seasonal fluctuations expand in proportion to the overall level of generation rather than remaining constant.

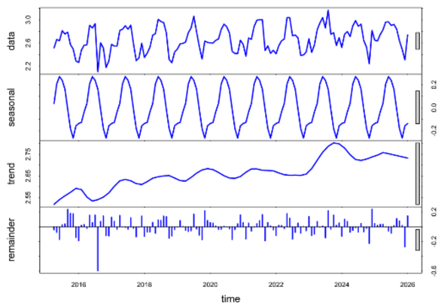
These patterns indicate that wind energy generation in Rajasthan is governed by systematic structural growth and stable seasonal dynamics rather than random variation. These characteristics justify the application of analytical approaches that explicitly account for both trend and seasonality, such as decomposition-based methods and time-series forecasting models.

Decomposition-Based Structural Separation: To understand the underlying dynamics of wind energy generation in Rajasthan, the monthly time series was decomposed into its fundamental components—trend, seasonal, and irregular variations. Both classical multiplicative decomposition and STL decomposition were applied to examine the structural behaviour of the wind generation series (Figures 3a and 3b).

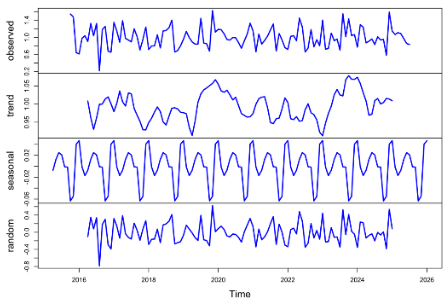
The results from both decomposition approaches reveal a consistent temporal structure in the wind energy generation data. The observed series in both models exhibits pronounced cyclical fluctuations throughout the study period, indicating strong recurring seasonal behaviour in wind energy production. The trend components extracted from both the classical multiplicative and STL methods display a gradual upward trajectory from the beginning of the sample period until approximately 2023–2024, suggesting sustained structural growth in wind energy generation in Rajasthan. This upward movement likely reflects the expansion of installed wind capacity, improved grid connectivity, and policy-driven renewable energy development within the state. Although moderate short-term variations appear along the trend curve, the overall direction remains upward, indicating that the increase in wind generation is structural rather than random.



(a) Classical decomposition



(b) STL decomposition



(c) Remainder component

Figure 3. Decomposition of Rajasthan Wind energy generation data using classical, STL, and remainder component methods.

The seasonal components obtained from both decomposition methods further confirm the presence of a stable and persistent annual cycle in wind energy generation (Figures 3a and 3b). The seasonal pattern consistently rises during the mid-year months and declines during the winter period, reflecting the influence of monsoon wind regimes that increase wind speeds and electricity generation during specific months in Rajasthan. The repetitive and stable shape of the seasonal curve across years indicates that seasonal effects are systematic and predictable. Within the multiplicative framework, seasonal indices vary proportionally with the level of the series, implying that seasonal fluctuations increase as overall wind generation rises. The STL decomposition reinforces this interpretation, as the seasonal component frequently extends beyond the confidence limits indicated on the right side of the figure, demonstrating that the seasonal effect is statistically significant rather than random variation.

After extracting the primary structural components, the irregular or remainder series from both decompositions represents the short-term fluctuations that remain after removing trend and seasonal effects. In both cases, the residual values oscillate around a constant level without exhibiting persistent patterns or systematic behaviour, indicating that most of the variability in wind energy generation is explained by the identified trend and seasonal components. While a few isolated spikes appear in the residual series, the majority of observations remain within the confidence limits shown in the figures, suggesting that these variations represent statistically insignificant random disturbances. Only occasional observations extend beyond these limits, which can be interpreted as temporary anomalies caused by short-term meteorological variability or operational factors.

To further assess whether any residual structure persisted after the extraction of primary components, an additional decomposition of the remainder series was performed (Figure 3c). The remainder fluctuates irregularly around a constant level, while the corresponding trend component remains essentially flat, indicating the absence of any residual long-term pattern. The seasonal component exhibits only minimal and inconsistent variation, suggesting that systematic seasonality has been effectively removed. The residual variation is characterised by random fluctuations around zero without evidence of recurring cycles or clustering, implying that the remaining dynamics are primarily stochastic in nature. This confirms that the initial decomposition successfully captured the dominant trend and seasonal structure of the series. Consequently, the residuals approximate white noise, supporting the adequacy of the decomposition and providing a reliable basis for subsequent seasonal time-series modelling and forecasting.

4.2 *Trend Quantification and Growth Dynamics*

Following the structural decomposition analysis, a semi-logarithmic regression model was estimated to quantify the long-term growth pattern in Rajasthan's wind energy generation. The general semi-log trend model is expressed as:

$$\ln(Wind_t) = \alpha + \beta t + \varepsilon_t \quad (1)$$

where $Wind_t$ represents monthly wind energy generation at time t, α denotes the intercept term capturing the baseline level of generation, β represents the time-based growth parameter, and ε_t denotes the stochastic error term. Based on the estimated regression results, the fitted semi-log trend equation becomes:

$$\ln(Wind_t) = 5.9306 + 0.003139t$$
$$(\text{SE}) \quad (0.0874) \quad (0.001157)$$

The regression estimates are summarized in Table 1, which reports the parameter estimates, standard errors, and statistical significance levels for the semi-log trend model. The coefficient associated with time is positive and statistically significant ($\beta = 0.003139,\ p = 0.0076$), indicating that wind energy generation in Rajasthan exhibits a statistically significant upward trend over the study period. Interpreting the semi-log coefficient suggests an approximate average monthly growth rate of about 0.31% in wind energy generation. The intercept term is highly significant ($p < 0.001$), indicating a stable baseline generation level at the beginning of the observation period. The overall regression model is statistically significant, as indicated by the F-statistic ($F = 7.36,\ p = 0.0076$), confirming that the time trend provides meaningful explanatory power in describing long-term growth in wind energy production.

Table 1: Semi-log Regression Results for Monthly Wind Energy Generation in Rajasthan

Variable	Estimate	Std. Error	t-value	p-value
Intercept	5.9306	0.0874	67.891	$< 0.001^{***}$
Time (t)	0.003139	0.001157	2.713	0.0076^{**}
Residual Std. Error = 0.4951 (df = 128)				
R^2 = 0.0544, Adjusted R^2 = 0.0470				
F-statistic = 7.36 (p = 0.0076)				
Significance levels: $^{***}p < 0.001$, $^{**}p < 0.01$				

Although the coefficient of determination is relatively modest ($R^2 = 0.054$), this outcome is expected for wind energy data because generation levels are strongly influenced by short-term meteorological variability, atmospheric conditions, and seasonal wind regimes that cannot be fully explained by a deterministic time trend alone. Therefore, the semi-log regression should be interpreted primarily as a measure of long-term structural growth rather than a complete predictive representation of wind generation dynamics.

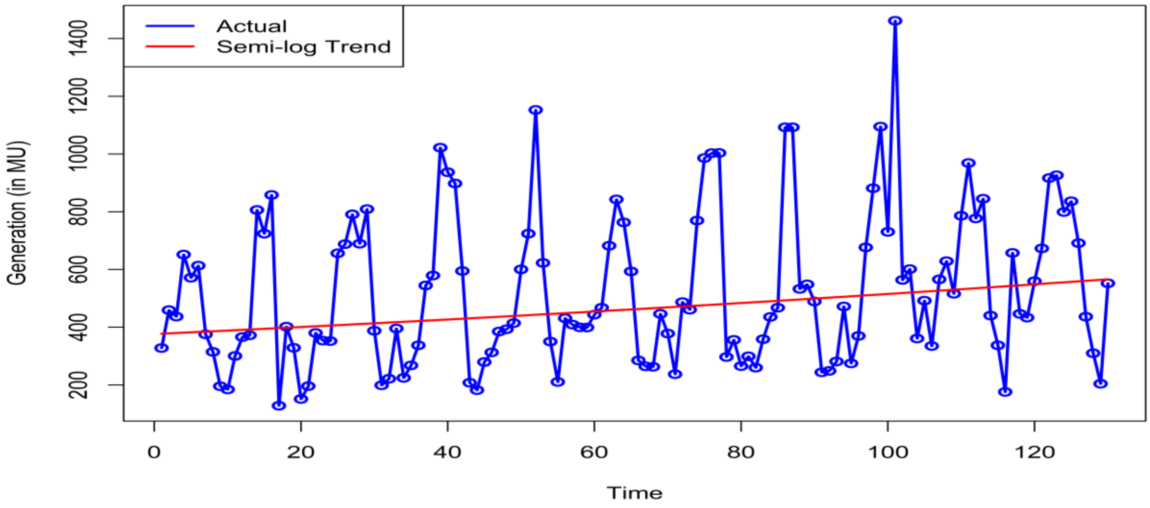


Figure 4. Semi-log trend estimation for monthly wind energy generation in Rajasthan.

Figure 4 illustrates the observed monthly wind energy generation series together with the fitted semi-log trend line. The observed series displays pronounced fluctuations and sharp seasonal peaks, particularly during the monsoon months when wind speeds are typically higher in Rajasthan. Despite these short-term variations, the estimated semi-log trend line exhibits a clear upward slope, indicating gradual long-term expansion in wind energy generation. This growth pattern likely reflects increasing installed wind capacity, improvements in grid infrastructure, and sustained policy support for renewable energy development in the region.

The semi-log trend estimation complements the earlier decomposition results by providing quantitative evidence of structural growth in wind energy production. While the decomposition analysis demonstrated that the majority of variability in the series is explained by systematic trend and seasonal components, the semi-log regression formally measures the long-term growth trajectory of the series. The combined evidence confirms that Rajasthan's wind energy generation is characterized by a persistent upward trend alongside strong seasonal variability, providing a reliable empirical foundation for subsequent time-series forecasting analysis.

4.3 *Stationarity and Unit Root Behaviour*

To examine the stochastic properties of the wind energy generation series, two complementary unit root tests were employed: the Augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. These tests are widely used in time-series analysis due to their opposing null hypotheses, where the ADF test assumes non-stationarity and the KPSS test assumes stationarity. The results of the stationarity tests are reported in Table 2. The ADF test yields a test statistic of -8.175 with a p-value less than 0.01. Since the p-value is smaller than the conventional significance level, the null hypothesis of a unit root is rejected, indicating that the wind energy generation series is stationary. The KPSS test provides additional evidence supporting this conclusion. The KPSS test statistic is 0.3171 with a p-value greater than 0.10. As the p-value exceeds standard significance levels, the null hypothesis of stationarity cannot be rejected. This suggests that the series is stationary in its level form.

Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

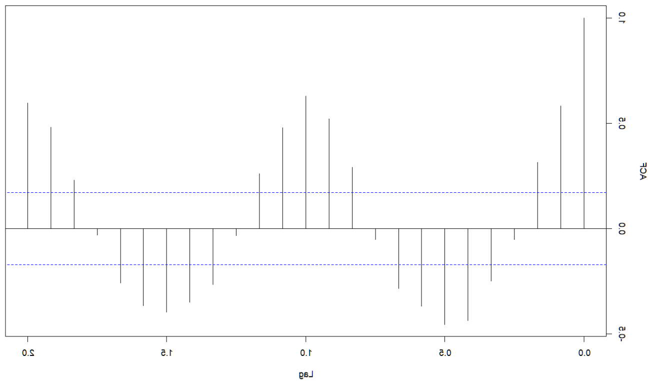
Table 2: Stationarity Test Results for Wind Energy Generation Series

Test	Test Statistic	Lag	p-value	Conclusion
ADF Test	-8.175	5	< 0.01	Reject H_0 (Stationary)
KPSS Test	0.3171	4	> 0.10	Fail to Reject H_0 (Stationary)

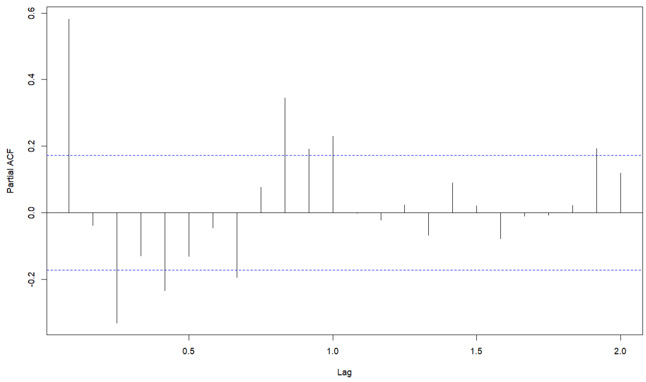
The consistency between the ADF and KPSS test results strengthens the reliability of the stationarity conclusion, as both tests, despite having opposite null hypotheses, indicate that the wind energy generation series is stationary. Therefore, the original series does not require differencing and can be directly used for subsequent time-series modelling and forecasting.

4.4 *ACF and PACF Analysis for Model Identification*

The autocorrelation and partial autocorrelation structures of the monthly wind energy generation series are examined using the ACF and PACF plots (Figure 5). The ACF plot (Figure 5a) exhibits a gradual decay pattern with multiple significant spikes extending beyond the confidence bounds, indicating strong persistence and temporal dependence in the series. Notably, prominent spikes are observed at seasonal intervals, particularly around lag 12 and its multiples, confirming the presence of pronounced annual seasonality in wind energy generation. The alternating pattern of positive and negative correlations at intermediate lags further suggests cyclical behaviour, which is consistent with the seasonal wind patterns observed in Rajasthan. The PACF plot (Figure 5b) complements this finding by showing a significant spike at lag 1, followed by smaller but still notable spikes at seasonal lags. The sharp spike at the first lag indicates the presence of a short-term autoregressive component, suggesting that current wind generation is influenced by its immediate past value. Additionally, the presence of significant spikes around the seasonal lag supports the existence of a seasonal autoregressive structure. Unlike the ACF, which captures both direct and indirect correlations, the PACF isolates the direct relationship, thereby confirming that both short-term (non-seasonal) and seasonal dependencies coexist in the series.



(a) ACF plot



(b) PACF plot

Figure 5. Autocorrelation (ACF) and partial autocorrelation (PACF) Plots

Both the ACF and PACF plots indicates that the wind energy generation series is characterized by strong persistence, clear annual seasonality, and a low-order autoregressive structure. The slow decay in the ACF and the significant spike at lag 1 in the PACF suggest the inclusion of autoregressive terms, while the repeated seasonal spikes support the need for a seasonal component with periodicity of 12 months. These patterns justify the use of seasonal time-series models such as SARIMA, ETS, or TBATS for accurate modelling and forecasting. In particular, the evidence supports a specification that incorporates both non-seasonal AR components and seasonal dynamics, making the series suitable for advanced seasonal forecasting frameworks.

4.5 *Model Selection Justification*

The selection of forecasting models is guided by the statistical properties identified through structural and stationarity analysis of the wind energy generation series for Rajasthan. The series exhibits a strong upward trend, pronounced seasonality with a 12-month periodicity, and increasing variance over time, indicating a non-stationary process with multiplicative seasonal behaviour. Decomposition further reveals systematic long-term growth alongside stable but scaling seasonal fluctuations, while short-term irregular movements remain bounded.

These characteristics impose specific modelling requirements. The presence of non-stationarity arising from seasonal dependence necessitates seasonal differencing, while the proportional expansion of seasonal amplitude supports multiplicative formulations and variance-stabilizing transformations such as logarithmic or Box–Cox adjustments. The evolving nature of the trend, as captured through STL decomposition, requires flexible trend specifications rather than rigid deterministic structures. Additionally, the presence of short-run dependence in residual dynamics indicates the need for autoregressive components.

Accordingly, a diverse set of model families was considered to capture different aspects of the underlying temporal dynamics, as illustrated in Figure 6. Classical approaches such as ARIMA and Holt–Winters exponential smoothing provide interpretable benchmarks for linear and seasonal dynamics. State-space models such as ETS offer a flexible framework for jointly modelling level, trend, and seasonality. Decomposition-based approaches (e.g., STLM) explicitly separate structural components prior to forecasting, while advanced seasonal models such as TBATS are capable of handling complex seasonal patterns and time-varying behaviour. In addition, nonlinear approaches such as neural network autoregression (NNETAR) are included to account for potential nonlinearities in wind generation dynamics.

Further guidance for model specification is obtained from the autocorrelation structure of the series. The ACF and PACF diagnostics (Figure 5) indicate strong persistence and clear seasonal dependence, with significant autocorrelations at seasonal lags and a dominant short-term autoregressive structure. These empirical patterns support the use of a Seasonal ARIMA framework.

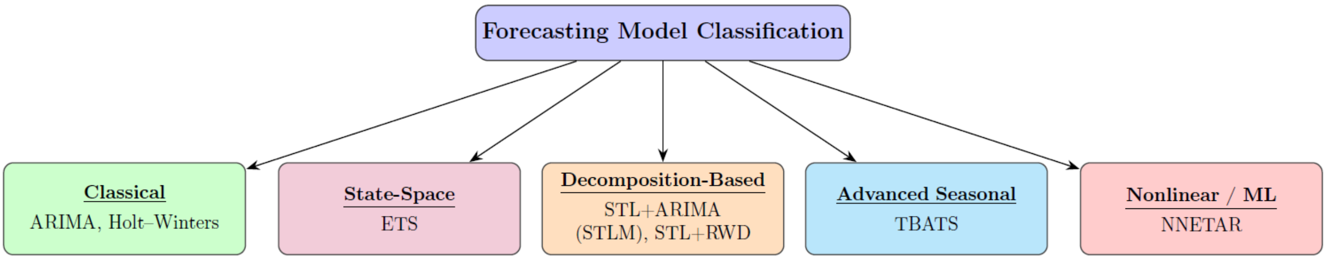


Figure 6. Classification of forecasting models considered in the study.

Stationarity tests indicate that non-seasonal differencing is not required ($d = 0$). However, the presence of strong seasonal dependence necessitates seasonal differencing ($D = 1$) with a periodicity of 12 months. The general specification is therefore given by:

$$SARIMA(p, 0, q)(P, 1, Q)_{12}$$

Based on parsimony and the observed ACF–PACF structure, a baseline specification of the form:

$$SARIMA(1,0,0)(1,1,0)_{12}$$

is adopted. The non-seasonal autoregressive component captures short-term dependence, while the seasonal autoregressive term accounts for annual cyclical behaviour.

This SARIMA model serves as a benchmark against which more flexible frameworks such as ETS, TBATS, decomposition-based models, and nonlinear approaches are evaluated, enabling a comprehensive assessment of forecasting performance across alternative modelling paradigms.

4.6 *Forecast Performance Comparison*

To evaluate forecasting performance, out-of-sample accuracy measures were computed using RMSE, MAE, and MAPE. Table 3 presents the comparative statistics across all candidate forecasting models based on the test dataset.

Table 3. Model Accuracy Comparison

Model	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	U
ETS	-1.8845	130.3735	110.0399	-4.6809	22.8532	0.7233	0.2191	0.6201
STL + ARIMA (STLM)	-42.7191	117.1817	96.2492	-15.6608	23.9289	0.6327	0.0031	0.5460
TBATS	2.2503	117.2044	100.9052	-5.6302	22.2260	0.6633	0.0259	0.5559
Holt–Winters (HW)	-22.4466	135.7357	109.6438	-8.3114	22.6789	0.7207	0.1450	0.5583
ARIMA	-29.9942	120.6982	101.1607	-10.8591	22.5769	0.6650	0.1742	0.5811
STL + RWD	-129.1172	171.2511	148.4329	-34.0042	37.0909	0.9757	0.0408	0.6250

NNETAR	60.2975	163.4998	131.4009	5.7115	23.8990	0.8637	0.3564	0.5806

Table 3 reveals a clear empirical pattern. STLM achieves the lowest RMSE (117.18) and MAE (96.25), indicating superior performance in minimizing absolute forecast errors, while TBATS records the lowest MAPE (22.23), reflecting stronger proportional accuracy. In contrast, STL+RWD performs worst across all metrics, and NNETAR shows comparatively weak performance relative to leading statistical models. These results suggest that models which explicitly separate seasonal structure prior to forecasting tend to perform more reliably than approaches that model the original time series directly.

The strong performance of STLM is consistent with theoretical and empirical insights from time-series literature. Wind generation data are characterized by non-stationarity and pronounced seasonality, and decomposition-based approaches improve forecast accuracy by isolating these components before modelling stochastic dependence [21, 24, 18]. In this context, the results indicate that relatively simple statistical models can remain highly effective when applied to appropriately transformed data. At the same time, TBATS demonstrates competitive performance, particularly in terms of MAPE, highlighting its ability to capture complex seasonal behaviour through trigonometric representations and variance stabilization.

A comparison between ARIMA and STLM further underscores the importance of explicitly modelling seasonal structure. While ARIMA provides reasonable forecasts, accuracy improves once STL decomposition is introduced, confirming that gains arise from isolating systematic components rather than increasing model complexity. The comparatively weaker performance of ETS and Holt–Winters models suggest limited flexibility in capturing irregular seasonal variation driven by meteorological factors. Similarly, the underperformance of NNETAR indicates that nonlinear models may not offer advantages in settings where strong deterministic seasonality dominates or data availability is limited [34, 30]. The poor results of STL+RWD further demonstrate that decomposition alone is insufficient without an appropriate stochastic model to capture residual dependence.

To assess whether these differences are statistically significant, the DM test was applied. The results, reported in Table 4, indicate that none of the pairwise differences in forecast accuracy are statistically significant. The near-zero DM statistic for TBATS versus ARIMA, along with consistently high p-values, suggests that observed differences in accuracy metrics may reflect sampling variability rather than systematic performance differences. This implies that, once the dominant seasonal structure is adequately captured, alternative modelling approaches tend to converge in predictive performance.

Table 4. DM test results for pairwise forecast comparison

Model Pair	**DM Statistic**	**p-value**	**Inference**
TBATS vs ARIMA	0.0028	0.9978	Fail to reject H_0
TBATS vs STL+RWD	-0.6376	0.5301	Fail to reject H_0
ARIMA vs STL+RWD	-0.4390	0.6647	Fail to reject H_0

Based on the empirical evidence, the STLM model is selected as the preferred forecasting framework due to its superior performance in RMSE and MAE, along with its interpretability and alignment with the underlying data structure.

These findings carry important implications. From a theoretical perspective, they reinforce the effectiveness of decomposition-based approaches in modelling renewable energy time series characterized by strong seasonal structure. From a policy and practical standpoint, the results suggest that interpretable statistical models can provide reliable forecasts for planning purposes without requiring highly complex modelling frameworks. However, the analysis is subject to certain limitations. The evaluation relies on RMSE, MAE, and MAPE, which do not capture all aspects of forecast performance, and does not incorporate exogenous variables or probabilistic uncertainty. Future research should extend this framework through rolling validation, inclusion of external drivers, and probabilistic forecasting approaches to enhance both robustness and policy relevance.

5. Final Model Adequacy for Wind Energy Forecasting in Rajasthan

Having established the relative forecasting performance of competing models, the focus now shifts to evaluating the adequacy of the selected STLM framework in capturing the underlying characteristics of the wind energy generation series. Model adequacy is assessed in terms of its ability to represent systematic structure, eliminate residual dependence, and produce statistically well-behaved errors.

5.1 *Econometric Specification*

The STLM model follows a decomposition-based framework in which the observed wind energy generation series is expressed as the sum of its structural components:

$$Y_t = T_t + S_t + R_t \tag{2}$$

where Y_t denotes wind energy generation at time t, T_t represents the trend component, S_t denotes the seasonal component, and R_t is the irregular or remainder component.

After removing the seasonal component using STL decomposition, the seasonally adjusted series is modelled using an ARIMA process:

$$\phi(B)(1-B)^d X_t = \theta(B)\varepsilon_t \tag{3}$$

where $X_t = Y_t - S_t$ is the deseasonalized series, $\phi(B)$ and $\theta(B)$ are the autoregressive and moving average polynomials respectively, d is the order of differencing, and ε_t is a white noise error term.

The final forecasts are obtained by combining the ARIMA-based forecasts of the adjusted series with the estimated seasonal component derived from the STL decomposition.

5.2 *Final 24-Month Forecast*

Building upon the selected STLM framework, the final 24-month forecasts of wind energy generation are generated to examine the expected future dynamics of the series over the period February 2026 to January 2028. The forecasts capture the continuation of historical seasonal patterns and provide a structured representation of anticipated variations over the forecast horizon. These projections offer insights into both the expected trajectory of wind energy generation and the associated uncertainty, supporting medium-term planning and policy formulation.

The out-of-sample forecasts are presented in Table 5 and illustrated in Figure 7. The forecast trajectory closely follows the historical seasonal pattern observed in wind energy generation, indicating the strong persistence of seasonal dynamics in Rajasthan's wind energy system.

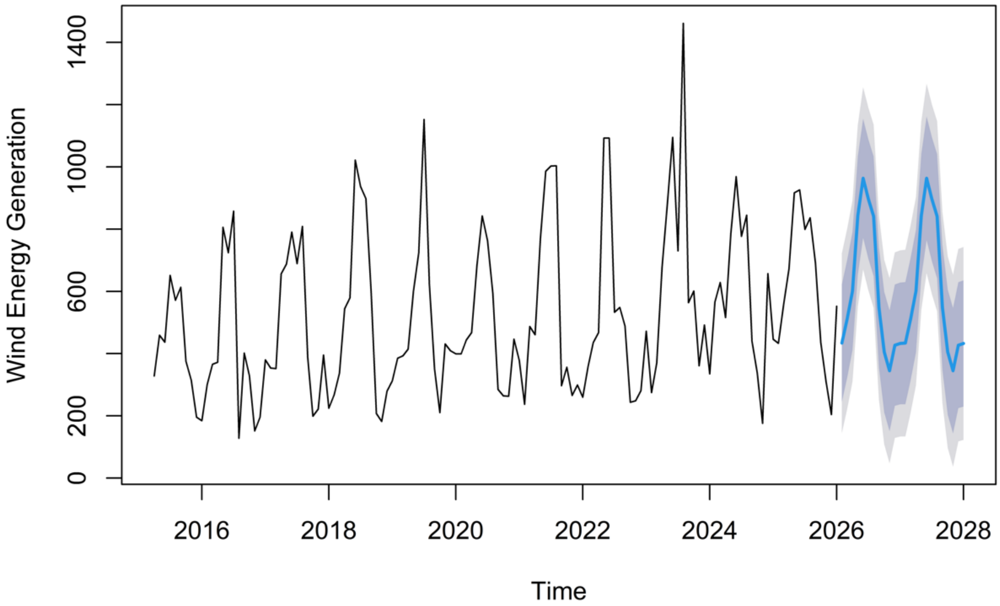


Figure 7. STLM forecast of monthly wind energy generation in Rajasthan.

Figure 7 illustrates the forecasting performance of the STLM model, where the black line represents historical observations and the blue line denotes the projected values, while the shaded regions correspond to the 80% and 95% prediction intervals, reflecting increasing uncertainty over the forecast horizon. The forecasted trajectory exhibits pronounced seasonal fluctuations, with wind energy generation rising sharply during the monsoon months (May–August) and reaching peak levels exceeding 950 MU, particularly in June and July. In contrast, generation declines during the winter months (October–January), where forecasted values remain below 450 MU. This cyclical behaviour highlights the dominant influence of seasonal wind regimes and confirms that the STLM model effectively captures the recurring seasonal dynamics of wind energy generation in Rajasthan.

Table 5. STLM forecast of wind energy generation (Feb 2026 – Jan 2028)

Month	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Feb 2026	433.71	245.06	622.37	145.19	722.24
Mar 2026	511.82	322.53	701.11	222.32	801.32
Apr 2026	601.05	411.12	790.98	310.58	891.52
May 2026	843.04	652.48	1033.60	551.60	1134.47
Jun 2026	963.38	772.19	1154.57	670.98	1255.78
Jul 2026	896.04	704.22	1087.86	602.68	1189.40
Aug 2026	841.38	648.93	1033.82	547.06	1135.69
Sep 2026	548.15	355.08	741.22	252.87	843.42
Oct 2026	404.87	211.18	598.56	108.65	701.09

Nov 2026	344.79	150.48	539.10	47.61	641.96
Dec 2026	427.12	232.20	622.05	129.01	725.24
Jan 2027	432.66	237.12	628.21	133.61	731.72
Feb 2027	433.71	237.56	629.87	133.72	733.71
Mar 2027	511.82	315.05	708.59	210.89	812.75
Apr 2027	601.05	403.67	798.43	299.18	902.92
May 2027	843.04	645.05	1041.02	540.24	1145.83
Jun 2027	963.38	764.78	1161.97	659.65	1267.10
Jul 2027	896.04	696.84	1095.24	591.39	1200.69
Aug 2027	841.38	641.57	1041.18	535.80	1146.95
Sep 2027	548.15	347.74	748.55	241.66	854.64
Oct 2027	404.87	203.87	605.87	97.46	712.28
Nov 2027	344.79	143.19	546.38	36.47	653.11
Dec 2027	427.12	224.93	629.32	117.89	736.35
Jan 2028	432.66	229.88	635.45	122.53	742.80

Residual Independence and Serial Correlation: The adequacy of the STLM model is further assessed by examining the independence and serial correlation properties of the residuals. The residual time series fluctuates randomly around zero without exhibiting any visible trend or systematic pattern, indicating that the model has effectively captured the dominant structure of the wind energy generation series. Additionally, the distribution of residuals appears approximately symmetric, suggesting that the model errors are not systematically biased.

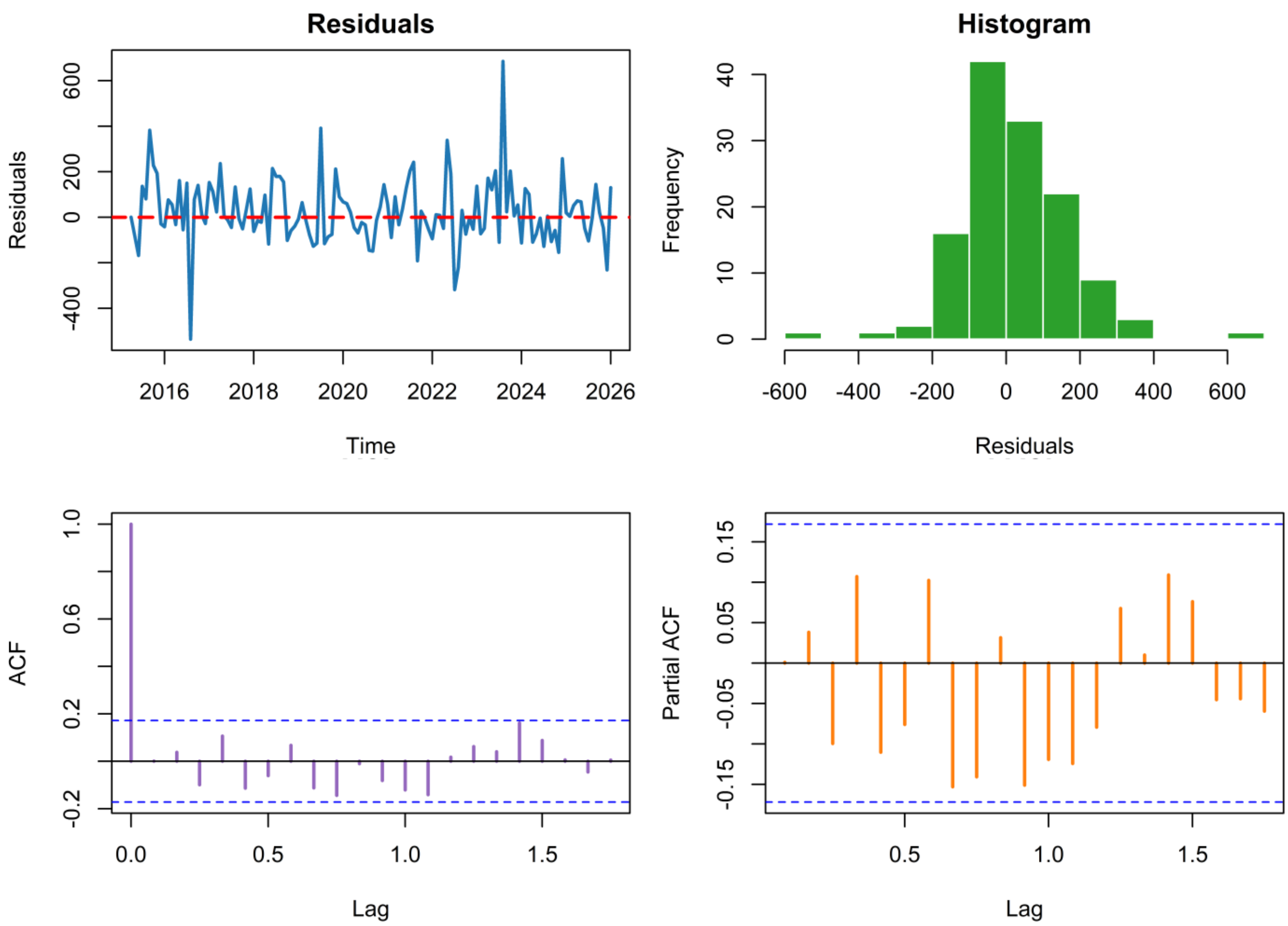


Figure 8. Residual diagnostics of the STLM model, including residual time plot, histogram, autocorrelation function (ACF), and partial autocorrelation function (PACF).

The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots presented in Figure 8 show that nearly all autocorrelation coefficients lie within the confidence bounds, with no significant spikes at any lag. This indicates the absence of residual serial dependence and suggests that the remaining variations behave as random noise rather than containing any systematic structure.

To formally test for serial correlation, the Ljung–Box test is employed using model-adjusted residuals. The Ljung–Box test statistic is defined as:

$$Q^* = n(n+2)\sum_{k=1}^{h} \frac{\hat{\rho}_k^2}{n-k} \tag{4}$$

where n is the sample size, h is the number of lags, and $\hat{\rho}_k$ represents the sample autocorrelation at lag k. Under the null hypothesis of no serial correlation, the test statistic follows a chi-square distribution with $(h - p - q)$ degrees of freedom. The results of the test are reported in Table 5.

Table 5: Ljung–Box test results for residual independence

Model	**Q^* Statistic**	**df**	**p-value**	**Inference**
STL+ARIMA (STLM)	23.979	23	0.405	Fail to reject H_0

Advanced International Journal for Research (AIJFR)
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The Ljung–Box test yields a p-value greater than 0.05, indicating that the null hypothesis of no serial correlation cannot be rejected. This confirms that the residuals are approximately independent and behave as white noise. The absence of significant autocorrelation in the residuals demonstrates that the STLM model adequately captures both the seasonal and stochastic dynamics of wind energy generation in Rajasthan, thereby validating its suitability for forecasting applications.

Conditional Heteroskedasticity: To assess the presence of volatility clustering in the residuals, the ARCH LM test is employed. The test examines whether the conditional variance of the residuals depends on past squared errors, as specified by:

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + u_t \tag{5}$$

where ε_t denotes the residual at time t, α_0 is a constant term, α_i represents the coefficients capturing the influence of past squared residuals (ARCH effects), and u_t is a white noise error term.

The results of the ARCH LM test are reported in Table 6. The test yields a Chi-squared statistic of 3.7324 with 12 degrees of freedom and a p-value of 0.9878. Since the p-value is substantially greater than conventional significance levels, the null hypothesis of no ARCH effects cannot be rejected.

Table 6: ARCH LM test results

Model	**Chi-square**	**df**	**p-value**	**Inference**
STLM	3.7324	12	0.9878	Fail to reject H_0

The absence of statistically significant ARCH effects indicates that the residual variance remains stable over time and does not exhibit volatility clustering. This suggests that the STLM model not only captures the mean dynamics and seasonal structure effectively but also produces homoskedastic residuals. Consequently, the model satisfies the assumption of constant variance, further reinforcing its adequacy and reliability for forecasting wind energy generation in Rajasthan.

5.3 *Implications for Energy Planning in Rajasthan*

The forecasting results carry implications that go well beyond model comparison. In substantive terms, the evidence suggests that Rajasthan's wind energy system is not dominated by random short-term fluctuations alone; rather, it is shaped by a stable seasonal structure, a modest long-run growth trajectory, and a forecastable intra-annual cycle. That matters for planning because energy policy is rarely framed around hourly deviations. It is framed around procurement windows, reserve requirements, maintenance schedules, seasonal adequacy, and infrastructure readiness. In that context, the strong performance of the STLM model is especially relevant. A decomposition-based model that explicitly separates seasonality from the stochastic remainder is not only statistically efficient; it is also easier to interpret for planning purposes, since it produces a forecast that mirrors the actual seasonal logic of Rajasthan's wind regime rather than treating all variation as undifferentiated noise [24, 18, 20].

For Rajasthan specifically, the practical value of this seasonal structure is clear. The state already has a large and policy-relevant wind base, with installed wind capacity reported at 4,414.12 MW by December 2024, and state planning documents explicitly position renewable expansion, storage integration, and clean-energy investment as core elements of future development strategy [7]. Against that backdrop, the forecast profile obtained in this study—high generation during the monsoon-linked months and comparatively low output during winter—can be read as a planning signal rather than merely a statistical pattern. In high-wind months, the forecast can inform transmission preparedness, maintenance scheduling, and the management of potential renewable surpluses. In low-wind months, it can support more realistic reserve planning, targeted procurement, and coordination with thermal, hydro, or storage-based balancing resources. In other words, seasonal forecasting helps move planning from reactive balancing to anticipatory management, which is exactly the kind of shift that high-renewable systems require [28, 13].

These implications also connect directly to sustainability. A state that can better anticipate seasonal wind availability is better positioned to reduce avoidable fossil-fuel dependence, lower curtailment, and make more efficient use of storage and transmission infrastructure. Forecasting, in this sense, supports sustainability not only by enabling more renewable electricity to enter the grid, but also by reducing the inefficiencies that often accompany renewable integration when variability is poorly anticipated. The literature is quite clear that the value of forecasting lies in better decision-making under uncertainty, especially for market participants and system operators who must manage both reliability and cost [28]. When translated into the Rajasthan context, that means seasonal wind forecasts can strengthen sustainable energy planning by improving the timing of procurement, reducing unnecessary thermal commitment during expected high-wind periods, and identifying the months in which flexibility resources will be most needed. The sustainability contribution is therefore operational as much as environmental: fewer balancing inefficiencies, better use of renewable capacity, and more credible progress toward clean-energy targets [28]. A second implication concerns model choice for public decision-making. The findings do not support the increasingly common assumption that more complex machine-learning structures are always preferable. In this study, NNETAR underperformed relative to the leading statistical specifications, while STLM and TBATS produced more reliable results on the principal error measures. This is important for planning institutions, because interpretability and robustness often matter as much as raw predictive sophistication. Forecasts used in government and utility settings must often be defended before non-technical stakeholders, linked to policy actions, and updated with limited computational burden. In such settings, decomposition-based statistical models may be more useful than black-box alternatives, especially when the policy question is seasonal adequacy rather than ultra-short-term dispatch optimization. This interpretation is consistent with wider forecasting research showing that model usefulness depends on horizon, data structure, and decision context, not simply on algorithmic novelty [11, 34].

The results also suggest that seasonal wind forecasting should be embedded within a broader renewable planning framework in Rajasthan. Recent work on solar irradiance prediction in Rajasthan shows that machine-learning-based forecasting is already being positioned as a tool for improving renewable energy planning and implementation in the state [29]. That parallel evidence implies that Rajasthan’s sustainability agenda would benefit from integrated seasonal forecasting across both wind and solar resources, rather than treating them as isolated sectors. This is particularly important because the planning problem is no longer whether renewables should expand, but how multiple variable renewable resources can be synchronized with storage, network capacity, and demand management in a financially and environmentally sustainable way. Seasonal wind forecasting adds one essential part of that planning architecture: it clarifies when wind is likely to carry a larger share of the burden and when complementary resources must step in. There is, however, a cautionary implication as well.

The DM tests indicate that some apparent differences in forecasting accuracy are not statistically strong enough to be interpreted as decisive. This means energy planners should avoid over-reading small differences in RMSE, MAE, or MAPE when selecting a model for operational use. Where forecast performance is broadly similar, criteria such as interpretability, ease of updating, data requirements, and institutional usability may legitimately outweigh marginal differences in numerical accuracy. For Rajasthan, that point is particularly relevant because planning agencies and utilities require forecast systems that are reproducible, transparent, and scalable across decision contexts. The present results therefore support the use of STLM not because it is universally superior in every possible setting, but because it combines strong empirical performance with a structure that is intelligible and policy-compatible.

The findings imply that seasonal forecasting can become a practical sustainability instrument for Rajasthan. It can improve the temporal alignment of renewable generation with procurement and flexibility decisions, strengthen the credibility of clean-energy planning, and reduce the hidden costs of uncertainty that often slow renewable transitions. If Rajasthan is to deepen renewable integration while maintaining affordability and reliability, then forecasting must be treated not as a narrow technical exercise, but as part of the state's broader sustainability infrastructure.

6. Conclusion

This study investigates the decadal evolution, seasonal structure, and forecasting behaviour of wind energy generation in Rajasthan, with the objective of identifying a reliable and policy-relevant forecasting framework. Using monthly data from 2015 to 2025, the analysis integrates structural decomposition, semi-log trend estimation, stationarity testing, autocorrelation diagnostics, and comparative model evaluation. The results reveal that wind energy generation in Rajasthan is characterized by a statistically significant upward trend and a strong, stable seasonal cycle driven by monsoon wind regimes. Decomposition confirms that most variability is explained by systematic trend and seasonal components, while residual fluctuations behave as white noise. Among the competing models, the STLM framework provides the most reliable performance, achieving superior accuracy in terms of RMSE and MAE while maintaining structural interpretability. The resulting forecasts indicate a highly predictable intra-annual pattern, with peak generation concentrated in monsoon months and reduced output during winter. These findings contribute to the literature by reinforcing the importance of decomposition-based approaches in renewable energy forecasting, particularly in contexts where seasonality is dominant. From a practical perspective, the results provide actionable insights for energy planners, grid operators, and policymakers. The ability to anticipate seasonal wind availability enables more efficient procurement planning, improved reserve management, and better alignment of maintenance and infrastructure decisions with expected generation cycles. Such improvements are critical in high-renewable systems, where uncertainty can impose high operational and economic costs.

The study also highlights the relevance of forecasting for sustainability-oriented energy transitions. By improving predictability, seasonal forecasting supports greater integration of renewable energy, reduces dependence on fossil-fuel-based balancing sources, and enhances the efficient utilization of grid and storage infrastructure. In this sense, forecasting is not merely a technical tool but a strategic component of sustainable energy planning. However, the analysis is subject to certain limitations. The use of univariate monthly data excludes important exogenous factors such as meteorological variables, grid constraints, and policy interventions. Future research should extend this framework by incorporating multivariate models, higher-frequency data, and probabilistic forecasting approaches, as well as spatially disaggregated analysis across wind corridors.

This study advances understanding of how structural trends and seasonal dynamics shape renewable energy systems and demonstrates that interpretable statistical models can provide robust and policy-relevant forecasts. Such evidence is essential for supporting data-driven decision-making and strengthening the transition toward a more resilient and sustainable energy future.

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