Wind speed prediction and energy estimation using the SARIMA method in Banyumas Regency

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ABSTRACT

Electricity consumption in Banyumas Regency shows a significant upward trend, indicating growing energy needs across various sectors. Dependence on fossil fuels poses challenges, including environmental pollution, limited resources, and price fluctuations. As a strategic solution, developing new and renewable energy, especially wind energy, is crucial to achieving energy independence and environmental sustainability. This study aims to analyze and predict wind speed in Banyumas Regency and calculate the potential electricity production that residential-scale wind turbines can generate. The method used is the seasonal auto regressive integrated moving average (SARIMA). This study applies it within a machine learning framework, using a grid search for hyperparameter tuning, to accurately predict wind speed from historical NASA POWER data. The results show that the SARIMA (1, 0, 0)×(0, 1, 1, 52) model is the optimal model with the best prediction accuracy, as evidenced by the root mean squared error (RMSE) value of 0.516 m/s and the mean absolute error (MAE) of 0.441 m/s. Based on the model, the predicted average wind speed for the next three months is 3.41 m/s, potentially generating an average daily electricity output of 1.44 kWh. These results indicate that Banyumas Regency has promising potential for the development of small-scale wind power plants to support household energy needs or public street lighting.

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1. INTRODUCTION

Electrical energy demand in Banyumas Regency is steadily increasing, reaching 1,094,198,518 kWh in 2023 [1]. Since this demand is predominantly met by fossil fuels, which pose significant environmental and economic risks [2], transitioning to renewable sources is imperative for sustainable energy independence [3]. This transition directly supports the national energy policy (KEN) target of a 23% renewable energy mix [4] and builds on the proven viability of wind energy demonstrated by large-scale projects such as the Sidrap wind farm [5].

Wind energy represents a highly potential renewable source for this region [6], [7]. Geographically, the diverse topography of Banyumas naturally generates local mountain and valley winds [8]. However, optimizing this potential requires a rigorous analysis of wind speed, as it is the primary determinant in electrical energy production [9], [10].

To address these challenges, accurate wind speed prediction is essential for reliably estimating energy production. Therefore, this study proposes a seasonal auto regressive integrated moving average (SARIMA) model, systematically optimized via Grid Search hyperparameter tuning to ensure maximum forecasting accuracy. Ultimately, the research aims to forecast wind speeds in Banyumas Regency and quantitatively estimate the resulting power and electrical energy output from wind turbines.

Recent forecasting approaches, including LSTM [11], regression [12], [13], neural networks [14], [15], and hybrid models [16], [17], offer high accuracy but often demand massive datasets and resource-intensive architectures. Conversely, simpler models like Prophet [18] may rely on aggregated data that obscures critical short-term volatility. Although SARIMA is highly reliable for time-series forecasting [19], [20], it is rarely optimized systematically for topographically complex regions. Furthermore, a critical gap remains in integrating these localized forecasts with practical energy estimates to assess the feasibility of small-scale turbines in areas like Banyumas Regency.

Table 1 compares this study with recent related works. While advanced deep learning hybrids like VMD-GDPSO-TCN-BiLSTM and DWT-BiLSTM-BiGRU achieve high accuracy, they require significant computational resources and complex architecture. In contrast, Siregar and Putri reported a lower RMSE (0.19 m/s) with Prophet; however, their use of monthly-aggregated data smoothed out volatility, sacrificing the granular detail needed for operational planning. Liu *et al*. [19] demonstrated that, for short-term forecasting, SARIMA can outperform complex models such as LSTM. Bridging these gaps, this study utilizes an Optimized SARIMA model on weekly data, maintaining competitive accuracy (RMSE 0.516 m/s) while offering computational efficiency and interpretability essential for preliminary feasibility analysis.

The novelty of this research lies in three main aspects:

a. The application of the Seasonal ARIMA method within a machine learning framework that includes parameter optimization for maximum accuracy.
b. The use of local data from Banyumas Regency, which has unique topographic characteristics.
c. The integration of wind speed prediction results with quantitative estimates of power and electrical energy production is applicable for feasibility analysis of small-scale wind power plant construction.

Table 1. Method comparison

No	Author (Ref)	Method	Region	Best Accuracy	Limitations/Notes
1	Chen *et al.* (2025) [15]	VMD-Hybrid DL	Offshore	RMSE: 0.14 m/s	High computational complexity and training time.
2	Barjasteh *et al.* (2024) [16]	DWT-Hybrid DL	Land-based	RMSE: 0.25 m/s	Complex "black-box" architecture; harder to interpret.
3	Siregar and Putri (2025) [17]	Prophet	Medan	RMSE: 0.19 m/s	Used monthly data; loses short-term fluctuation details.
4	Liu *et al.* (2021) [18]	SARIMA vs LSTM	Offshore	RMSE: 1.43 m/s	Proved SARIMA is competitive against deep learning.
5	This Study	Optimized SARIMA	Banyumas	RMSE: 0.516 m/s	Balanced accuracy for weekly granular data; efficient for feasibility study.

2. METHOD

2.1. Flowchart

The research methodology follows a structured framework illustrated in Figure 1, beginning with the systematic acquisition of historical wind speed data (WS10M) for the Banyumas region from the NASA POWER database. This raw dataset underwent rigorous preprocessing, including forward-fill imputation to correct anomalies, weekly resampling to mitigate stochastic noise, and stationarity verification using the augmented Dickey-Fuller (ADF) test to establish a reliable statistical foundation. Subsequently, the data were chronologically partitioned into training and testing subsets to support robust model development. An automated grid search was then executed to identify the optimal SARIMA parameters by minimizing the Akaike information criterion (AIC), with predictive accuracy validated using RMSE and MAE metrics. In the final stage, the optimized model generated a 13-week wind speed forecast, which was seamlessly integrated into wind kinetic energy equations to quantitatively assess the power and energy production potential for residential-scale turbines in the region.

2.2. Dataset

The dataset used in this study is historical time-series data from the NASA POWER database. The data covers daily climatological variables in Banyumas Regency from early 2022 to mid-2025, totaling 1,277 rows. The primary variable used is wind speed at 10 meters (WS10M).

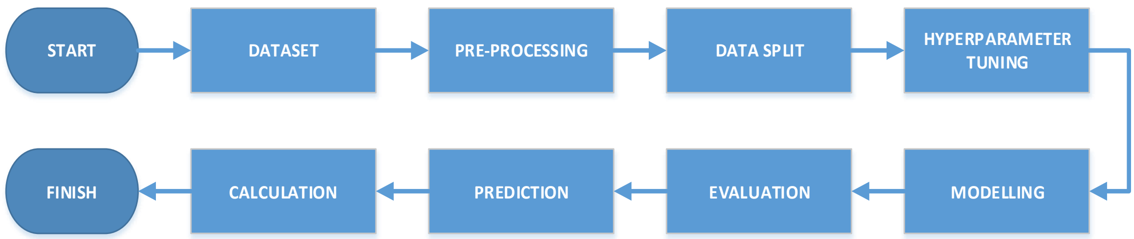

Figure 1. Research flowchart

2.3. Preprocessing data

Data preprocessing steps are carried out to ensure data quality and readiness before the modelling process [21], which consist of:

a. Date column arrangement: the year (YEAR), month (MO), and day (DY) columns are combined into a single 'Date' column to facilitate time series analysis.
b. Anomalous value handling: A value of -999, which indicates unavailable data, is converted to Not a Number (NaN) and then imputed using the previous valid value (forward fill).
c. Data Resampling: To reduce noise and computational burden, daily data is resampled to a weekly frequency by averaging over 7 days.
d. Data stationarity is tested using the ADF test to ensure that the data's statistical properties, such as the mean and variance, do not change over time. If the data is not stationary, a differencing process is applied to stabilize the mean. In this study, achieving stationarity is a critical prerequisite for the SARIMA model to produce reliable and mathematically valid forecasts.

2.4. Modeling and evaluation

The modelling process begins by dividing the dataset into 80% for training and 20% for testing, in time-sequential order. Since the data shows an annual seasonal pattern, the model used is SARIMA [22]. The optimal parameters for the SARIMA model (p, d, q) and the seasonal parameters (P, D, Q, s) are determined through a hyperparameter tuning process using the Grid Search method, with the Akaike information criterion (AIC) as the reference metric for model efficiency [23].

The trained model is then evaluated on test data using two main metrics: root mean squared error (RMSE) and mean absolute error (MAE). Lower RMSE and MAE values indicate higher prediction accuracy. The model with the best accuracy is then used for the prediction stage [24], [25].

2.5. Electrical power and energy calculation

The results of the wind speed prediction are used to estimate the potential electrical power that can be generated by the wind turbine. This calculation uses the physics equation for wind kinetic energy [26]:

$$P = \frac{1}{2} \rho A v^3 C_p$$

where P: electrical power generated (watt), ρ: air density (1.225 kg/m^3), A: propeller swept area, assumed to be 7.07 m^2 (3 m diameter residential turbine), v: Wind speed (m/s), predicted result, C_p: Power coefficient (turbine efficiency), assumed to be 35%.

This calculation also takes into account the turbine's operational limitations, specifically a cut-in speed of 3 m/s, the minimum speed required to generate electricity, and a rated capacity of 1000 watts, the maximum power limit [27]. By applying these constraints, the estimation model prevents unrealistic overestimations during periods of extreme wind speeds. Finally, the total estimated electrical energy in kilowatt-hours (kWh) is determined by multiplying the resulting power (P) by the total duration of a week (168 hours) and dividing by 1000 [28].

$$E = \frac{P \times t}{1000}$$

where E is energy produced (kWh), P is electrical power (watt), and t is time/duration in hours during a week (168 hours).

3. RESULTS AND DISCUSSION

3.1. Hyperparameter optimization and best model selection

To identify the optimal forecasting model, a grid search optimization was performed over the SARIMA (p, d, q)×(P, D, Q)52 parameter space within a machine learning framework. A total of 16 different model combinations were trained and evaluated to systematically determine the configuration that best captures the wind speed characteristics in Banyumas.

The selection process prioritized minimizing error metrics (RMSE and MAE) to ensure predictive accuracy. While the AIC is traditionally used as a measure of statistical efficiency and model parsimony [29], recent studies emphasize that, for practical renewable energy feasibility analysis, minimizing the physical prediction error is more critical for reducing operational risk [30]. Consequently, although several models exhibited competitive AIC scores, the SARIMA (1, 0, 0)×(0, 1, 1, 52) configuration was selected as the optimal model because it yielded the lowest RMSE and MAE values.

To rigorously evaluate the performance of the proposed model, it was compared against two baseline models: a standard ARIMA (1, 0, 0) without seasonality and a seasonal Naive model. The comparative performance results are summarized in Table 2. As shown in Table 2, the proposed SARIMA model outperforms both baselines across all evaluation metrics. The model achieved the lowest prediction errors with an RMSE of 0.5160 m/s and a MAPE of 19.43%, significantly outperforming the Seasonal Naive benchmark (RMSE 0.7336 m/s, MAPE 26.70%).

It is important to note that the coefficient of determination (R2) values for all models was negative. This is a common phenomenon in high-volatility wind-speed forecasting when the variance of the prediction errors exceeds that of the data, particularly in weekly-aggregated data. However, the proposed SARIMA model achieved the highest R2 value (-0.1910) compared to the significantly lower values of the baselines (-0.4792 and -1.4047). This indicates that the proposed model captures the complex seasonal dynamics of the Banyumas wind profile far more effectively than traditional methods, providing the most reliable basis for energy estimation.

Table 2. Performance comparison proposed model and baselines

Model Type	Parameters/Method	AIC	MAE (m/s)	RMSE (m/s)	MAPE (%)	R2
Proposed	SARIMA (1, 0, 0)×(0, 1, 1, 52)	83.816	0.4409	0.516	19.43	-0.191
Baseline 1	ARIMA (1, 0, 0) (non-seasonal)	219.512	0.4849	0.5753	21.2	-0.4792
Baseline 2	Seasonal Naive	N/A	0.6005	0.7336	26.7	-1.4047

3.2. Wind speed prediction results

The optimal SARIMA model was subsequently applied to forecast wind speeds over a 13-week horizon, spanning from July to October 2025. This specific prediction window was deliberately selected to capture the meteorological transition into the peak dry season, which is historically characterized by stronger easterly monsoon currents. The quantitative outcomes of this forecasting process, synthesized to highlight the dominant trend, are presented in Table 3.

Table 3. Weekly wind speed prediction results

Date	Wind speed prediction results (m/s)
13/07/2025	3.05
27/07/2025	3.11
03/08/2025	3.13
24/08/2025	3.79
07/09/2025	3.4
28/09/2025	3.28
05/10/2025	3.3

3.2.1. Trend interpretation and seasonal pattern confirmation

The prediction results, as shown in Figure 2, are depicted by the red line, indicating an evident trend. The model predicts that wind speeds will increase significantly from late July, peaking at 3.79 m/s on August 24, 2025, before gradually decreasing through October. This pattern is not simply a statistical anomaly but a relatively strong confirmation of a climatological phenomenon in Indonesia: the influence of the easterly monsoon (from Australia), which occurs during the dry season, generally from June to September. These winds tend to be drier, firmer, and more consistent. The SARIMA model's ability to capture and extrapolate this annual cycle without external data input demonstrates the effectiveness of the model's seasonal component. It provides strong validity to the prediction results [31].

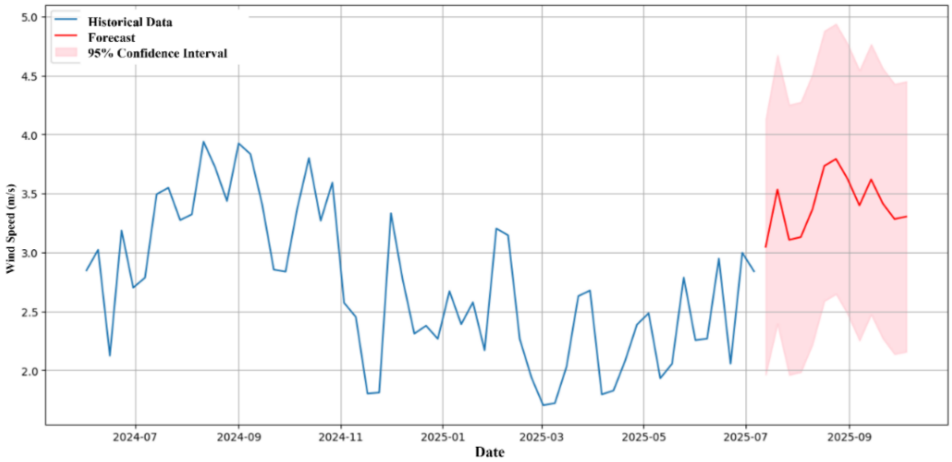

Figure 2. Weekly wind speed prediction chart

3.2.2. Uncertainty analysis: 95% confidence range

The pink area on the graph represents the 95% confidence interval, which quantifies the level of uncertainty in the prediction. For example, at the peak prediction point of 3.79 m/s, the confidence interval ranges from approximately 3.0 m/s to 5.0 m/s. This wide interval underscores the volatility of wind speeds. Furthermore, this interval widens over time, reflecting the fundamental principle that uncertainty is cumulative and that long-term predictions are inherently less accurate than short-term ones [32].

3.3. Estimated electrical power (watt)

Electrical power represents the rate of energy generated by a turbine at a given time. Power calculations are highly sensitive to changes in wind speed because of the exponential relationship, in which power (P) is proportional to the cube of the wind speed (v3). This implies that a slight increase in wind speed will result in a much more significant power surge [33].

Based on Table 4, the analysis data shows that an increase in wind speed from 3.05 m/s on July 13 to 3.79 m/s on August 24, or approximately 24%, resulted in an estimated power increase from 42.89 watts to 82.68 watts, a 93% surge. This underscores the importance of periods of strong winds, even if brief, to a wind power plant's potential power output. The graph in Figure 3 visualizes the estimated average weekly power generated during the forecast period, which follows the pattern of wind speed fluctuations.

3.4. Estimated electrical energy (kWh)

Electrical energy is the accumulated power over a specific period of time and is the most fundamental metric for evaluating the technical and economic viability of a power plant. In this study, energy is measured in kilowatt-hours (kWh), a commonly used unit for household electricity consumption. Weekly energy estimates are obtained by multiplying the average power (watts) by the total number of hours in a week (168 hours) [34].

Based on the calculations in Table 5 and Figure 4, the total energy production during the 3-month prediction period in a realistic scenario, based on the average predicted value, is estimated at 133.23 kWh. On average, this figure corresponds to approximately 1.44 kWh of daily energy production. This energy value serves as the primary basis for analyzing the feasibility of practical applications, both for household needs and for other uses such as street lighting, as it can be directly compared with daily energy consumption requirements.

Table 4. Estimated electrical power

Date	Wind Speed (m/s)	Power Estimation (watt)	Power Min (watt)	Power Max (watt)
13/07/2025	3.05	42.89	0	106.8
27/07/2025	3.11	45.45	0	116.48
03/08/2025	3.13	46.49	0	118.48
24/08/2025	3.79	82.68	0	182.51
07/09/2025	3.4	59.51	0	142.24
28/09/2025	3.28	53.64	0	131.65
05/10/2025	3.3	54.67	0	133.53

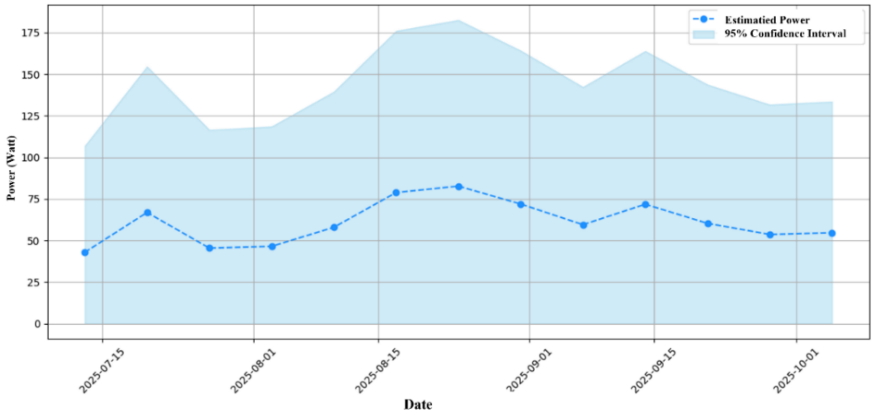

Figure 3. Weekly electric power estimation chart

Table 5. Weekly energy production estimate

Date	Wind Speed (m/s)	Energy Estimation (kWh)	Energy Min (kWh)	Energy Max (kWh)
13/07/2025	3.05	7.21	0	17.94
27/07/2025	3.11	7.64	0	19.57
03/08/2025	3.13	7.81	0	19.9
24/08/2025	3.79	13.89	0	30.66
07/09/2025	3.4	10	0	23.9
28/09/2025	3.28	9.01	0	22.12
05/10/2025	3.3	9.18	0	22.43

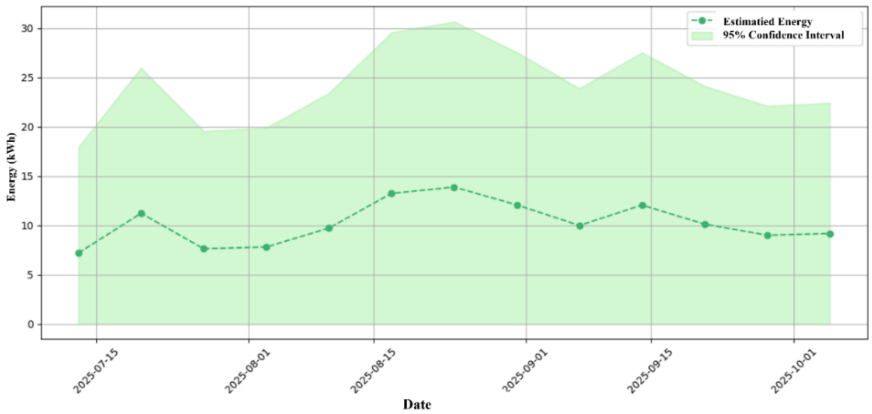

Figure 4. Weekly energy production estimate chart

3.5. Application feasibility and potential analysis

Based on the estimated average daily energy production of 1.44 kWh, the implementation of a residential-scale wind power plant in Banyumas Regency demonstrates significant practical feasibility. For household applications, this system can serve as a highly effective supplementary energy source. It provides ample energy to sustain essential daily loads, such as household LED lighting (requiring approximately 1.2 kWh per night) and low-power electronic devices, including Wi-Fi routers, chargers, and laptops. Alternatively, the system is highly viable for public infrastructure, particularly street lighting. A standard 40-watt LED street light consumes roughly 0.48 kWh per night; thus, a single wind turbine generating 1.44 kWh daily could independently power three street lights, making it an ideal solution for off-grid areas.

From an economic perspective, generating a daily average of 1.44 kWh amounts to approximately 43.2 kWh per month. Based on Indonesia's non-subsidized household electricity tariff of approximately IDR 1,444.70/kWh, this supplementary system offers potential cost savings of roughly IDR 62,411 per month. This reduction in monthly expenditure underscores the system's practical value, offering an affordable and sustainable energy solution to support household needs or public facilities in the region.

4. CONCLUSION

This study demonstrates that the optimal SARIMA (1,0,0)×(0,1,1,52) model effectively predicts seasonal wind dynamics in Banyumas Regency, achieving strong predictive performance (RMSE=0.516 m/s). Translating these forecasts into energy estimates yields a daily output of 1.44 kWh, confirming the viability of small-scale wind turbines for essential household loads or public lighting. However, this univariate approach does not account for other meteorological variables, such as temperature or humidity. Future research should explore multivariate methods or hybrid architectures to capture complex climate interactions, thereby refining assessments of renewable energy potential.

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AUTHOR CONTRIBUTIONS STATEMENT

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Hardeka Muhammad Arsyad			✓	✓		✓	✓			✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in NASA POWER at *https://power.larc.nasa.gov/data-access-viewer/*, reference number [35].

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