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Combining IoT and Time Series Model for Minute-Level Outlier Detection in Wind Speed Forecasting

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Abstract

Renewable energy optimisation and early warning systems require accurate short-term wind speed forecast. Anomalies in environmental data impair forecasting model reliability. This paper presents an integrated approach using IoT-based remote sensing and time series modelling to address the issue. IoT-based anemometer sensors collected wind speed data at one-minute intervals from December 24, 2024, to January 10, 2025. Aggregating the raw data into 5-minute intervals prepared it for the ARIMA model. This model determined temporal patterns and predicted short-term wind speeds. Analyzing residuals between observed and predicted results helped identify wind outliers. This approach is novel because it uses IoT-based continuous sensing and time series modeling for real-time environmental monitoring. Studies showed that a 65-minute frame with 5-minute intervals was best for replicating wind speed dynamics. Six cycles of outlier detection found 87 outliers. The ARIMA model improved predictions by include these outliers as exogenous variables. This emphasizes the importance of fixing time series model anomalies to improve prediction. The augmented ARIMA model with outlier corrections provides minute-level forecasts and reliable anomaly identification for renewable energy optimization and early warning systems. This study shows that new statistical methods and the Internet of Things (IoT) can improve real-time environmental and energy decisions.

Keywords: extreme, accuracy, autoregressive, sensor

1 Introduction

The Autoregressive Integrated Moving Average (ARIMA) time series model is an established technique extensively employed in studying non-stationary data, particularly for modelling and forecasting meteorological phenomena such as temperature, precipitation, and wind velocity [1]–[4]. The model functions by integrating autoregressive (AR), differencing (I), and moving average (MA) elements to capture short-term patterns and long-term trends. Several prior studies have utilised ARIMA to model wind speed on both daily and monthly scales, including research

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by some researchers [5]–[7]. When applied to high-resolution data, however, conventional ARIMA models frequently face a loss in performance. This is because these models do not explicitly handle the presence of outliers, which are common in short-time-dimensional weather data.

In the West Kalimantan region, wind speed shows noticeable variability, particularly around the year's end during the monsoon transition period [8]. Toward late 2024, fluctuations in wind conditions, along with meteorological irregularities, were reported at several monitoring sites. Such variability can influence sectors including shipping safety, agriculture, and forest fire management [9], underscoring the need for reliable forecasting systems. While minute-by-minute wind speed data provide detailed temporal insights, they also pose challenges due to high volatility and the presence of outliers. These outliers may arise from genuine localised turbulence or transient weather phenomena, but they may also result from sensor noise or equipment interference, making it essential to distinguish between true meteorological events and artifacts.

Advancements in Internet of Things (IoT) technology facilitate the acquisition of real-time atmospheric data at minute intervals. This detailed data enhances the precision of forecasts, particularly within locally-focused early warning systems [10], [11]. The primary issue with high-resolution data is the significant noise and the occurrence of outliers, including Additive Outliers (AO) and Innovation Outliers (IO), which can affect the noise model parameters. Some studies demonstrated the significance of outlier detection and correction in minute-level data to enhance the precision of ARIMA models; however, the methodology remains confined to small-scale experiments and has not been evaluated under extreme climate conditions in West Kalimantan [12]–[14].

This study applies ARIMA modelling with iterative outlier detection and adjustment for minute-level wind speed forecasting. While ARIMA and outlier correction are established techniques in time series analysis, their integration with IoT-based real-time monitoring systems for high-frequency environmental data remains underexplored, particularly in regions prone to sudden wind fluctuations such as West Kalimantan. Rather than introducing a new forecasting algorithm, this work demonstrates the practical effectiveness of an outlier-aware ARIMA framework for enhancing short-term wind speed prediction. Although the present study does not compare ARIMA against modern machine learning methods such as LSTM or GRU, it provides a statistical baseline that highlights the importance of addressing anomalies in high-resolution environmental data.

The remainder of this paper is organised as follows. Section 2 details the methodological framework, covering the baseline ARIMA model, the outlier-augmented ARIMA formulation, and the IoT-based wind/rain detection system. Section 3 reports the empirical results and their discussion, including model identification, diagnostics, and the impact of outlier adjustments on forecast accuracy. Section 4 summarises the main findings and outlines practical implications and directions for future work. The Appendix compiles the complete iteration history and parameter tables.

2 Methods

This section outlines the methodological framework adopted in this study. We begin by describing the classical ARIMA model, which serves as the foundation for time series forecasting. The discussion then extends to the ARIMA model with outlier factors, designed to handle anomalies in the data. Finally, we present the rain and wind detection system that integrates sensor-based measurements with forecasting techniques.

2.1 ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model is a prevalent statistical method in time series forecasting. Since its inception by Box and Jenkins in 1976, ARIMA has been extensively utilised across diverse domains, including economics, finance, meteorology, and epidemiology. Numerous prior studies have demonstrated the efficacy of ARIMA in modeling non-stationary data, including the research on stock price forecasting [15] and predicting daily COVID-19 case numbers [16]–[18]. The primary benefit of ARIMA is its proficiency in effectively managing historical data patterns via Autoregressive (AR), differencing (I), and Moving Average (MA) components. The ARIMA(p,d,q) model is characterized by [19],

$$\phi(B)(1-B)^d Y_t = \theta(B)e_t$$

where

$$\begin{aligned}
\phi(B) &= (1-\phi_1 B - \phi_2 B^2 - \dots) \\
\theta(B) &= (1-\theta_1 B - \theta_2 B^2 - \dots) \\
B^d Y_t &= Y_{t-d}
\end{aligned}$$

The ARIMA approach begins by determining the stationarity of the data. If not, the differentiation process continues until the data attains stationarity. Subsequently, the identification and parameter estimation of the ARIMA(p,d,q) model are conducted, where p denotes the autoregressive order, d represents the degree of differencing, and q signifies the moving average order. Optimal model selection typically relies on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), or Mean Absolute Percentage Error (MAPE) metrics. After establishing the model, a diagnostic test is conducted on the residuals to verify that the model satisfies the white noise assumption [19]. The ultimate outcome of an effective ARIMA model can facilitate short-term forecasts with a comparatively narrow margin of error.

2.2 ARIMA Model with Outlier Factor

Outliers in time series data are points that drastically diverge from the overall trend and may result from multiple sources, including recorded inaccuracies, external disruptions, or infrequent occurrences (e.g., natural disasters or economic crises) [20], [21]. In time series analysis, outliers can be categorised into many categories, including Additive Outliers (AO), Innovation Outliers (IO), and level shifts. Identifying and categorising outliers compromises the model's accuracy [14].

The primary risk posed by outliers in time series data is their potential to undermine fundamental model assumptions, including stationarity and the normality of residuals. Outliers can lead to skewed parameter estimate findings, diminish forecasting accuracy, and elevate error metrics such as MAPE or RMSE [22]–[24]. In an ARIMA model, an extreme outlier might result in overfitting or erroneous model selection. Consequently, identifying and managing outliers is an essential phase before constructing a dependable time series model. A traditional visual technique for identifying outliers is the utilisation of box plots [25]. Upon detecting an outlier via the box plot, the subsequent action may involve eliminating the data if deemed erroneous or applying transformations such as winsorising, interpolation, or smoothing techniques to mitigate its impact. In time series analysis, it is crucial to ascertain whether outliers possess any particular significance (e.g., resulting from notable events) before making alterations or eliminations.

Two categories of outliers exist: Additive Outliers (AO) and Innovative Outliers (IO). Each sort of outlier serves a distinct function based on its influence. AO outliers directly influence when $t = T$, but IO outliers impact all subsequent observations following the detection of the outlier, specifically $Y_T, Y_{T+1}, \dots$. The ARIMA model incorporating outlier factors is [26].

$$Y_t = \begin{cases} X_t + \omega I_t^{(T_A)} & \text{AO} \\ X_t + \frac{\theta(B)}{\phi(B)}\omega I_t^{(T_I)} & \text{IO} \end{cases}$$

with

$$I_t^{(T_u)} = \begin{cases} 1 & t = T \\ 0 & t \neq T \end{cases}$$

and $u = \{I, A\}$.
In general, the ARIMA model used when more than one outlier is detected is defined by

$$Y_t = \sum_{j=1}^{k} \omega_j v_j(B) I_t^{T_u} + X_t \tag{1}$$

where

$$X_t = \frac{\theta(B)}{\phi(B)} a_t$$

$$v_j(B) = \begin{cases} 1 & \text{AO} \\ \frac{\theta(B)}{\phi(B)} & \text{IO} \end{cases}$$

The methodology for identifying outliers in time series data follows an iterative procedure [26], [27]. The process begins with obtaining the residuals of the fitted ARIMA model and proceeds through several stages of detection, adjustment, and re-estimation until no further outliers are detected, as outlined below.

1. `Initialization.` The algorithm starts with the residuals from the ARIMA model:

$$\begin{aligned} \hat{e}_t &= \hat{\pi}(B) X_t \\ &= \frac{\hat{\phi}(B)}{\hat{\theta}(B)} X_t. \end{aligned}$$

2. `Residual variance estimation.` Compute the variance of the residuals to obtain the initial estimate of the innovation variance:

$$\hat{\sigma}_a^2 = \frac{1}{n} \sum_{t=1}^{n} \hat{e}_t^2.$$

3. `Outlier test statistics.` For each observation $t = 1, 2, \ldots, n$, compute the statistics

$$\hat{\lambda}_{1,t} = \frac{\tau \hat{\omega}_{AT}}{\hat{\sigma}_a}, \qquad \hat{\lambda}_{2,t} = \frac{\hat{\omega}_{IT}}{\hat{\sigma}_a}.$$

An outlier is identified if either statistic exceeds the threshold C (commonly set to 3 or 4). In this study, $C = 3$ was selected, corresponding to a 99.7% confidence level under normality. This threshold provides a balance between sensitivity and false positives. Specifically:

- If $\hat{\lambda}_T = |\hat{\lambda}_{1,t}| > C$, then an Additive Outlier (AO) is identified at time T.
- If $\hat{\lambda}_T = |\hat{\lambda}_{2,t}| > C$, then an Innovation Outlier (IO) is identified at time T, with

$$\hat{\lambda}_T = \max\{\hat{\lambda}_{1,t}, \hat{\lambda}_{2,t}\}.$$

4. `Residual adjustment.` Once an outlier is detected, adjust the residuals accordingly:

$$\tilde{e}_t = \begin{cases} \hat{e}_t - \hat{\omega}_A \hat{\pi}(B) I_t^{(T_A)}, & \text{AO}, \\ \hat{e}_t - \hat{\omega}_I I_t^{(T_I)}, & \text{IO}. \end{cases}$$

5. `Iteration.` Repeat the outlier detection and adjustment steps (Steps 3 and 4) using the updated residuals. The procedure terminates when no additional outliers are identified.

Once all outliers have been identified, the ARIMA modelling is re-executed by incorporating the outlier factor corresponding to the identified instances. After the model is conducted and all the parameters are estimated, repeat the first until the fifth process till no more outlier is detected. The ARIMA modelling technique using outlier factors is illustrated in Figure 1.

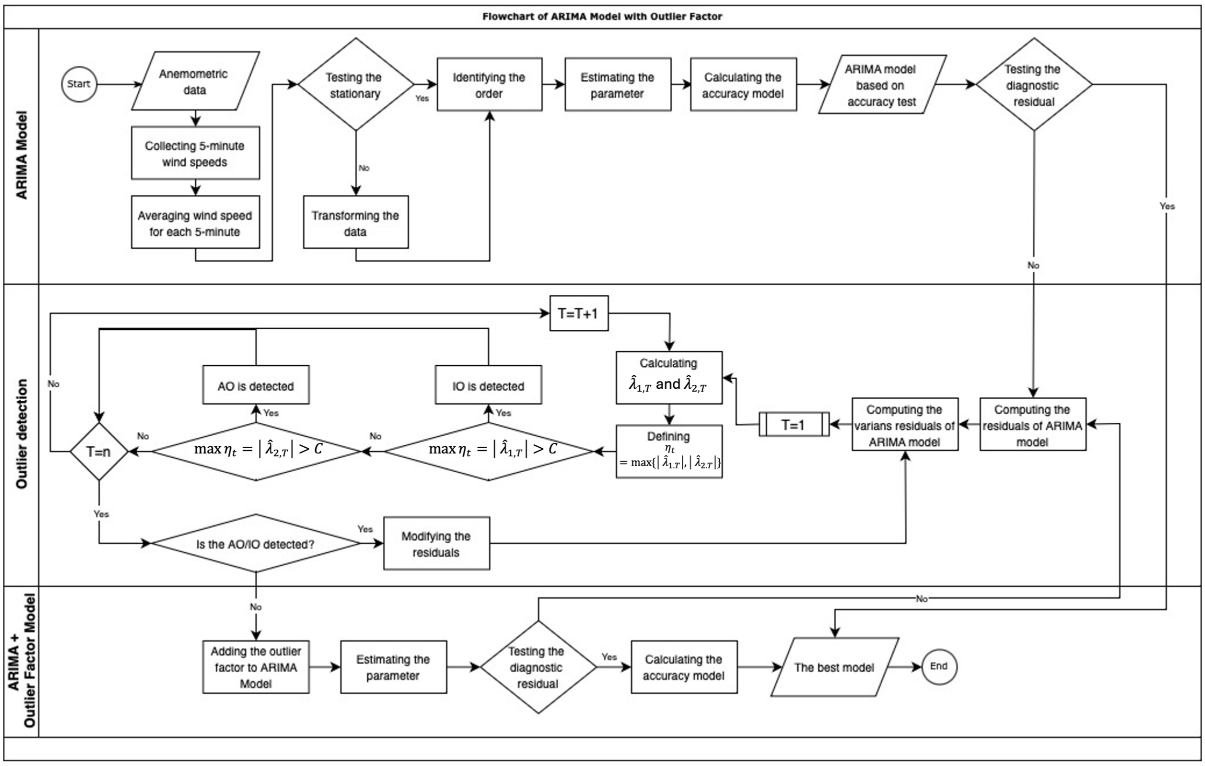


Figure 1: Flowchart ARIMA model, outlier detection, and ARIMA model + outlier factor model.

2.3 Wind Detection System

This rain and wind detection system is developed by merging multiple environmental sensors linked via a Wireless Sensor Network (WSN) [28]. Rain sensors employ optical or electrically conductive mechanisms to identify precipitation. In contrast, wind speed and direction are gauged using an anemometer and wind vane, which rely on magnetic or ultrasonic sensors [29]. Each sensor is linked to a microcontroller, such as the ESP32, which regularly gathers data. Sensor data is automatically calibrated for precision and transmitted via an Iot network utilising communication modules such as Wi-Fi, LoRa, or GSM (e.g., SIM800L) to a server or cloud platform. Data is received and saved in a database for visualisation and analysis on the backend. The system facilitates real-time and historical monitoring, allowing for the prompt identification of severe weather and expeditious, data-informed decision-making [30].

3 Results and Discussion

This section presents the empirical findings and their interpretation. We begin with a descriptive overview of the wind speed data and the preprocessing steps applied. Next, the results of ARIMA model identification and parameter estimation are reported, followed by the incorporation of outlier factors into the modelling framework. Finally, the discussion highlights the implications of these findings for short-term wind speed forecasting and IoT-based monitoring systems.

3.1 Results

Wind speed data is acquired by an automatic detection instrument, a cup-type anemometer that operates to catch wind gusts and turn them into rotational motion. Each cup rotation is measured by magnetic or optical sensors within the device, subsequently converted into speed units (meters per second). The apparatus is positioned at a conventional elevation of 10 meters above ground level, adhering to meteorological measurement regulations to prevent interference from structures or vegetation. Data recording was automated at one-minute intervals, yielding about 25,920 data points from 24 December 2024 to 10 January 2025. This data represents real-time wind speed variations, encompassing minor and significant swings.

The data were averaged at five-minute intervals to enhance analysis and mitigate the impact of brief, dramatic changes. This methodology was employed due to the propensity of 1-minute intervals to provide extremely volatile data, but not all minor fluctuations are pertinent for medium-term analytical requirements. A more stable representation of the wind speed trend is achieved by averaging every five minutes without compromising its fundamental properties. Consequently, the data volume was diminished to approximately 5,184 points, enhancing processing and visualisation efficiency. The preprocessing phase involved addressing missing values via linear interpolation and identifying outliers using the interquartile range (IQR) approach, yielding a refined dataset prepared for subsequent analysis.

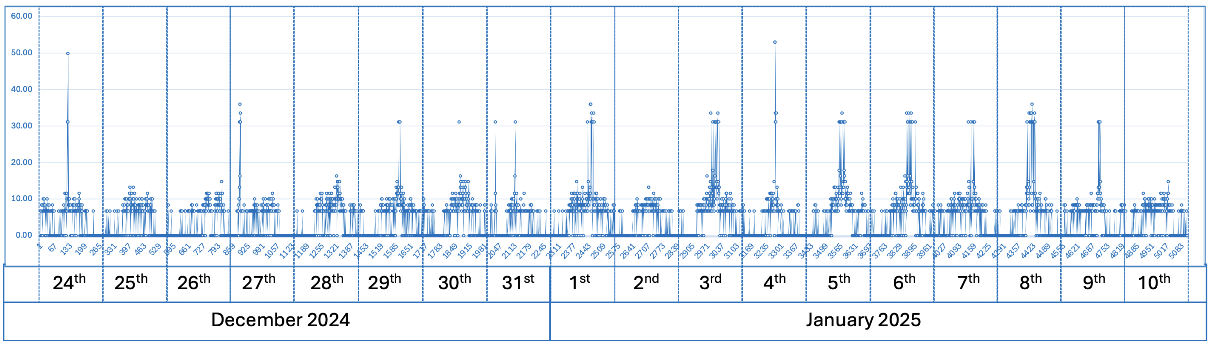


Figure 2: Time Series Data Plot.

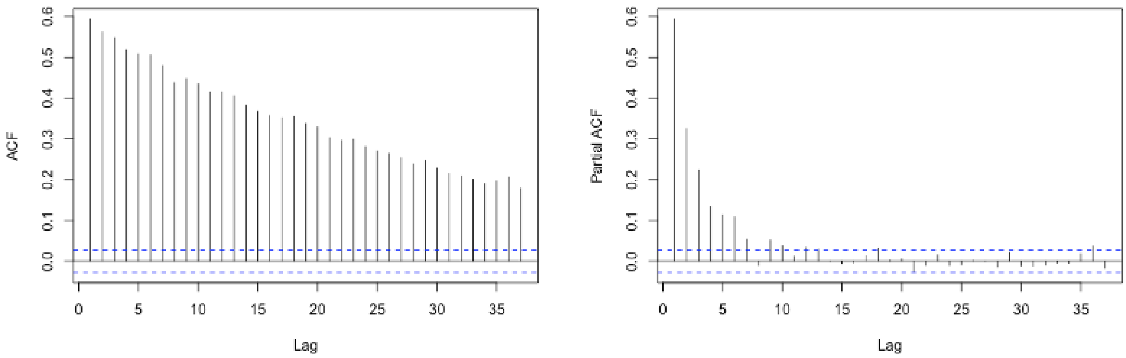
The time series plots illustrate wind speed variations from 24 December 2024 to 10 January 2025 (shown in Figure 2), with data averaged at five-minute intervals to mitigate noise and enhance analytical stability. Most wind speed measurements remain consistent within the range of 0–10 m/s, indicative of the climatic traits of West Kalimantan, which typically experiences low to moderate surface winds.

Nevertheless, distinct spikes manifest at specific intervals, signifying the existence of outliers or extraordinary wind phenomena. This phenomenon may be attributed to local atmospheric dynamics during the rainy season, which often occurs in West Kalimantan from late December to early January. These spikes may represent actual events, such as abrupt strong gusts preceding substantial rainfall, or may simply result from sensor interference.

Acknowledging the presence of outliers is crucial, as they can impair the efficacy of predictive models like ARIMA if left unaddressed. Therefore, outlier detection and remediation are incorporated into the preprocessing stage to enhance the accuracy of predictive models and to strengthen IoT-based wind monitoring systems in tropical locations. The subsequent steps involve the implementation of the ARIMA model considering outlier factors:

3.1.1 ARIMA Modelling

Model identification was conducted using ACF and PACF diagnostics (Figure 3). Following the order selection criteria in [26], candidate models were ARIMA$(p, 0, 0)$ with $p \in \{1, 7, 10, 13\}$ and $q = 0$. Parameters for each candidate were then estimated by maximum likelihood (MLE).



(a) (b)

Figure 3: (a) ACF Plot and (b) PACF Plot.

The parameter estimation results for each possible model are given in Table 1.

Table 1: ARIMA model based on ACF and PACF plot (Figure 3).

Ordo	Model
AR(1)	$Y_t = 4.09 + 0.59\,Y_{t-1}$
AR(7)	$Y_t = 4.09 + 0.26\,Y_{t-1} + 0.17\,Y_{t-2} + 0.14\,Y_{t-3} + 0.07\,Y_{t-4} + 0.07\,Y_{t-5} + 0.09\,Y_{t-6} + 0.05\,Y_{t-7}$
AR(10)	$Y_t = 4.09 + 0.26\,Y_{t-1} + 0.17\,Y_{t-2} + 0.13\,Y_{t-3} + 0.06\,Y_{t-4} + 0.07\,Y_{t-5} + 0.09\,Y_{t-6} + 0.04\,Y_{t-7}$ $-0.03\,Y_{t-8} + 0.04\,Y_{t-9} + 0.04\,Y_{t-10}$
AR(13)	$Y_t = 4.09 + 0.26\,Y_{t-1} + 0.17\,Y_{t-2} + 0.13\,Y_{t-3} + 0.06\,Y_{t-4} + 0.07\,Y_{t-5} + 0.07\,Y_{t-6} + 0.08\,Y_{t-7}$ $+0.04\,Y_{t-8} - 0.04\,Y_{t-9} + 0.03\,Y_{t-10} + 0.03\,Y_{t-11} - 0.01\,Y_{t-12} + 0.03\,Y_{t-13}$

The final phase of the modelling process is the diagnostic assessment. According to the diagnostic test in Table 2, none of the models satisfied normality and residual independence criteria. Consequently, the model exhibits outliers, necessitating the implementation of an outlier detection algorithm based on model residuals. The selected model has the lowest RMSE value (bold text in Table 2), specifically the AR(13) model.

Table 2: Diagnostic Test.

Ordo	Dependency Test	Normality Test	RMSE
AR(1)	Not fulfilled	Not fulfilled	4.607
AR(7)	Not fulfilled	Not fulfilled	4.151
AR(10)	Not fulfilled	Not fulfilled	4.143
AR(13)	Not fulfilled	Not fulfilled	**4.138**

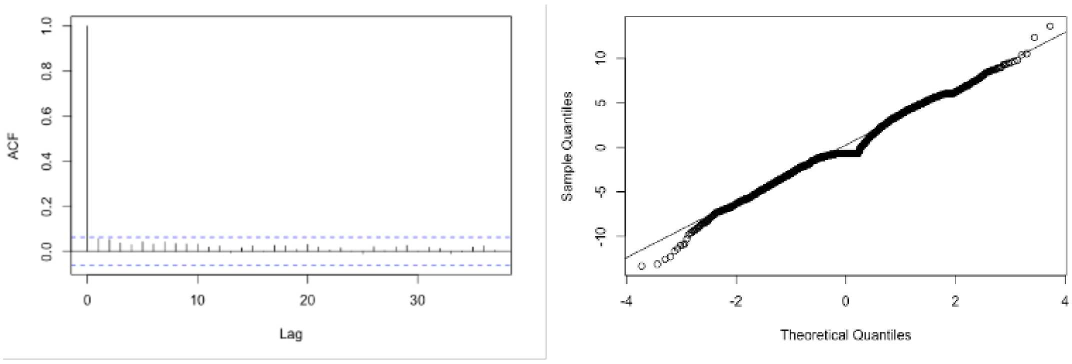
3.1.2 ARIMA Model with Outlier Factor

As seen in the flowchart in Figure 1, the subsequent step involves identifying outliers based on the residuals of the AR(13) model. Iteration 0 represents the AR(13) model. Iteration 1 results from outlier detection with the model derived from iteration 0, and so forth. Table 3 presents the outcomes of outlier detection throughout six iterations. No outliers were identified following the sixth round. Most outliers were identified in the initial round.

Upon completing the iteration 1 process, proceed to estimate the parameters of the ARIMA model by incorporating the outlier component (refer to Equation 1). The resultant parameters are presented in Table 4. Upon the completion of parameter estimation in iteration 1, the outlier detection process for iteration 2 is conducted by examining the residuals of the ARIMA model, incorporating the outlier factor from iteration 1. The outlier detection time from the second iteration is subsequently incorporated into the ARIMA model along with the outlier factor derived from the first iteration. Additionally, parameter estimation for the ARIMA model

Table 3: Outlier's Time Detected. The blue text indicates the number of outliers detected in that iteration.

Itr.	Innovative Outlier	Additive Outlier
1	120; 121; 886; 888; 892; 1596; 2436; 2449; 2450; 2453; 2454; 2458; 2994; 3002; 3005; 3014; 3017; 3270; 3271; 3277; 3557; 3562; 3575; 3856; 3860; 3872; 3876; 3878; 4142; 4154; 4155; 4393; 4402; 4405; 4408; 4416; 4711; 4712 → (38)	122; 890; 891; 1599; 1601; 1864; 2026; 2114; 2452; 2463; 2465; 2985; 3016; 3021; 3268; 3269; 3276; 3567; 3570; 3578; 3582; 3863; 3867; 3881; 3883; 3896; 4131; 4156; 4160; 4407; 4417; 4422; 4428; 4717 → (34)
2	3006; 3272; 3558; 4406 → (4)	2460; 3015; 3564; 3576; 4413; 4426 → (6)
3	2459 → (1)	3009; 3563; 4713 → (3)
4	3275 → (1)	123 → (1)
5	3278 → (1)	→ (0)
6	→ (0)	3008 → (1)



(a) (b)

Figure 4: Diagnostic Test (a) Dependency Residual and (b) Normality Residual for ARIMA Model with Outlier Factors

is conducted by incorporating outlier components identified in iterations one and two. This procedure is reiterated until a model with residuals no longer identifiable as outliers is generated.

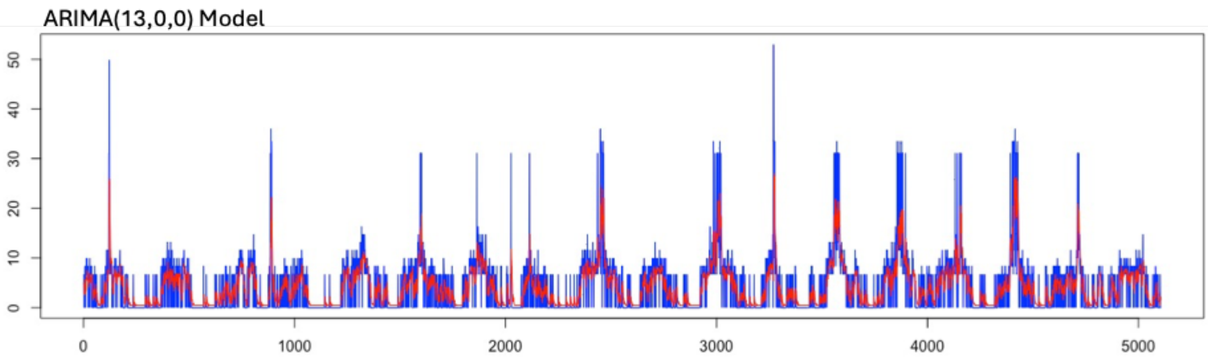
Table 4: ARIMA, Innovative Outlier (IO), and Additive Outlier (AO) per Iteration

Itr.	ARIMA $(\mu; \phi_1; \dots; \phi_{13})$	IO $(\omega_{T_{I1}} I_t^{(T_{I1})}; \dots; \omega_{T_{In}} I_t^{(T_{In})})$	AO $(\omega_{T_{A1}} I_t^{(T_{A1})}; \dots; \omega_{T_{An}} I_t^{(T_{An})})$
0	4.09; 0.26; . . . ; 0.03		
1	3.87; 0.23; . . . ; 0.01	24.18; 20.18; . . . ; 18.65	35.01; 18.67; . . . ; 17.29
2	3.84; 0.21; . . . ; 0.01	24.32; 20.05; . . . ; 12.83	35.13; 20.52; . . . ; 16.49
3	3.84; 0.20; . . . ; 0.01	23.62; 21.46; . . . ; -8.23	37.59; 18.73; . . . ; 15.81
4	3.84; 0.20; . . . ; 0.01	25.75; 22.03; . . . ; -9.76	36.44; 19.26; . . . ; 14.82
5	3.84; 0.20; . . . ; 0.01	25.87; 22.19; . . . ; -16.88	36.49; 19.32; . . . ; 14.85
6	3.84; 0.20; . . . ; 0.01	24.33; 19.65; . . . ; -7.19	34.40; 19.12; . . . ; 15.41

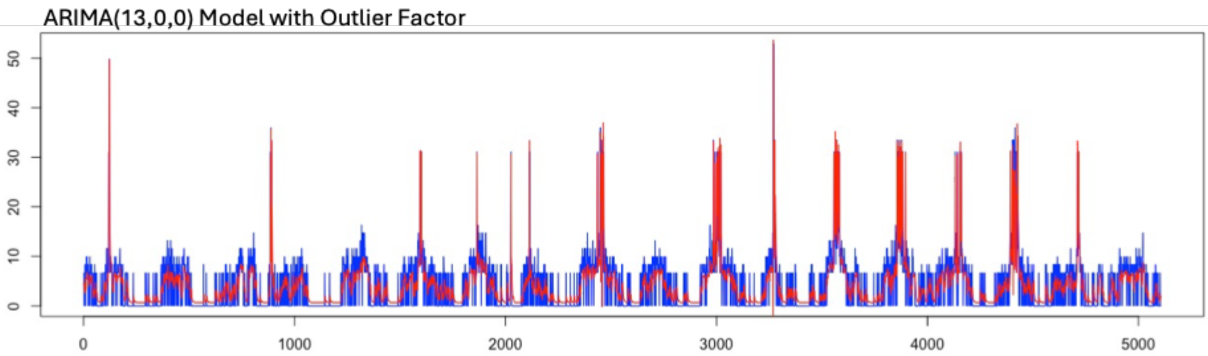
Upon obtaining the ARIMA model with the outlier component, a diagnostic test is subsequently performed to assess the influence of the outlier factor on the model. According to Table 4, outliers influenced model residuals that failed to meet the diagnostic criteria. The diagnostic test outcomes for the ARIMA model incorporating the outlier component are presented in Figure 4, indicating that the ARIMA model with the outlier factor has satisfied both diagnostic tests.

Table 4 presents the brief of re-estimated ARIMA parameters along with the number of outliers identified at each iteration, the results are presented in more detail in the appendix. While the complete iteration history is provided for transparency, the primary value of this table lies in showing how the parameter estimates stabilize after successive adjustments. Specifically, the initial iterations reveal relatively large shifts in parameter values as the model accounts for the presence of outliers. In contrast, by the final iterations, both ARIMA parameters and the number of newly detected outliers converge, indicating that the model has effectively adjusted for the underlying anomalies. This progression highlights the iterative nature of outlier detection and re-estimation, demonstrating that stable parameter estimates are only achieved once the majority of influential outliers have been incorporated into the model.

In addition to the diagnostic perspective, outliers also influence model accuracy. The baseline ARIMA model produced an RMSE of 4.138, whereas the ARIMA model incorporating outlier components improved the fit with an RMSE of 3.259. A comparison of the observed data to the fitted values for both models is presented in Figure 5. To further evaluate predictive performance, the mean absolute percentage error (MAPE) was also calculated, yielding 17.09% for the outlier-adjusted ARIMA model. These results demonstrate that accounting for outliers improves short-term forecasting accuracy. Nevertheless, they are based primarily on in-sample evaluation.



(a)



(b)

Figure 5: Wind Speed Data (Blue Line) and Fitted Values (Red Line) (a) ARIMA Model without Outlier Factor and (b) ARIMA Model with Outlier Factor

Figure 5 illustrates that the ARIMA model incorporating outlier effects significantly influences the ability to get extreme data points. Considering several factors, including diagnostic tests, model correctness, and the capacity to identify extreme values, the model incorporating the outlier component is highly effective for analysing wind speed data patterns. The model can be employed to forecast wind speed.

3.2 Discussion

The ARIMA model utilised in this study demonstrates significant efficacy in modelling high-resolution wind speed data patterns, particularly following an iterative outlier detection and adjustment process. This procedure involves detecting outliers from the original model residuals, examining the ACF and PACF patterns, and assessing the RMSE value for each iteration. The results indicate that the AR(13) model exhibits the optimal performance, evidenced by the lowest RMSE, suggesting that the wind speed at any point is significantly affected by the speed data from the preceding 13 periods, around 65 minutes prior (with a 5-minute interval every observation). This indicates that wind speed dynamics exhibit significant autoregressive behaviour beyond one hour, which is crucial for short-term forecasting. The use of this comparatively elevated AR order signifies that local atmospheric processes exhibit significant temporal dependency at high time resolution.

Besides their statistical efficacy, ARIMA models have demonstrated considerable reliability when applied to 5-minute data, capturing short-term dynamics more precisely than daily or hourly data. The model's responsiveness to minute-scale variations renders it appropriate for real-time monitoring or control systems, including wind turbine regulation and innovative grid applications. This study's minute-level forecasting methodology is a distinctive feature of the research focused on hourly or daily predictions. Minute-level forecasting offers substantial benefits in enhancing the accuracy of swift decision-making, particularly during abrupt weather fluctuations. The model employed for minute-level wind speed forecasting for the subsequent hour is the ARIMA(13,0,0) model, incorporating outlier components (refer to Table 4, at the sixth iteration of the model). However, because

$$I_t^{(T_u)} = \begin{cases} 1 & t = T \\ 0 & t \neq T \end{cases}$$

Then, for forecasting, $I_t^{(T_u)}$ it will always be 0. Consequently, the model at the sixth iteration becomes

$$\begin{aligned} \hat{Y}_{5107+h} = 3.831 &+ 0.202Y_{5107+h-1} + 0.176Y_{5107+h-2} + 0.120Y_{5107+h-3} \\ &+ 0.057Y_{5107+h-4} + 0.052Y_{5107+h-5} + 0.049Y_{5107+h-6} + 0.033Y_{5107+h-7} \\ &- 0.005Y_{5107+h-8} + 0.011Y_{5107+h-9} + 0.025Y_{5107+h-10} + 0.006Y_{5107+h-11} \\ &+ 0.020Y_{5107+h-12} + 0.014Y_{5107+h-13} \end{aligned} \tag{2}$$

The prediction results for the next hour are given in Figure 6 below.

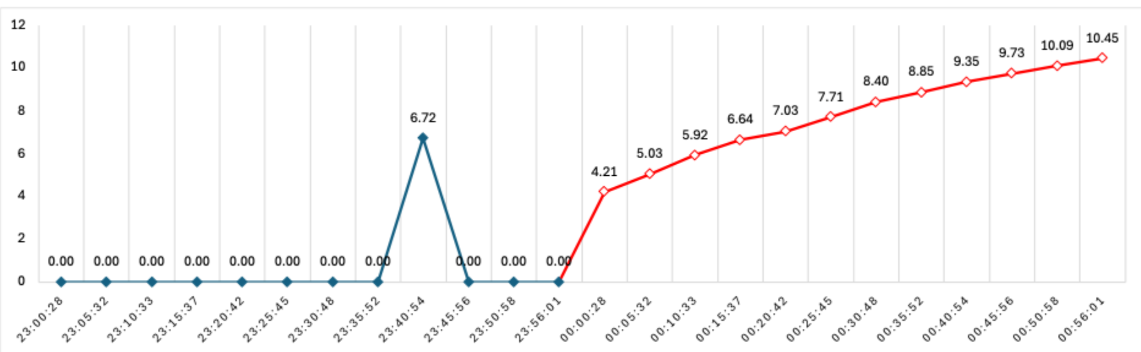


Figure 6: Minute-Level Prediction Result for 1 Hour (Red Line) based on The ARIMA Model With Outlier Factors

The efficacy of this concept is predominantly contingent upon the backing of an Internet of Things (IoT)-driven data gathering system, facilitating continuous, automated, and real-time documentation of wind speed. The Internet of Things (IoT) technology offers benefits related to temporal precision, seamless system integration, and enhanced operational efficiency. Incorporating minute-level data, iterative outlier detection and adjustment, ARIMA modelling, and IoT data collecting establishes a refined and practical framework for accurate short-term wind speed modelling.

4 Conclusions

This study shows that incorporating Additive Outliers (AO) and Innovative Outliers (IO) into the ARIMA framework improves 5-minute wind-speed forecasts. Using a six-stage iterative procedure, an AR(13) specification was selected as optimal. The outlier-adjusted ARIMA model achieved an in-sample RMSE of 3.259 and a MAPE of 17.09%, improving upon the baseline ARIMA RMSE of 4.138. These results indicate that short-term variability at a 5-minute resolution can be effectively captured by dependencies extending up to 65 minutes (13 lags). The use of granular IoT-based sensing is essential, as it enables the identification of micro-patterns and transient disturbances that may be missed at coarser resolutions. Together, IoT sensing and outlier-aware ARIMA modelling provide accurate and timely short-horizon forecasts, supporting real-time wind monitoring and early warning applications.

CRediT Authorship Contribution Statement

Nur'ainul Miftahul Huda: Conceptualization, Methodology, Formal Analysis, Writing–Original Draft, Visualization. **Nurfitri Imro'ah:** Data Curation, Writing–Review & Editing. **Rahmi Hidayati:** Software, Validation. **Kartika Sari:** Project Administration, Validation

Declaration of Generative AI and AI-assisted technologies

No generative AI or AI-assisted technologies were used during the preparation of this manuscript.

Declaration of Competing Interest

The authors declare no competing interests.

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Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request and subject to confidentiality agreements.

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Appendix

ARIMA, Innovative Outlier (IO), and Additive Outlier (AO) per Iteration

Itr.	**ARIMA** ($\mu; \phi_1; \ldots; \phi_{13}$)	**IO** ($\omega_{T_{I1}} I_t^{(T_{I1})}; \ldots; \omega_{T_{In}} I_t^{(T_{In})}$)	**AO** ($\omega_{T_{A1}} I_t^{(T_{A1})}; \ldots; \omega_{T_{An}} I_t^{(T_{An})}$)
0	4.09; 0.26; 0.16; 0.13; 0.06; 0.07; 0.08; 0.04; -0.04; 0.03; 0.03; -0.01; 0.03; 0.03		
1	3.87; 0.23; 0.17; 0.12; 0.07; 0.05; 0.06; 0.03; -0.01; 0.01; 0.04; -0.02; 0.03; 0.01	24.18; 20.18; 24.12; 25.46; -20.15; 24.72; 23.59; 27.26; 25.27; 9.93; 10.62; -23.94; 23.05; 20.95; 19.05; 18.44; -7.80; 37.79; 33.82; -10.18; 21.19; 14.96; 19.51; 25.46; 22.62; 18.94; 20.27; 19.93; 26.59; 24.05; 23.04; 23.13; 22.22; 19.57; 13.24; -17.86; 22.09; 18.65	35.01; 18.67; 12.18; 22.72; 19.92; 24.19; 26.04; 23.41; -9.97; 23.09; 20.17; 25.15; 19.28; 19.89; -8.68; -8.64; 14.35; 16.55; 19.13; 16.88; 15.75; 19.32; 23.09; 17.54; 16.95; 23.28; 22.89; 19.22; 19.09; -14.17; -18.64; -18.06; 14.35; 17.29
2	3.84; 0.21; 0.17; 0.13; 0.05; 0.05; 0.05; 0.05; -0.01; 0.01; 0.04; -0.01; 0.03; 0.01	24.32; 20.05; 25.50; 25.25; -12.63; 21.70; 23.58; 26.27; 24.48; 11.71; 11.21; -17.32; 21.91; 20.64; 19.53; 18.85; -12.75; 41.61; 39.21; -14.39; 21.14; 18.01; 19.13; 25.22; 20.55; 18.67; 21.99; 20.49; 27.14; 22.27; 21.16; 23.07; 24.35; 17.99; 11.01; -17.28; 24.52; 20.14; 13.21; 11.84; 16.86; 12.83	35.13; 20.52; 13.59; 21.84; 19/26; 24.17; 25.51; 24.71; -9.85; 20.85; 19.71; 25.11; 15.89; 20.19; -8.69; -7.57; 13.88; 16.67; 19.54; 17.14; 15.34; 19.22; 23.19; 17.61; 16.66; 22.49; 23.04; 20.48; 19.69; -16.23; -13.99; -15.79; 15.55; 18.65; 10.52; 15.61; 15.03; 15.71; -14.02; 16.49
3	3.84; 0.20; 0.18; 0.13; 0.06; 0.05; 0.05; 0.05; 0.04; -0.05; 0.03; 0.04; -0.01; 0.02; 0.01	23.62; 21.46; 25.69; 24.76; -13.03; 21.52; 22.85; 24.01; 21.93; 12.48; 11.97; -23.07; 21.30; 23.07; 15.58; 18.05; -13.90; 41.21; 33.58; -13.95; 21.09; 20.84; 20.49; 25.44; 20.81; 19.54; 20.63; 21.28; 27.05; 23.45; 19.75; 24.49; 24.80; 19.37; 10.33; -18.53; 24.29; 21.54; 12.15; 8.37; 18.02; 10.58; -8.23	37.59; 18.73; 12.85; 20.87; 19.72; 23.83; 26.79; 24.59; -9.32; 21.27; 20.18; 24.94; 15.76; 19.41; -7.76; -9.37; 11.93; 18.36; 19.56; 15.50; 16.72; 19.14; 23.19; 17.94; 17.75; 23.30; 22.27; 17.26; 19.04; -13.95; -17.11; -15.83; 14.22; 19.30; 17.58; 14.35; 17.54; 14.79; -15.17; 15.84; 11.98; 20.10; 15.81
4	3.84; 0.20; 0.18; 0.13; 0.6; 0.05; 0.05; 0.02; -0.01; 0.02; 0.04; -0.01; 0.03; 0.01	25.75; 22.03; 24.27; 24.22; -17.14; 22.34; 23.48; 25.13; 21.75; 10.56; 14.25; -21.11; 22.37; 21.14; 18.35; 17.84; -12.20; 42.53; 32.75; -12.83; 21.69; 19.62; 20.47; 27.76; 22.69; 19.84; 21.05; 23.68; 26.57; 22.29; 18.33; 24.70; 23.36; 14.98; 8.08; -20.39; 23.00; 21.91; 11.75; 4.88; 19.46; 17.43; -14.82; -9.76	36.44; 19.26; 13.13; 21.32; 19.05; 24.14; 26.92; 24.63; -10.66; 21.57; 19.63; 24.65; 16.84; 19.77; -6.99; -9.20; 7.61; 17.97; 20.01; 16.68; 17.44; 17.64; 21.93; 17.85; 18.28; 24.24; 22.38; 17.22; 18.57; -16.33; -19.30; -16.87; 13.86; 19.99; 9.57; 14.84; 17.65; 17.13; -16.35; 14.56; 10.56; 18.60; 18.19; 14.82
5	3.84; 0.20; 0.19; 0.13; 0.06; 0.06; 0.05; 0.03; -0.01; 0.01; 0.03; -0.01; 0.02; 0.01	25.87; 22.19; 25.07; 24.01; -16.98; 22.34; 23.24; 25.06; 21.81; 10.87; 14.06; -21.13; 21.87; 20.21; 17.76; 17.78; -11.98; 42.53; 34.53; -16.12; 21.67; 19.61; 19.57; 27.38; 23.07; 20.37; 23.57; 20.47; 26.77; 22.27; 18.44; 24.21; 22.99; 15.34; 7.11; -20.56; 22.65; 20.10; 14.96; 5.55; 19.00; 17.86; -12.99; -12.34; -16.88	36.49; 19.32; 13.15; 21.69; 19.14; 24.87; 27.55; 24.64; -10.93; 21.35; 19.49; 24.68; 16.57; 19.62; -7.21; -8.72; 7.26; 17.67; 20.05; 15.82; 17.76; 17.54; 22.17; 17.17; 17.04; 24.16; 22.32; 16.79; 18.16; -16.69; -19.25; -16.89; 14.04; 20.31; 10.55; 15.59; 18.08; 15.19; -17.78; 15.36; 11.92; 17.87; 18.47; 14.85
6	3.84; 0.20; 0.18; 0.12; 0.06; 0.05; 0.05; 0.03; -0.01; 0.01; 0.03; 0.01; 0.02; 0.01	24.33; 19.65; 24.67; 25.90; -12.86; 22.21; 23.31; 25.61; 22.41; 15.37; 11.49; -22.87; 21.03; 22.18; 19.02; 18.49; -13.55; 44.54; 32.70; -8.70; 21.07; 20.09; 18.96; 27.37; 19.39; 20.51; 20.28; 19.91; 26.35; 22.22; 17.89; 23.67; 23.99; 15.88; 7.66; -18.27; 25.01; 22.27; 15.61; 9.85; 16.56; 13.74; -4.67; -13.49; -7.19	34.40; 19.12; 13.33; 21.61; 19.97; 24.26; 25.55; 24.45; -8.67; 22.58; 20.06; 25.09; 15.65; 19.34; -8.54; -8.92; 13.91; 17.94; 19.79; 16.51; 15.95; 19.09; 22.26; 17.44; 16.56; 23.20; 22.53; 16.89; 18.45; -14.69; -13.67; -15.82; 14.97; 19.40; 12.86; 14.56; 16.97; 14.74; -17.33; 14.64; 13.15; 19.84; 18.79; 13.82; 15.41