FORECASTING OF MAXIMUM TEMPERATURE IN YOGYAKARTA WITH SEASONAL AUTOREGRESSION MOVING AVERAGE (SARMA) MODEL

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ABSTRACT

This study seeks to provide accurate maximum air temperature forecasts for Yogyakarta using the Seasonal Autoregressive Moving Average (SARMA) model, a time series method that accounts for both short-term and seasonal variations. As Yogyakarta experiences a steady rise in temperatures with significant seasonal fluctuations, accurately predicting these changes is essential for public health planning and energy management. Utilizing daily maximum temperature data, the SARMA model identified critical seasonal patterns and showed robust performance in predicting future temperature values. The model's accuracy was validated through residual and Mean Absolute Percentage Error (MAPE) tests, demonstrating its effectiveness in generating reliable forecasts. This research offers valuable insights for urban planning and climate-related decision-making, particularly in managing the health risks posed by rising temperatures in Yogyakarta.

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1. INTRODUCTION

Indonesia is the fourth most populous country in the world, with a population of around 281.6 million in 2024 [1]. A large portion of this population resides on Java Island, where approximately 55.7% of Indonesia's people are concentrated [2]. The growing population has increased the demand for land, particularly for agriculture, housing, and other infrastructure [3]. However, limited land availability has resulted in the conversion of agricultural land and green spaces into residential areas, government offices, and other public facilities [4, 5].

Rapid global population growth, urbanization, and economic development, especially in emerging countries, have pushed energy needs to unprecedented levels [6]. Fossil fuel dependency in energy systems contributes significantly to greenhouse gas emissions [7]. In Indonesia, greenhouse gases like carbon dioxide (CO_2) and methane (CH_4) show an upward trend [8]. This increase is part of a global trend, accompanied by rising global temperatures, with the first half of 2024 marking the hottest temperatures since pre-industrial times [9].

Global warming has major implications for climate change, potentially leading to more frequent natural disasters and affecting various sectors, including natural resources, the economy, and communities [10]. In urban areas, rising temperatures increase the demand for cooling systems, which further raises energy consumption, anthropogenic heat release, and greenhouse gas emissions [11]. This creates a feedback loop where increased greenhouse gas emissions contribute to climate change, which in turn worsens urban warming [12].

The Yogyakarta Provincial Health Office has reported that high temperatures can impact health by causing fatigue, organ damage, dehydration, respiratory issues, cardiovascular stress, mental health challenges, and worsening of preexisting medical conditions. Vulnerable groups include the elderly, young children, pregnant women, individuals with chronic diseases, and people living in poverty [13]. During hot weather, the human body may generate or absorb more heat than it can release, resulting in discomfort, heat-related illnesses, and, in severe cases, death [14]. Comfortable temperatures (not too hot or too cold) significantly influence outdoor activities like tourism, sports, construction, and transportation [15]. According to projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6), thermal comfort levels will change, with areas of low per capita GDP, often located in lower latitudes, expected to face worsening thermal discomfort due to rising air temperatures [16].

Air temperature fluctuates daily and monthly. Daily variations are due to the Earth's rotation, which causes day and night, while monthly changes are influenced by the Earth's orbit around the sun. Maximum daily temperatures usually occur shortly after peak sunlight, around solar noon when the sun is directly overhead [17]. Temperatures peak when the sun is in its primary culmination phase, directly overhead, creating a phenomenon known as "no-shadow day" when shadows of upright objects disappear [18].

The Special Region of Yogyakarta, a province on Java Island, is known for its tourism, cultural heritage, and educational institutions. It is also recognized as the second most comfortable retirement city after Solo [19]. This makes Yogyakarta one of the most densely populated areas and vulnerable to high temperatures. Analysis shows that air temperatures in Yogyakarta have steadily risen over recent years [20]. Thus, accurate air temperature predictions in Yogyakarta are crucial to support tourism, public activities, and to mitigate the health risks posed by high temperatures, particularly for young children, pregnant women, the elderly, and those with chronic illnesses. While daily or monthly maximum temperature forecasts are available, no hourly maximum air temperature predictions, with their higher variability, have been conducted in Yogyakarta. This presents a challenge in developing statistical methods or models to predict hourly maximum air temperatures accurately.

Statistical methods, especially time series analysis, can help predict air temperatures by using historical data to forecast future values. Among these methods, ARIMA, PROPHET, and LST are commonly used. ARIMA works well for short-term predictions, PROPHET is suited for capturing trends and seasonality, and LST is ideal for long-term forecasting [21]. SARIMA, an extension of ARIMA, incorporates seasonal components when historical data show seasonal patterns [22].

2. METHOD

1) Data Plotting and Initial Analysis
   a. Begin by plotting the hourly maximum air temperature data from Yogyakarta covering the period from September 20, 2023, to September 30, 2023.
   b. This dataset includes 264 data points. Upon examining the data, a repeating pattern indicative of seasonality was identified. Given this observation, the Seasonal Autoregressive Moving Average (SARMA) model is chosen for forecasting.
2) Dummy Regression Modeling
   a. Implement a dummy regression model using artificial variables with values of 0 or 1 to capture specific trends or seasonal effects in the data.
   b. Define and assign dummy variables:

      d_1 : Trend Dummy for the entire dataset.

      d_2 : Trend Dummies segmented every 24 data points.

      d_3 : Binary Dummy for specific points.

      d_4 : Binary Dummy for ranges within the dataset.

   The purpose of creating this regression model is to produce a model with strong predictive ability for the temperature variable, where the model's success is measured by a high R^2 value.
3) Stationarity Testing for the ARIMA Model

   Stationarity is tested using a residual plot and the Augmented Dickey-Fuller (ADF) test to ensure the data is stationary.

2. ARIMA Model Selection Based on ACF and PACF
Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) analysis are used to determine the appropriate ARIMA model.
3. Parameter Estimation for the ARIMA Model
After selecting the best ARIMA model, parameter estimation is conducted on this model to determine the significant parameter values. These significant parameters strengthen the model's validity, making it reliable for prediction or forecasting.
4. White Noise Test on Residuals
The white noise test is conducted to assess whether the residuals from the ARIMA model meet the white noise criteria. The results, with all p-values greater than 0.05, indicate that the residuals satisfy the white noise condition, thus validating the model for use.
5. Residual Normality Test
The normality of the residuals is tested using a residual normality plot, which indicates that the data points follow a straight line, suggesting that the residuals are normally distributed.
6. Maximum Air Temperature Forecasting
The developed model is utilized to predict the temperature for the next 52 periods (equivalent to 20% of the initial data). The prediction results are compared with the actual data and visualized, demonstrating that the model's predictions closely follow the actual data patterns.
7. Model Evaluation Using MAPE
The model's accuracy is evaluated using Mean Absolute Percentage Error (MAPE), demonstrating the model's effectiveness in temperature prediction.

Method

Time Series Analysis

A time series is a sequence of observations of a variable collected over time and recorded in order at fixed intervals [23]. Recognizing the data pattern is essential in forecasting, as it helps choose the most appropriate time series forecasting method. Data patterns can be categorized into four types: horizontal, seasonal, cyclical, and trend.

Time Series Stationarity

Stationarity is a critical property in time series analysis, allowing us to predict future behavior based on historical data. Stationarity can be tested in several ways, including:

8. Graphical analysis to observe data deviations and trends,
9. Plotting the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), where slow decay in the ACF/PACF plots typically indicates non-stationarity,
10. Unit root tests, such as the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

Autocorrelation Function (ACF)

The ACF is a plot of the autocorrelation of a stationary time series (Z_t) which has a mean $E(Z_t) = \mu$, constan variance $Var(Z_t) = E(Z_t - \mu)^2 = \sigma^2 = \gamma_0$ and a covariance $Cov(Z_t, Z_s)$, that depends only on the time lag between observations. Since autocorrelation is typically difficult to calculate for the entire population, it is estimated from the sample data. The ACF values can be used to determine the order of the Moving Average (MA) model within a SARIMA model, as formulated below [23]:

$$\gamma_k = \hat{\rho}_k = corr(Z_t, Z_{t-k}) = \frac{\sum_{t=1}^{n-k}(Z_t - \bar{Z})(Z_{t-k} - \bar{Z})}{\sum_{t=1}^{n}(Z_t - \bar{Z})^2}, \quad (1)$$

where γ_k is autocorrelation coefficient at lag k, $corr(Z_t, Z_{t-k})$ is covariance between two points in the series Z (i.e., between Z at time t and Z at time waktu $t - k$), Z_t is value time series value at time t, $\bar{Z}$ is mean of the time series, n total number of observations in time series, and k is time lag (interval between two compared values).

Partial Autocorrelation Function (PACF)

The PACF shows the degree of partial correlation between observations at time t (Z_t) and observations from previous times $(Z_{t-1}, Z_{t-2}, \ldots, Z_{t-k})$. PACF values are used to determine the order of the Autoregressive (AR) component in the SARIMA model. The formula to obtain the PACF value at lag k is as follows [23]:

$$\hat{\phi}_{11} = \hat{\rho}_1 \quad (2)$$

$$\hat{\phi}_{22} = \frac{\hat{\rho}_2 - \hat{\rho}_2^2}{1 - \hat{\rho}_1^2} \quad (3)$$

$$\hat{\rho}_{k+1,k+1} = \frac{\hat{\rho}_{k+1} - \sum_{j=1}^{k} \hat{\phi}_{kj}\,\hat{\rho}_{k+1-j}}{1 - \sum_{j=1}^{k} \hat{\phi}_{kj}\,\hat{\rho}_j}, \quad (4)$$

where ϕ_{kk} is PACF value at lag k and ρ_k is ACF value at lag k.

Autoregresive Moving Average (ARMA)

ARMA(p,q) is a statistical method for analyzing and forecasting stationary time series data (data that do not require differencing). The ARMA(p,q) model combines autoregressive (AR) and moving average (MA) components, where AR models the relationship between current and past values, while MA models the impact of past prediction errors (residuals) on current values. The general form of an ARMA(p,q) model is:

$$Z_t = \phi_1 Z_{t-1} + \cdots + \phi_p Z_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}), \quad (5)$$

where ε_t is current error term, $\varepsilon_{t-1}, \dots \varepsilon_{t-q}$ is past error term, $\phi_1, \dots, \phi_p$ is autoregressive coefficients, and $\theta_1, \dots, \theta_p$ is moving average coefficients.

Seasonal Autoregresive Integrated Moving Average (SARMA)

SARMA extends the ARMA model to handle time series data with seasonal patterns. In a SARMA model, both non-seasonal (short-term) and seasonal (same period) relationships are considered. A general form of the SARMA model is written as:

$$\text{SARMA}(p, q)(P, Q) \quad (6)$$

General formula $SARMA(p, q)(P, Q)$ is as follows:

$$(1 - \phi_1 B - \cdots - \phi_p B^p)(1 - \Phi_1 B^S - \cdots - \Phi_p B^{PS}) Z_t = (1 + \theta_1 B + \cdots + \theta_q B^q)(1 + \Theta_1 B^S + \cdots + \Theta_Q B^{QS}) \varepsilon_t \quad (7)$$

where:

- B : backshift operator that shifts data back by one period
- p : non-seasonal AR order
- q : non-seasonal MA order
- P : seasonal AR order
- Q : seasonal MA order
- S : seasonal period

Residual Assumptions Testing

To select the best SARMA model, the chosen model should have all significant parameters and meet two residual assumptions: normal distribution and white noise.

Normality Test

The Kolmogorov-Smirnov test is often used to test normality, assessing the probability of the Kolmogorov-Smirnov Z-statistic. The decision criteria for the Kolmogorov-Smirnov test are as follows:

Hypothesis:

$H_0: F(x) = F_0(x)$ Residuals are normally distributed

$H_1: F(x) \neq F_0(x)$ Residuals are not normally distributed

Statistic Test:

$$D_{calculate} = \sup_x \left| S_{(x)} - F_0(x) \right|$$

Rejection Criteria: Reject H_0 jika $D_{calculate} > D_{\alpha,n}$ or $P_{value} < \alpha$ using a significance level of $\alpha = 0.05$

White Noise Test

A model meets the white noise assumption if its residuals are identically distributed (homogeneous variance) and independent (uncorrelated). The Ljung-Box test is used to test the white noise assumption with the following formula:

$$Q = n(n+2) \sum_{k=1}^{k} \frac{\rho_k^2}{n - K} \quad (8)$$

where:
n : number of observations
k : lag k
K : maximum lag
ρ_k: autocorrelation at lag k

Hypothesis:
H_0: No significant autocorrelation in residuals
H_1: significant autocorrelation in residuals
Rejection Criteria: Reject H_0 jika $Q > \chi^2_{\left(\frac{\alpha}{df:K-k}\right)}$ or $P_{value} < \alpha$ with $\alpha = 0.05$
Therefore, a time series is considered white noise if its mean and variance are constant and observations are independent of each other.

Model Selection Criteria

To select the most suitable SARMA model from several alternatives, the best model must be chosen using specific evaluation criteria. Among the methods for determining the optimal model are by Akaike's Information Criterion (AIC). AIC is a statistical tool used to select the best model by evaluating both model complexity and its fit to the data. The fundamental principle of AIC is to favor models that provide good estimates while using the fewest parameters possible, thereby reducing the risk of overfitting. The AIC formula is:

$$AIC = 2k - 2\ln(L) \qquad (9)$$

where:
k is the number of parameters in the model L is the likelihood of the estimated model A lower AIC value indicates a better-fitting model.

Mean Absolute Percentage Error (MAPE)

MAPE represents the average absolute difference between forecasted and actual values, expressed as a percentage of the actual values. The formula for MAPE is as follows:

$$MAPE = \left(\frac{1}{n}\sum_{t=1}^{n}\left|\frac{Z_t - \dot{Z}_t}{Z_t}\right|\right)100\% \qquad (10)$$

where:
Z_t: observed value at time t
$\dot{Z}_t$: predicted value at time t
n : total number of observations

3. RESULTS AND DISCUSSION

This section presents the results of the maximum air temperature forecasting for the Yogyakarta region during the out-of-sample period. Below is the initial plot of hourly maximum air temperature data from September 20, 2023, to September 30, 2023, comprising a total of 264 data points.

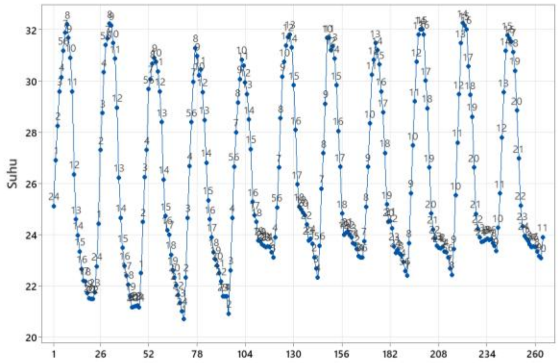


Figure 1. Hourly Temperature Plot for Yogyakarta

Based on Figure 1 above, the data appears to exhibit a repeating pattern, known as a seasonal pattern. Therefore, the SARMA model will be used for forecasting.

Dummy Regression Modeling

Dummy regression modeling is a type of regression modeling that uses additional variables in the form of artificial variables assigned values of 0 or 1. The dummy variables used are shown in Table 1 below.

Table 1. Dummy Define

Variable	Point to-	Information
d_1	1-264	Trend Dummy
d_2	1-24;25-48;49-72;73-96;97-120;121-144;145-168;169-192;193-216;217-240;241-264	Trend Dummy
d_3	8;31;55;77;102;128;149;174;199;221;246	Binary Dummy
d_4	5-10;29-34;53-57;77-80;101-103;124-129;148-152;172-176;196-201;220-223;224-249;	Binary Dummy

The obtained regression model is as follows:

$$Y_t = 28.098 + 0.00325d_{1t} - 0.2670d_{2t}$$
$$+0.514d_{3t} + 4.350d_{3t} + \varepsilon_t,$$

With the summary model as follows:

Table 2. Model Summary

S	R^2	R^2_{adj}
1.44265	82.56%	82.29%

Data source: Minitab software Output, results of times series regression model of the temperature data in Yogyakarta

The coefficient of determination from the regression equation is 82.56%, which means that the model has explained the Y variable very well. Therefore, the researchers used the regression model equation above to predict the temperature in Yogyakarta for the upcoming period.

ARIMA Modeling
The plot of training residual data is as follows:

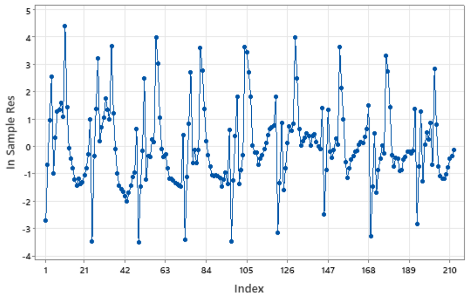
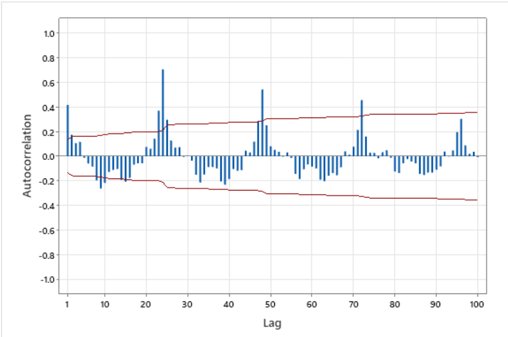
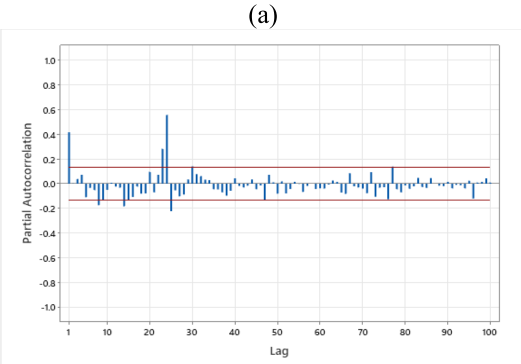


Figure 2. Time Series Plot Residual Data of the Temperature in Yogyakarta

Based on Figure 2, it is observed that the errors are stationary with respect to variance due to their constant variance. Similarly, the errors are stationary with respect to the mean based on the statistical test. The Augmented Dickey-Fuller test shows a value of -9.38170 and a p-value of 0.000, which rejects the null hypothesis because -9.38170is less than the critical value of -2.8859. Therefore, it can be concluded that the data is stationary and does not require differencing. Next, plot ACF and PACF on training data to determine which ARIMA models may be formed as follows:



(a)



(b)

Figure 3. (a) ACF (b) PACF Plot Training Data of the Temperature in Yogyakarta

Based on Figure 3 above, the presumed models are as follows:

Table 3. ARIMA Models

Models	AIC
$ARIMA(0,0,1)(2,0,1)^{24}$	607.313
$\boldsymbol{ARIMA(0,0,2)(2,0,2)^{24}}$	**580.436**
$ARIMA(0,0,1)(2,0,2)^{24}$	591.009
$ARIMA(0,0,2)(2,0,0)^{24}$	581.567
$ARIMA(1,0,1)(0,0,1)^{24}$	656.514
$ARIMA(1,0,2)(0,0,2)^{24}$	692.509

Models	AIC

Data source: Minitab software Output, results of presumed ARIMA models of the temperature data in Sumatra

Based on Table 3, the model with the smallest AIC value is Model $ARIMA(0,0,2)(2,0,2)^{24}$. The estimation results for Model 1 are as follows:

Table 4. Parameters Estimation

Type	Coef	SE Coef	T-Value	P-Value
SAR 24	0.421	0.226	1.86	0.064
SAR 48	0.546	0.218	2.50	0.013
MA 1	-0.2587	0.0705	-3.67	0.000
MA 2	-0.1151	0.0694	-1.66	0.099
SMA 24	-0.125	0.215	-0.58	0.559
SMA 48	0.550	0.116	4.72	0.000
Constant	-0.0029	0.0469	-0.06	0.950
Mean	-0.09	1.40		

Data source: Minitab software Output, results of $ARIMA(0,0,2)(2,0,2)^{24}$ model of the temperature data in Yogyakarta.

Based on Table 4, the majority of the parameter estimation results are significant, indicating that they can be used for forecasting.

Table 5. Ljung-Box Chi Square Statistic

Lag	12	24	36	48
Chi-Square	8.56	17.37	25.86	46.38
DF	5	17	29	41
P-Value	0.128	0.430	0.633	0.260

Data source: Minitab software Output, results of of $ARIMA(0,0,2)(2,0,2)^{24}$ model of the temperature data in Yogyakarta

Based on Table 5, it is known that all P-Value > 0.05 (Failed to Reject H_0) which means that Model $ARIMA(0,0,2)(2,0,2)^{24}$ exhibits white noise characteristics. Next, it is necessary to check whether the residuals from the model are normally distributed.

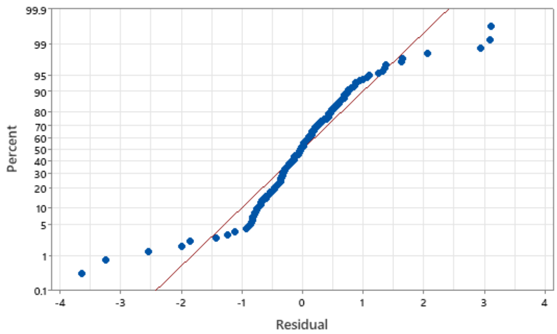


Figure 4. Residual Normality Plot Training Data of the Temperature in Yogyakarta

Based on Figure 4, it is known that the points tend to follow a sloped curve, which suggests that the residuals are normally distributed. Thus, the model to be used in this study for forecasting data in the next period is Model $ARIMA(0,0,2)(2,0,2)^{24}$, with the following equation:

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \Phi_1 Z_{(t-24)} + \Phi_2 Z_{t-48} + \Theta_1 \varepsilon_{t-24} + \Theta_2 \varepsilon_{t-48} + \varepsilon_t$$

Next, a forecast will be performed on Yogyakarta temperature data for the next 52 periods, matching the out-sample data, which is 20% of the initial data. Then, a comparison will be made with the available test data.

Table 6. Forecasting

Time	Actual Data	Forecasting
9/28/2023 19:00	23.32	22.8627
9/28/2023 20:00	23.12	22.5350
9/28/2023 21:00	22.7	22.1805
9/28/2023 22:00	22.44	23.4973
9/28/2023 23:00	23.45	25.9120
9/29/2023 24:00	25.54	27.4994
9/29/2023 1:00	27.6	29.0145
9/29/2023 2:00	29.49	32.0117
9/29/2023 3:00	31.48	31.9740
9/29/2023 4:00	32.27	31.6431
9/29/2023 5:00	32.17	31.4560
9/29/2023 6:00	32.01	27.8323
9/29/2023 7:00	30.57	27.3058
9/29/2023 8:00	29.46	28.6172
9/29/2023 9:00	28.61	26.9917
9/29/2023 10:00	26.62	25.1658
9/29/2023 11:00	24.82	24.4393
9/29/2023 12:00	24.24	24.2045
9/29/2023 13:00	23.91	23.9766
9/29/2023 14:00	23.72	23.8418
9/29/2023 15:00	23.74	23.7521
9/29/2023 16:00	23.8	23.7243
9/29/2023 17:00	23.84	23.5735
9/29/2023 18:00	23.81	23.5030
9/29/2023 19:00	23.82	23.1670
9/29/2023 20:00	23.68	22.9470
9/29/2023 21:00	23.58	22.7722
9/29/2023 22:00	23.36	23.6834
9/29/2023 23:00	24.27	25.7994
9/30/2023 24:00	25.61	27.3459
9/30/2023 1:00	27.8	28.8806
9/30/2023 2:00	29.56	31.6545
9/30/2023 3:00	31.17	31.4153
9/30/2023 4:00	31.78	32.1418
9/30/2023 5:00	31.65	31.5754
9/30/2023 6:00	31.53	31.5440
9/30/2023 7:00	31.13	32.5181
9/30/2023 8:00	30.41	28.7919
9/30/2023 9:00	28.85	27.4139
9/30/2023 10:00	26.98	25.5994
9/30/2023 11:00	25.15	24.8644
9/30/2023 12:00	24.33	24.6353
9/30/2023 13:00	23.95	24.3587
9/30/2023 14:00	23.85	24.0331
9/30/2023 15:00	23.75	23.8233
9/30/2023 16:00	23.62	23.6932
9/30/2023 17:00	23.52	23.5346
9/30/2023 18:00	23.55	23.3930
9/30/2023 19:00	23.52	23.0891
9/30/2023 20:00	23.35	22.8284
9/30/2023 21:00	23.16	22.5657
9/30/2023 22:00	23.09	23.6588
9/30/2023 23:00	23.9	22.8627

Data source: *Minitab software Output*, **forecasting result of** $ARIMA(0,0,2)(2,0,2)^{24}$ *model of the temperature data in Yogyakarta*

Based on Table 6, the forecasting results indicate values that are very close to the actual data, demonstrating that the forecasting model is appropriate. The comparison of actual data with the forecasted data can be displayed in the form of the following plot:

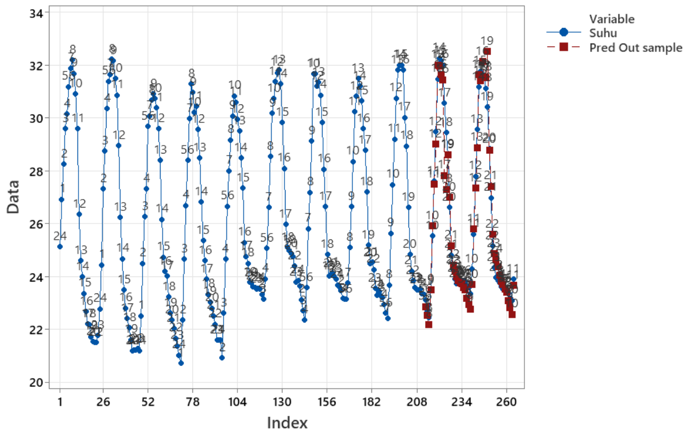


Figure 5. Time Series Data and Forecasting Plot of the Temperature in Yogyakarta

The plot in Figure 5 shows that the forecasted results tend to follow the pattern of the actual data. Next, the Mean Absolute Percentage Error (MAPE) will be calculated to assess the criteria of the forecasting model, with the results presented in the following table:

Table 7. MAPE

Training	Testing
1.94%	1.64%

Data source: Excel software Output, forecasting result model

Based on the obtained MAPE values, it is evident that the model used is highly accurate for forecasting the temperature data in Yogyakarta.

4. CONCLUSION

This research successfully developed and validated a SARMA model that can accurately forecast daily air temperatures in Yogyakarta, capturing essential seasonal temperature patterns. The findings highlight the model's capability to predict temperature variations effectively, offering a crucial tool for cities like Yogyakarta where seasonal changes significantly impact the urban environment. This model not only serves as a reliable forecasting tool but also underscores the importance of seasonal analysis in time series forecasting for climates with notable variability. The SARMA model's predictions align closely with observed data, emphasizing its applicability for areas with similar seasonal temperature characteristics.

Suggestion

1. Wider Application of SARMA for Temperature Monitoring: It is recommended that similar SARMA models be utilized for temperature forecasting in other regions with pronounced seasonal climates. This could enhance early-warning systems for climate-sensitive areas, improving responsiveness to environmental changes.
2. Support for Climate and Health Policy Development: The model provides a basis for implementing informed policies addressing climate change impacts on public health and energy demands, particularly in urban areas vulnerable to heat-related stress. Decision-makers can leverage these forecasts to mitigate risks associated with rising temperatures.
3. Further Research for Model Enhancement: Future studies should consider expanding the model with additional datasets across varying temporal resolutions, such as hourly or monthly data, to increase forecast accuracy and adapt the model to diverse environmental conditions. Incorporating broader data sources will allow the SARMA model to be refined and applied across more diverse geographical regions.
4. Future research should use data with different frequencies, such as monthly data, to capture varying temperature conditions, such as during dry and rainy seasons.

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