

Comparative Analysis of ARIMA and Fourier Series Methods for Air Temperature Forecasting in Surabaya

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ABSTRACT

Urban climate change, particularly rising temperatures and the Urban Heat Island (UHI) phenomenon, poses challenges for cities like Surabaya, Indonesia. This study compares the forecasting performance of ARIMA and ARIMA-Fourier models using daily air temperature data from 2020 to 2024. The analysis involved stationarity testing, model estimation, and evaluation across four forecasting horizons. ARIMA models (especially ARIMA(0,1,1) and ARIMA(1,1,0)) showed reliable short-term forecasts, but were less effective in capturing seasonal patterns. To address this, Fourier terms were integrated into the ARIMA framework. The ARIMA-Fourier model achieved better accuracy and higher R^2 values in short- and medium-term forecasts, particularly with an oscillation parameter of $k = 150$. However, its performance declined in long-term predictions due to overfitting risks. Overall, the ARIMA-Fourier model is more adaptive for capturing complex temperature seasonality and can support more accurate urban climate forecasting in Surabaya.

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1. INTRODUCTION

Global climate change is a critical issue that directly impacts various aspects of life, including the environment, economy, and human health. The rising Earth surface temperature, a key manifestation of global warming, is primarily driven by anthropogenic activities such as urbanization, deforestation, and greenhouse gas emissions. Air temperature, defined as the kinetic energy level of molecules in the atmosphere, is a crucial indicator for monitoring these changes [1]. Projections indicate that global air temperatures could increase by up to 0.8°C by 2030, potentially disrupting various socio-economic activities and raising public health risks [2], [3].

The effects of climate change are not only felt globally but also significantly at a local scale, especially in densely populated cities like Surabaya, the capital of East Java Province, Indonesia. As one of the largest cities in Indonesia with a continuously growing population, Surabaya faces serious challenges due to temperature instability. These unpredictable temperature fluctuations can affect community comfort and productivity and increase the risk of weather-related health problems [4]. A relevant health impact is the rise in vector-borne diseases such as Dengue Hemorrhagic Fever (DHF), Chikungunya, and Malaria [5]. Studies indicate a strong correlation between temperature and the life cycle of mosquitoes, as well as the development of parasites within the vector, making temperature monitoring crucial for disease mitigation [6].

Furthermore, Surabaya experiences the Urban Heat Island (UHI) phenomenon, where urban area temperatures are significantly higher than surrounding rural areas [7]. This phenomenon is

exacerbated by rapid urbanization, the widespread use of heat-absorbing and radiating building materials (e.g., concrete and asphalt), and a lack of green spaces [8]. Previous research shows that average surface air temperatures in Surabaya fluctuated between 2002 and 2019, with a consistent UHI distribution observed in highly urbanized areas like industrial zones and city centers [9], [10]. UHI intensity is classified into categories based on temperature differences, with Class 3 UHI ($>4^{\circ}\text{C}$) indicating the most severe and potentially serious warming impacts. This UHI phenomenon is not unique to Surabaya; it's also observed in other major cities like Jakarta, where high CO₂ emissions correlate with surface temperature increases exceeding 34°C within the city [11].

To anticipate and mitigate the adverse effects of rising temperatures and the UHI phenomenon, an accurate air temperature forecasting system is essential. In the literature, various time series models have been applied for climate and temperature prediction [12]. Among these, the Autoregressive Integrated Moving Average (ARIMA) model is commonly used to model and forecast future data based on historical patterns [13]. However, ARIMA has limitations in capturing strong seasonal or periodic patterns [14]. To address this, the Fourier Series serves as an effective complement due to its ability to decompose data into frequency components, thus capturing the inherent periodic variations in temperature data [15], [16].

Therefore, this study aims to develop and implement a combined ARIMA and Fourier Series model to predict air temperatures in Surabaya. The expectation is that by integrating the strengths of both models, where ARIMA manages long-term trends and Fourier Series captures seasonal fluctuations and recurring cyclic patterns the accuracy of air temperature predictions can be significantly enhanced. This will provide more reliable information for future climate change planning and adaptation strategies.

2. RESEARCH METHOD

This chapter outlines the research design and specific methods utilized to compare the effectiveness of ARIMA and Fourier Series for air temperature forecasting in Surabaya. The sequential steps and interdependencies of the research process are visually depicted in Figure 1, which presents the overarching methodology flow adopted for this comparative analysis.

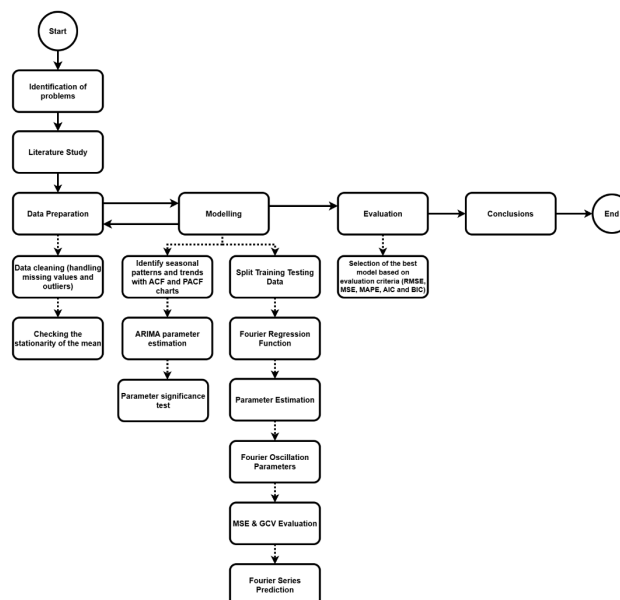


Figure 1. Research Methodology

2.1. Autoregressive Moving Average (ARIMA) & Seasonal Autoregressive Moving Average (SARIMA)

The Autoregressive Integrated Moving Average (ARIMA) model is a widely used method for time series analysis due to its ability to model non-stationary data by combining autoregressive

(AR), differencing (I), and moving average (MA) components. Introduced by Box and Jenkins [14], the ARIMA model is denoted as ARIMA(p,d,q), where p represents the order of the autoregressive part, d the degree of differencing, and q the order of the moving average. The appropriate values of these parameters are typically determined using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The general form of the ARIMA model is [14]:

$$\phi_p(B)(1-B)^d Z_t = \theta_q \quad (1)$$

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model extends ARIMA by incorporating seasonal differencing and seasonal AR and MA components to capture periodic patterns in the data. SARIMA is expressed as SARIMA(p,d,q)(P,D,Q)_S, where (P,D,Q) are the seasonal parameters and S is the seasonal period. Parameter identification is also guided by ACF and PACF analysis. The SARIMA model is formulated as follows [15]:

$$\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D \dot{Z}_t = \theta_q(B)\Theta_Q(B^S)a_t \quad (2)$$

Both ARIMA and SARIMA are effective tools for forecasting, with SARIMA being particularly suitable for time series data exhibiting seasonal patterns.

2.2. Fourier Series and ARIMA-Fourier

The Fourier Series is a powerful mathematical technique used to represent periodic functions as a sum of sine and cosine terms, making it particularly useful in modeling seasonality and cyclic behavior in time series data, such as temperature patterns [16]. For a periodic function $f(t)$ with period T, the general form of the Fourier series is given by [17]:

$$f(t) = a_0 \sum_{n=1}^{\infty} \left(a_n \sin\left(\frac{2n\pi t}{T}\right) + b_n \cos\left(\frac{2n\pi t}{T}\right) \right) \quad (3)$$

Where:

a_0, a_n and b_n are the Fourier coefficients, determined by integrals over one period of $f(t)$.

n represents the harmonic number.

T is the period of the function.

To address the limitations of traditional ARIMA in modeling complex or non-integral seasonality, the ARIMA-Fourier approach was introduced. This method integrates sinusoidal Fourier terms as external regressors into the ARIMA model, allowing it to better capture irregular seasonal variations without requiring seasonal differencing [18][19]. The key challenge lies in selecting the optimal number of harmonics K , which is typically guided by information criteria such as AIC or BIC to balance fit and complexity [20].

The general form of the ARIMA-Fourier model can be expressed as:

$$f(t) = a_0 \sum_{n=1}^{\infty} \left(a_n \sin\left(\frac{2n\pi t}{T}\right) + b_n \cos\left(\frac{2n\pi t}{T}\right) \right) + ARIMA(p, d, q) + \varepsilon_t \quad (4)$$

This combination enhances forecasting accuracy, especially for data exhibiting subtle or irregular seasonal behaviors.

2.3. Stationary Analysis

Stationarity, a critical property in time series analysis, implies that a series' statistical characteristics (mean, variance, and autocovariance) remain constant over time. This is crucial as many time series models, including ARIMA, assume stationary data for valid parameter estimation and reliable forecasting. The absence of stationarity necessitates appropriate transformations before model application.

To formally assess stationarity, the Augmented Dickey-Fuller (ADF) test is employed to determine the presence of a unit root, with the null hypothesis indicating non-stationarity.

The general form of the Augmented Dickey-Fuller (ADF) test equation is [21]:

$$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \sum_{i=1}^p \delta_i \Delta Y_{t-i} + \epsilon_t \quad (5)$$

Where:

$$\Delta Y_t = Y_t - Y_{t-1}$$

Y_t is the time series at time t .

α is a constant.

β is the coefficient for the time trend t .

γ is the coefficient of the lagged level of the series, Y_{t-1} .
 $\sum_{i=1}^p \delta_i \Delta Y_{t-i}$ are lagged difference terms for autocorrelation.
 p is the number of lagged difference terms.
 ϵ_t is the white noise error term.

2.4. Evaluation Metrics

To rigorously assess and compare the performance of the developed forecasting models, several key evaluation metrics were utilized. These metrics provide quantitative measures of forecasting accuracy and model fit, enabling a comprehensive analysis of both ARIMA and Fourier Series methods.

Table 1. Summary of Evaluation Metrics

Evaluation Metrics	Notation	Equation
Mean Square Error (MSE)	MSE quantifies the average squared difference between estimated and actual values, giving more weight to larger errors [17].	$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$
Root Mean Square Error (RMSE)	RMSE is the square root of MSE, returning the error in the same units as the original data, making it more interpretable for direct comparison [17].	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$
Mean Absolute Error (MAE)	MAE measures the average magnitude of errors without considering their direction. It is less sensitive to large errors or outliers compared to MSE and RMSE [17].	$MAE = \frac{1}{n} \sum_{i=1}^n \left \frac{y_i - \hat{y}_i}{y_i} \right $
Mean Absolute Percentage Error (MAPE)	MAPE expresses accuracy as a percentage, useful for comparing forecast accuracy across different time series scales. A common issue is its potential to be infinite or undefined if actual values are zero [17].	$MAPE = \frac{100\%}{N} \sum_{t=1}^N \left \frac{Y_t - \hat{Y}_t}{Y_t} \right $
Generalized Cross-Validation (GCV)	GCV is a robust method for model selection and parameter tuning, balancing model fit and complexity by penalizing models with more parameters. A lower GCV value indicates a better model [17].	$GCV = \frac{MSE(k)}{\left(1 - \frac{trace(H)}{n}\right)^2}$
Akaike Information Criterion (AIC)	AIC balances a model's goodness of fit with its complexity, penalizing more parameters to avoid overfitting [22].	$AIC = 2k - 2\ln(L)$
Akaike Information Criterion (AIC)	Similar to AIC, BIC also penalizes the number of parameters but more strongly, favoring simpler models, especially for larger datasets [22].	$BIC = k\ln(n) - 2\ln(L)$

3. RESULTS AND DISCUSSION

This section presents the findings of the study along with interpretation and analysis. The discussion is divided into several subsections, starting with a descriptive analysis of the air temperature data in Surabaya, followed by modeling processes using ARIMA and ARIMA-Fourier methods. Each stage includes statistical tests, model selection, parameter estimation, forecasting results, and performance evaluations. The goal is to provide a comprehensive understanding of the effectiveness and accuracy of each forecasting approach in capturing the temporal dynamics of air temperature in Surabaya.

3.1. Descriptive analysis of air temperature in the city of Surabaya

This study utilizes daily air temperature data recorded in Surabaya from January 1, 2020, to December 31, 2024 obtained from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) Climatology Station Surabaya. The dataset consists of three temperature metrics for each day: average, maximum, and minimum temperatures. A sample of the dataset is presented in Table 1, which illustrates typical values such as an average daily temperature ranging between 26.0°C and 30.0°C, with extremes reaching a maximum of 34.2°C and a minimum of 25.5°C.

Through exploratory data analysis, the dataset was found to be complete, with no missing values. Furthermore, a detailed analysis through boxplots as depicted in Figure 2 confirmed the absence of significant outliers across all temperature metrics, indicating the data's robustness and suitability for direct analysis without the need for specific pre-processing steps for missing values or extreme anomalies.

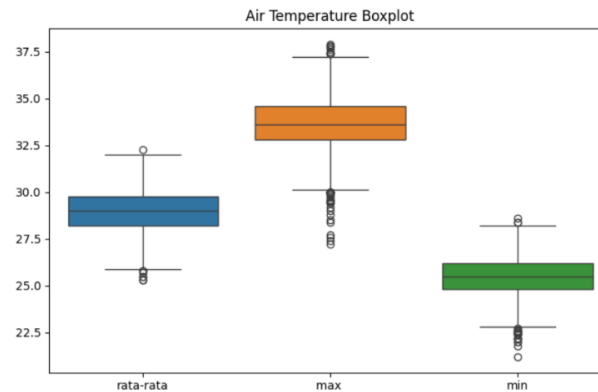


Figure 2. Air Temperature Boxplot 2020-2024 in Surabaya

To visualize the temporal pattern, a time series plot of average daily temperatures is shown in Figure 3. The plot reveals recurring fluctuations that suggest a seasonal trend across the years. The temperature tends to oscillate within a relatively narrow band, indicating stable climatic behavior, but with visible periodic spikes and drops that imply the presence of both annual cycles and short-term variations.

From 2020 to 2024, the average temperature appears to maintain a consistent trend without extreme long-term drift, which is characteristic of many climate variables influenced by cyclical weather phenomena. However, there are noticeable short-term variations that could be attributed to local meteorological events or shifts in seasonal patterns.

This descriptive analysis indicates that the air temperature data contains seasonality and fluctuations, which are important characteristics to consider in selecting an appropriate forecasting model. Further analysis and model development will take into account these characteristics through transformations and fitting seasonal-capable models such as ARIMA and ARIMA with Fourier terms.

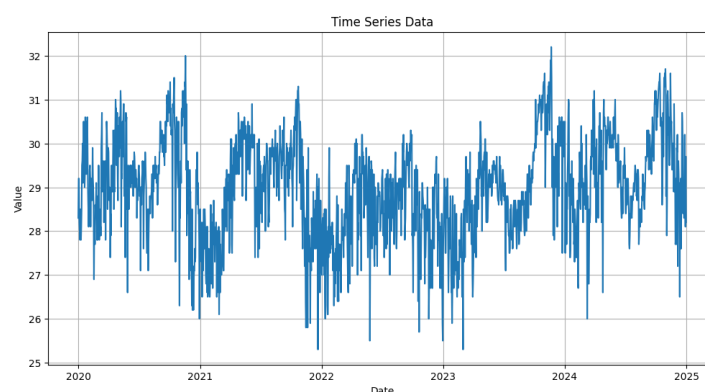


Figure 3. Time Series Plot of Air Temperature 2020-2024 in Surabaya

Table 2. Air Temperature Dataset 2020-2024

Date	Average	Max	Min
01/01/2020	28.3	32.8	25.5
02/01/2020	29.2	34.2	26.2
⋮	⋮	⋮	⋮
30/12/2024	29.7	34.2	26.0
31/12/2024	28.2	32.8	25.6

3.2. Modeling and Predicting Air Temperature in Surabaya Using the ARIMA Method

The ARIMA modeling approach is widely used in time series forecasting due to its ability to capture patterns in trends and fluctuations. In this study, the ARIMA method was employed to model and predict daily air temperature in Surabaya. The modeling process began with a stationarity check through both graphical analysis and statistical testing.

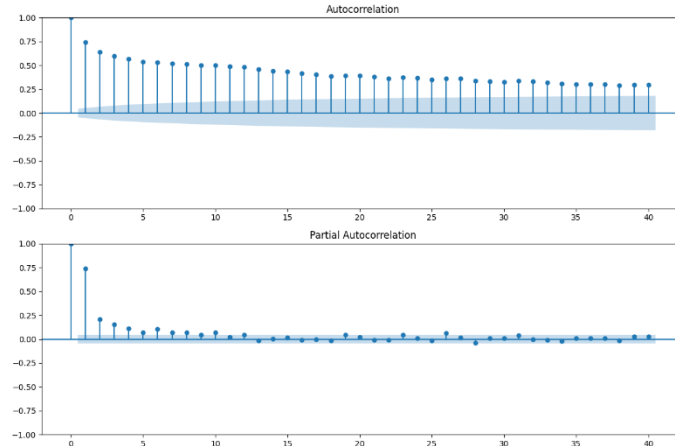


Figure 4. ACF and PACF before Differencing

Figure 4 presents the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the original temperature data before transformation. The ACF plot shows a slow decay that does not cut off immediately, suggesting the presence of trend and seasonality components, indicating that the series is non-stationary. This observation is supported by the result an ADF statistic of -4.903 and a p-value of 3.4×10^{-5} , below the 0.05 significance level.

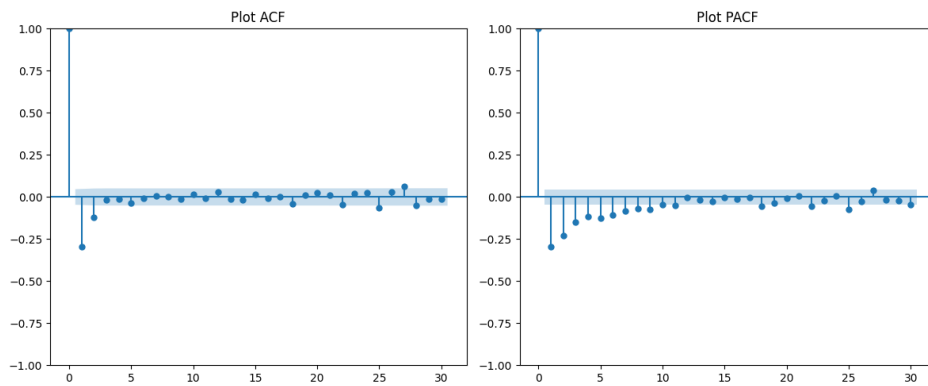


Figure 5. Plots ACF and PACF Plots after Differencing

Table 3. ADF Test for One-Month Data Scenario

Parameter	Value
ADF Statistic	-18.820574
p-value	2.02×10^{-30}
Critical Value (5%)	-2.863
Remank	Stationary because $p < 0.05$

Table 4. ADF Test for Three-Month Data Scenario

Parameter	Value
ADF Statistic	-18.088491
p-value	2.57×10^{-30}
Critical Value (5%)	-2.863
Remank	Stationary because $p < 0.05$

Table 5. ADF Test for Six-Month Data Scenario

Parameter	Value
ADF Statistic	-18.028269
p-value	2.68×10^{-30}
Critical Value (5%)	-2.863
Remank	Stationary because $p < 0.05$

Table 6. ADF Test for Twelve-Month Data Scenario

Parameter	Value
ADF Statistic	-17.884169
p-value	2.99×10^{-30}
Critical Value (5%)	-2.863
Remank	Stationary because $p < 0.05$

After achieving stationarity through differencing, the next crucial step involved identifying the appropriate ARIMA model structure, specifically determining the orders of the autoregressive (p) and moving average (q) components. This process was guided by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the differenced series (Figure 5), in conjunction with theoretical patterns presented in Table 7.

Table 7. Theoretical Patterns of ACF and PACF for Stationary Series

Proses	ACF	PACF
$AR(p)$	Dies down gradually	Cuts off after lag p
$MA(q)$	Cuts off after lag q	Dies down gradually
$ARMA(p,q)$	Dies down gradually	Dies down gradually
$AR(p)$ or $MA(p)$	Cuts off after lag q	Cuts off after lag p
White noise (Random)	No significant lags (all within limits)	No significant lags (all within limits)

Table 7, adapted from standard time series literature, provides a guideline for interpreting the behavior of ACF and PACF plots to identify suitable $AR(p)$, $MA(q)$, or $ARMA(p,q)$ processes. Based on the post-differencing ACF and PACF plots (Figure 6):

- The ACF showed a significant cutoff at lag 1, suggesting a Moving Average (MA) component. This led to the consideration of an $ARIMA(0,1,1)$ model.
- The PACF exhibited an initial significant spike, indicating an Autoregressive (AR) component. This supported the inclusion of an $ARIMA(1,1,0)$ model.
- Additionally, an $ARIMA(1,1,1)$ model was considered to explore a combined AR and MA process.

Based on the post-differencing ACF and PACF plots (Figure 6), several candidate models were selected, as outlined in Table 8: $ARIMA(0,1,1)$, $ARIMA(1,1,0)$, and $ARIMA(1,1,1)$. The $ARIMA(0,1,1)$ model was chosen due to the ACF's significant cutoff at lag 1, indicating a moving average component. The $ARIMA(1,1,0)$ model was supported by the PACF's initial spike, suggesting an autoregressive component. The $ARIMA(1,1,1)$ model combined both AR and MA terms and was included to test whether a combined model could offer improved forecasting performance.

Table 8. Candidate ARIMA Models

Model Candidate
$ARIMA(0,1,1)$
$ARIMA(1,1,0)$
$ARIMA(1,1,1)$

Table 9. Parameter Estimation Results of ARIMA Model in Scenario 1

ARIMA Model	Parameter	Coefficient	Std Err	t-statistic	p-value	Remark
$ARIMA(0,1,1)$	ma.L1	-0.9999	0.2309	-4.3307	0.00002	Significant
	Σ^2	0.6565	0.1536	4.2734	0.00002	Significant
$ARIMA(1,1,0)$	ar.L1	-0.5672	0.0163	-34.8658	0.0	Significant
	Σ^2	1.1520	0.0297	38.7917	0.0	Significant
$ARIMA(1,1,1)$	ar.L1	-0.2952	0.0187	-15.7677	0.0	Significant
	ma.L1	-1.0	5.1269	-0.1950	0.84538	Not Significant
	Σ^2	0.5991	3.0725	0.1950	0.84543	Not Significant

Table 10. Parameter Estimation Results of ARIMA Model in Scenario 2

ARIMA Model	Parameter	Coefficient	Std Err	t-statistic	p-value	Remark
ARIMA (0,1,1)	ma.L1	-0.9999	0.2426	-4.122	0.0004	Significant
	Sigma ²	0.6556	0.1612	4.0665	0.0005	Significant
ARIMA (1,1,0)	ar.L1	-0.5682	0.0166	-34.1314	0.0	Significant
	Sigma ²	1.1529	0.0345	34.6707	0.0	Significant
ARIMA (1,1,1)	ar.L1	-0.2992	0.0189	-15.8084	0.0	Significant
	ma.L1	-1.0	1.0476	-0.9545	0.33996	Not Significant
	Sigma ²	0.5966	0.6262	0.9527	0.34086	Not Significant

Table 11. Parameter Estimation Results of ARIMA Model in Scenario 3

ARIMA Model	Parameter	Coefficient	Std Err	t-statistic	p-value	Remark
ARIMA (0,1,1)	ma.L1	-1.0	1.0244	-0.9761	0.32915	Not Significant
	Sigma ²	0.6829	0.7014	0.9737	0.33034	Not Significant
ARIMA (1,1,0)	ar.L1	-0.5675	0.0174	-32.5786	0.0	Significant
	Sigma ²	1.2044	0.0331	36.4066	0.0	Significant
ARIMA (1,1,1)	ar.L1	-0.3002	0.0197	-15.204	0.0	Significant
	ma.L1	-1.0	0.4498	-2.2231	0.02035	Significant
	Sigma ²	0.6217	0.2814	2.2096	0.02727	Significant

Table 12. Parameter Estimation Results of ARIMA Model in Scenario 4

ARIMA Model	Parameter	Coefficient	Std Err	t-statistic	p-value	Remark
ARIMA (0,1,1)	ma.L1	-0.9996	0.0765	-13.0608	0.0	Significant
	Sigma ²	0.6765	0.0573	11.8056	0.0	Significant
ARIMA (1,1,0)	ar.L1	0.5665	0.0186	-30.495	0.0	Significant
	Sigma ²	1.1969	0.0345	34.6707	0.0	Significant
ARIMA (1,1,1)	ar.L1	-0.3013	0.0208	14.5093	0.0	Significant
	ma.L1	-1.0	0.724	1.3812	0.16743	Not Significant
	Sigma ²	0.6142	0.4465	1.3754	0.16921	Not Significant

Parameter estimation was carried out for each candidate model under all scenarios, with results detailed in Tables 9 to 12. In general, ARIMA(0,1,1) and ARIMA(1,1,0) models exhibited statistically significant parameters ($p\text{-value} < 0.05$), particularly in short- and medium-term scenarios. In contrast, for the ARIMA(1,1,1) model, some parameters such as MA(1) were not significant in certain scenarios (e.g., $p\text{-value} > 0.3$ in Tables 9, 10 and 12), suggesting potential overfitting or model complexity.

Table 13. ARIMA Model Evaluation in Scenario 1 (One-Month Test Data)

Model	RMSE	MAE	MSE	MAPE	AIC	BIC
ARIMA(0,1,1)	1.05	0.88	1.11	3.05%	3695.13	3706.11
ARIMA(1,1,0)	1.40	1.19	1.96	4.06	3846.53	3857.52

Table 14. ARIMA Model Evaluation in Scenario 2 (Three-Month Test Data)

Model	RMSE	MAE	MSE	MAPE	AIC	BIC
ARIMA(0,1,1)	0.98	0.77	0.96	2.62%	3520.51	3531.43
ARIMA(1,1,0)	1.04	0.80	1.09	2.74%	3675.66	3686.58

Table 15. ARIMA Model Evaluation in Scenario 3 (Six-Month Test Data)

Model	RMSE	MAE	MSE	MAPE	AIC	BIC
ARIMA(0,1,1)	0.91	0.73	0.83	2.46%	3523.38	3534.19
ARIMA(1,1,1)	0.89	0.71	0.79	2.41%	3276.74	3292.95

Table 16. ARIMA Model Evaluation in Scenario 4 (Twelve-Month Test Data)

Model	RMSE	MAE	MSE	MAPE	AIC	BIC
ARIMA(0,1,1)	1.66	1.48	2.77	5.10%	2990.24	3000.92
ARIMA(1,1,0)	1.55	1.36	2.41	4.69%	3137.40	3147.97

Subsequently, model performance was evaluated using test data for four training data duration scenarios: one month, three months, six months, and twelve months. Evaluation metrics included Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The evaluation results are presented in

Tables 13 to 16. The ARIMA(0,1,1) model delivered the best performance in the one-month, three-month, and six-month scenarios, showing lower RMSE values than the other models. However, for the twelve-month forecast, the ARIMA(1,1,0) model outperformed others with an RMSE of 1.55 compared to 1.66 from ARIMA(0,1,1).

3.2. Modeling and Predicting Air Temperature in Surabaya Using the SARIMA Method

aa Given the observed seasonal patterns in the daily air temperature data, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model was considered a suitable approach to capture both trend and periodicity. This model extends the conventional ARIMA framework by incorporating seasonal autoregressive and moving average components, making it theoretically appropriate for time series exhibiting strong cyclical behavior.

After a thorough model identification and parameter estimation process, the SARIMA(2,0,0)(2,1,0)[12] configuration was selected for this study. This model consistently demonstrated statistically significant parameter estimates across all forecasting scenarios, with p-values well below the 0.05 threshold for both seasonal and non-seasonal components. Such results indicate that the model effectively captures the autocorrelation structure present in the historical temperature series.



Figure 6. Visualization of Forecasting Results Using the SARIMA Model: (a) One-Month Forecast (December 2024), (b) Three-Month Forecast (October–December 2024), (c) Six-Month Forecast (July–December 2024), (d) Twelve-Month Forecast (January–December 2024)

However, despite its theoretical suitability and strong in-sample fit, the SARIMA model exhibited poor out-of-sample forecasting performance. This is evident from the prediction results visualized in Figure 6.

In these visualizations, the SARIMA model's predictive intervals become increasingly wide with longer horizons, reflecting greater uncertainty. Additionally, the forecasted values tend to diverge from the actual testing data, particularly in Scenario 3 and Scenario 4. The model produces overly smoothed patterns that fail to capture short-term temperature fluctuations and irregular seasonal dynamics, which are critical in climate-related forecasting.

These findings suggest that although SARIMA(2,0,0)(2,1,0)[12] is statistically valid, it lacks robustness in forecasting daily temperature with complex intra-annual variations. Its reduced adaptability to high-frequency changes renders it less suitable for the forecasting objectives of this study.

In contrast, the ARIMA and ARIMA-Fourier models—discussed in the subsequent sections—achieved more accurate predictions, narrower confidence intervals, and better alignment with real observations, especially for short- and medium-term forecasting. Therefore, they are considered more appropriate models for forecasting air temperature in Surabaya.

3.3. Modeling and Predicting Air Temperature in Surabaya Using the ARIMA-Fourier Series Method

To enhance the forecasting capability of traditional time series models in capturing seasonal patterns, this study implements a hybrid approach that integrates Fourier series into the ARIMA framework, known as the ARIMA-Fourier model. The Fourier terms are introduced to model periodic components, with the number of harmonics controlled by the oscillation parameter k . The goal is to identify the optimal k that balances model complexity and predictive accuracy.

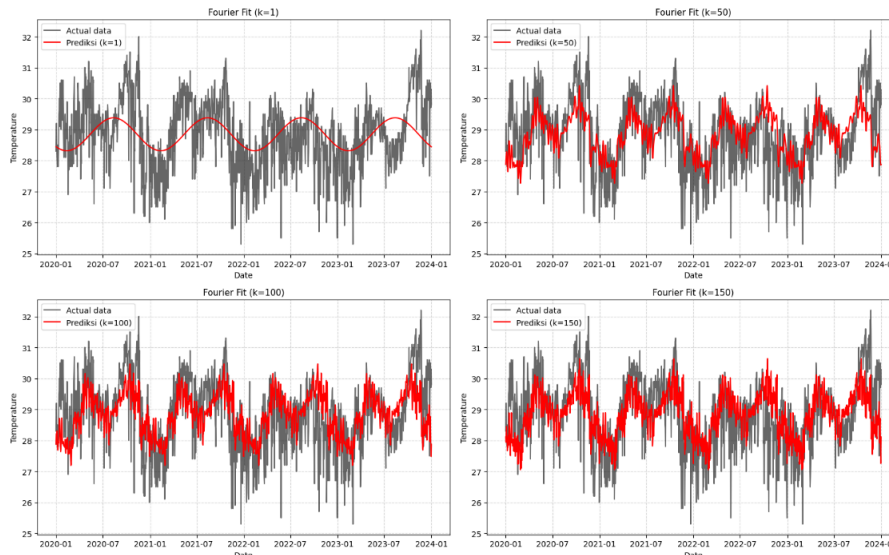


Figure 7. Visualization of the prediction results of the Fourier model with variations in the value of the oscillation parameter k

Figure 8 shows the visualization of the air temperature fitting results using the Fourier series model with different values of the oscillation parameter $k = 1, 50, 100$, and 150 . It can be observed that higher k values improve the model's ability to follow short-term variations and seasonal patterns in the data.

To support the visual inspection, the model's performance was quantitatively evaluated using three metrics: Mean Squared Error (MSE), Generalized Cross-Validation (GCV), and coefficient of determination (R^2). The results for the four forecasting scenarios (one month, three months, six months, and twelve months) are summarized in Tables 17 through 30.

Table 17. Performance Comparison of Fourier Model in One-Month Scenario

K	MSE	GCV	R^2
1	1.187869	1.191847	0.092382
50	0.875854	0.983343	0.330784
100	0.847903	1.075071	0.353141
150	0.829343	1.196918	0.366322

Table 18. Performance Comparison of Fourier Model in Three-Month Scenario

k	MSE	GCV	R^2
1	1.139951	1.143904	0.091313
50	0.862241	0.972128	0.312684
100	0.832254	1.064644	0.336587
150	0.812564	1.189482	0.352283

Table 19. Performance Comparison of Fourier Model in Six-Month Scenario

k	MSE	GCV	R^2
1	1.165547	1.169816	0.095290
50	0.894337	1.015330	0.305807
100	0.862255	1.119387	0.330709
150	0.841253	1.260947	0.347011

Table 20. Performance Comparison of Fourier Model in Six-Month Scenario

k	MSE	GCV	R ²
1	1.160425	1.165202	0.108715
50	0.872929	1.007296	0.329532
100	0.838139	1.126629	0.356252
150	0.814605	1.291747	0.374328

Across all scenarios, increasing k results in a consistent decrease in MSE and a steady increase in R^2 , indicating improved model accuracy and explanatory power. For instance, in the one-month scenario (Table 27), R^2 improves from 0.092 at $k = 1$ to 0.366 at $k = 150$. A similar trend is observed in the three-month (Table 28), six-month (Table 29), and twelve-month (Table 30) scenarios, where R^2 values increase to 0.352, 0.347, and 0.374, respectively, when $k = 150$ is used.

While a moderate rise in GCV values was observed at higher ' k ' values, suggesting increased model complexity, this trade-off was considered acceptable given the significant improvement in the model's ability to closely track the actual data and its enhanced explanatory power (as indicated by R^2). As visually evident in Figure 6, the model with $k=150$ demonstrated the most adaptive fit, accurately capturing the short-term variations and seasonal patterns within the air temperature data.

Despite a moderate rise in GCV values at higher k , this trade-off is considered acceptable given the significant improvement in accuracy and variance explanation. Therefore, based on both visual and statistical evidence, the value $k = 150$ is selected as the optimal configuration for the Fourier component in the ARIMA-Fourier model used in this study.

Therefore, based on both visual inspection and these quantitative evaluation results, the value $k=150$ is selected as the optimal configuration for the Fourier component in the ARIMA-Fourier model used in this study. This configuration will subsequently be used for forecasting temperature in the next evaluation stages and model comparison sections.

3.4. Comparison of Prediction Result of the ARIMA and ARIMA-Fourier Series

This section presents a comparative analysis of two time series forecasting models: the conventional ARIMA model and the ARIMA model integrated with Fourier series. The goal is to evaluate each model's ability to capture the underlying patterns of daily average air temperature in Surabaya and to determine which approach yields better predictive accuracy across four forecasting horizons: one month, three months, six months, and twelve months.



Figure 8. Visualization of Forecasting Results Using the ARIMA Model: (a) One-Month Forecast (December 2024), (b) Three-Month Forecast (October–December 2024), (c) Six-Month Forecast (July–December 2024), (d) Twelve-Month Forecast (January–December 2024)

Figure 8 illustrates the forecasting results obtained using the traditional ARIMA model. In the short-term scenarios (Figures 8a and 8b), the predicted values closely follow the actual data, *Comparative Analysis of ARIMA and Fourier Series Methods for Air Temperature Forecasting..(Annas THS)*

and the confidence intervals remain relatively narrow, indicating reliable forecast precision. However, as the forecasting horizon increases (Figures 8c and 8d), the ARIMA model exhibits increased prediction uncertainty, evidenced by the widening confidence bands and noticeable deviation from actual temperature values. This suggests that the ARIMA model alone may have limitations in capturing the seasonal and periodic characteristics inherent in temperature data.

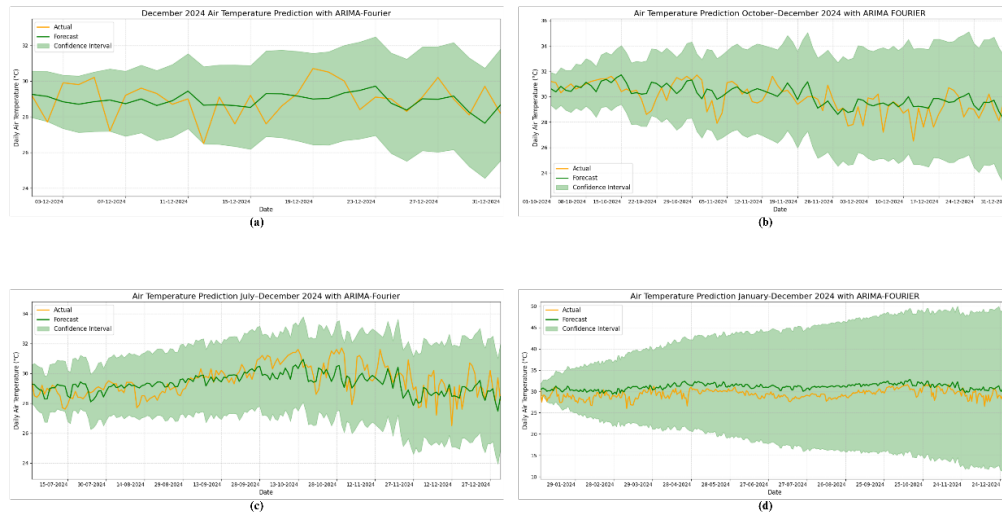


Figure 9. Visualization of Forecasting Results Using the ARIMA-Fourier Model: (a) One-Month Forecast (December 2024), (b) Three-Month Forecast (October–December 2024), (c) Six-Month Forecast (July–December 2024), (d) Twelve-Month Forecast (January–December 2024)

In contrast, Figure 9 displays the results of temperature forecasting using the ARIMA-Fourier model, which integrates Fourier terms to account for seasonal components within the ARIMA framework. The ARIMA-Fourier model demonstrates improved performance in tracking the actual temperature across all forecasting periods. Particularly in the medium-range forecasts (three to six months; Figures 9b and 9c), the predicted values show better alignment with the observed data, and the model preserves a more structured representation of periodic fluctuations.

Table 21. Performance Comparison of SARIMA, ARIMA and Fourier Model in All Scenario

Model	Scenario	RMSE
ARIMA(0,1,1)	Scenario 1	1.05
ARIMA(0,1,1)	Scenario 2	0.98
ARIMA(1,1,1)	Scenario 3	0.89
ARIMA(1,1,0)	Scenario 4	1.55
ARIMA-Fourier	Scenario 1	1.04
ARIMA-Fourier	Scenario 2	0.97
ARIMA-Fourier	Scenario 3	0.87
ARIMA-Fourier	Scenario 4	1.93

The quantitative evaluation is provided in Table 31, which compares the Root Mean Squared Error (RMSE) of both models across all scenarios:

- In Scenario 1 (one-month forecast), ARIMA-Fourier achieves a lower RMSE of 1.04 compared to 1.05 from the ARIMA model.
- In Scenario 2 (three-month forecast), the ARIMA-Fourier model again performs slightly better, with an RMSE of 0.97 versus 0.98.
- In Scenario 3 (six-month forecast), the ARIMA-Fourier model records the lowest RMSE of 0.87, indicating a more accurate prediction than ARIMA (RMSE = 0.89).
- However, in Scenario 4 (twelve-month forecast), the ARIMA-Fourier model shows a noticeable drop in performance, with a higher RMSE of 1.93 compared to 1.55 for the ARIMA model.

From the table, the ARIMA-Fourier model consistently achieves lower RMSE values than the traditional ARIMA model in short- to medium-term scenarios (Scenarios 1–3), indicating superior predictive accuracy. The inclusion of Fourier terms enables the model to account for periodic seasonal components that are not captured by ARIMA alone.

However, in the twelve-month forecasting scenario (Scenario 4), the ARIMA-Fourier model exhibits a noticeable decline in performance, with an RMSE of 1.93—higher than ARIMA’s 1.55. This suggests that the added complexity of Fourier terms may introduce overfitting or error accumulation over extended horizons, particularly when high-frequency seasonal components are overemphasized.

In conclusion, the ARIMA-Fourier model is better suited for short- and medium-term forecasting due to its ability to capture daily seasonal patterns and fluctuations. On the other hand, the simpler ARIMA model provides more stable long-term forecasts. Therefore, the model selection should be guided by the intended forecasting horizon and the nature of the underlying time series patterns.

3.4. Comparison of Prediction Result of the ARIMA and ARIMA-Fourier Series using Simulation Data

This section presents an evaluation of the predictive performance of the ARIMA and ARIMA-Fourier models using simulated temperature data. The simulated dataset was generated to statistically mimic the temporal characteristics of historical daily temperature observations in Surabaya from 2020 to 2024. This allows the models to be assessed under controlled conditions, free from extreme noise or irregularities typically present in real-world data.

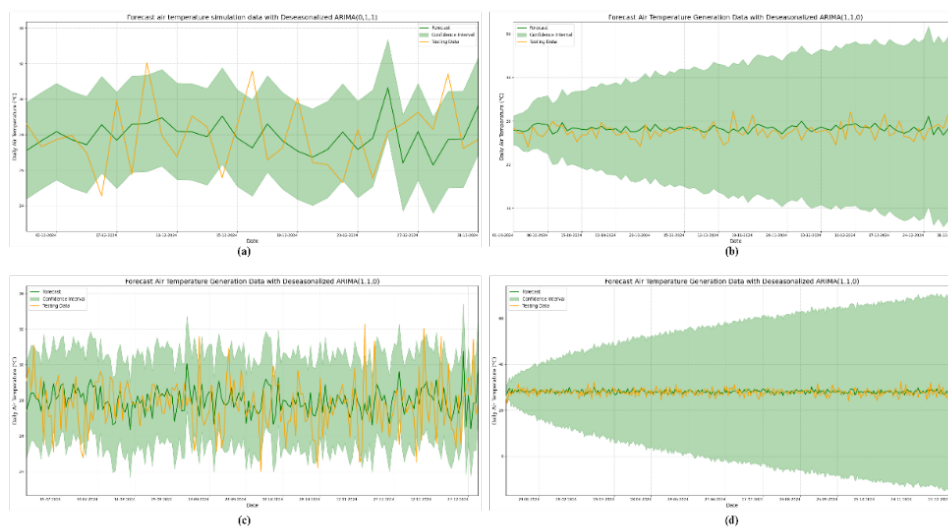


Figure 10 Visualization of Forecasting Results Using the ARIMA Model with Simulated Data: (a) One-Month Forecast (December 2024), (b) Three-Month Forecast (October–December 2024), (c) Six-Month Forecast (July–December 2024), (d) Twelve-Month Forecast (January–Dec)

Figure 10 illustrates the forecasting results produced by the ARIMA model across four forecasting horizons: one month (December 2024), three months (October–December 2024), six months (July–December 2024), and twelve months (January–December 2024). In the short-term forecast, the ARIMA(0,1,1) model demonstrates a reasonably accurate reconstruction of the simulated data, with predicted values closely aligned with the actual observations. However, as the forecasting horizon extends, particularly at the twelve-month level, the prediction intervals widen significantly, indicating increasing uncertainty. Despite this, the model remains capable of capturing the overall trend, although some deviations from the finer daily fluctuations are apparent.

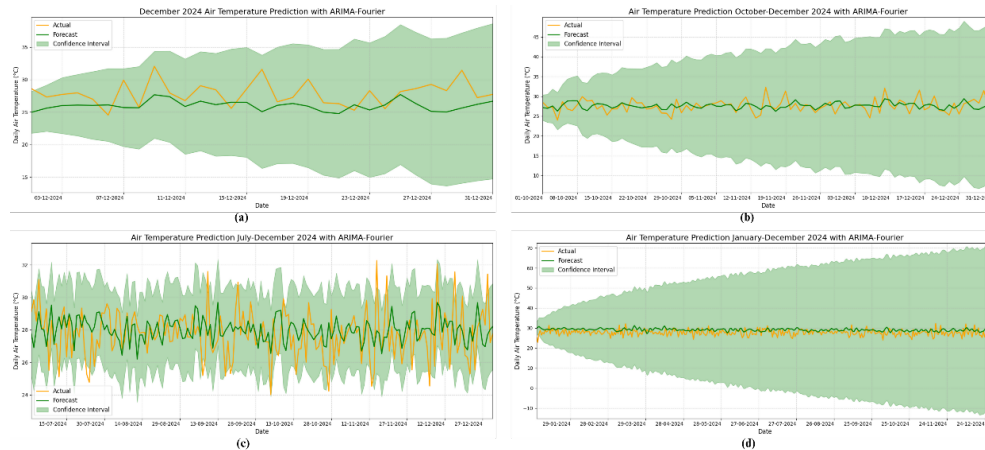


Figure 11. Visualization of Forecasting Results Using the ARIMA-Fourier Model with Simulated Data: (a) One-Month Forecast (December 2024), (b) Three-Month Forecast (October–December 2024), (c) Six-Month Forecast (July–December 2024), (d) Twelve-Month Forecast (January–December)

Figure 11 displays the results of the ARIMA-Fourier model, which incorporates seasonal components modeled using Fourier terms. Visually, the model yields smoother forecasts that more clearly reflect periodic seasonal patterns, especially in the three- and six-month scenarios. The model appears better suited to capturing complex cyclical variations in the data. However, at the twelve-month horizon, the uncertainty also increases considerably, sometimes exceeding that of the ARIMA model. This suggests that while the Fourier-based approach enhances the representation of seasonality, it can introduce higher forecast variability if the number of harmonics is not optimally chosen.

Table 22. Performance Comparison of Fourier Model in Six-Month Scenario with Simulated Data

Model	Scenario	RMSE
ARIMA(0,1,1)	Scenario 1	2.14
ARIMA(0,1,1)	Scenario 2	1.92
ARIMA(1,1,0)	Scenario 3	1.72
ARIMA(1,1,0)	Scenario 4	1.52
ARIMA-Fourier	Scenario 1	2.69
ARIMA-Fourier	Scenario 2	1.72
ARIMA-Fourier	Scenario 3	1.66
ARIMA-Fourier	Scenario 4	2.06

The quantitative evaluation shown in Table 32 supports these visual insights. In the six-month forecasting scenario, the ARIMA(1,1,0) model achieves the lowest RMSE of 1.52, indicating superior performance in capturing trend and moderate variability under simulated conditions. The ARIMA-Fourier model performs competitively in mid-range scenarios, particularly Scenario 3, where it achieves an RMSE of 1.66. However, in Scenarios 1 and 4, its performance deteriorates relative to the simpler ARIMA models. This decline may be attributed to overfitting in short-term forecasts or insufficient harmonic terms to model longer-term seasonality.

Based on the simulation-based evaluation, the decision can be made that the conventional ARIMA model offers more stable and generally better forecasting performance across longer horizons. The ARIMA-Fourier model, while effective in capturing periodicity, demonstrates more variability in its accuracy depending on the forecasting window and model complexity. Therefore, the choice between models should consider both the intended forecast horizon and the complexity of seasonal behavior in the temperature data.

4. CONCLUSION

This study aimed to comprehensively compare the forecasting performance of three distinct time-series models the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, the traditional Autoregressive Integrated Moving Average (ARIMA) model, and the

ARIMA model augmented with Fourier series (ARIMA-Fourier) in predicting daily average air temperature in Surabaya using historical data from 2020 to 2024. The objective, as stated in the "Introduction," was to identify the most effective methodology for forecasting time-series data with inherent seasonality, and this has been addressed through rigorous analysis presented in the "Results and Discussion" chapter.

The analysis demonstrated that the traditional ARIMA model effectively captured short-term trends and fluctuations, particularly when applied to datasets with limited training durations. Among the tested configurations, ARIMA(0,1,1) and ARIMA(1,1,0) consistently exhibited statistically significant parameters and low error values, indicating reliable short-term forecasting performance. However, the traditional ARIMA model showed limitations in modeling complex or non-integral seasonal patterns over longer horizons, as its forecasting uncertainty increased significantly.

To address the complexities of seasonality, the study explored two advanced approaches: the SARIMA model and the ARIMA-Fourier hybrid model. The SARIMA model, specifically the SARIMA(2,0,0)(2,1,0)[12] configuration, was selected for its consistent statistical significance across all its parameters, ensuring a robust and interpretable structure. However, quantitative evaluation using Root Mean Squared Error (RMSE) revealed that the chosen SARIMA model consistently yielded higher RMSE values across all forecasting horizons compared to both the standard ARIMA and ARIMA-Fourier models in this specific application. This suggests that while SARIMA's identified parameters were significant for explaining the data's underlying structure, this did not translate into superior out-of-sample predictive accuracy in terms of RMSE for this dataset.

In contrast, the ARIMA-Fourier model, by incorporating sine and cosine harmonic terms as exogenous regressors, successfully captured nuanced periodic patterns that were not effectively modeled by ARIMA alone. Experimental results indicated that the ARIMA-Fourier model generally outperformed standard ARIMA in short- and medium-term forecasting scenarios, evidenced by lower RMSE values and improved tracking of actual temperature fluctuations. This was particularly notable when the oscillation parameter $k=150$ was used, striking an optimal balance between model complexity and predictive power. Nonetheless, the performance of the ARIMA-Fourier model declined in long-term forecasts (twelve months), likely due to the accumulation of errors introduced by high-frequency components, which can lead to overfitting and increased forecast variability.

In conclusion, while the SARIMA model provided a statistically robust representation of the time series, the ARIMA-Fourier model presented the most adaptive and accurate approach for forecasting urban air temperature series with complex seasonal characteristics, particularly over short- to medium-term periods, in terms of RMSE. The traditional ARIMA model also demonstrated surprisingly stable performance for longer horizons compared to ARIMA-Fourier. These findings underscore that the optimal model choice depends critically on the intended forecast horizon and the specific characteristics of the data.

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