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Agra City Air Quality Index Forecasting and Future Prediction Using the ARIMA Time Series Model

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Abstract

Air is one of the most essential parts for life to continue on Earth. Air pollution continuously rises due to weather, traffic, non-renewable energy use, and industrial reasons. These elements have an impact on the well-being and success of all species on Earth, thus it is necessary to regularly assess the state of the air quality in our surroundings. The Air Quality Index (AQI), which measures the quality of the air, is affected by several different factors, including the growth of Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2), Particulate Matter ($PM_{2.5}$, and PM_{10}). The present study uses an Autoregressive Integrated Moving Average (ARIMA) model for the forecasting and future prediction of monthly AQI, several individual factors such as the accumulation of NO_2, SO_2, $PM_{2.5}$, and PM_{10} in Agra City. The forecast's low accuracy for the best ARIMA model is evaluated using the following measurements: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Percentage Error (MPE), and Root Mean Square Error (RMSE). Additionally, the study predicts the AQI in Agra City for the next 15 months using the most suitable ARIMA model.

Keywords: AQI, $PH_{2.5}$, PH_{10}, NO_2, SO_2, ARIMA.

1. INTRODUCTION

Air quality in India has become an increasing issue, with many major cities facing low air quality levels (Kumari & Jain, 2018). The Air Quality Index (AQI) is commonly utilized to inform the public about pollution levels and related health hazards (Kumari & Jain, 2018; Chelani *et al*., 2002). Research indicates that pollutants like SO_2, NO_2, PM_{10}, and $PM_{2.5}$ significantly contribute to the poor air quality in India (Raja *et al*., 2019; Chaudhary *et al*., 2013). The AQI in India is determined according to national standards for various pollutants and regions, categorizing air quality into five levels from clean to hazardous (Chelani *et al*., 2002). Studies in different Indian cities have shown that particulate matter concentrations often surpass WHO guidelines, with commercial areas generally exhibiting higher AQI values than residential zones (Chaudhary *et al*., 2013). India's main sources of air pollution include vehicle emissions, industrial activities, waste burning, and construction work (Chaudhary *et al*., 2013).

Liang and Gong (2020) conducted a multi-city study that examined the long-term effects of urban landscape patterns on air quality trends. Their findings suggest that urban planning and landscape design significantly influence air pollution levels. This is pertinent to Agra, where urban expansion and inadequate green spaces could exacerbate air quality issues.

Zhao et al. (2016) provided a comprehensive analysis of annual and diurnal variations of gaseous and particulate pollutants across 31 provincial capital cities in China. Their findings illustrate that pollution levels can fluctuate significantly based on time of day and seasonal factors. This variability highlights the need for localized studies in Agra to understand specific pollution patterns and develop targeted interventions.

Recent advancements in technology offer promising avenues for air quality monitoring and prediction. Montori et al. (2018) proposed a collaborative Internet of Things (IoT) architecture for smart cities, which could be adapted for real-time environmental monitoring in Agra. Similarly, Bekkar et al. (2021) explored the use of deep learning for air pollution prediction, indicating the potential for machine learning models to enhance forecasting accuracy. These technological innovations could be implemented in Agra to provide timely data for policymakers and residents.

The health implications of air pollution are well-documented. Ding et al. (2017) conducted a case-crossover analysis that linked air pollution to asthma attacks in children, emphasizing the vulnerability of specific populations to air quality issues. In the context of Agra, understanding the health impacts on local populations, particularly children and the elderly, is crucial for addressing public health concerns linked to poor air quality.

Air Quality Index (AQI) forecasting has gained importance due to its impact on public health. Various approaches have been explored, including artificial neural networks, regression models, and time series analysis. Ensemble models combining neural networks and regression techniques have shown high efficiency in AQI prediction (Sankar Ganesh, *et al.*, 2019). Statistical models like ARIMA, principal component regression, and their combinations have been applied to forecast daily AQI, with combined models performing better (Kumar, & Goyal, 2011). Neural network-based models incorporating meteorological data have been developed for short-term AQI forecasting, proving useful for public information dissemination (Sharma, *et al.*, 2003). Recent research has employed seasonal ARMA models for AQI prediction, demonstrating effectiveness in capturing seasonality and providing valuable insights for health-related decision-making (Pant, *et al.*, 2023). These diverse approaches highlight the ongoing efforts to improve AQI forecasting accuracy and potential applications in air quality management and public health protection.

The main aim of this work is to predict the nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter ($PM_{2.5}$, and PM_{10}) in Agra using the best-fitted model. The use of the ARIMA technique for future prediction has become more and more popular in recent years It is used to improve the quality of the air in Agra in a variety of real-world situations.

2. Materials and Methods

This study used secondary data on the AQI for Agra, collected from January 2022 to September 2024 from the source https://airquality.cpcb.gov.in. The data analysis was carried out using R software and MS Excel.

2.1 Autoregressive Integrated Moving Average (ARIMA) model

Auto-Regressive Moving Average (ARMA), a technique for evaluating stationary univariate time series data, was created by Box and Jenkins in 1970. Box and Jenkins have increased the flexibility and power of modeling features by combining previously recognized techniques. The created model serves as a basis for forecasting and explains the fundamental process of developing the data. The ARMA model is modified by the ARIMA. An ARMA model expressed the conditional average of Y_t as a function of both previous observations $Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$, and previous innovations, $\varepsilon_{t-1}, \varepsilon_{t-q}$. The number of previous observations that depends on p is the AR degree, and the number of previous innovations that Y_t depends on q, which is the MA degree. In general, these methodologies are denoted by ARMA (p, q). The form of the ARMA (p, q) approach is given below:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \varepsilon_t + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \cdots + \varphi_q \varepsilon_{t-q} \quad (1)$$

where α is a constant term; $\beta_1, \ldots, \beta_p$ are AR coefficients; φ_1, …., φ_q are MA coefficients; $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}$ are AR lags corresponding to non-zero and $\varepsilon_{t-1}, \ldots, \varepsilon_{t-q}$ MA lags corresponding to non-zero. The ARIMA technique was developed by Box and Jenkins in 1976, and its structure is shown in Figure 1.

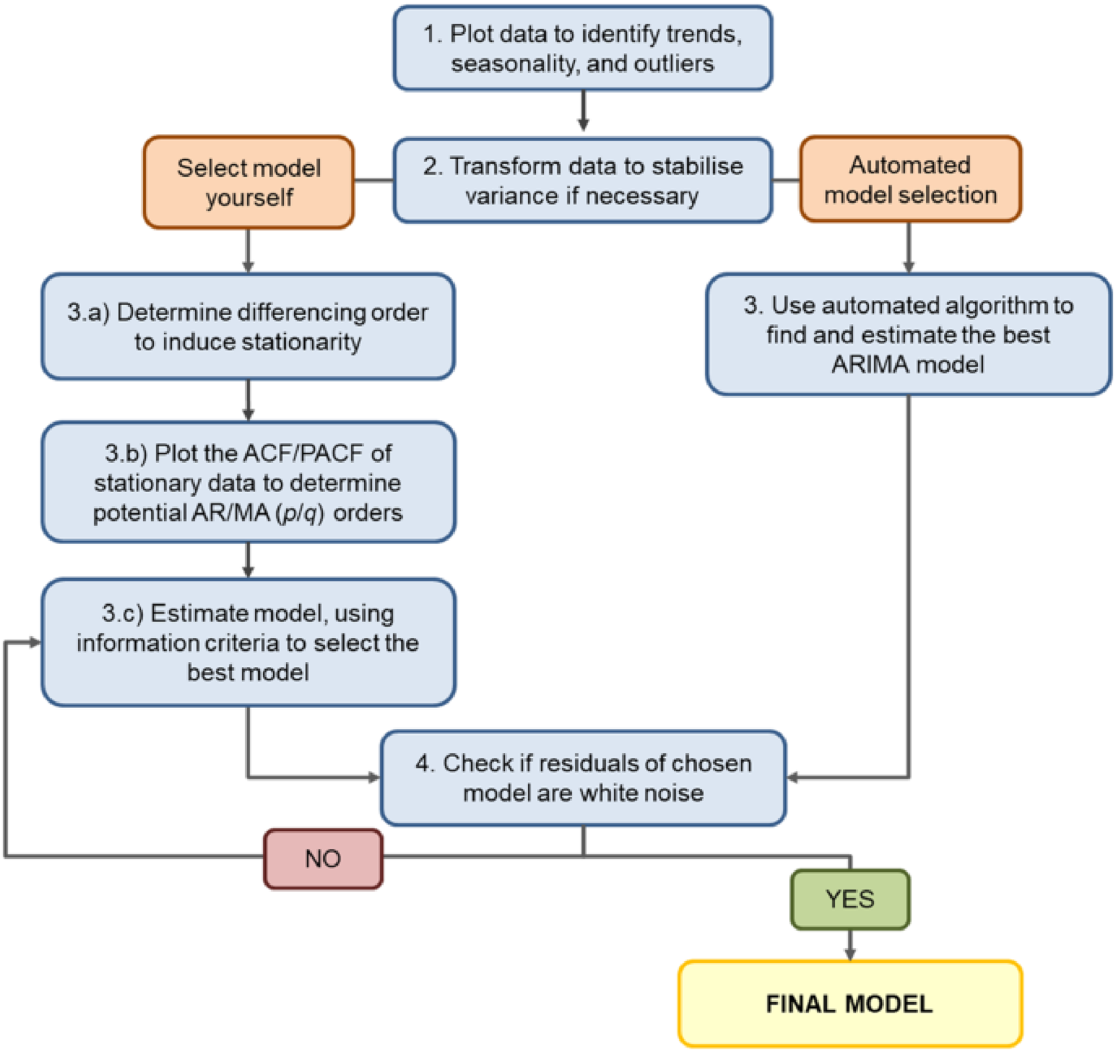

Figure 1: Time Series Analysis Using ARIMA Model for Air Pollution Prediction in Agra City of India

The Box-Jenkins approach's linearity restriction has been solved by statisticians in many different kinds of methods, and in addition to nonlinear time series models, robust versions of a number of ARIMA models have been developed (Makridakis and Hibon, 1997; Al-Masudi, 2011; Dash *et al*., 2017). If the X_t sequence is a random non-stationary time series, then the X sequence for the D order difference (Wang, 2008) is given by the below expression:

$$Y_t = \nabla^d X_t \quad (2)$$

where, ∇ is the differential operation and d is the differential order. After the difference, sequence Y_t has the following structure model, which is referred to as the ARIMA (p, d, q):

$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots .. + \beta_p Y_{t-p} + \varepsilon_t - \varphi_1 \varepsilon_{t-1} - \varphi_2 \varepsilon_{t-2} - \ldots .. - \varphi_q \varepsilon_{t-q}$ (3)

where the degree of the AR model is denoted by p, the degree of the MA model by q, the number of differences required to stabilize the data is denoted by d (Yonar *et al.*, 2020), $\{\varepsilon_t\}$is the white noise sequence, φ_i (i = 1, 2, 3,...,p) indicates the AR coefficient, and q_i (i = 1, 2, 3,...,q) is the MA coefficient.

2.2 Model Selection Criteria

Model selection criteria like mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE) are widely used to evaluate forecasting models. While RMSE is commonly accepted, it may not always be the best choice (Hodson, 2022). RMSE is optimal for Gaussian errors, while MAE is better for Laplacian errors (Hodson, 2022). Some researchers argue that MAE is a more natural and unambiguous measure of average error compared to RMSE, which can be misinterpreted due to its dependence on error variability and sample size (Willmott and Matsuura, 2005). However, others suggest that MAE may be redundant when used alongside RMSE, as they often provide similar information (Romanuke, 2021). The maximum absolute error (MaxAE) has been proposed as a complementary measure to RMSE, as it captures information about outliers that averaged measures might miss (Romanuke, 2021). Ultimately, the choice of criteria depends on the specific model structure and data characteristics (Wu, *et al*., 2011). The most popular metric used by corporations and organizations to assess forecast accuracy is the mean absolute percentage error, or MAPE. Additionally, while selecting a forecasting approach, it is utilized to compare accuracy across multiple data sets (Tofallis, 2013).

The performance of the models under consideration has been compared using several comparison metrics, including mean absolute error (MAE), mean absolute percentage error (MAPE), mean square error (MSE), and root mean square error (RMSE). Therefore, smaller values of MAE, MAPE, MSE, and RMSE are the most straightforward ways to determine the best forecast.

The average value of the absolute difference between the actual value and the prediction of the data set is represented by the average absolute error. The residuals of the data set are averaged out in this measurement.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}\,| \tag{4}$$

Where

$\hat{y}$ = Predicted value of y

y_i = mean value of y

Mean Square Error (MSE) is a common metric used to evaluate the performance of a regression model. It measures the average squared difference between the actual values and the predicted values.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \tag{5}$$

Root Mean Square Error (RMSE) is a commonly used metric for measuring the accuracy of a model, particularly in regression tasks. It represents the standard deviation of the residuals (prediction errors) and indicates how much the predicted values deviate from the actual values.

$$RMSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{6}$$

The Mean Absolute Percentage Error (MAPE) is widely used for measuring forecast accuracy but has significant limitations. Tofallis, (2013) demonstrates that MAPE systematically favors methods that under-forecast, introducing bias in model selection. To address this, Tofallis proposes an alternative measure based on the log of the accuracy ratio, which is particularly useful for heteroscedastic data. (Montaño Moreno, *et al*., 2013)

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_i-\hat{y}}{y_i}\right|\times 100 \qquad (7)$$

3. Result and Dissection

3.1 $PM_{2.5}$ Air Quality Index in Agra

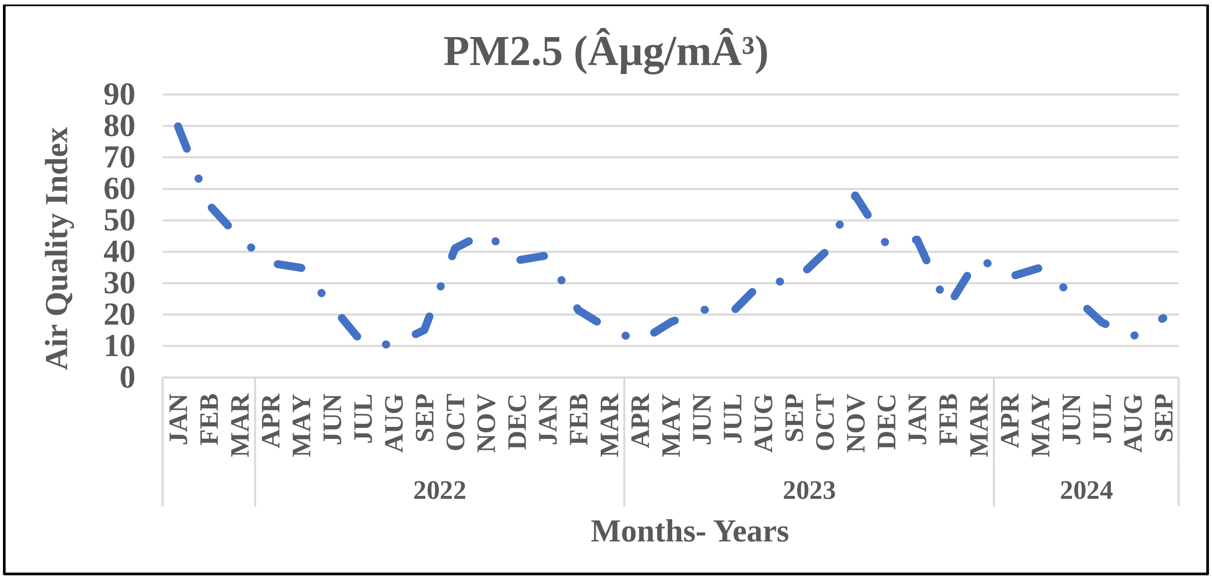

Figure 2: Actual Air Quality Index $PM_{2.5}$ in Agra City (JAN-2022 to SEP-2024)

From [Figure 2], the decreasing and increasing non-stationarity of the specified period for Agra City's $PM_{2.5}$ air quality index (January 2022 to September 2024) is represented in Figure 1.

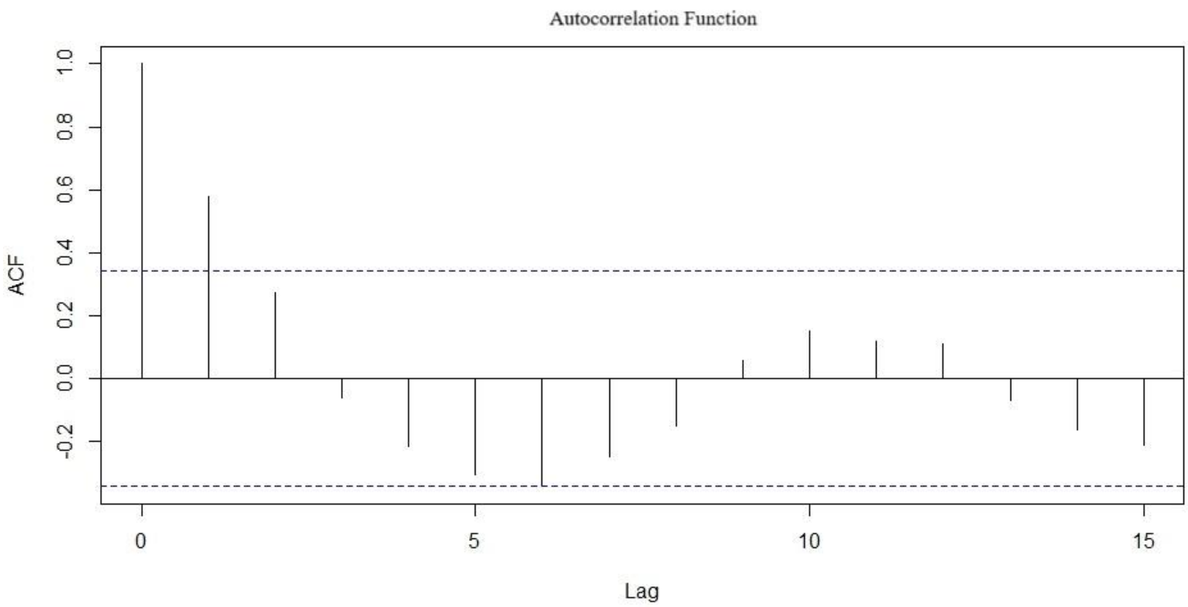

Figure 3: ACF at the Lag= 14 Air Quality Index $PM_{2.5}$ in Agra City (JAN-2022 to SEP-2024)

From [Figure 3], an autocorrelation function (ACF) is used to plot Agra City's $PM_{2.5}$ air quality index as a function of lag number. For confidence limits, $PM_{2.5}$ is utilized.

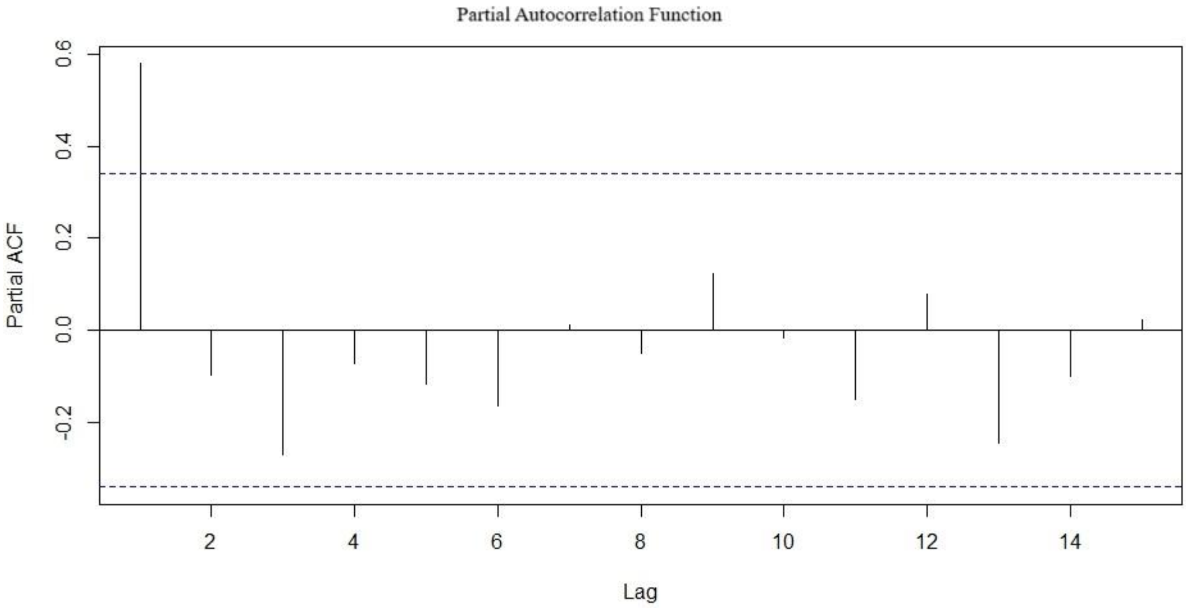

Figure 4: PACF at the Lag= 14 Air Quality Index $PM_{2.5}$ in Agra City (JAN-2022 to SEP-2024)

From [Figure 4], a partial autocorrelation function (PACF) is used to plot Agra City's $PM_{2.5}$ air quality index as a function of lag number. For confidence limits, $PM_{2.5}$ is utilized.

Table 1: ARIMA model selection criteria Air Quality Index $PM_{2.5}$ in Agra City

Model	ARIMA
Best parameters	p = 8, d = 2, q = 4
MSE	55.5472
RMSE	7.453
MAE	5.884498
MAPE	25.20587

From [Table 1], the ARIMA (8,2,4) model is the best model for the Air Quality Index $PM_{2.5}$ in Agra City. The ARIMA model accuracy is determined by four measures: MSE, RMSE, MAE, and MAPE values are used to determine the most suitable model for the Air Quality Index $PM_{2.5}$ in Agra City.

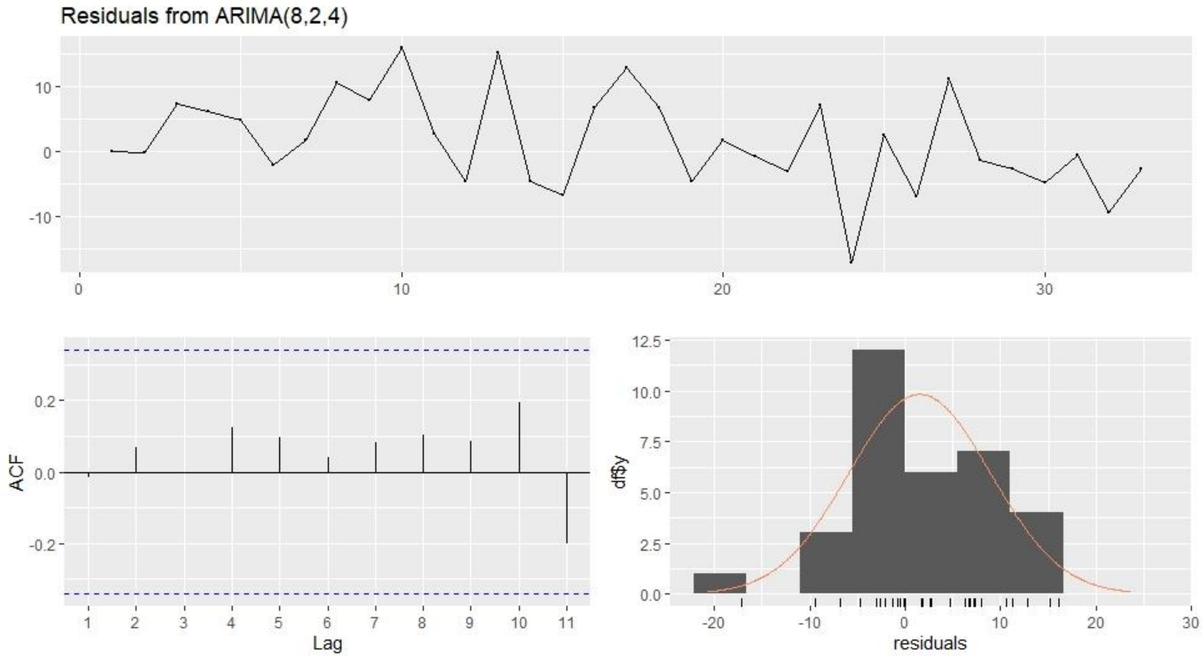

Figure 5: Residual plots for ARIMA model Air Quality Index $PM_{2.5}$ in Agra City (JAN-2022 to SEP-2024)

In the study, we used [Figure 5], from the ARIMA (8,2,4) model for the Air Quality Index $PM_{2.5}$ in Agra City, which was statistically significant. The residuals were tested for normality using a normality test.

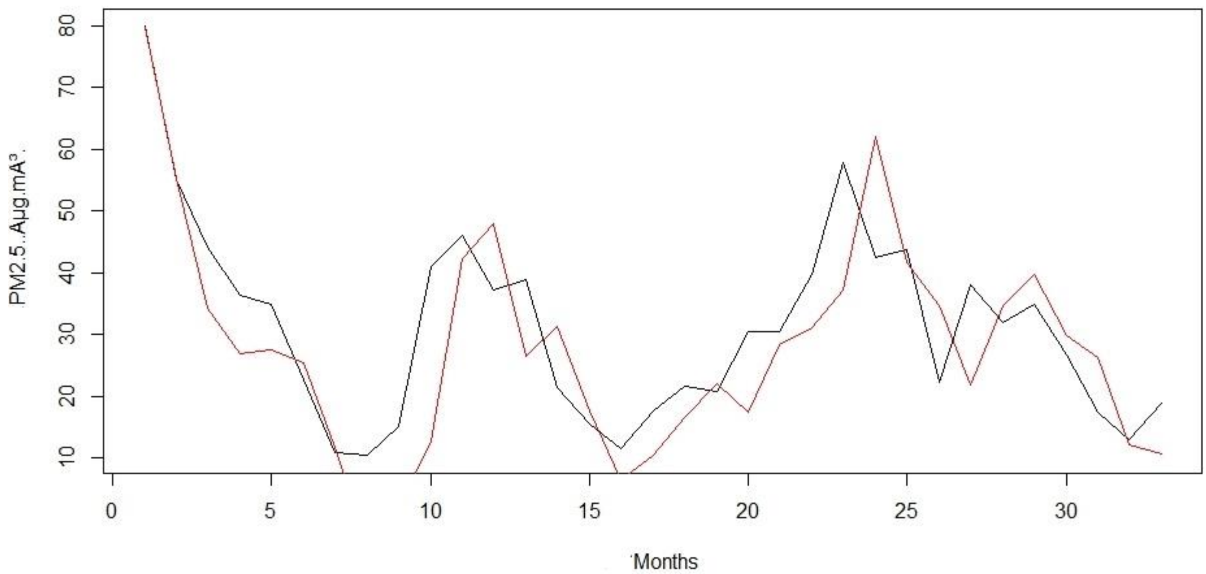

Figure 6: The Actual and Forecast plot of Air Quality Index $PM_{2.5}$ in Agra City (JAN-2022 to SEP-2024)

From [Figure 6], relatively few differences exist between the predicted data using the ARIMA (8,2,4) model and the real data on the Air Quality Index $PM_{2.5}$ in Agra City. The $PM_{2.5}$ levels, however, reduced gradually from January 2022 to September 2024.

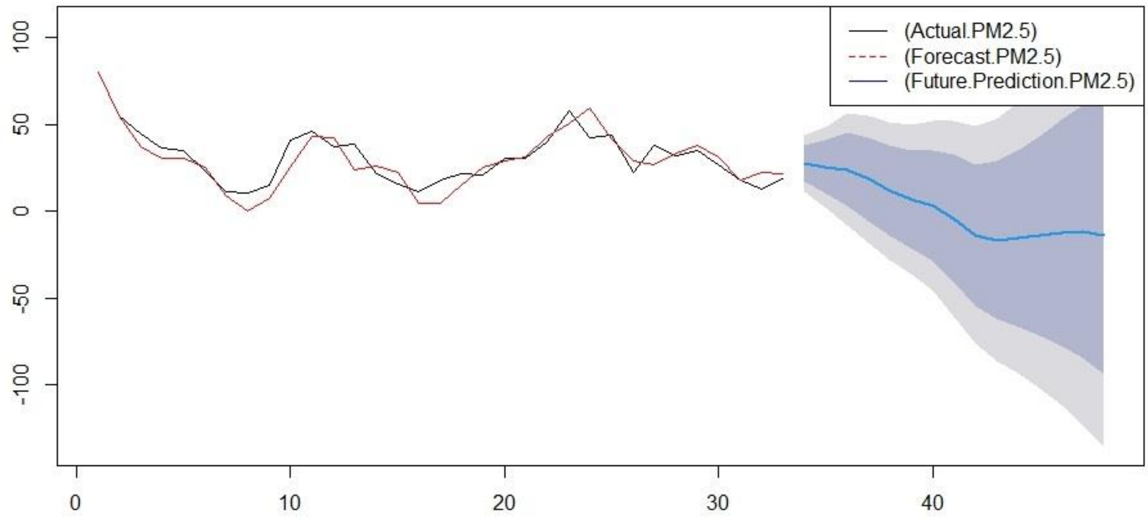

Figure 7: The Future Prediction Plot of Air Quality Index $PM_{2.5}$ in Agra City (OCT-2024 to DEC-2025)

According to [Figure 7], the in-sample forecast of $PM_{2.5}$ from January 2022 to September 2024 using the ARIMA (8,2,4) model is closely aligned with the observed and historical rates. The future projection line (blue) continues from the conclusion of the actual line (black) into the future for $PM_{2.5}$ in Agra. The following are future forecasts derived from the ARIMA (8,2,4) model for $PM_{2.5}$ levels in Agra. Utilizing the ARIMA (8,2,4) model, we generated a forecast for the anticipated behaviour of the verified and $PM_{2.5}$ time series in Agra for the next 15 months. The subsequent 15-month forecast for $PM_{2.5}$, based on verified air quality index data, is shown in Figure 7. Over the next 15 months, the ARIMA model forecasts a continued drop and subsequent rise in India's air quality index.

3.2 PM_{10} Air Quality Index in Agra

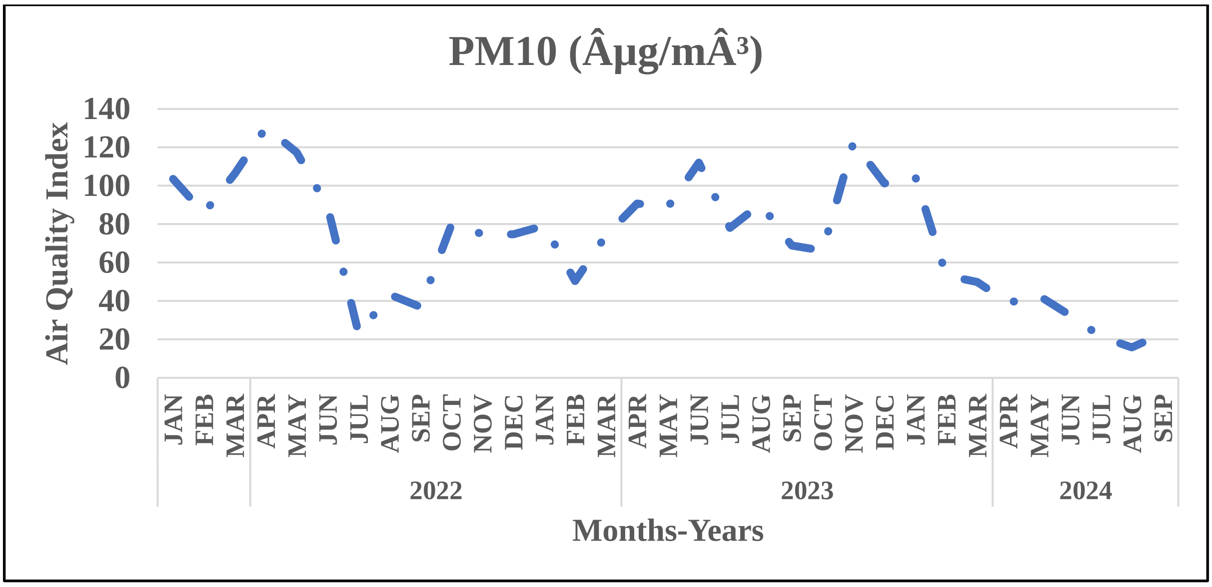

Figure 8: Actual Air Quality Index PM_{10} in Agra City (JAN-2022 to SEP-2024)

From [Figure 8], the decreasing and increasing non-stationarity of the specified period for Agra City's PM_{10} air quality index (January 2022 to September 2024) is represented in Figure 8.

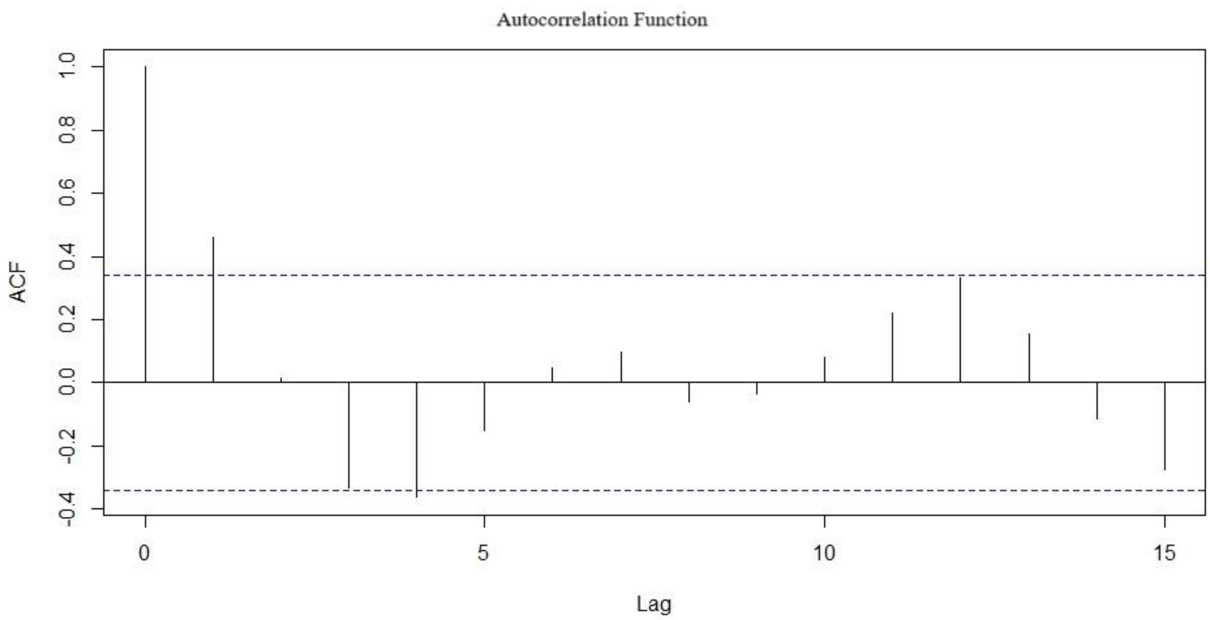

Figure 9: ACF at the Lag= 14 Air Quality Index PM_{10} in Agra City (JAN-2022 to SEP-2024)

From [Figure 9], an autocorrelation function (ACF) is used to plot Agra City's PM_{10} air quality index as a function of lag number. For confidence limits, PM_{10} is utilized.

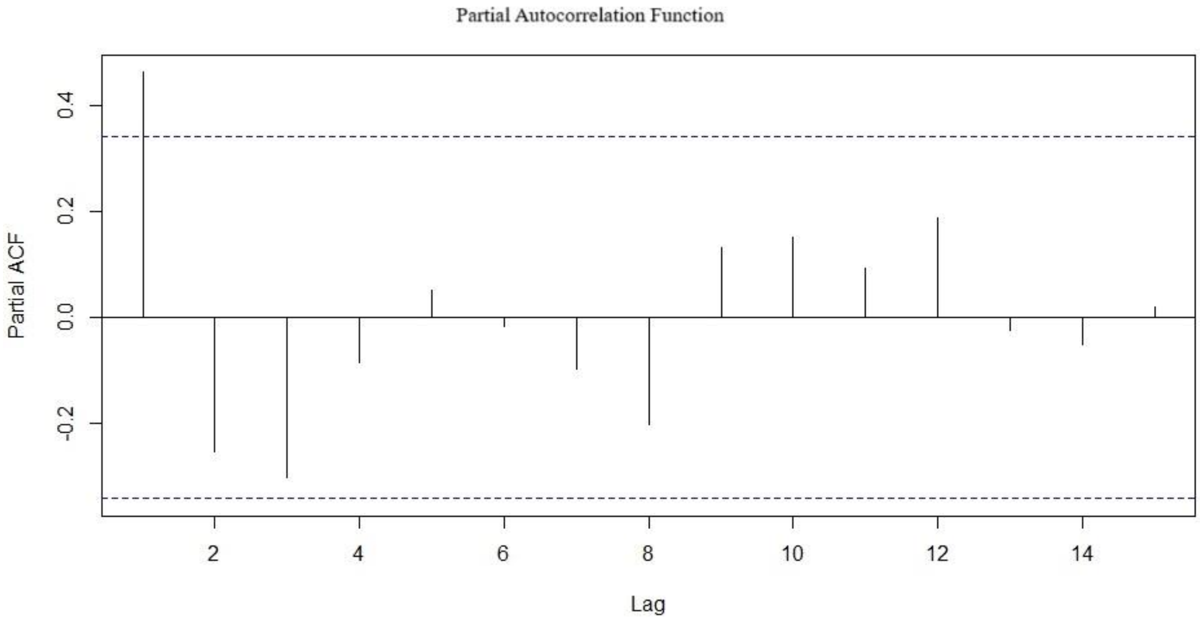

Figure 10: PACF at the Lag= 14 Air Quality Index PM_{10} in Agra City (JAN-2022 to SEP-2024)

From [Figure 10], a partial autocorrelation function (PACF) is used to plot Agra City's PM_{10} air quality index as a function of lag number. For confidence limits, PM_{10} is utilized.

Table 2: ARIMA model selection criteria Air Quality Index PM_{10} in Agra City

Model	ARIMA
Best parameters	**p = 7, d = 2, q = 6**
MSE	**213.9345**

RMSE	**14.6265**
MAE	**12.47918**
MAPE	**24.90483**

From [Table 2], the ARIMA (7,2,6) model is the best model for the Air Quality Index PM_{10} in Agra City. The ARIMA model accuracy is determined by four measures: MSE, RMSE, MAE, and MAPE values are used to determine the most suitable model for the Air Quality Index PM_{10} in Agra City.

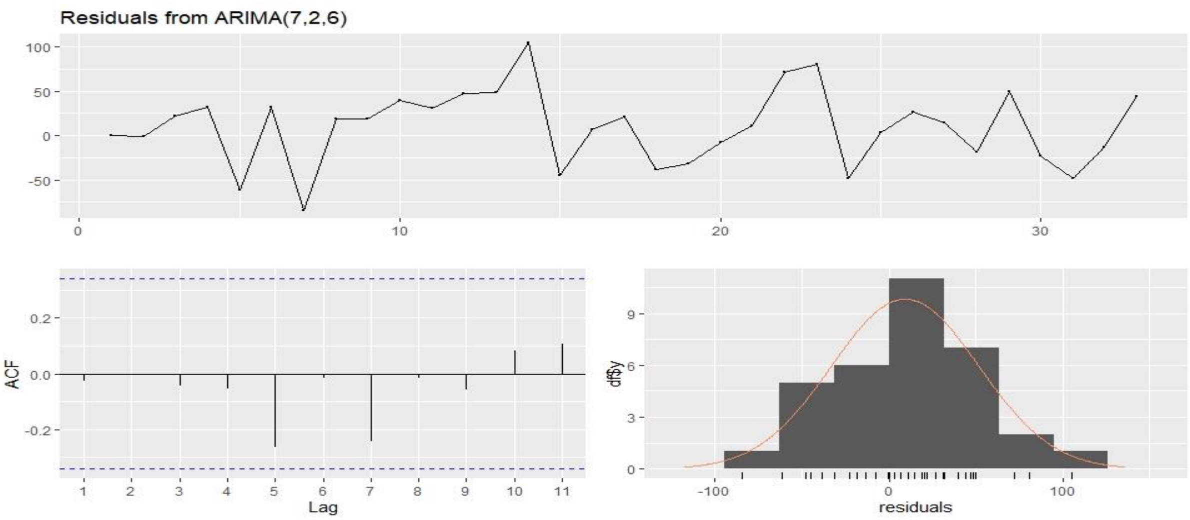

Figure 11: Residual plots for ARIMA model Air Quality Index PM_{10} in Agra City (JAN-2022 to SEP-2024)

In the study, we used [Figure 11], from the ARIMA (7,2,6) model for the Air Quality Index PM_{10} in Agra City, which was statistically significant. The residuals were tested for normality using a normality test.

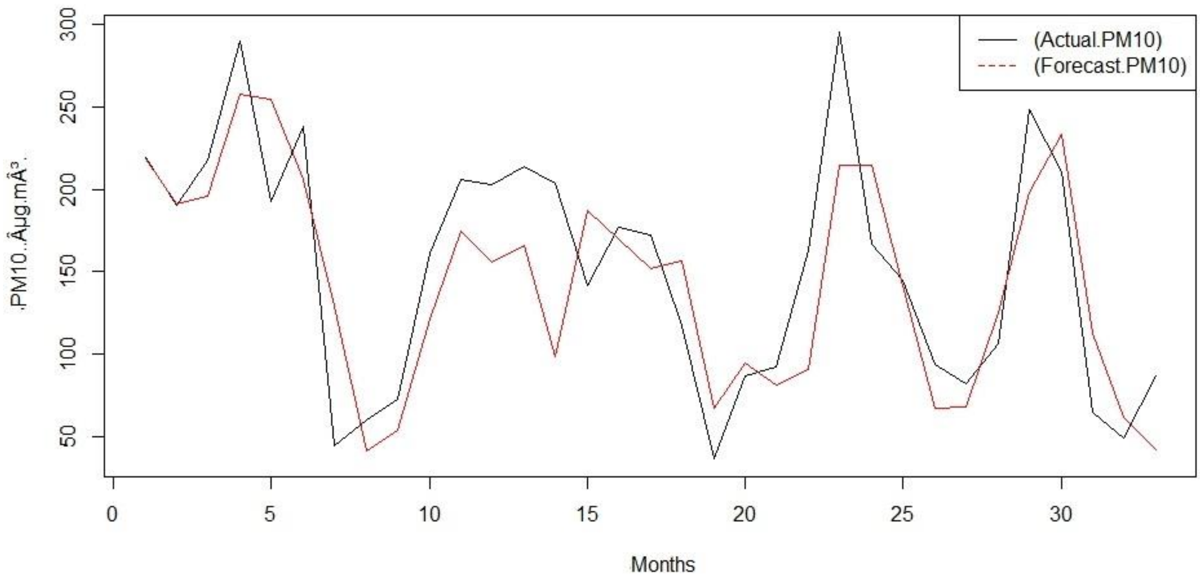

Figure 12: The Actual and Forecast plot of Air Quality Index PM_{10} in Agra City (JAN-2022 to SEP-2024)

From [Figure 12], there are relatively few differences between the predicted data using the ARIMA (7,2,6) model and the real data on the Air Quality Index PM_{10} in Agra City. The PM_{10} levels, however, reduced gradually from January 2022 to September 2024.

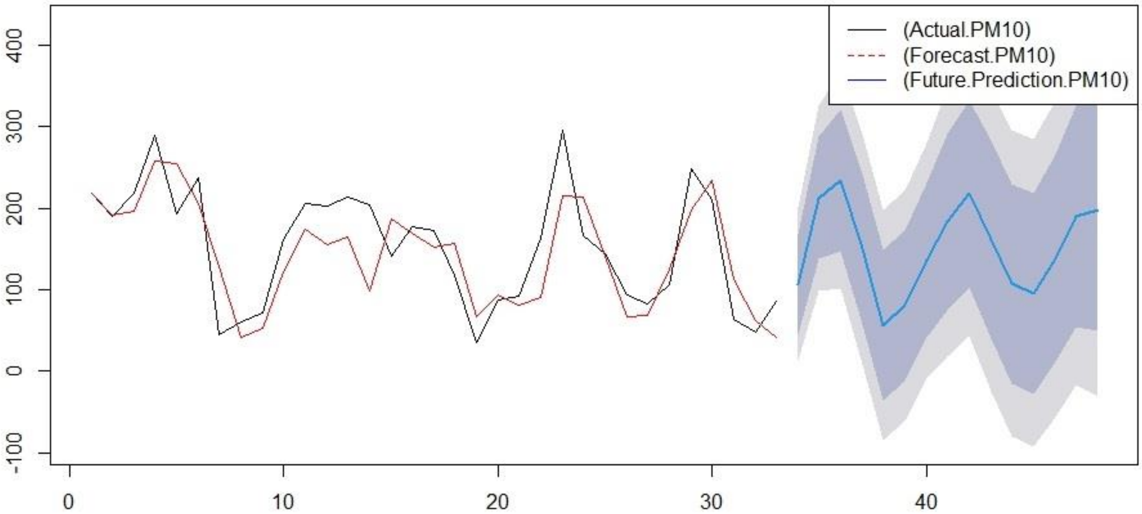

Figure 13: The Future Prediction Plot of Air Quality Index $PM_{2.5}$ in Agra City (OCT-2024 to DEC-2025)

According to [Figure 13], the in-sample forecast of PM_{10} from January 2022 to September 2024 using the ARIMA (7,2,6) model closely aligned with the observed and historical rates. The future projection line (blue) continues from the conclusion of the actual line (black) into the future for PM_{10} in Agra. The following are future forecasts derived from the ARIMA (7,2,6) model for PM_{10} levels in Agra. Utilising the ARIMA (7,2,6) model, we generated a forecast for the anticipated behaviour of the verified and PM_{10} time series in Agra for the next 15 months. The subsequent 15-month forecast for PM_{10}, based on verified air quality index data, is shown in Figure 13. Over the next 15 months, the ARIMA model forecasts a continued drop and subsequent rise in India's air quality index.

3.3 No_2 Air Quality Index in Agra

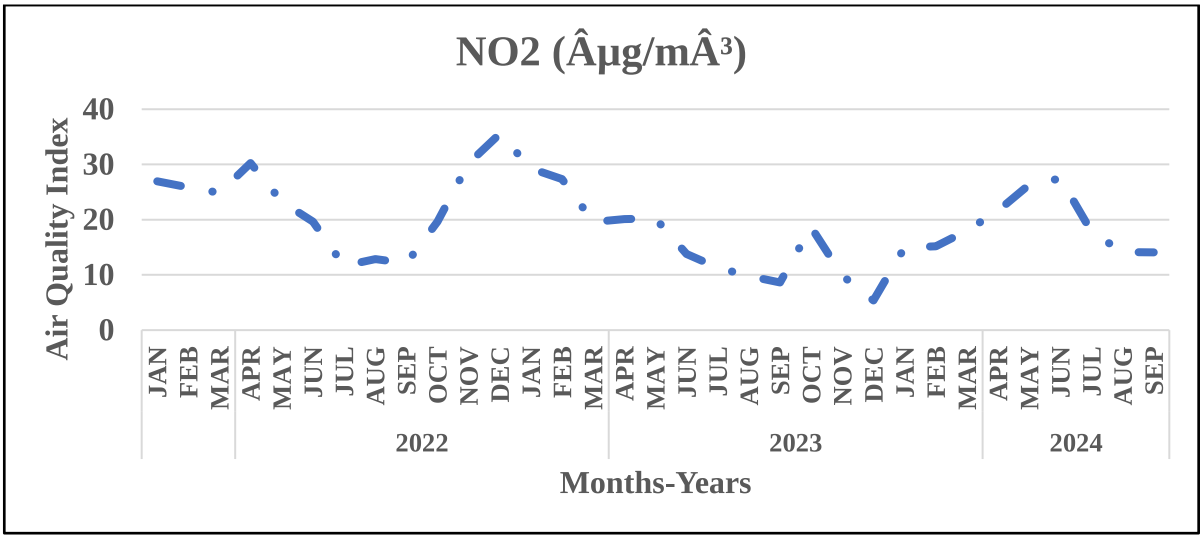

Figure 14: Actual Air Quality Index No_2 in Agra City (JAN-2022 to SEP-2024)

From [Figure 14], the decreasing and increasing non-stationarity of the specified period for Agra City's No_2 air quality index (January 2022 to September 2024) is represented in Figure 14.

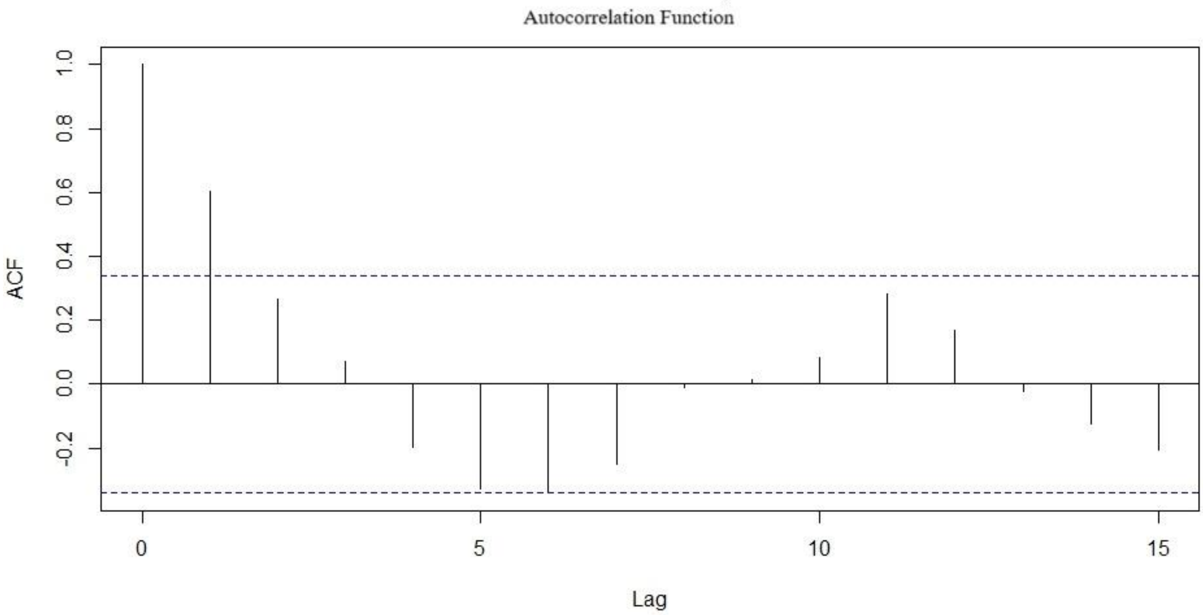

Figure 15: ACF at the Lag= 15 Air Quality Index No_2 in Agra City (JAN-2022 to SEP-2024)

From [Figure 15], an autocorrelation function (ACF) is used to plot Agra City's No_2 air quality index as a function of lag number. For confidence limits, No_2 is utilized.

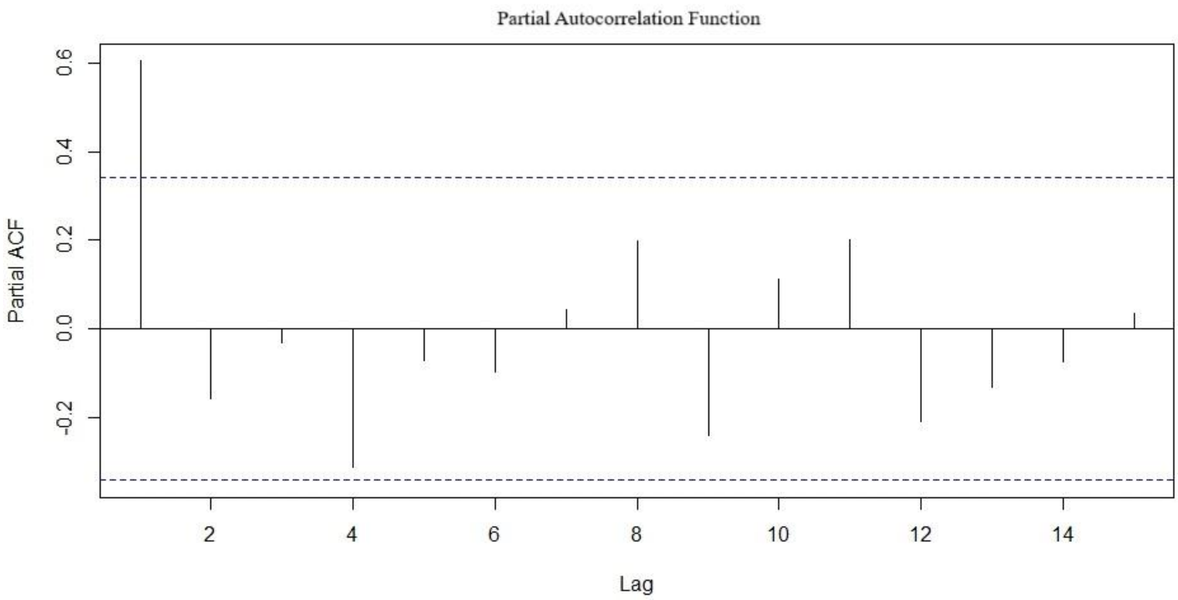

Figure 16: PACF at the Lag= 14 Air Quality Index No_2 in Agra City (JAN-2022 to SEP-2024)

From [Figure 16], a partial autocorrelation function (PACF) is used to plot Agra City's No_2 air quality index as a function of lag number. For confidence limits, No_2 is utilized.

Table 3: ARIMA model selection criteria Air Quality Index No_2 in Agra City

Model	ARIMA

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Best parameters	p = 7, d = 2, q = 6
MSE	234.9905
RMSE	15.32943
MAE	10.83723
MAPE	37.40949

From [Table 3], the ARIMA (7,2,6) model is the best model for the Air Quality Index No_2 in Agra City. The ARIMA model accuracy is determined by four measures: MSE, RMSE, MAE, and MAPE values are used to determine the most suitable model for the Air Quality Index No_2 in Agra City.

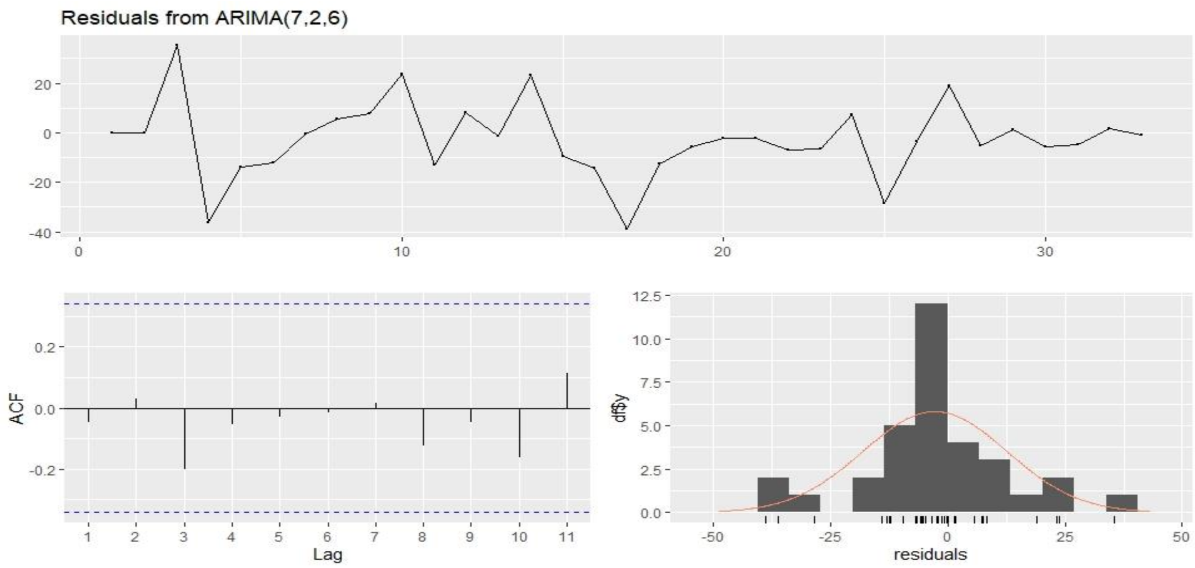

Figure 17: Residual plots for ARIMA model Air Quality Index No_2 in Agra City (JAN-2022 to SEP-2024)

In the study, we used [Figure 17], from the ARIMA (7,2,6) model for the Air Quality Index No_2 in Agra City, which was statistically significant. The residuals were tested for normality using a normality test.

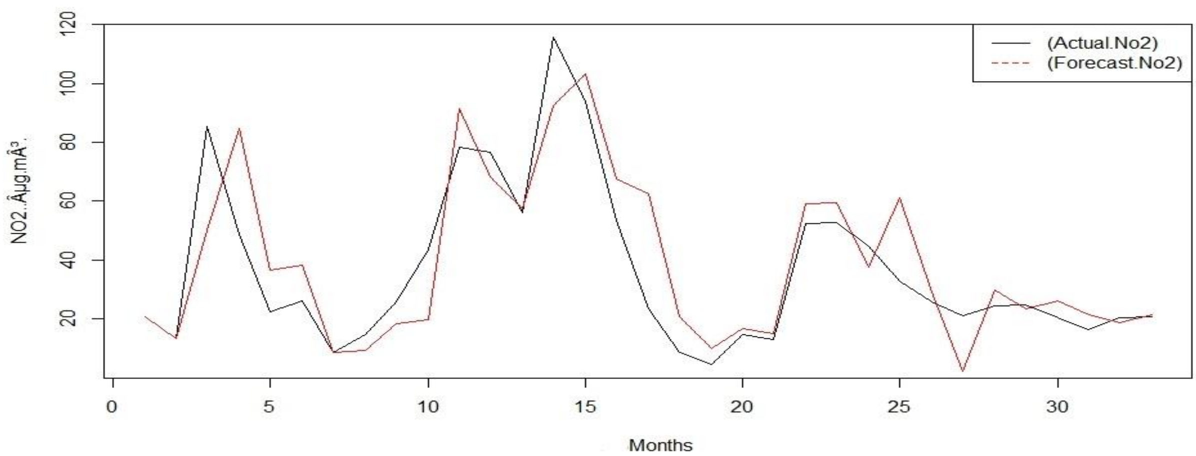

Figure 18: The Actual and Forecast plot of Air Quality Index No_2 in Agra City (JAN-2022 to SEP-2024)

From [Figure 18], there are relatively few differences between the predicted data using the ARIMA (7,2,6) model and the real data on the Air Quality Index No_2 in Agra City. The No_2 levels, however, reduced gradually from January 2022 to September 2024.

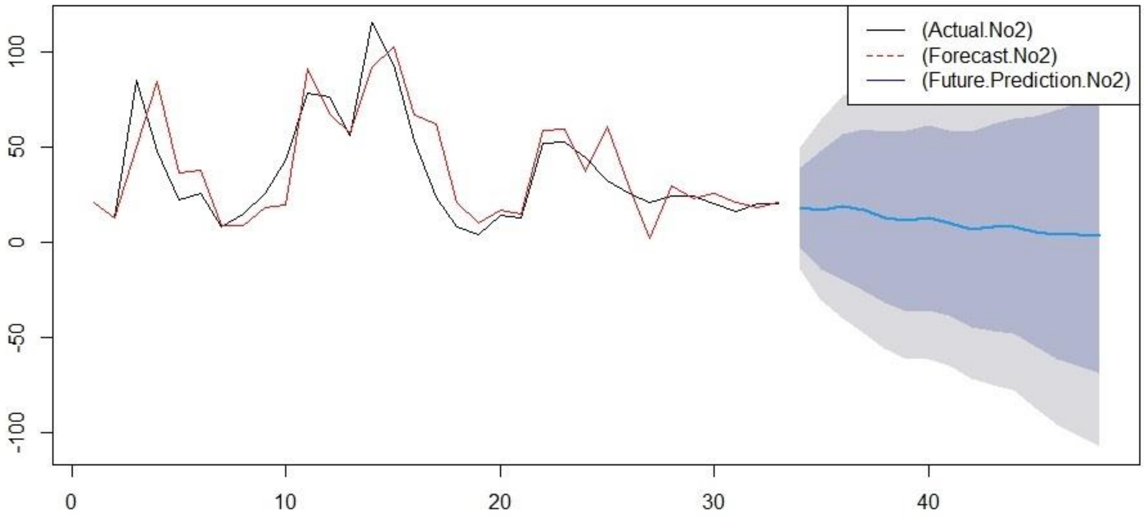

Figure 19: The Future Prediction Plot of Air Quality Index No_2 in Agra City (OCT-2024 to DEC-2025)

According to [Figure 19], the in-sample forecast of No_2 from January 2022 to September 2024 using the ARIMA (7,2,6) model is closely aligned with the observed and historical rates. The future projection line (blue) continues from the conclusion of the actual line (black) into the future for No_2 in Agra. The following are future forecasts derived from the ARIMA (7,2,6) model for No_2 levels in Agra. Utilizing the ARIMA (7,2,6) model, we forecasted the predicted behaviour of the verified and No_2 time series in Agra for the next 15 months. The subsequent 15-month forecast for No_2, based on verified air quality index data, is shown in Figure 19. Over the next 15 months, the ARIMA model forecasts a continued drop and subsequent rise in India's air quality index.

3.3 So_2 Air Quality Index in Agra

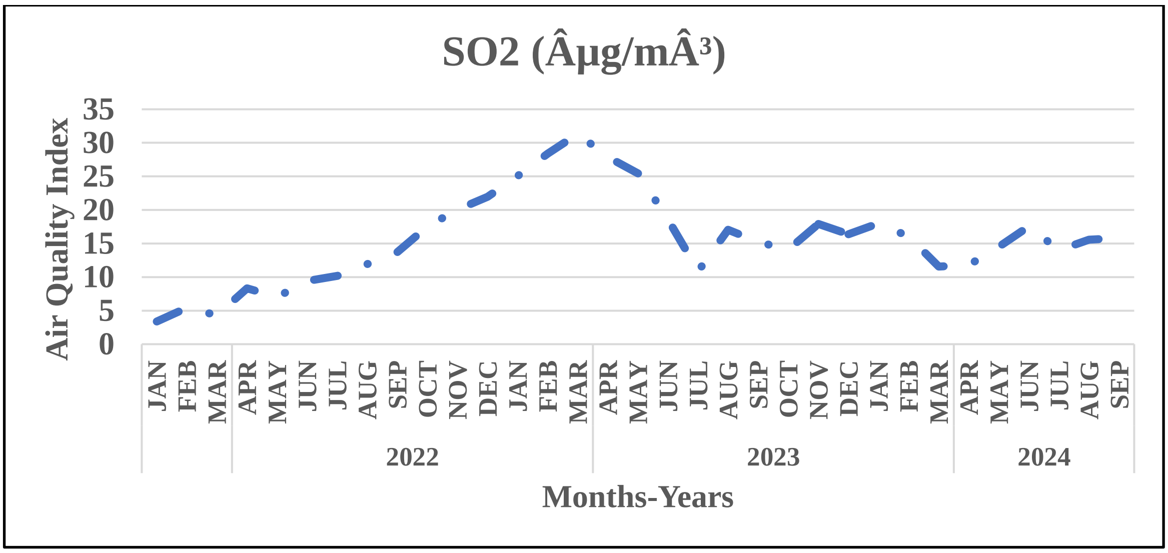

Figure 20: Actual Air Quality Index So_2 in Agra City (JAN-2022 to SEP-2024)

From [Figure 20], the decreasing and increasing non-stationarity of the specified period for Agra City's So_2 air quality index (January 2022 to September 2024) is represented in Figure 2.

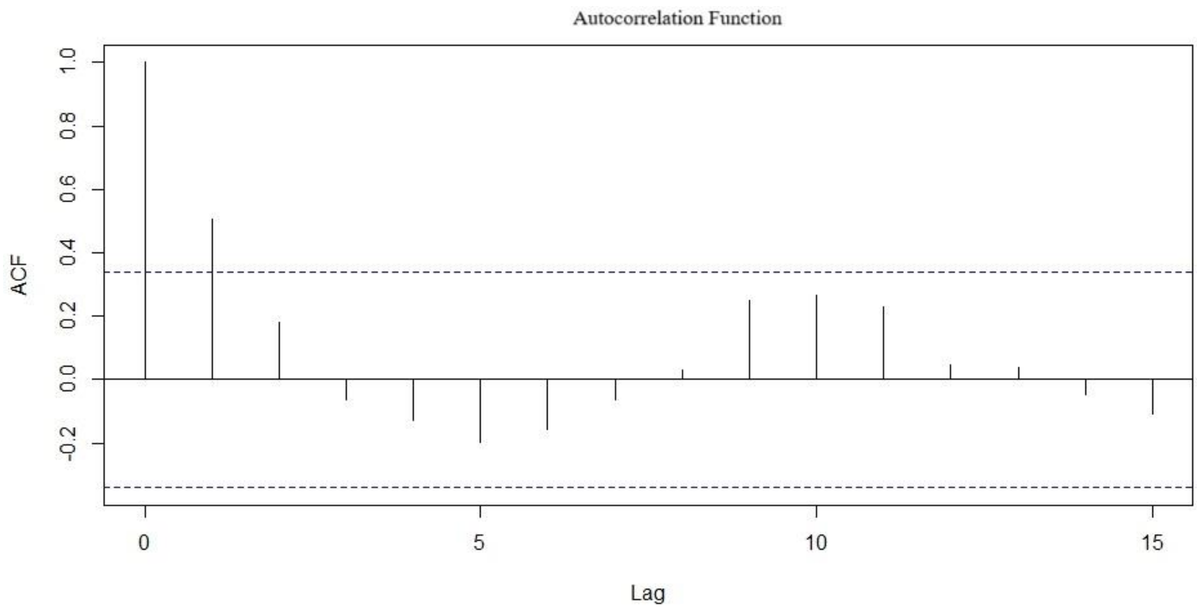

Figure 21: ACF at the Lag= 15 Air Quality Index So_2 in Agra City (JAN-2022 to SEP-2024)

From [Figure 21], an autocorrelation function (ACF) is used to plot Agra City's So_2 air quality index as a function of lag number. For confidence limits, So_2 is utilized.

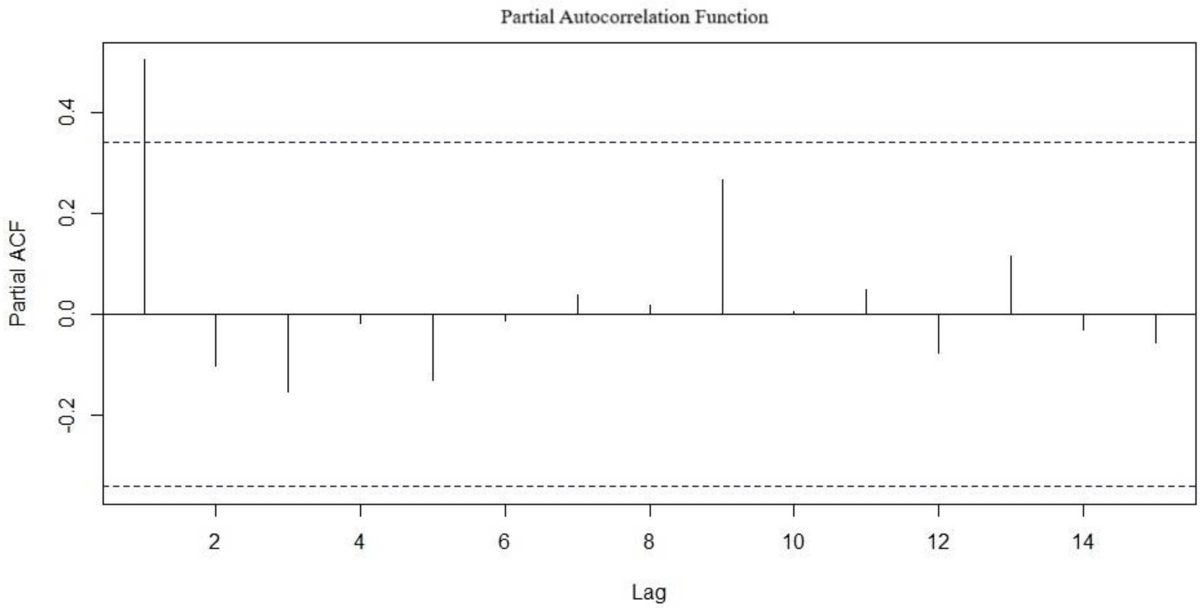

Figure 22: PACF at the Lag= 14 Air Quality Index So_2 in Agra City (JAN-2022 to SEP-2024)

From [Figure 22], a partial autocorrelation function (PACF) is used to plot Agra City's So_2 air quality index as a function of lag number. For confidence limits, So_2 is utilized.

Table 4: ARIMA model selection criteria Air Quality Index So_2 in Agra City

Model	ARIMA

Best parameters	p = 7, d = 2, q = 6
MSE	6.6172
RMSE	2.572488
MAE	1.855501
MAPE	13.72959

From [Table 4], the ARIMA (7,2,6) model is the best model for the Air Quality Index So_2 in Agra City. The ARIMA model accuracy is determined by four measures: MSE, RMSE, MAE, and MAPE values are used to determine the most suitable model for the Air Quality Index So_2 in Agra City.

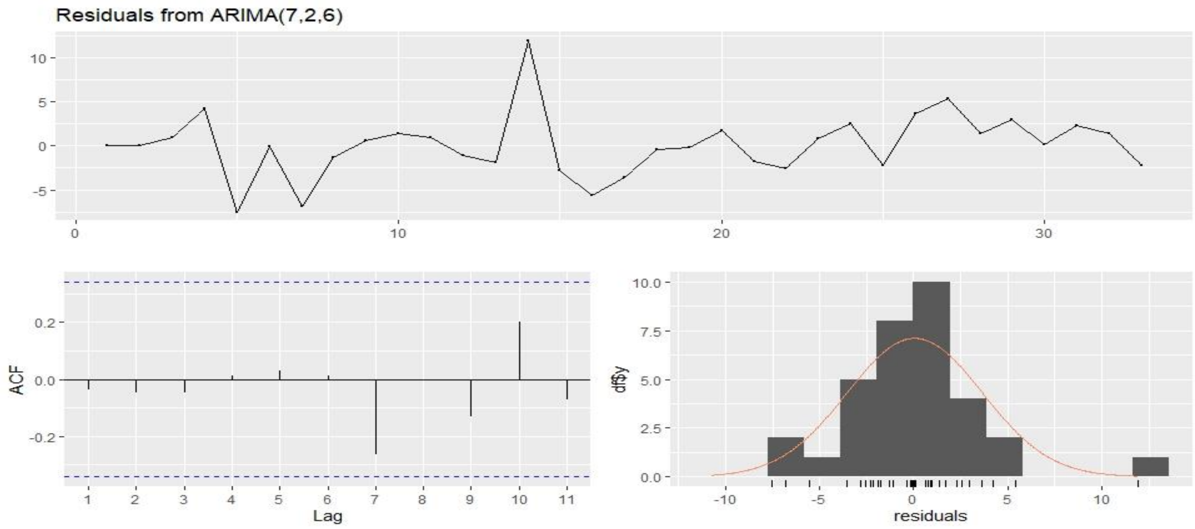

Figure 23: Residual plots for ARIMA model Air Quality Index So_2 in Agra City (JAN-2022 to SEP-2024)

In the study, we used [Figure 23], from the ARIMA (7,2,6) model for the Air Quality Index So_2 in Agre City, which was statistically significant. The residuals were tested for normality using a normality test.

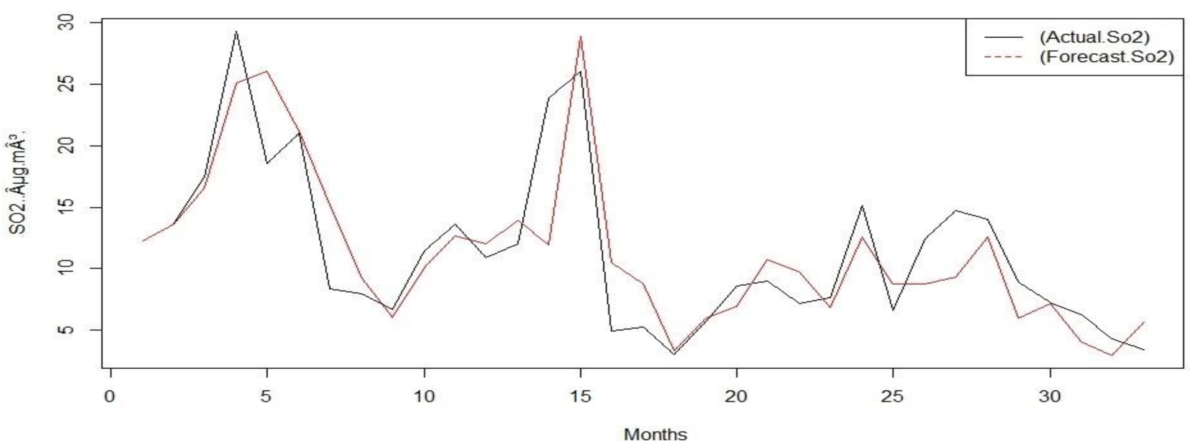

Figure 24: The Actual and Forecast plot of Air Quality Index So_2 in Agra City (JAN-2022 to SEP-2024)

From [Figure 24], there are relatively few differences between the predicted data using the ARIMA (7,2,6) model and the real data on the Air Quality Index So_2 in Agra City. The So_2 levels, however, reduced gradually from January 2022 to September 2024.

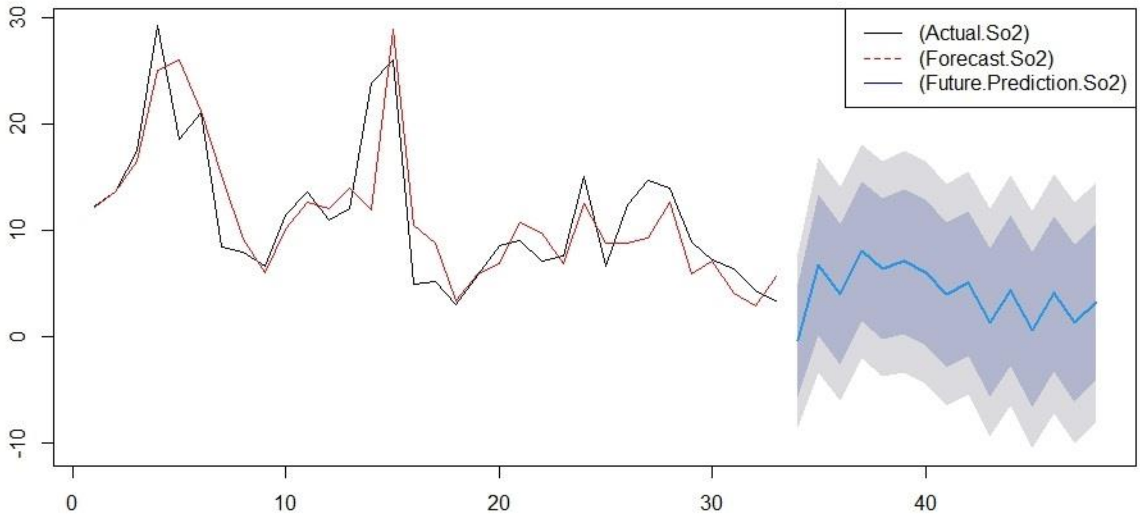

Figure 25: The Future Prediction Plot of Air Quality Index So_2 in Agra City (OCT-2024 to DEC-2025)

According to [Figure 25], the in-sample forecast of So_2 from January 2022 to September 2024 using the ARIMA (7,2,6) model closely aligned with the observed and historical rates. The future projection line (blue) continues from the conclusion of the actual line (black) into the future for So_2 in Agra. The following are future forecasts derived from the ARIMA (7,2,6) model for So_2 levels in Agra. Utilising the ARIMA (7,2,6) model, we forecasted the predicted behaviour of the verified and So_2 time series in Agra for the next 15 months. The subsequent 15-month forecast for So_2, based on verified air quality index data, is shown in Figure 25. Over the next 15 months, the ARIMA model forecasts a continued drop and subsequent rise in India's air quality index.

4. Conclusion

The present study uses an Autoregressive Integrated Moving Average (ARIMA) model for the forecasting and future prediction of monthly AQI, several individual factors such as the buildup of NO_2, SO_2, $PM_{2.5}$, and PM_{10} in Agra City. The forecast's low accuracy for the best ARIMA model is evaluated using the following measurements: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). For the next 15 months, we will also predict the future AQI in Agra City using the best ARIMA model. Air quality in Agra is a multifaceted issue that requires a comprehensive understanding of environmental, health, and socio-economic factors. By synthesizing existing research and addressing knowledge gaps, future studies can contribute to informed decision-making and effective interventions aimed at improving air quality in this historically rich city. Through collaborative efforts and the integration of modern technology, Agra can work towards a sustainable urban environment that prioritizes the health and well-being of its residents.

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