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# ARIMA Modeling for Forecasting Indonesia's Per Capita $CO_2$ Emissions and Literature Study of Photobioreactor-Based Mitigation

Henny Syahrani[1]*, Fadli Ardiansyah[2], Nabil Nur Faiza[3], Samuel Kevin[4], & Neli Agustina[5]

*Department of D-III Statistics, Politeknik Statistika STIS*

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**Abstract:**

Increasing $CO_2$ emissions from fossil fuels, industrial activities, and transportation drives climate change. Although Indonesia has committed to reducing emissions by 29% unconditionally and up to 43% with international support by 2030 through its Nationally Determined Contribution, per capita $CO_2$ emissions rise. This study forecasts Indonesia's per capita $CO_2$ emissions using ARIMA based on data from 1950-2024 from Our World in Data. Data from 1950-2009 served as training and 2010-2024 as testing. The Augmented Dickey-Fuller test indicated non-stationarity at level and stationarity after first differencing. ARIMA(0,1,10) was selected based on the lowest AIC and SC, highest adjusted $R^2$, and satisfactory diagnostics. MAPE was 13.19%. Forecasts for 2025-2030 show emissions increasing from 2.95 to 3.75 tons per capita. The study evaluates IMC-$CO_2$PBR, which removes atmospheric $CO_2$ through photosynthesis while generating biomass.

## 1. Introduction

The increasing concentration of $CO_2$ resulting from anthropogenic activities such as fossil fuel combustion, transportation, and industrial activities has become one of the major drivers of global climate change (Anugrah Putra & Andryana, 2025). This condition is exacerbated by continuously increasing energy consumption, causing $CO_2$ emissions from these sectors to further accelerate global warming. This increasing emission trend is also observed in Indonesia. Based on data from Our World in Data, Indonesia's per capita $CO_2$ emissions generally show an increasing trend during the 1950-2024 period, as presented in Figure 1.

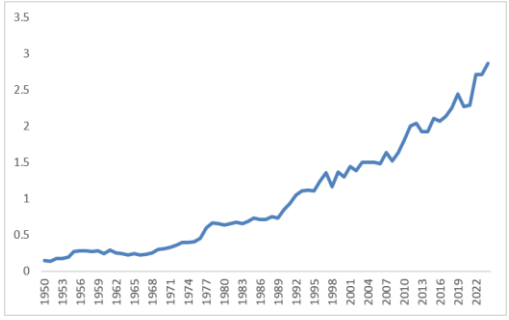



**Figure 1.** Graph of Indonesia's Per Capita $CO_2$ Emissions, 1950-2024

* Corresponding author.
*E-mail address*: 112413599@stis.ac.id

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Based on Figure 1, Indonesia's per capita $CO_2$ emissions generally show an increasing trend over time. The increase in emissions indicates that emission control efforts continue to face various challenges, particularly alongside increasing industrial activities, energy consumption, and national development needs. The government has implemented various efforts to control increasing emissions, including carbon tax implementation, the development of new and renewable energy (NRE), energy efficiency programs, forest and land rehabilitation, and commitments under the *Nationally Determined Contribution* (NDC) based on the Paris Agreement. Indonesia has targeted a reduction in greenhouse gas emissions of 29% by 2030 through its own efforts, or up to 43% with international support. However, the increasing trend in per capita $CO_2$ emissions indicates that emission control remains an issue requiring attention.

In this context, per capita $CO_2$ emissions are an important indicator for describing emission levels relative to population size and supporting environmental policy planning. Therefore, information regarding future emission trends is needed to support the planning and evaluation of climate change mitigation policies. Forecasting can be used to estimate future emission conditions based on historical data patterns. One commonly used method in time series analysis is the *Autoregressive Integrated Moving Average* (ARIMA), particularly when non-stationary data can be handled through differencing. The application of ARIMA enables historical emission patterns to be analyzed to produce projections of future emission conditions (Jannah & Hasanah, 2025).

Previous studies have shown varying results regarding the application of ARIMA for forecasting carbon emissions. A study by Mandala Anugrah Putra and Septi Andryana found that ARIMA had less optimal performance than the LSTM method (Anugrah Putra & Andryana, 2025). Meanwhile, a study by Muhammad Hakam Fardana et al. showed that the ARIMA-LSTM hybrid model provided better prediction results by combining ARIMA's ability to capture linear patterns with LSTM's ability to model nonlinear patterns (Fardana et al., 2025). On the other hand, a study by Agnes Pramita et al. demonstrated that ARIMA (0,1,2) was the best model for predicting greenhouse gas emissions in Indonesia's energy sector based on the lowest RMSE value (Pramita et al., 2023). These findings indicate that ARIMA performance may vary depending on the characteristics of the data and the object being analyzed.

Although studies on carbon emission forecasting have been conducted, research specifically using long-term historical data on Indonesia's per capita $CO_2$ emissions to evaluate ARIMA performance through the division of training and testing data remains limited. Furthermore, previous studies have demonstrated differences in ARIMA performance in forecasting carbon emissions. This condition represents a research gap that needs to be further investigated to obtain empirical evidence regarding the ability of ARIMA to forecast Indonesia's per capita $CO_2$ emissions. Therefore, this study uses annual data for the 1950-2024 period from Our World in Data, with data from 1950-2009 used as training data and 2010-2024 as testing data, to develop and evaluate an ARIMA model for forecasting Indonesia's per capita $CO_2$ emissions.

In addition to producing emission projections, increasing $CO_2$ emissions also indicate the need for alternative mitigation strategies that can support emission control efforts. One approach that can be considered is microalgae-based carbon capture technology using photobioreactors. Microalgae can absorb $CO_2$ through photosynthesis and convert it into biomass, making them a potential alternative technology for supporting $CO_2$ emission reduction (Cahyadi et al., 2023). Thus, this study not only focuses on forecasting emission trends but also examines microalgae photobioreactor technology as an alternative mitigation approach through a literature study.

Based on these problems and research gaps, this study aims to develop an appropriate ARIMA model for forecasting Indonesia's per capita $CO_2$ emissions, evaluate the model's forecasting accuracy using testing data, and produce projections of per capita $CO_2$emissions through 2030. This study also aims to examine the potential of the *Immobilized Microalgae-Based Photobioreactor* (IMC-$CO_2$PBR) as an alternative emission mitigation technology through a literature study. The novelty of this study lies in combining the forecasting analysis of Indonesia's per capita $CO_2$ emissions using ARIMA with a literature review of microalgae photobioreactor technology as an alternative mitigation approach, thereby providing a quantitative overview of future emission trends alongside an alternative technology that can be considered to support climate change mitigation efforts.

The results of this study are expected to provide information regarding the trend of Indonesia's per capita $CO_2$ emissions through 2030, which can support the planning and evaluation of climate change mitigation efforts. For academics, this study can serve as a reference for future research on carbon emission forecasting using time series methods, particularly ARIMA, as well as research on microalgae photobioreactor technology. For the government, the findings can serve as one consideration in evaluating per capita $CO_2$ emission trends and planning emission control strategies. For the public,

this study is expected to improve understanding of the development of per capita $CO_2$ emissions and the importance of mitigation efforts in supporting sustainable development.

## 2. Literature Review

### *2.1. Significance of Per Capita $CO_2$ Emissions*

Per capita $CO_2$ emissions describe the average individual contribution to a region's total carbon emissions, and are therefore often used as an indicator in evaluating climate change mitigation policies such as NDCs (Nationally Determined Contributions) and the SDGs (Sustainable Development Goals) (Ubaidillah et al., 2025). This indicator is considered more representative than absolute total emissions because it accounts for population size, allowing fairer comparisons between countries or regions. In addition, per capita $CO_2$ emissions also reflect a country's energy consumption patterns and lifestyle, which are closely related to its level of economic development and industrial structure, so that regular monitoring and projection of this indicator is an important step in assessing the effectiveness of emission control policies. To produce accurate projections, a forecasting approach is needed that is capable of systematically capturing the historical patterns in emissions data.

### *2.2. Forecasting Concept and Data Splitting*

Forecasting is the process of estimating future conditions based on historical patterns in time series data. So that the resulting model can be evaluated objectively, time series data is generally divided into two parts: training data, which is used to build and estimate the model, and testing data, which is used to evaluate how accurately the model forecasts values that were not used during the estimation process (Hyndman & Athanasopoulos, 2021).

### *2.3. The ARIMA Model*

One of the most widely used time series forecasting methods is the Autoregressive Integrated Moving Average (ARIMA) model, denoted as ARIMA(p, d, q). This model combines three main components: the Autoregressive (AR) component of order p, which represents the relationship between the current observation and previous values; the Integrated (I) component of order d, which represents the number of differencing operations required to make the data stationary; and the Moving Average (MA) component of order q, which represents the relationship between the current observation and the error (residual) from previous periods. The general ARIMA(p, d, q) model (Khikmah & Sofro, 2025) is written as:

$$\phi_p(\mathrm{B})(1-B)^d Y_t = \theta_q(B)\varepsilon_t \tag{1}$$

Where:

- $\phi_p(B) = 1 - \phi_1 B - \phi_1 B^2 - \cdots - \phi_p B^p$ is the AR component of order p
- $(1-B)^d$ is the differencing operator of order d
- $\theta_q(B) = 1 + \theta_1 B + \theta_2 B_2 + \cdots + \theta_q B_q$ is the MA component of order q
- B = *backshift* operator ($BY_t = Y_{t-1}$)
- $\varepsilon_t$ = residual/*error* at time

### *2.4. Stationarity Requirement and the ADF Test*

For the ARIMA model to be applied, the main requirement that must be met is that the data is stationary, meaning it has a constant mean and variance over time. The Augmented Dickey-Fuller (ADF) test checks for the presence of a unit root through the following regression equation:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-1} + \varepsilon_t \tag{2}$$

with the hypotheses $H_0$: γ = 0 (the data contains a unit root and is not stationary) and $H_1$: γ < 0 (the data is stationary). If the p-value is greater than the 5% significance level, $H_0$ fails to be rejected, meaning that a differencing process is required (Pramita et al., 2023), formulated as:

$$\Delta Y_t = Y_t - Y_{t-1} \tag{3}$$

*2.5. Model Order Identification (ACF and PACF)*

Once the data is stationary, model order identification is carried out by visually analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The ACF plot is used to identify the possible MA order (q), while the PACF plot is used to identify the possible AR order (p), by observing which lags exceed the confidence bounds on the resulting graph. Based on these patterns, several candidate ARIMA models are obtained, which are then estimated and compared to find the best model.

*2.6. Model Selection Criteria*

The best model is determined based on the smallest Akaike's Information Criterion (AIC) and Schwarz Criterion (SC) values, as well as the largest Adjusted $R^2$, formulated as:

$$\text{AIC} = -2\ln(\text{L}) + 2\text{k} \tag{4}$$
$$\text{SC} = -2\ \ln(\text{L}) + \text{k}\ \ln(\text{n}) \tag{5}$$

where L is the model's likelihood value, k is the number of parameters, and n is the number of observations (Hyndman & Athanasopoulos, 2021).

*2.7. Residual Diagnostic Tests*

After a model is selected, its adequacy is verified through residual diagnostic testing. This includes a white noise test using the Ljung-Box test:

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{n-k} \tag{6}$$

a normality test using the Jarque-Bera test:

$$JB = \frac{n}{6}\left(\frac{(K-3)^2}{4}\right) \tag{7}$$

and a homoscedasticity test using ARCH-LM (Famuji et al., 2024; Jannah & Hasanah, 2025), with the test statistic:

$$LM = n \times R^2 \tag{8}$$

*2.8. Forecast Accuracy Measurement (MAPE)*

If all diagnostic tests are satisfied, the model is declared adequate, and its forecasting accuracy is then measured using the Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{1}{n}\sum_{t-1}^{n}\left|\frac{Y_t-\hat{Y}_t}{Y_t}\right| \times 100\% \tag{9}$$

where $Y_t$ is the actual value, $\hat{Y}_t$ is the forecasted value, and n is the number of data points.

*2.9. Implications of Forecasting Results for Climate Mitigation*

Accurate forecasting results can provide a picture of future $CO_2$ emission conditions. If the projection shows an increasing emissions trend, concrete mitigation efforts are needed to curb the accumulation of $CO_2$ in the atmosphere. One mitigation approach currently being widely developed is microalgae-based carbon capture technology, which harnesses microalgae's natural ability to absorb $CO_2$ through photosynthesis and convert it into value-added biomass (Ubaidillah et al., 2025). This technology is considered promising because it not only reduces atmospheric $CO_2$ concentration but also produces by products that can be further utilized, providing both economic value and environmental benefits.

*2.10. IMC-$CO_2$PBR: Immobilized Microalgae Carbon Capture Photobioreactor*

IMC-$CO_2$ PBR uses microalgae immobilized in an alginate matrix to capture $CO_2$ through photosynthesis. This immobilization process allows the microalgae to maintain their stability and activity over a certain period, enabling

$CO_2$ absorption to take place more efficiently and sustainably. This technology increases biomass concentration and culture stability compared to conventional systems, while also producing value-added biomass that can be used as raw material for biofuel, organic fertilizer, or other biotechnology products (Dębowski et al., 2021).

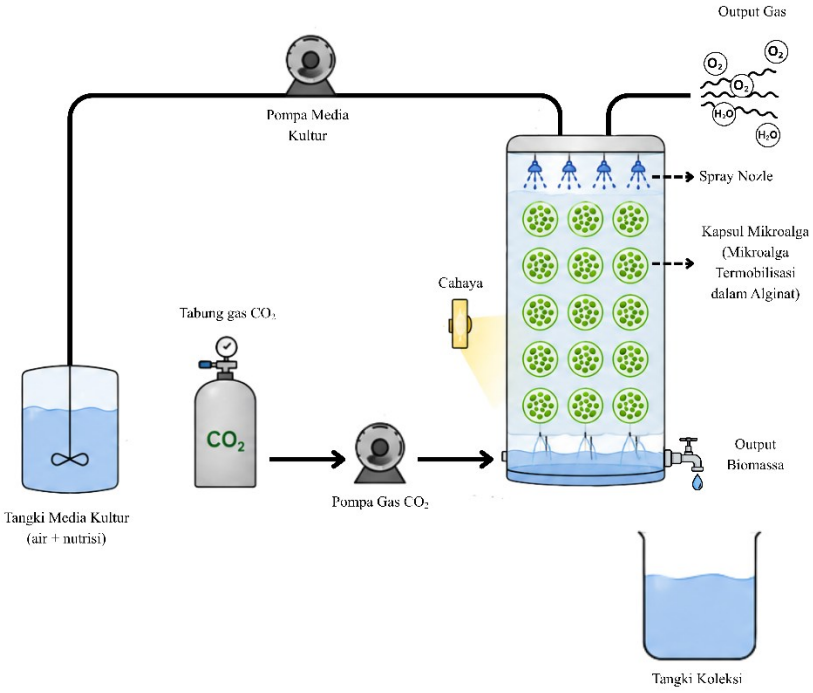



**Figure 2.** Working Scheme of the Immobilized Microalgae Photobioreactor (IMC-$CO_2$PBR)

*2.11. Carbon Capture Process Workflow (Based on the Figure)*

Based on the figure above, the carbon capture process begins with $CO_2$ gas being pumped from a storage cylinder into the photobioreactor using a gas pump. At the same time, culture media consisting of water and nutrients is pumped from the culture media tank to a spray nozzle and sprayed into the reactor to wet the microalgae capsules immobilized in the alginate matrix. The microalgae receive light from an external light source as an energy source for photosynthesis, allowing the supplied $CO_2$ to be absorbed and converted into biomass. During this process, the output gas from the photobioreactor contains lower $CO_2$ levels because part of it has already been utilized by the microalgae, while the biomass formed can be harvested as a value-added product. The culture media that has passed through the reactor is then collected in a collection tank to be recirculated back into the system, making the use of water and nutrients more efficient. Through this mechanism, IMC-$CO_2$PBR technology not only helps reduce carbon dioxide emissions in the atmosphere but also produces biomass that can be used as raw material for biofuel, organic fertilizer, animal feed, or other biotechnology products. This technology is therefore considered one of the alternative carbon capture approaches that not only supports climate change mitigation efforts but also creates added value through the utilization of biomass resulting from photosynthesis (Dębowski et al., 2021).

## 3. Research Methods

Pada This study uses secondary data on Indonesia's per capita $CO_2$ emissions for the period 1950-2024 (annual), sourced from the *Our World in Data* website (https://ourworldindata.org). The data constitute a time series with units of tons of $CO_2$ per capita and consist of 100 annual observations. The variable used in this study is a single variable, namely Indonesia's per capita $CO_2$ emissions, which are analyzed and projected using a univariate time series approach. The data are then divided into two parts: training data covering 1950-2009 (60 observations), which are used to

construct and estimate the ARIMA model, and testing data covering 2010-2024 (15 observations), which are used to evaluate the accuracy of the forecasting model. The data analysis is conducted through the following stages:

a) Data Pattern Identification, by plotting per capita $CO_2$ emissions data to observe trends and indications of seasonality.

b) Stationarity Test, conducted on the training data using the Augmented Dickey-Fuller (ADF) test. If the probability value is greater than the 5% significance level, the data are considered non-stationary and differencing is performed until the data become stationary.

c) Model Identification, conducted by analyzing the ACF and PACF plots of the stationary data. The ACF plot is used to identify the possible order of the MA (q) component, while the PACF plot is used to identify the possible order of the AR (p) component by observing which lags exceed the confidence bounds in the resulting graphs, thereby obtaining several candidate ARIMA models.

d) Parameter Estimation and Significance Testing, by estimating the parameters of each candidate model and testing their significance using the hypotheses $H_0$ and $H_1$, with the criterion that $H_0$ is rejected when the p-value < 0.05. Models containing insignificant parameters are excluded from the candidates.

e) Best Model Selection, based on the smallest Akaike's Information Criterion (AIC) and Schwarz Criterion (SC), the largest Adjusted $R^2$, and the significance of the model parameters.

f) Residual Diagnostic Testing of the selected model, including the white noise test (Ljung-Box), normality test (Jarque-Bera), and homoscedasticity test, to ensure that the model satisfies the required assumptions and is suitable for forecasting.

g) Forecasting Model Accuracy, evaluated using the Mean Absolute Percentage Error (MAPE) by comparing the forecasts generated for the testing data (2010-2024) with the actual values. A smaller MAPE value indicates a more accurate forecasting model.

h) The best model that passes all the preceding stages is used to project Indonesia's per capita $CO_2$ emissions through 2030. The projection results subsequently serve as a basis for examining the potential of the Immobilized Microalgae-Based Photobioreactor (IMC-$CO_2$ PBR) as a relevant carbon capture solution to support emission mitigation efforts in Indonesia, which is discussed through a literature study approach focusing on the technical parameters and efficiency of the system

## 4. Results and Discussion

### *4.1. Overview of Per Capita $CO_2$ Gas Emissions in Indonesia, 1950-2024*

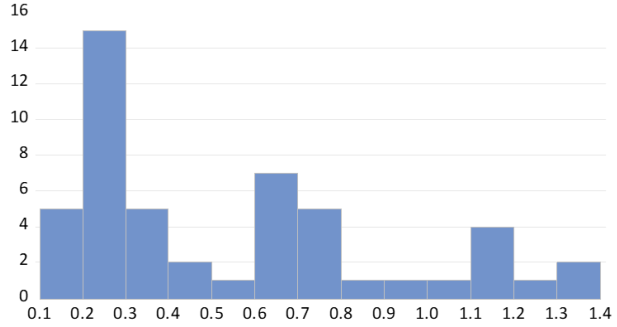



**Figure 3.** Histogram of Indonesia's Per Capita $CO_2$ Emissions, 1950-2024

Indonesia's per capita $CO_2$ gas emissions during the 1950-2024 period show a fluctuating pattern with an increasing tendency from year to year, as shown in Figure 1. Based on the descriptive statistics, the average per capita $CO_2$ emissions during the observation period were 1.013 tons per capita, with a minimum value of 0.134 tons per capita and a maximum value of 2.865 tons per capita. The minimum value reflects Indonesia's condition at the beginning of the observation period, when the levels of industrialization, energy consumption, and fossil fuel use were still relatively

low. Conversely, the maximum value indicates the increase in emissions that occurred along with economic development, population growth, and increasing energy needs and industrial activities in Indonesia. The considerable difference between the minimum and maximum values reflects an increase in emissions over time, although accompanied by fluctuations during several periods. This condition indicates that the data have a trend, meaning that the mean of the data is not constant over time. Due to the presence of a trend, the data are likely not stationary in the mean, so a differencing process is required before modeling is performed (Box et al., 2016).

In addition, Figure 3. shows that the distribution of Indonesia's per capita $CO_2$ emissions during the observation period tends to be right-skewed (*positively skewed*), as indicated by a skewness value of 0.795. This characteristic indicates the presence of several observations with relatively high emission values compared with most observations. Furthermore, the time series plot shows that the magnitude of data fluctuations tends to increase over time, indicating unstable variance. Therefore, a logarithmic transformation (ln) is required to stabilize the variance before conducting stationarity testing and ARIMA modeling (Hyndman & Athanasopoulos, 2021).

### *4.2. Forecasting Indonesia's Per Capita $CO_2$ Gas Emissions Using the ARIMA Method*

ARIMA modeling can be conducted by first determining the basic ARIMA model. The first step is to identify the data pattern. As shown in Figure 1., Indonesia's $CO_2$ gas emission data tend to fluctuate and show an increasing trend each year. Subsequently, stationarity testing is conducted on the training data using the Augmented Dickey-Fuller (ADF) test, where if the p-value is less than the significance level (5%), the data are considered stationary at level. However, if this condition is not satisfied, an order differencing process must be performed on the training data.

**Table 1.** ADF Test of Per Capita $CO_2$ Gas Emissions, 1950-2009

| | **Test** | **t-Statistic** | **Probability** | **Decision** |
|---|---|---|---|---|
| Level | Augmented Dickey Fuller | -1.000556 | 0.7492 | Non-stationary at level |
| 1st Differencing | Augmented Dickey Fuller | -9.873063 | 0.0000 | Stationary at first order |

The ADF test results at the level presented in Table 1. show a probability value of 0.7492, which is greater than the 5% significance level. Based on these results, the decision is to fail to reject $H_0$, meaning that the per capita $CO_2$ gas emission data are not yet stationary at the level. Therefore, a differencing process must be performed until the data reach a stationary condition. After first-order differencing is performed, the data are tested again using the ADF test to ensure that the data have become stationary. Table 1. shows that after first-order differencing, the decision is to reject $H_0$, meaning that the data have reached a stationary condition at the first order.

Next, model order identification is performed by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the stationary data. The ACF plot is used to identify the possible order of the Moving Average (MA) component, while the PACF plot is used to identify the possible order of the Autoregressive (AR) component. Based on the correlogram results, the PACF plot shows the most prominent spike at lag 10, with a partial autocorrelation value of -0.232, followed by several spikes at subsequent lags with increasingly smaller values, most of which are within the confidence bounds. This pattern indicates that after first-order differencing, the data have become more stationary. Based on the ACF and PACF patterns, several candidate ARIMA models, such as ARIMA(10,1,0), ARIMA(0,1,10), and ARIMA(10,1,10), are subsequently estimated to obtain the best model. From the several candidate ARIMA models formed, the process proceeds to the best model selection stage. The determination of the best model is based on statistical information criteria such as the smallest Akaike's Information Criterion (AIC) and Schwarz Criterion (SC), the largest Adjusted $R^2$, and the significance of the model parameters. This information is presented in Table 2.

Based on the comparison of several models in Table 2., ARIMA(0,1,10) is selected because it has the smallest AIC and SC values, the largest Adjusted $R^2$, and significant MA components. After the best ARIMA model is selected, an evaluation stage is conducted through residual tests. The residual evaluation includes a normality test to determine whether the residuals are normally distributed, a white noise test using the Ljung-Box test to determine whether the residuals are random and no longer contain remaining autocorrelation patterns, and a homoscedasticity test to ensure that the residuals have constant (homogeneous) variance across the observation periods, so that the resulting model satisfies the diagnostic assumptions and is suitable for forecasting.

**Table 2.** ARIMA Model Comparison

| ARIMA Model | AR(10) | MA(10) | AIC | SC | Adj R^2 | White Noise Test | Normality Test | Homoscedasticity Test |
|---|---|---|---|---|---|---|---|---|
| ARIMA (0,1,10) | | -0.321737* | -1.884571 | -1.778934 | 0.04791 | + | + | + |
| ARIMA (10,1,0) | -0.288392* | | -1.879633 | -1.773995 | 0.03955 | + | + | + |
| ARIMA (10,1,10) | -1.000000* | 0.999884* | -1.841102 | -1.700252 | 0.134928 | + | - | - |

The selected best model is subsequently used to assess the accuracy of the forecasting model. Forecasting accuracy is very important because it is useful for evaluating the results of the forecasting process. The accuracy of the forecasting model is measured using the *Mean Absolute Percentage Error* (MAPE) function (Hyndman & Athanasopoulos, 2021).

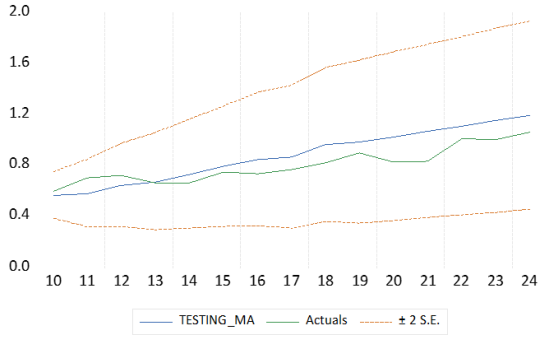



**Figure 4.** Forecasting Results for Testing Data, 2010-2024

Figure 4 shows a comparison between the testing data and the forecasted data, namely the data for the 2010 period, which are used to measure the forecasting accuracy of the ARIMA (0,1,10) model for Indonesia's per capita $CO_2$ gas emissions. This comparison is then evaluated based on its error value using MAPE, which is 13.19% and is still categorized as good for forecasting.

After completing the previous stages, the ARIMA(0,1,10) model is obtained as the best model and is used to forecast Indonesia's per capita $CO_2$ gas emissions for the next six years in accordance with the SDGs, namely from 2025 to 2030.

**Table 3.** Forecasting Results of the ARIMA(0,1,10) Model for Indonesia's Per Capita $CO_2$ Emissions, 2025–2030

| Year | $\ln(CO_2)$ | $CO_2$ per Capita |
|---|---|---|
| 2025 | 1.083051 | 2.953677 |
| 2026 | 1.141964 | 3.132915 |
| 2027 | 1.179510 | 3.252779 |
| 2028 | 1.228773 | 3.417034 |
| 2029 | 1.253227 | 3.501624 |
| 2030 | 1.321754 | 3.749993 |

Based on Table 3, the forecasting results of the ARIMA(0,1,10) model indicate that Indonesia's per capita $CO_2$ emissions are expected to continue increasing during 2025-2030, from 2.953677 to 3.749993 tons per capita. This trend indicates that without significant changes in policies or mitigation efforts, carbon-emitting activities such as fossil fuel use in the energy, industrial, and transportation sectors will continue to dominate. Therefore, emission control policies need to be strengthened through the development of renewable energy, energy efficiency, low-carbon transportation, and sustainable development strategies so that Indonesia's SDG targets and climate commitments can be achieved.

One technology that has the potential to support these mitigation efforts is the *Immobilized Microalgae-Based Photobioreactor* (IMC-$CO_2$PBR), a photobioreactor system that utilizes immobilized microalgae to capture and convert $CO_2$ through photosynthesis. Based on the study by Dębowski et al. (2021), the immobilization of *Chlorella vulgaris* in an alginate matrix was able to produce a biomass concentration of up to 100 g DM/$dm^3$, which is much higher than that of conventional photobioreactors and open pond systems, which produce only approximately 3–5 g DM/$dm^3$. This high biomass concentration is an important factor in supporting the overall efficiency of $CO_2$ absorption.

In relation to the projected increase in Indonesia's per capita $CO_2$ emissions through 2030, IMC-$CO_2$PBR technology has the potential to become a relevant mitigation solution. Although its implementation on a national scale still requires further investigation regarding land, infrastructure, and operational costs, its advantage in producing value-added biomass while simultaneously capturing $CO_2$ makes it a promising alternative for carbon capture. This technology has the potential to provide benefits not only to the environment but also to Indonesia's economy in the long term.

## 5. Conclusion

Based on the analysis results, ARIMA(0,1,10) was selected as the most appropriate model for forecasting per capita $CO_2$ emissions in Indonesia. The model had the lowest AIC and SC values and the highest Adjusted $R^2$ compared with other candidate models. In addition, the residual diagnostic tests indicated that the model satisfied the white noise, normality, and homoscedasticity assumptions. The model produced a MAPE of 13.19% on the testing data, indicating good forecasting accuracy. The forecasting results suggest that Indonesia's per capita $CO_2$ emissions are expected to increase continuously from 2025 to 2030, rising from 2.95 tons per capita in 2025 to 3.75 tons per capita in 2030. This upward trend indicates that achieving emission reduction targets under the NDC and SDGs may require stronger mitigation efforts, particularly given the continued dominance of fossil-fuel-based activities in the energy, industrial, and transportation sectors.

As a potential mitigation option, a literature review of Immobilized Microalgae-Based Photobioreactor (IMC-PBR) technology indicates promising potential for carbon capture. This technology can facilitate $CO_2$ absorption through photosynthesis under more controlled conditions than conventional cultivation systems. In addition to carbon capture, the resulting biomass can potentially be utilized as a raw material for biofuels, organic fertilizers, and other biotechnological products. Therefore, integrating historical-data-based forecasting with a review of carbon mitigation technologies can provide useful input for developing more targeted emission-control policies. This approach may also encourage further research that connects predictive modeling with the practical implementation of mitigation technologies to support Indonesia's national emission reduction targets.

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