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IMPLEMENTATION OF THE ARIMA ALGORITHM FOR ENHANCING AND FORECASTING COMPANY REVENUE

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Abstract

In an increasingly competitive business environment, accurate revenue forecasting is crucial for strategic decision-making. This study implements the ARIMA (AutoRegressive Integrated Moving Average) model to predict the monthly revenue of CV. Yusindo Mega Persada using historical data from January to December 2024. The ARIMA(1,1,1) model was selected based on stationarity tests and analysis of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Diagnostic tests confirmed that the model met key assumptions, including normality of residuals and absence of significant autocorrelation, ensuring reliable predictions. The forecasting results for January to March 2025 indicated a relatively stable revenue trend, with values ranging from IDR 483 million to IDR 489 million. Model accuracy was evaluated using the Mean Absolute Percentage Error (MAPE), which resulted in 9.41%, suggesting reasonable predictive performance. The findings demonstrate that ARIMA is capable of capturing trends and fluctuations in dynamic revenue data, providing actionable insights for management in financial planning, resource allocation, and risk mitigation. Despite the model's effectiveness, external factors such as market fluctuations and seasonal events may influence actual revenue, indicating the need to combine quantitative forecasts with expert judgment. Overall, this study confirms that the ARIMA(1,1,1) model is a practical and reliable tool for revenue forecasting in a dynamic business environment.

Keywords: ARIMA; revenue forecasting; time series analysis; MAPE; financial planning.

1. INTRODUCTION

In an increasingly competitive business environment, the ability to predict future conditions has become a key factor in strategic decision-making [1]–[3]. Forecasting, particularly in the fields of economics and finance, enables companies to design more robust planning and anticipate potential risks. One statistical approach widely used for predictive purposes is the ARIMA (AutoRegressive Integrated Moving Average) algorithm, which has proven effective in analyzing time series data with complex and dynamic historical patterns [4].

Company revenue is a primary indicator of financial health and operational performance. Fluctuations in revenue over time can be influenced by numerous factors, ranging from market changes and sales strategies to macroeconomic conditions. Therefore, companies need a system capable of identifying revenue trends, detecting anomalies, and accurately forecasting future values. With reliable predictive capabilities, management can implement strategic measures to increase revenue and optimize available resources [5].

CV. Yusindo Mega Persada, a company operating in the electronics sector, faces challenges in mapping and projecting revenue based on historical sales data throughout 2024. Preliminary analysis of the company's monthly revenue reports indicates significant fluctuations between months. This uncertainty in revenue trends makes it difficult for the company to develop effective and sustainable long-term business strategies. Consequently, an analytical method is required to transform historical sales data into highly predictive information.

As a solution to this problem, implementing the ARIMA algorithm is an appropriate approach for forecasting the company's monthly revenue. By applying the ARIMA model, the company can identify seasonal patterns, long-term trends, and fluctuations, thereby providing a more accurate revenue forecast [6]–[8]. These predictive results can be used not only as a reference for financial planning but also as a basis for strategic decision-making to improve the business performance of CV. Yusindo Mega Persada in the future.

Previous research was conducted by [9] which developed a web-based stock price prediction system using a hybrid ARIMA-LSTM algorithm and the Extreme Programming method. Stock data was collected from Yahoo Finance for the period 2018–2022. The evaluation results showed that the hybrid model performed well with MSE of 0.0078, MAE of 0.556, and MAPE of 41.89%, closely approximating actual data. Subsequently, another study was conducted by [10] which compared three models for aerosol sales forecasting: ARIMA, LSTM, and GRU. ARIMA was used as a traditional statistical model, while LSTM and GRU, based on deep learning, aimed to capture more complex patterns. The study results showed that LSTM provided the highest accuracy with a MAPE of

10.76%, followed by ARIMA (11.23%) and GRU (11.47%). LSTM excelled at recognizing long-term trends and seasonal patterns, whereas GRU required shorter training time while achieving accuracy close to that of LSTM.

The objective of this study is to develop a predictive system for forecasting the monthly revenue of CV. Yusindo Mega Persada using the ARIMA algorithm. Specifically, the research aims to: 1) analyze historical sales data to identify trends, seasonal patterns, and fluctuations in revenue, 2) build an accurate ARIMA-based forecasting model capable of predicting future revenue, and 3) provide actionable insights that can support strategic decision-making and financial planning [11], [12]. By achieving these objectives, the study intends to assist the company in optimizing its resources, improving revenue management, and formulating effective business strategies in a dynamic and competitive market environment[10], [13].

2. RESEARCH METHOD

2.1. ARIMA Algorithm

ARIMA stands for AutoRegressive Integrated Moving Average, a statistical method used in time series analysis to model and forecast data based on past values. This model is widely used due to its ability to handle data exhibiting trends and fluctuations, especially when the data has been made stationary [14]. ARIMA consists of three main components:

1. AR (AutoRegressive): The autoregressive component indicating that the current value has a linear relationship with a number of past values (lags).
2. I (Integrated): The integration component that represents the process of differencing the data to make it stationary.
3. MA (Moving Average): The moving average component showing that the current value is influenced by past errors.

The ARIMA model is commonly denoted as ARIMA (p, d, q), where:

1. p is the lag order of the AR model (number of previous values used),
2. d is the differencing order to make the data stationary,
3. q is the lag order of the MA model (number of past errors used).

ARIMA is applied when the data is not naturally stationary but can be made stationary through differencing. Once the data becomes stationary, the AR and MA models can be applied effectively. In general, the ARIMA(p, d, q) model can be expressed as:

$$Y'_t = c + \sum_{i=1}^{p} \phi_i Y'_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \quad (1)$$

Where :

Y'_t : the data after differencing d times,
c : constant (intercept),
ϕ_i : parameter of the AutoRegressive (AR) model,
θ_j : parameter of the Moving Average (MA) model,
ϵ_t : error term (white noise) at time t,
p : order of AR,
d : number of differencing (integration level),
q : order of MA.

If differencing is not required (d = 0), ARIMA reduces to ARMA, a combination of AR and MA models.

2.1. Time Series

A time series is a collection of data points recorded or observed sequentially over time. Each observation is associated with a specific time interval, such as daily, weekly, monthly, or yearly. Time series data is used to analyze historical patterns and make forecasts or predictions about future values. In statistics and data analysis, time series is an important object of study because many real-world phenomena occur dynamically over time. Examples include sales data, temperature, stock prices, inflation, and consumer demand. Analyzing time series allows users to understand past behavior, detect patterns, and anticipate future changes quantitatively [15].

3. RESULTS AND DISCUSSION

After the revenue prediction system was developed using the ARIMA algorithm on Google Colab, the next step is to analyze and evaluate the obtained results. This discussion aims to assess how well the model predicts the company's revenue based on the available historical data. Additionally, visualization and statistical evaluation are used to determine the model's accuracy and its relevance to the company's needs.

3.1. Monthly Revenue Visualization

Before modeling and prediction, the initial step was to visualize the company's historical revenue data for the period from January to December 2024. The purpose of this visualization is to provide a general overview of the patterns, trends, and fluctuations in monthly revenue, as well as to identify potential increases, decreases, or anomalies in the data that could affect the accuracy of the prediction model.

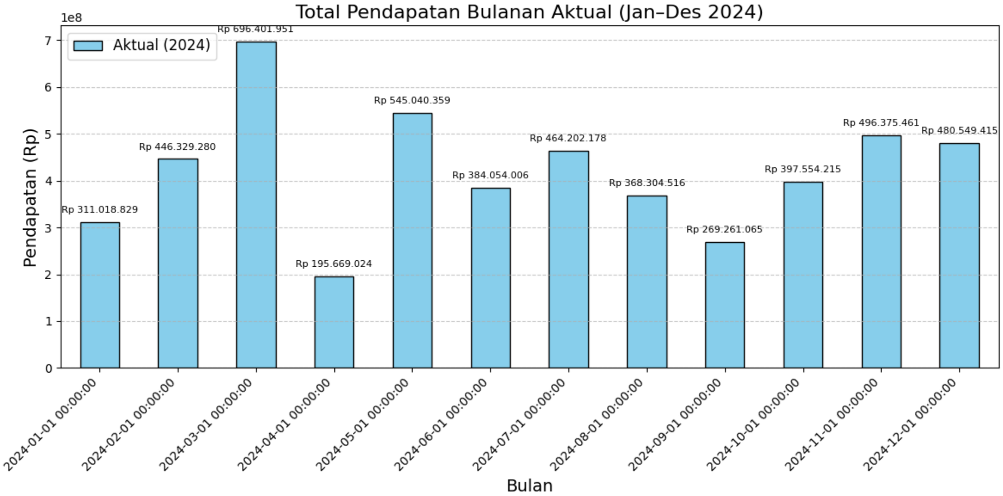

Figure 1. Total Revenue from January to December

The visualization in the figure shows the actual total revenue of CV. Yusindo Mega Persada during the period from January to December 2024. This chart uses a bar chart to represent the revenue value for each month individually, with nominal labels in Indonesian Rupiah placed above each bar to clarify the achieved values. Based on the chart, it can be observed that monthly revenue fluctuated significantly throughout the year. The highest revenue was recorded in March 2024, amounting to IDR 696,401,951, followed by May 2024 with IDR 545,040,359, and November 2024 with IDR 496,375,461. These three months demonstrated outstanding financial performance compared to the other months. Conversely, the lowest revenue occurred in April 2024, at only IDR 195,669,024. This indicates a sharp decline compared to the previous month (March) and the subsequent month (May), which was caused by external factors such as extended public holidays.

In general, the pattern of monthly revenue tends to be unstable and does not exhibit a clear linear trend. Some months show significant increases, while others experience drastic decreases. This condition demonstrates that revenue patterns are dynamic and can be influenced by various factors, making the selection of a time series model such as ARIMA appropriate for modeling and forecasting future revenue behavior. This visualization is crucial as a basis for conducting stationarity tests and selecting ARIMA model parameters, as it helps identify the presence of trends, seasonal cycles, or anomalies that may affect the performance of the predictive model.

3.2. ARIMA Model Development

After the monthly revenue data was visualized and initially analyzed, the next step was to develop a prediction model using the ARIMA (AutoRegressive Integrated Moving Average) method. In this stage, the entire historical data from January to December 2024 was used to train the model. The objective was to capture the trends and fluctuations present in the monthly revenue data so that the model could generate predictions with optimal accuracy.

```
import seaborn as sns
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
```

Figure 2. Libraries Used

Figure 2 illustrates the initial stage of ARIMA model development, where several important libraries and functions are imported to support the time series analysis and modeling process. The Seaborn library is imported as sns; although it is not directly used at this stage, it is commonly employed to create more interactive and informative data visualizations. The adfuller function from the statsmodels.tsa.stattools module is used to perform the Augmented Dickey-Fuller (ADF) Test, a statistical test used to evaluate whether a time series is stationary or not. Additionally, from the statsmodels.graphics.tsaplots module, two key functions are imported: plot_acf and plot_pacf. These functions are used to generate Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The ACF plot assists in identifying the Moving Average (MA) component of the model, while the PACF plot helps determine the Autoregressive (AR) component. Both plots serve as the basis for selecting the parameters p and q in the ARIMA model. Finally, the ARIMA function is imported from

statsmodels.tsa.arima.model. This function is the main component used to construct and train the ARIMA model based on the preprocessed data. The ARIMA model will be built using parameters (p, d, q) determined from the stationarity test results and the ACF/PACF analysis.
Before building a time series forecasting model, the first step is to test the stationarity of the data. The stationarity test aims to determine whether the statistical properties of the data, such as mean and variance, remain constant over time. One commonly used method for testing stationarity is the Augmented Dickey-Fuller (ADF) Test.

```
ADF Statistic: -6.783339318906199
p-value: 2.467479025753529 6e-09
```

Figure 3. Stationarity Test
Based on the results of the ADF test shown in Figure 3, the ADF statistic value was -6.7383, and the p-value was 2.467490257535296e-09. This p-value is far below common significance levels such as 0.05, 0.01, and 0.1. Therefore, the null hypothesis (H_0), which states that the data is non-stationary, is rejected. This indicates that the data used is already stationary, and no additional differencing is required to achieve stationarity. After confirming that the data is stationary, the next step is to analyze the correlation patterns of the data with its lags using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. These plots are used to assist in determining the order of the ARIMA model to be built, particularly to identify the autoregressive (AR) and moving average (MA) components based on the lag correlation patterns.

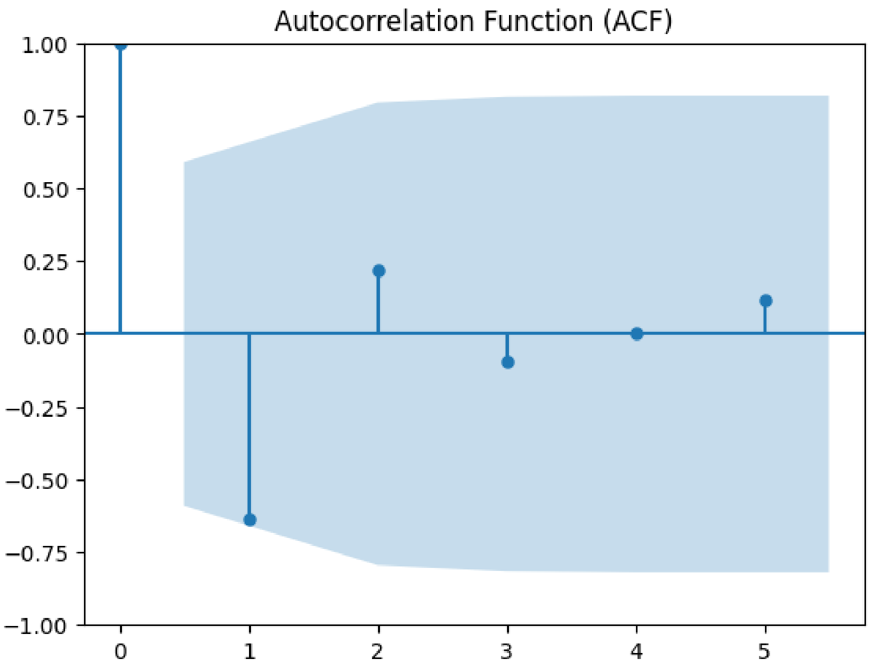

Figure 4. ACF Plot
Based on the ACF plot shown in Figure 4, it can be observed that at lag 1, the autocorrelation value is negative and significant, as it falls outside the confidence interval (indicated by the shaded blue area). This indicates a significant relationship between the current value and the previous period, suggesting the presence of a first-order Moving Average (MA(1)) component in the model. Meanwhile, the subsequent lags (lag 2 to lag 5) show relatively small autocorrelation values that fall within the confidence interval, indicating that they are not significant. Therefore, this pattern supports that the appropriate structure for this data likely involves an MA(1) component without the need to include higher-order MA terms. In addition to the ACF analysis, the Partial Autocorrelation Function (PACF) is also examined to identify the partial correlation between a value and its lag after removing the influence of previous lags. The PACF plot is particularly useful for determining the order of the autoregressive (AR) component in the ARIMA model, that is, to identify how many previous lags significantly affect the current value.

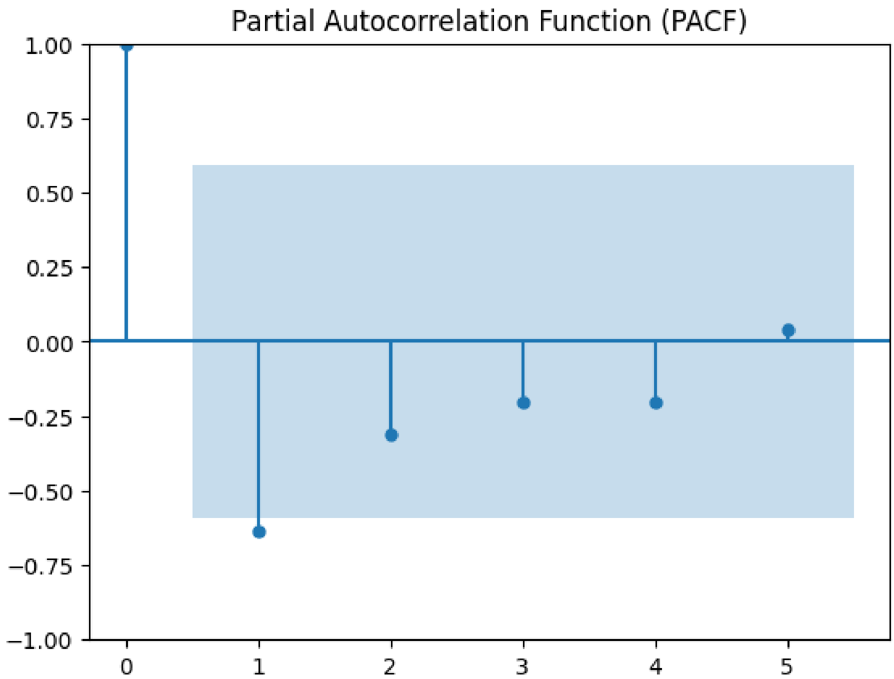

Figure 5. PACF Plot

Figure 5 illustrates the results of the analysis using the Partial Autocorrelation Function (PACF) plot. It can be observed that the partial autocorrelation is significant only at lag 1, as indicated by the bar extending beyond the confidence interval. This shows a direct and significant relationship between the current value and the previous period (lag 1), after eliminating the influence of other lags. Meanwhile, the PACF values for lags 2 to 5 fall within the confidence interval, indicating that they are not statistically significant. This pattern generally suggests that only a first-order autoregressive (AR(1)) component is dominant in the data. Therefore, the appropriate ARIMA model likely includes an AR(1) component. After identifying the model order using the ACF and PACF plots, the next step is to estimate the parameters of the selected ARIMA model. In this case, an ARIMA(1,1,1) model was chosen because it corresponds to the patterns shown in the ACF and PACF plots and satisfies the stationarity requirement. Parameter estimation was conducted using the SARIMAX approach, and the results are presented in the output below.

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  Total   No. Observations:                   12
Model:                 ARIMA(1, 1, 1)   Log Likelihood                -234.488
Date:                Wed, 21 May 2025   AIC                            474.976
Time:                        16:36:32   BIC                            476.170
Sample:                    01-01-2024   HQIC                           474.224
                         - 12-01-2024
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.7195      0.147     -4.889      0.000      -1.008      -0.431
ma.L1          0.3719      0.183      2.036      0.042       0.014       0.730
sigma2      8.624e+15        nan        nan        nan         nan         nan
===================================================================================
Ljung-Box (L1) (Q):                   0.86   Jarque-Bera (JB):                 1.71
Prob(Q):                              0.35   Prob(JB):                         0.42
Heteroskedasticity (H):               0.19   Skew:                            -0.94
Prob(H) (two-sided):                  0.14   Kurtosis:                         3.46
===================================================================================
```

Figure 6. SARIMAX Results

Based on the estimation results of the ARIMA (1,1,1) model, the coefficient of the autoregressive component (AR1) is -0.7195 with a p-value of 0.000, indicating that the parameter is statistically significant at the 5% significance level. Meanwhile, the coefficient of the moving average component (MA1) is 0.3719 with a p-value of 0.042, also showing statistical significance. This means that both the AR and MA components make a meaningful contribution to the model. The AIC value is 474.976, BIC is 476.170, and HQIC is 474.224, which are used to evaluate the model's suitability; lower values indicate a better-fitting model. The model also passed diagnostic tests, such as the Ljung-Box test, with a p-value of 0.35, which is greater than 0.05, indicating that the residuals of the model do not exhibit significant autocorrelation (i.e., behave as white noise). Furthermore, the Jarque-Bera (JB) test yielded a p-value of 0.42, also greater than 0.05, indicating that the residuals are normally distributed. Based on all these results, it can be concluded that the ARIMA(1,1,1) model satisfies the fundamental assumptions and is suitable for performing revenue forecasting.

3.3. Revenue Forecasting

After the ARIMA (1,1,1) model was successfully estimated and satisfied the diagnostic assumptions, the next step was to perform **revenue forecasting** for the upcoming period. This forecasting process aims to provide an overview of future revenue values based on the historical patterns captured by the model. The resulting predictions are expected to serve as a reference for strategic decision-making by the company's management.

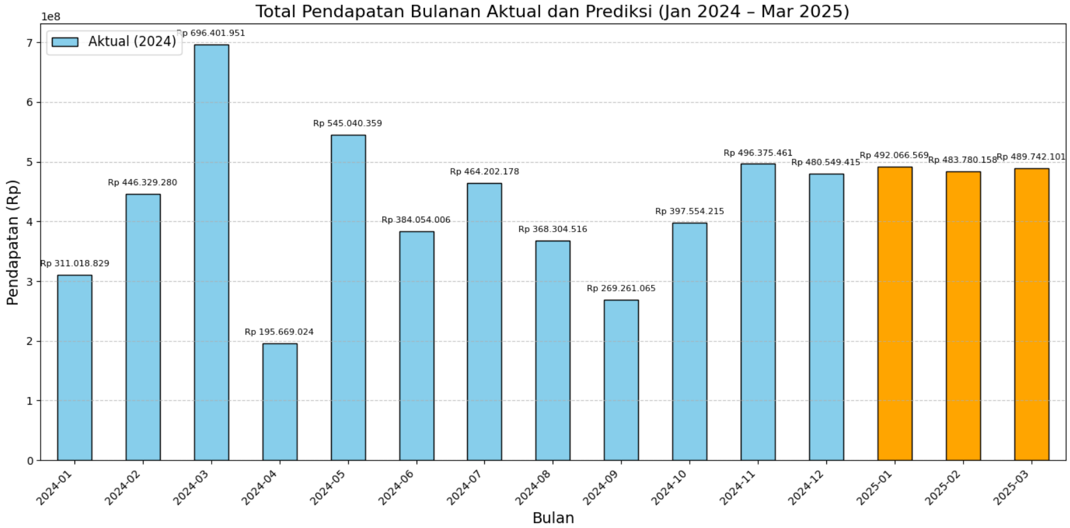

Figure 7. Forecasting Results

This chart presents the actual and predicted monthly revenue for the period from January 2024 to March 2025. The horizontal axis (x) represents the months, while the vertical axis (y) represents the revenue amount in Indonesian Rupiah (IDR). The blue bars represent the actual revenue data from January to December 2024, whereas the orange bars indicate the predicted revenue for January to March 2025.

The highest revenue during the actual period occurred in March 2024, approximately IDR 696 million, while the lowest revenue was in April 2024, around IDR 195 million. After fluctuations over several months, revenue appeared to stabilize and tended to increase toward the end of 2024. The predictions for early 2025 show a relatively stable trend with a slight decline from January to March, with values ranging between approximately IDR 483 million and IDR 489 million.

3.4. Model Evaluation

The model evaluation was carried out by developing an ARIMA-based prediction system using the entire historical monthly revenue data of the company for 2024. This model was then used to forecast revenue for the next three months (January to March 2025). The model's accuracy was measured using the Mean Absolute Percentage Error (MAPE) metric by comparing the predicted values with the available actual data.

Metrik	Nilai
MAPE (%)	9.41%

Figure 8. MAPE Value

Based on Figure 8, the displayed metric is the MAPE (Mean Absolute Percentage Error), which is 9.41%. This MAPE value indicates that, on average, the model's predictions deviate by 9.41% from the actual values. In the context of forecasting, MAPE is one of the most commonly used accuracy metrics because it is easy to interpret. The lower the MAPE value, the more accurate the forecasting model. A MAPE of 9.41% can be considered reasonably good; however, the interpretation of "good" or "poor" often depends on the industry context and the acceptable level of error. For instance, in some industries, a MAPE below 10% is regarded as excellent, while in others, an even lower value may be expected.

3.5. Discussion

The results of this study demonstrate the effectiveness of the ARIMA(1,1,1) model in forecasting monthly revenue for CV. Yusindo Mega Persada based on historical data from January to December 2024. The initial visualization of the revenue data revealed significant fluctuations throughout the year, with the highest revenue recorded in March 2024 (IDR 696 million) and the lowest in April 2024 (IDR 195 million). These fluctuations indicate that the revenue patterns are dynamic and non-linear, which justifies the use of a time series model like ARIMA for accurate forecasting.

The stationarity test using the Augmented Dickey-Fuller (ADF) Test confirmed that the revenue data was stationary, with a p-value far below the conventional significance levels. This allowed the model to be developed without the need for additional differencing. Further analysis using the Autocorrelation Function (ACF) and **Partial** Autocorrelation Function (PACF) plots suggested the presence of a first-order MA(1) and AR(1) component, which informed the selection of the ARIMA (1,1,1) model.

Parameter estimation using the SARIMAX approach confirmed that both the AR(1) and MA(1) coefficients were statistically significant, and diagnostic tests indicated that the residuals were normally distributed and free from significant autocorrelation. These results demonstrate that the ARIMA (1,1,1) model meets the fundamental assumptions required for reliable forecasting.

The forecast results for the period from January to March 2025 indicated a relatively stable revenue trend, ranging from approximately IDR 483 million to IDR 489 million. Evaluation using Mean Absolute Percentage Error (MAPE) showed a value of 9.41%, suggesting that, on average, the model's predictions deviate by less than 10% from the actual values. In the context of business forecasting, this level of accuracy is considered acceptable, although it may vary depending on the industry and tolerance for error.

Overall, the discussion highlights several key points. First, ARIMA is capable of capturing both trend and fluctuation patterns in historical revenue data, making it suitable for companies facing dynamic and unstable revenue streams. Second, the model provides actionable insights for management, enabling strategic decisions regarding financial planning, resource allocation, and risk mitigation. Finally, while the model shows good accuracy, it is important to note that external factors, such as market conditions or public holidays, may still cause deviations in actual revenue from predicted values. Therefore, combining ARIMA forecasts with expert judgment and additional qualitative information can further improve decision-making effectiveness.

4. CONCLUSION

This study demonstrates that the ARIMA(1,1,1) model is effective in forecasting the monthly revenue of CV. Yusindo Mega Persada using historical data from January to December 2024. The model successfully captured the trend and fluctuations in the revenue data, with diagnostic tests confirming that the residuals were normally distributed and free from significant autocorrelation. The forecast for January to March 2025 indicated a relatively stable revenue trend, with a Mean Absolute Percentage Error (MAPE) of 9.41%, suggesting reasonable predictive accuracy. These results provide valuable insights for management in strategic planning, resource allocation, and risk mitigation. However, it is important to note that external factors such as market conditions, seasonal events, and economic fluctuations may still influence actual revenue. Overall, the ARIMA(1,1,1) model proves to be a practical and reliable tool for revenue forecasting in a dynamic business environment.

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