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Production Planning Forecasting using Seasonal and Non-Seasonal ARIMA Method with Minitab Applications (Study Case: DC Company)

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A B S T R A C T

This study aims to forecast the production of DMG (Mugs) and TM (Salt and Pepper Shakers) at DC Company, one of the leading ceramic producers in Malang City. Accurate forecasting is essential to support production planning, resource optimization, and market demand fulfillment, especially since the company's primary market segment is wedding souvenirs with fluctuating demand. The research employs time series forecasting methods using ARIMA and SARIMA models, with historical production data from January 2021 to July 2025 as the dataset. Model identification, estimation, and verification were conducted using MINITAB 22, with performance evaluated through MSE, MAD, and MAPE values. The results show that the SARIMA $(0,1,1)(1,1,1)_{12}$ model provides the highest forecasting accuracy for both DMG and TM, outperforming ARIMA models. Forecasting results indicate a decline in DMG production for 2026, while TM production shows a relatively stable upward trend. These findings provide a practical basis for DC Company to develop production strategies, improve efficiency, and align marketing efforts with projected demand patterns.

KATA KUNCI

Perencanaan Produksi, Prakiraan, Deret Waktu, ARIMA, Minitab

A B S T R A K

Penelitian ini bertujuan untuk meramalkan produksi DMG *(Mugs)* dan TM *(Salt and Pepper Shakers)* di DC Company, salah satu produsen keramik terkemuka di Kota Malang. Peramalan yang akurat sangat penting untuk mendukung perencanaan produksi, optimasi sumber daya, dan pemenuhan permintaan pasar, terutama karena segmen pasar utama perusahaan adalah suvenir pernikahan dengan permintaan yang fluktuatif. Penelitian ini menggunakan metode peramalan deret waktu dengan model ARIMA dan SARIMA, dengan data produksi historis dari Januari 2021 hingga Juli 2025 sebagai dataset. Identifikasi, estimasi, dan verifikasi model dilakukan menggunakan MINITAB 22, dengan kinerja dievaluasi melalui nilai MSE, MAD, dan MAPE. Hasil menunjukkan bahwa model SARIMA $(0,1,1)(1,1,1)_{12}$ memberikan akurasi peramalan tertinggi untuk DMG dan TM, melebihi model ARIMA. Hasil peramalan menunjukkan penurunan produksi DMG pada tahun 2026, sementara produksi TM menunjukkan tren kenaikan yang relatif stabil. Temuan ini memberikan dasar praktis bagi DC Company untuk mengembangkan strategi produksi, meningkatkan efisiensi, dan menyelaraskan upaya pemasaran dengan pola permintaan yang diproyeksikan.

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1. Introduction

DC is a company engaged in the production of ceramic products. To maintain its position as one of the leading ceramic manufacturers in its region, DC must consistently uphold high product quality, as product quality has a significant effect on purchasing decisions [1]. Product quality greatly affects customer satisfaction because it reflects the product's reliability, durability, and overall value.

In addition, careful planning is required for the company's core activities, starting with production planning. Poorly planned production may lead to delays in fulfilling orders. Since production requires raw materials, labor, machinery, and time, proper production planning can optimize resource utilization, thereby reducing production costs.

The issue of ceramic slip raw materials is currently the main challenge faced by DC Company. Its primary supplier has limited production capacity, resulting in reduced slip supply for the company. In-house slip production also remains a constraint, as the quantity produced independently is still insufficient and cannot meet the monthly slip demand. Therefore, monthly production forecasting is required to estimate the necessary amount of slip each month.

Forecasting is an estimate or prediction of future events based on past data. Forecasting may involve taking historical data (such as past sales) and projecting them into the future with a mathematical model [2]. It may be based on demand-driven data, such as customer plans to purchase, and projecting them into the future. Demand-driven forecasts drive a company's production, capacity, and scheduling systems and serve as inputs to financial, marketing, and personnel planning [3]. In addition, the payoff in reduced inventory and obsolescence can be huge [4]. One of the methods used for forecasting is time series analysis [5]. To obtain accurate results in planning, real production data from previous years is required [6].

Time series forecasting is the process of predicting future values of a target variable $y_{i,t}$ for entity I at time t using historical data. This process involves developing a model capable of capturing underlying patterns as well as temporal dependencies in the data to generate accurate predictions. Thus, the main challenge lies in effectively identifying these patterns through historical data analysis [7].

Production forecasting can assist in formulating effective plans and optimizing the production process to achieve profitability and sustainable growth. The ARIMA (Autoregressive Integrated Moving Average) model is a widely used statistical technique in time series analysis and forecasting, making it an essential tool for decision-making [8]. By incorporating past values of time series data, ARIMA predicts future values through the application of autoregression (AR), integration (I), and moving average (MA) [9].

SARIMA (Seasonal Autoregressive Integrated Moving Average) is a time series forecasting model that is widely applied in various fields, and this model has proven to be effective in forecasting production [10]. It is an extension of ARIMA that incorporates seasonal and trend components. The parameters for the SARIMA model are expressed as SARIMA (p, d, q) × (P, D, Q, s) [11]. In this notation, p and P represent the autoregressive terms, which are the lags of the differenced stationary data; d and D indicate the differencing required to achieve stationarity; q and Q correspond to the moving average terms; while s denotes the length of the seasonal period in the data [12]. Seasonal variations in data are regular movements in a time series that relate to recurring events such as weather or holidays. Similarly, understanding seasonal variations is important for capacity planning in organizations that handle peak loads. Seasonality is expressed in terms of the amount that actual values differ from average values in the time series [4].

In a study on the Work Order Projects of Casting Construction at PT. Bumi Sarana Beton, ARIMA (2,0,0) provided the best forecast for K-225, while ARIMA (2,0,2) was the best fit for K-400 [13]. Similarly, rice production forecasting in Sleman Regency identified ARIMA (0,2,1) as the optimal model [14]. Forecasting of cereal production in Ethiopia tested several models, with results showing that ARIMA (1,1,1) achieved higher R^2 values across multiple commodities, indicating it as the best choice [15]. In a study on forecasting hydroelectric production in Tanzania, the SARIMA (0,1,3)(2,0,0) model was identified as the best-performing model for forecasting results [16]. In another study on forecasting Indonesian coffee production, the SARIMA $(2,1,0)(1,1,1)_{12}$ model was applied, and the results showed that the forecasted values closely approximated the actual coffee production in the previous periods [17].

2. Research Method

2.1. Methodological Steps

Several methodological steps were undertaken to analyze and forecast production at DC Company. This procedure is designed systematically so that the analysis and forecasting results obtained are more accurate and reliable as a basis for production planning. The steps are as follows:

a. Introduction and Literature Review. This study includes a literature review focusing on quantitative forecasting methods, particularly the time-series method. This review aims to identify relevant studies and theoretical frameworks that support the application of these methods in practical forecasting scenarios. In addition, the research emphasizes the use of MINITAB as the statistical software to facilitate forecasting analysis.

b. Data Collection. The data used in this study are primary data derived from the historical production records of DC Company. These data serve as the basis for analyzing production trends and developing accurate forecasting models for the company's future production planning. The research period covers January 2021 to July 2025.

c. Identification of Forecasting Methods. Several types of forecasting methods are identified and selected in accordance with the available production data. The selection process involves evaluating each method's suitability based on data characteristics such as trend, seasonality, and variability. This step ensures that the chosen forecasting approach provides accurate and reliable results for the company's production analysis.

d. Comparison of Forecasting Methods. Production forecasting for DC Company is conducted for the year 2026. After generating forecasting results, a comparison among the methods is carried out to determine accuracy by calculating the values of Mean Absolute Deviation (MAD), Mean Square

Deviation (MSD), and Mean Absolute Percentage Error (MAPE).

e. Result Analysis. The forecasting results are analyzed and evaluated based on MAD, MSD, and MAPE values. The method that yields the best performance according to these error measures is selected as the final result. This analysis provides a comprehensive understanding of the model's accuracy and reliability in predicting future production trends.

The use of MINITAB 22 as the statistical software in this study is carried out according to the following steps. This software was selected because it provides comprehensive tools for time series analysis, including SARIMA modeling and diagnostic checking. Through MINITAB 22, data processing and forecasting can be performed efficiently, ensuring accurate and reproducible analytical results.

a. Model Identification. Model identification is conducted to select the appropriate forecasting model. This process ensures that the chosen model accurately represents the underlying data pattern. The steps are as follows:

   1) Time Series Plot. The purpose of creating a time series plot is to observe the trend of the data. It also helps find seasonal changes, cyclical patterns, and probable outliers. We can better grasp how the data behaves as a whole and make better predictions by seeing it over time.

   2) Stationarity in Variance Test. Data are considered stationary in variance if the Rounded Value is close to 1. When the data are found to be non-stationary, a stationarization process is required, which can be achieved through transformation for data that are non-stationary in variance. Ensuring stationarity in variance is essential for obtaining reliable and consistent forecasting results.

   3) ACF and PACF Plots. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are generated to evaluate the stationarity of mean. If a visible pattern is observed in the ACF/PACF plots, the data is not stationary in mean. Thus, differencing must be applied to achieve stationarity in mean.

b. Model Estimation. Once model identification is complete, the next step is model estimation to determine whether the model is appropriate for forecasting. Estimation is carried out by examining the p-value from the Box-Cox test as well as the AR and MA parameters, which should not exceed 0.05. This step ensures that the selected model parameters provide an accurate representation of the underlying data pattern.

c. Model Verification. Verification is conducted after model estimation to identify the best model for forecasting. Verification is performed by comparing the error values across models, with the smallest error indicating the most suitable model. This step checks the model's performance and makes sure that it consistently represents the data that was seen.

d. Forecasting. After identifying the best model, forecasting is carried out using the selected model to obtain projected values for the specified time horizon. The forecasting results offer insights into forthcoming trends and possible alterations in the data pattern. These forecasts are crucial for facilitating decision-making and planning based on expected future circumstances.

2.2. Data Collection

The data used in this study consist of the production records of DMG (Mugs) and TM (Salt and Pepper Shaker) at DC Company. The data period spans from January 2021 to July 2025. These data serve as the foundation for analyzing production trends and developing accurate forecasting models.

Table 1. DC Company DMG Production Data (in pieces)

Month	2022	2023	2024	2025
January	6,543	9,155	2,441	5,522
February	6,253	5,901	5,115	4,287
March	7,417	5,658	8,000	5,225
April	11,819	7,995	3,191	5,710
May	4,695	5,283	6,976	5,138
June	10,776	9,445	4,162	4,655
July	8,965	7,522	8,937	5,371
August	10,060	6,690	10,567	-
September	10,383	6,279	9,458	-
October	9,011	6,626	8,532	-
November	7,200	10,755	6,548	-
December	8,425	3,835	3,609	-

From the production data table for DMG (Mugs) on Table 1, no clear seasonal pattern or consistent upward and downward trend in production can be observed. However, in 2022 and 2023, there was a noticeable increase in April, followed by a decline in demand, and then another rise in June. In 2024, production also showed an increase in March, a decrease in April, and another rise in May. Meanwhile, in 2025, the peak demand occurred in April. This pattern can be attributed to DC Company' target market, which is primarily wedding souvenirs, as weddings are predominantly held during those months.

Table 2. DC Company TM Production Data (in pieces)

Month	2022	2023	2024	2025
January	1,820	4,100	1,420	1,870
February	900	3,534	1,420	50
March	1,910	3,080	1,200	3,760
April	1,042	2,230	800	2,046
May	900	2,400	1,360	1,134
June	1,815	1,690	3,176	810
July	1,860	1,330	4,320	2,404
August	1,350	3,540	3,370	-
September	2,240	1,080	4,680	-
October	2,510	2,600	1,100	-
November	2,140	3,800	3,640	-
December	2,220	5,250	3,950	-

From the production data table for TM (Salt and Pepper Holders) on Table 2, no significant seasonal trend or consistent fluctuations in production can be observed. This is due to the fact that the demand for TM products is not as high as that for DMG.

3. Results and Discussion

Based on the time series plot results on Figure 1, the DMG (Mug) production graph shows a fluctuating trend. From early 2021 until mid-2022, production increased and reached a peak of more than 11,000 units. However, after that period, the graph gradually declined, displaying an alternating up-and-down pattern until 2025.

In contrast, the TM (Salt and Pepper Holder) production graph om Figure 2 exhibits sharper fluctuations. From 2021 until mid-2023, the trend generally increased. Overall, the production pattern of TM is unstable, characterized by significant spikes and declines throughout the observed period.

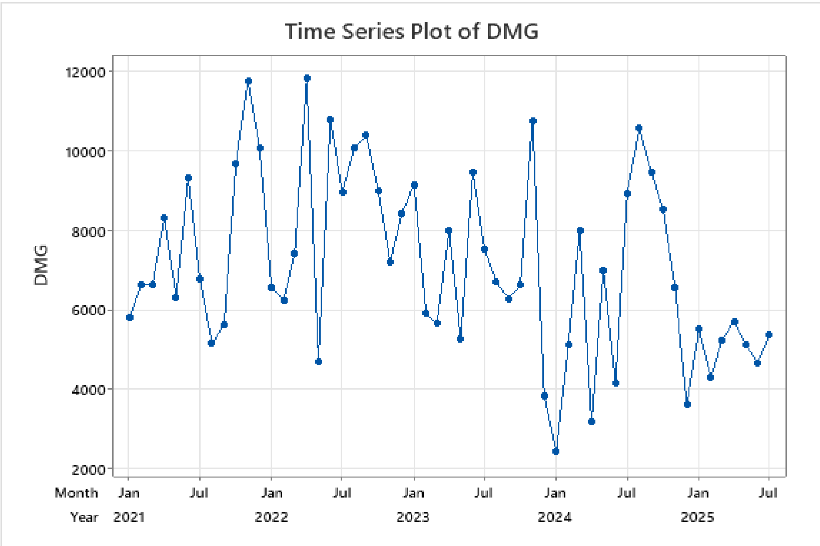

Figure 1. Time Series Plot of DMG

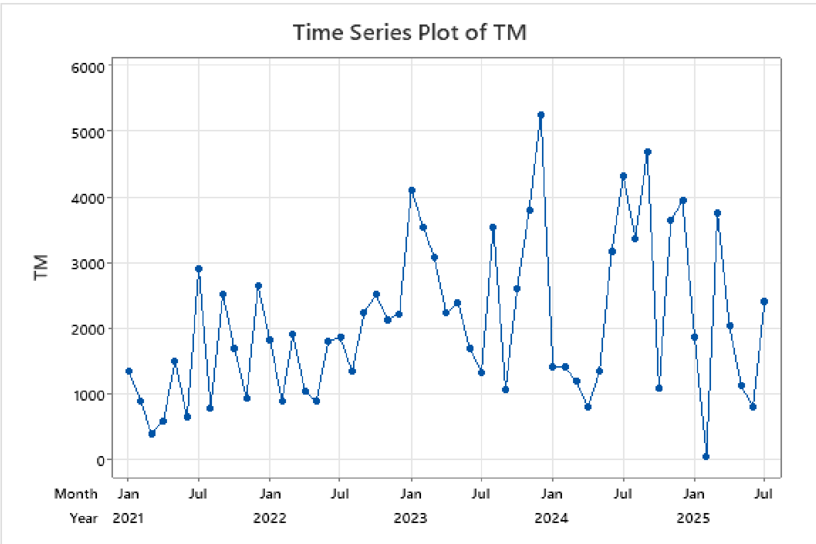

Figure 2. Time Series Plot of TM

The Box-Cox plots for both DMG and TM original data are presented in Figures 3 and 4 to visually assess the variance stationarity of each dataset. It can be observed from both Box-Cox plots that the Rounded Value is not equal to 1. This indicates that the data are non-stationary in terms of variance. Therefore, a transformation is required to achieve stationarity in variance.

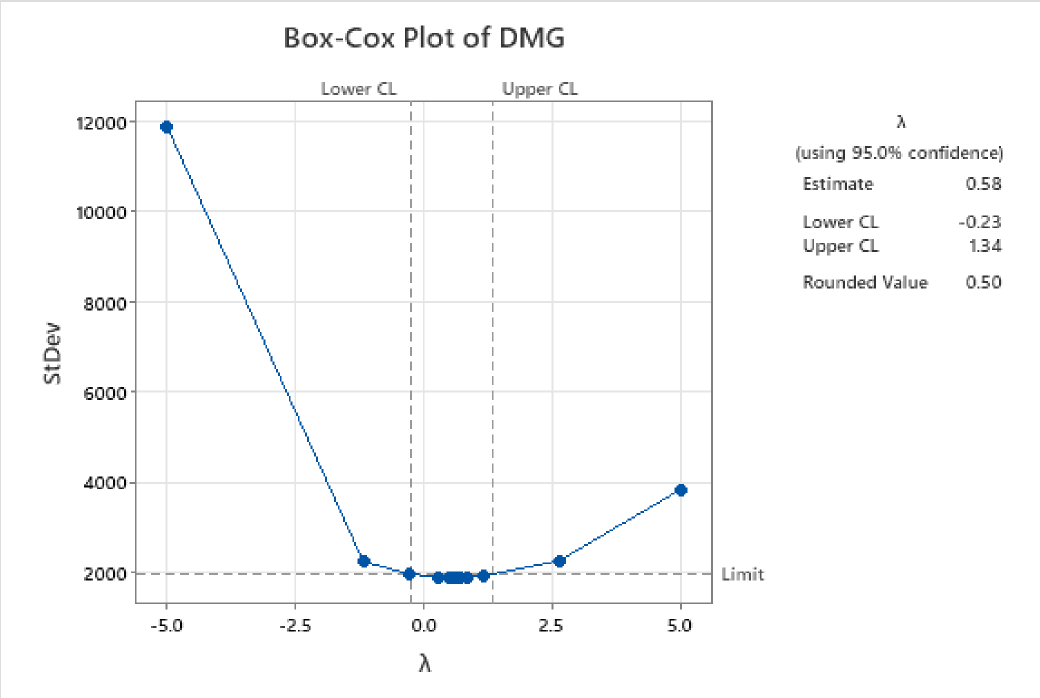

Figure 3. Box-Cox Plot of DMG (Original Data)

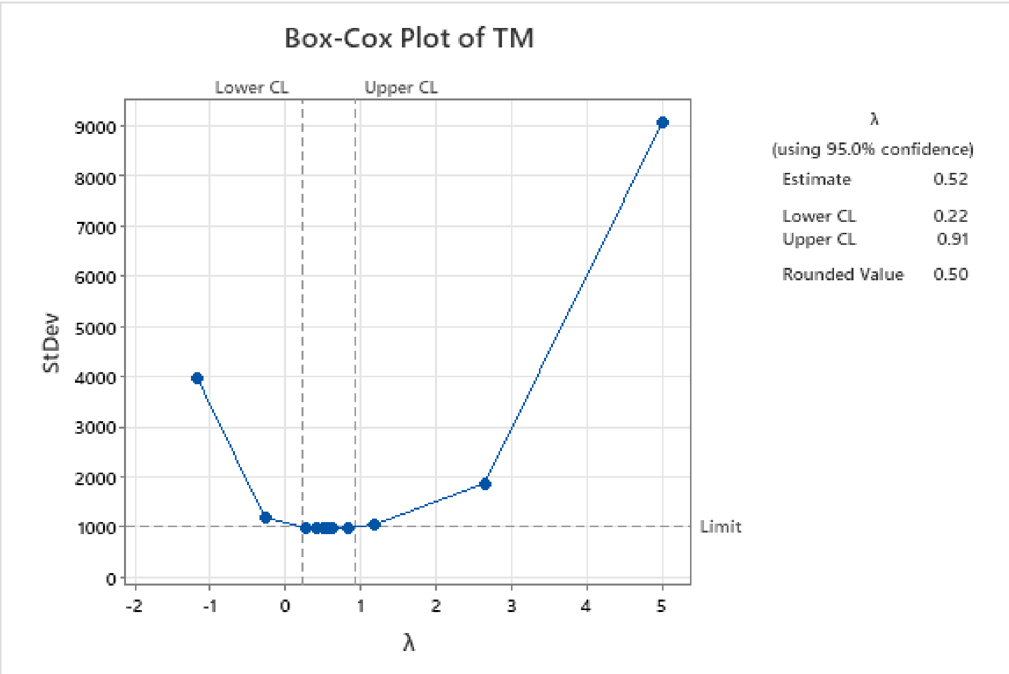

Figure 4. Box-Cox Plot of TM (Original Data)

The Box-Cox plots for the transformed data of DMG and TM are presented in Figures 5 and 6 to evaluate whether the variance has been stabilized after transformation. From the Rounded Value in both figures above, it can be observed that the Rounded Value has reached 1.00, indicating that the data are already stationary in terms of variance.

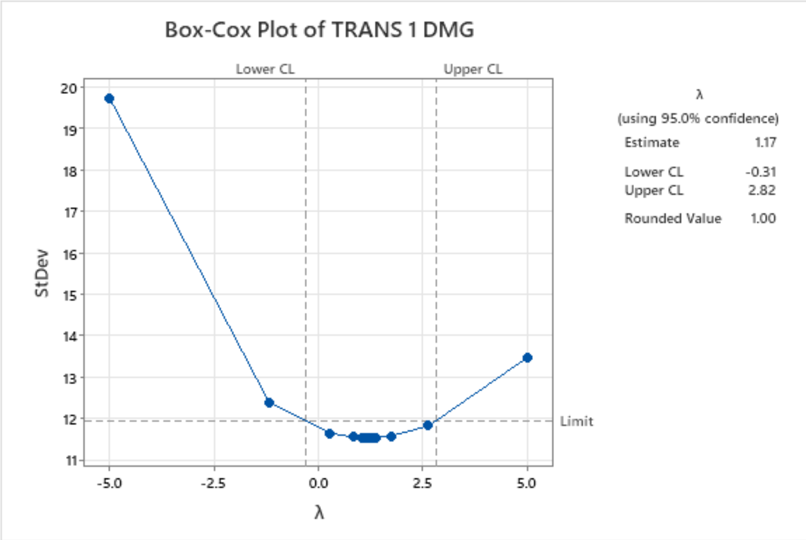

Figure 5. Box-Cox Plot of DMG (Transformation Data)

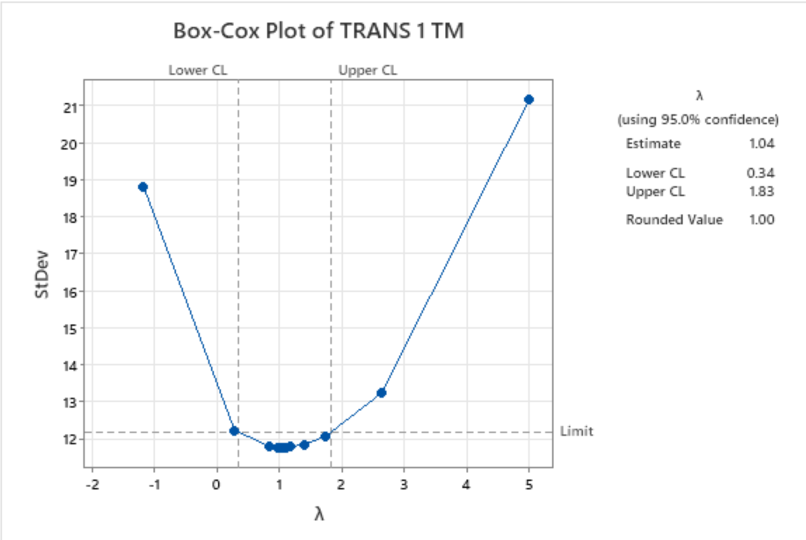

Figure 6. Box-Cox Plot of TM (Transformation Data)

The Autocorrelation Function (ACF) plots for the first transformed data of DMG and TM are presented in Figures 7 and 8 to examine whether the data are stationary in mean. It can be seen in the ACF plot for TRANS 1 DMG and TRANS 1 TM that there is still a relatively stable and significant up-and-down pattern, therefore differentiation is required to make the data stationary in mean.

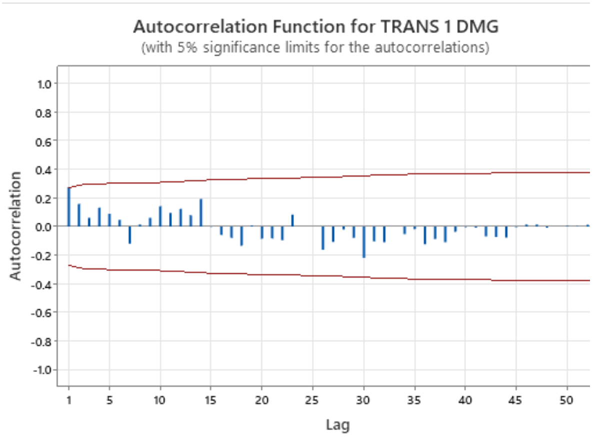

Figure 7. ACF Plot of TRANS 1 DMG

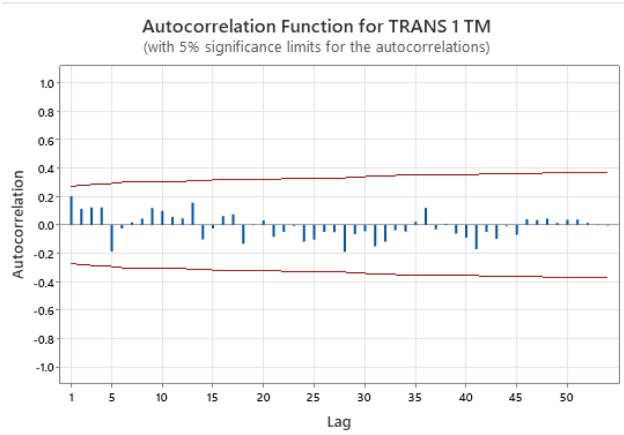

Figure 8. ACF Plot of TRANS 1 TM

To determine if the data have become stationary in mean following differentiation, the ACF and PACF plots for the first-differenced data of DMG and TM are shown in Figures 9 to 12. From the ACF and PACF plots for diff-1 DMG and diff-1 TM, it can be seen that there are data points that fall outside the significance limits. However, the errors caused by these data points are still within the <5% threshold. It can also be observed from the plots that no data pattern is found. This indicates that the data is considered stationary in mean after performing one-time differencing.

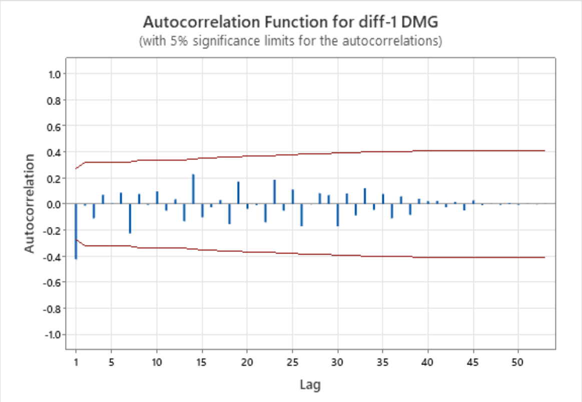

Figure 9. ACF Plot of diff-1 DMG

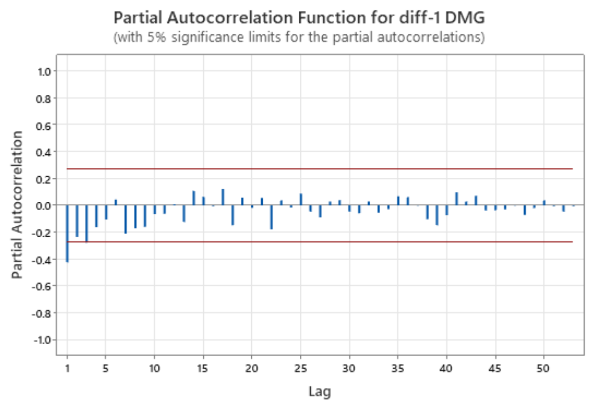

Figure 10. PACF Plot of diff-1 DMG

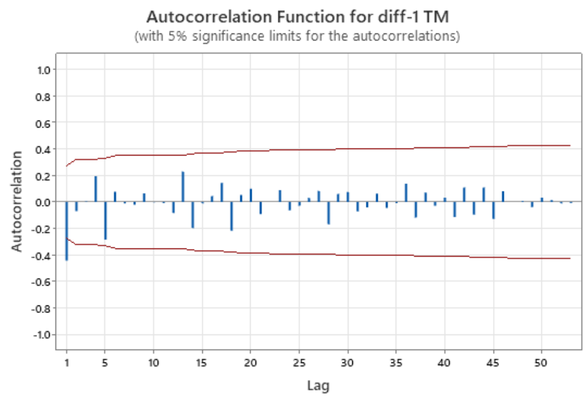

Figure 11. ACF Plot of diff-1 TM

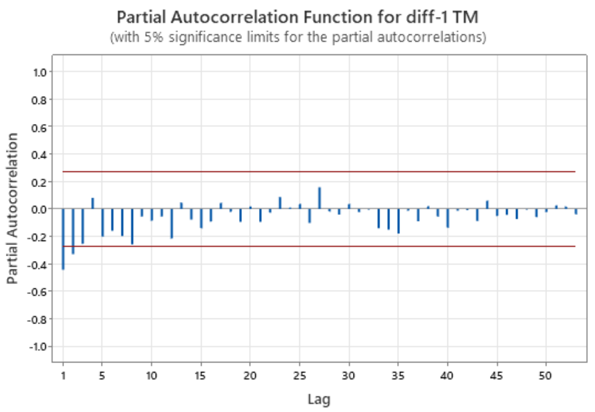

Figure 12. PACF Plot of diff-1 TM

The determination of an appropriate ARIMA model can be carried out through several stages, namely by entering different combinations of autoregressive, differencing, and moving average values to obtain the smallest p-value, which should be less than 0.05. The ARIMA dialog field can be seen on Figure 13.

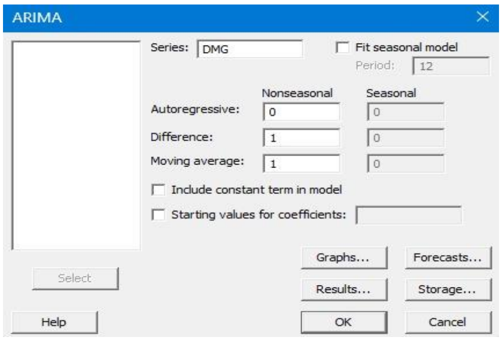

Figure 13. ARIMA Dialog Field

Meanwhile, the determination of a SARIMA model follows the same procedure, with the addition of checking the fit seasonal model option, specifying the seasonal period, and entering the autoregressive, differencing, and moving average values in the seasonal column. The best model is then selected based on the combination that yields the smallest p-value (less than 0.05). The SARIMA dialog field can be seen on Figure 14.

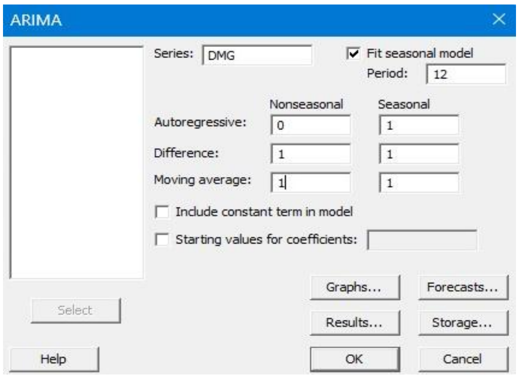

Figure 14. SARIMA Dialog Field

The results obtained from the determination of the ARIMA model using p-value parameters can be seen on Table 3 and Table 4.

Table 3. P-value for each ARIMA model for DMG

Type	ARIMA (0,1,1)	SARIMA (0,1,1) $(1,1,1)_{12}$
MA 1	0	0.000
SAR 12	-	0.000
SMA 12	-	0.026

Table 4. P-value for each ARIMA model for TM

Type	ARIMA (0,1,1)	SARIMA (0,1,1) $(1,1,1)_{12}$
MA 1	0	0.000
SAR 12	-	0.022
SMA 12	-	0.026

Verification was carried out by calculating the values of MSE (Mean Squared Error), MAD (Mean Absolute Deviation), and MAPE (Mean Absolute Percentage Error) for the three ARIMA and SARIMA models described above. These metrics help determine which model provides the most accurate predictions by comparing their respective error levels. The verification results can be seen on Table 5 and Table 6.

Table 5. Verification result for DMG

Model	MSE	MAD	MAPE (%)
ARIMA (0,1,1)	4,675,934	1,804	28.81
SARIMA $(0,1,1)(1,1,1)_{12}$	4,669,931	1,394	28.25

Table 6. Verification result for TM

Model	MSE	MAD	MAPE (%)
ARIMA (0,1,1)	1,390,091	990	155.78
SARIMA $(0,1,1)(1,1,1)_{12}$	1,204,266	890	154.55

Based on the verification results, the best model is SARIMA $(0,1,1)(1,1,1)_{12}$ for both DMG and TM products. This model achieved the lowest values of MSE, MAD, and MAPE for both product categories. By applying a seasonal period of 12 (annual), this indicates that the production of DMG and TM exhibits relatively stable upward and downward trends, recurring in the same months each year.

Table 7. Forecasting result of DMG (in pieces)

Month	2022	2023	2024	2025	Forecast 2025	Forecast 2026
January	6,543	9,155	2,441	5,522	-	775
February	6,253	5,901	5,115	4,287	-	3,446
March	7,417	5,658	8,000	5,225	-	6,473
April	11,819	7,995	3,191	5,710	-	2,616
May	4,695	5,283	6,976	5,138	-	5,294
June	10,776	9,445	4,162	4,655	-	2,195
July	8,965	7,522	8,937	5,371	-	6,898
August	10,060	6,690	10,567	-	5,562	8,881
September	10,383	6,279	9,458	-	4,690	7,775
October	9,011	6,626	8,532	-	5,718	6,871
November	7,200	10,755	6,548	-	9,353	4,951
December	8,425	3,835	3,609	-	1,601	1,957
Total	101,547	85,144	77,536	35,908	26,924	58,132

Based on the DMG forecasting results in Table 7, the highest forecasted production occurs in November 2025, reaching 9,353 units. In 2026, the peak is predicted in August with 8,881 units. The forecasting results for DMG indicate significant variations in monthly production volumes. Notably, a substantial increase is observed in March 2026 and May 2026 compared to the preceding months. This pattern is consistent with historical data trends, which show higher demand during periods approaching Eid al-Fitr and Eid al-Adha. These seasonal peaks are closely associated with the increased frequency of wedding ceremonies, thereby influencing the demand for ceramic products.

Table 8. Forecasting result of TM

Month	2022	2023	2024	2025	Forecast 2025	Forecast 2026
January	1,820	4,100	1,420	1,870	-	3,117
February	900	3,534	1,420	50	-	2,936
March	1,910	3,080	1,200	3,760	-	2,278
April	1,042	2,230	800	2,046	-	1,941
May	900	2,400	1,360	1,134	-	2,505
June	1,815	1,690	3,176	810	-	3,253
July	1,860	1,330	4,320	2,404	-	3,561
August	1,350	3,540	3,370	-	2,937	3,532
September	2,240	1,080	4,680	-	2,100	3,694
October	2,510	2,600	1,100	-	3,281	2,659
November	2,140	3,800	3,640	-	3,357	3,882
December	2,220	5,250	3,950	-	4,528	4,652
Total	20,707	34,634	30,436	12,074	16,203	38,010

According to the TM forecasting results in Table 8, the highest forecasted production is in December 2026 with 4,652 units. In the remaining months of 2025, production shows an upward trend from August to December. For 2026, the peak is also expected in December. The TM forecasts do not exhibit significant upward or downward trends, nor do they show a distinct seasonal pattern. The monthly forecast values for TM production remain relatively close, with a difference of 2,711 units between the highest and lowest forecasts in 2026.

The forecasting results for DMG and TM using the SARIMA $(0,1,1)(1,1,1)_{12}$ method show a clear seasonal trend in both products. As stated by certain study, understanding seasonal variations is crucial for production capacity planning in organizations when dealing with peak loads [4]. These seasonal variations also indicate the presence of regular recurring events. Strengthened by the fact that DC Company' main target market is souvenirs, it can be observed that certain months experience a surge in demand due to Indonesia's cultural tendency to hold weddings during specific months. This pattern is reflected in the forecasting results of DC Company.

In another research of forecasting Indonesian coffee production, has similar results to DC Company' forecasts, in which the SARIMA method with the same P, D, Q, s parameters, namely $(1,1,1)_{12}$, was used [18]. These findings reinforce that the SARIMA $(p,d,q)(1,1,1)_{12}$ model is widely applied and shows good forecasting performance. This consistency across several investigations demonstrates the SARIMA model's dependability and resilience for time series forecasting.

4. Conclusion

Based on the model identification, two models were applied—ARIMA (0,1,1) and SARIMA $(0,1,1)(1,1,1)_{12}$—and the comparison of their verification values (MSE, MAD, MAPE) showed that the SARIMA $(0,1,1)(1,1,1)_{12}$ model produced the lowest errors for both DMG and TM products, indicating higher forecasting accuracy for DC Company's production data. The 2026 forecast results show that DMG production is projected to decline to 58,132 units, while TM production is expected to increase to 38,010 units, following seasonal trends related to the wedding season and major holidays such as Eid al-Fitr and Eid al-Adha. These forecasting outcomes can serve as a valuable reference for DC Company in developing production and raw material planning, particularly for ceramic slip supply, encouraging the consideration of an in-house slip production facility to ensure consistent material availability. Furthermore, the decline in DMG production highlights the need to improve production efficiency and reduce unnecessary costs, while the overall forecast can also guide marketing strategy evaluations to help the company expand its market, maintain demand stability, and increase overall product demand.

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