International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 8, Issue 8, pp 17-25, August-2024

https://doi.org/10.47001/IRJIET/2024.808003

Demand Forecasting Analysis of Body Scrub Product at PT. XYZ Using Autoregressive Integrated Moving Average (ARIMA) Method

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***Abstract* - PT. XYZ is one of the private companies engaged in the cosmetics industry, especially as a manufacturer of SPA products with natural raw materials. The SPA products produced by PT. XYZ are various kinds of scrubs, body scrubs, masks, essential oils, soaps and other products. Body scrub is the most popular product or best seller in this company. The purpose of this study is to find the best ARIMA model in calculating demand forecasting of body scrub products at PT. XYZ for the period January to December 2024. The method used in this research is the Autoregressive Moving Average (ARIMA) method. There are two ARIMA models that can be used in this study, namely ARIMA (1,1,0) and ARIMA (0,1,1). The selected ARIMA model used to calculate body scrub forecasting at PT. XYZ is the ARIMA (1,1,0) model because it has a smaller error value, namely MSE = 745.46 and MAPE = 7.40%. The results of forecasting the demand for body scrub products at PT. XYZ for the period January to December 2024 using the ARIMA (1,1,0) model show that demand has increased every month with an average demand of 343.4 kg. The error obtained by comparing the forecasting results with the actual sales data for 6 months, namely January - June 2024 is 2.45%, which means that the accuracy of forecasting in 6 months reaches 97.55%.**

Keywords: ARIMA, body scrub, demand forecasting.

I. INTRODUCTION

The development of science and technology, followed by increased public awareness of the need for various products in the future, has led to increased market demand. Every company is expected to be able to meet market demand appropriately in order to maximize the revenue earned by the company. Erratic inventory needs to be anticipated by doing an appropriate demand forecasting so that there is no excess inventory which can result in excessive costs in storage and there is no shortage of inventory which can hinder smooth production in meeting consumer demand (Mashadihasanli, 2022). Forecasting is an activity to predict future events and is a tool that can be applied for effective and efficient planning (Hariadi & Sulantari, 2021). Forecasting has a very important role in managing the inventory of a company (Baser, *et al.*, 2018).

PT. XYZ is one of the private companies engaged in the field of cosmetics industry, especially as a manufacturer of SPA products with natural raw materials. SPA products produced by PT. XYZ, namely various kinds of scrubs, body scrubs, masks, essential oils, soap and shampoo, hair oil, aromatherapy, massage oil, and body mist. Body scrub is the most popular product or best seller in this company. Based on interviews, the average demand for body scrub products is 300 kg every month. The very high demand causes the company to be unable to fulfill the demand on time with the right amount. The large number of enthusiasts of body scrub products causes frequent inventory shortages (understock) of body scrub products at PT. XYZ. As a result, the company cannot meet the demand from consumers, causing discomfort to consumers and losing the opportunity to earn additional revenue.

Based on these problems, it is necessary to forecast demand so that the company can provide the right number of products and there is no longer a shortage or excess inventory. Several methods can be used to perform product forecasting demand forecasting, namely the moving average method, exponential smoothing, linear trend, Autoregressive Integrated Moving Average (ARIMA), and others. In this study, the method chosen for use is the Autoregressive Integrated Moving Average (ARIMA) method because it is considered quite precise and accurate (Tarmanini, *et al.*, 2023). The ARIMA method is a time series analysis forecasting model that aims to find suitable data patterns from a group of data and fully utilize past and present data (Fattah, et al, 2018).The ARIMA method is the model most often used in short-term forecasting (Dritsaki, *et al.*, 2021). The ARIMA method has the advantage of being able to accept all types of data patterns even though the process must be stationary first compared to the moving average, exponential smoothing, and linear trend methods which can only be used on certain types of data patterns (Dhyani, *et al.*, 2020).

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Some research with the ARIMA method includes research by Novyta & Alhazami (2022) ARIMA method is used to forecast nata de coco demand by comparing 7 ARIMA models obtained from the model parameter estimation process to get the best ARIMA model. In this study, the best ARIMA model was found to be ARIMA (0,2,1) with the smallest Mean Square Error (MSE) value. Another study conducted by Zulhamidi, *et al.*, (2017) the application of the ARIMA method was used in forecasting green tea sales at PT. MK by comparing 7 ARIMA models obtained from the model parameter estimation process and found the best ARIMA model, namely (2,2,4) with the smallest error value. Therefore, this study will compare several ARIMA models obtained from the model parameter estimation process which aims to find the best ARIMA model in forecasting the demand for body scrub products at PT. XYZ and calculate the demand forecasting results of body scrub products at PT. XYZ for the period January to December 2024.

II. LITERATURE REVIEW

2.1 Demand Forecasting

Forecasting is an activity to predict future events and is a tool that can be applied for effective and efficient planning (Hariadi & Sulantari, 2021). Basically, forecasting is the process of sequentially compiling information about past events to estimate future events. Demand forecasting is very important for companies in production planning because it can provide an overview of production activities to be carried out (Ingle, *et al.*, 2021). Forecasting in business activities is a form of planning that functions as a consideration tool in decision making or policy making in business. The decision or policy that the company wants to take must be in accordance with the company's objectives, therefore it is necessary to have careful planning. The success of a company can be seen from the management's ability to optimally utilize opportunities to be able to get sales and profits in accordance with previously set targets (Kerkkanen, *et al.*, 2009).

2.2 Demand Data Pattern

According to Wei (2006), the main factor influencing the selection of forecasting techniques for time series data is the identification and understanding of historical data patterns. There are four patterns of demand data, the picture of which can be seen in Figure 1 (Lusiana, A., & Yuliarty, P., 2020):

1. Trend (T), occurs when there is a gradual increase or decrease in the data over a long period of time.
2. Seasonality (S), seasonal patterns occur when the data pattern repeats after a certain period: days, weeks, months, quarters and years.
3. Cycles (C), cyclical is a data pattern that occurs every few years, usually influenced by long-term economic fluctuations related to the business cycle.
4. Horizontal (H), occurs when data values fluctuate around a fixed, stable or so-called stationary average value.

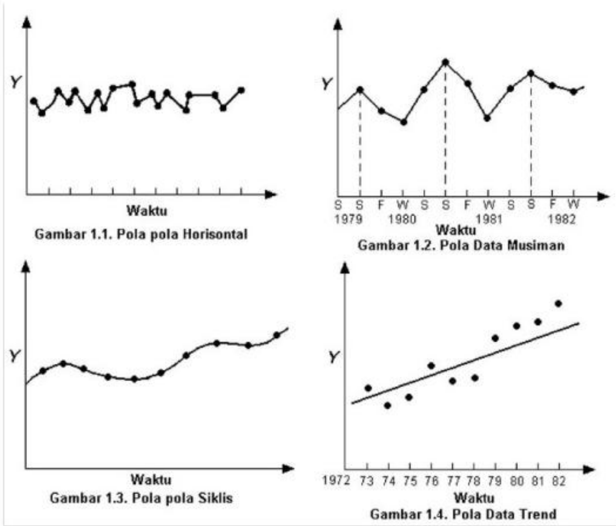

Figure 1: Demand data pattern

The figure above is a graph of the demand data pattern. Based on the four data patterns above, according to Hanke, et al. (2001), several forecasting techniques that can be used are as follows:

1. Trend data forecasting techniques
   Forecasting techniques to consider for trend data patterns are the simple moving average model, Holt linear exponential smoothing, simple linear regression, and the Autoregressive Integrated Moving Average (ARIMA) model.
2. Stationary data forecasting techniques
   Forecasting techniques to consider for stationary data patterns are the naive model, moving average model, simple moving average, linear exponential smoothing, and Autoregressive Integrated Moving Average (ARIMA) model or Box-Jenkins model.
3. Seasonal data forecasting techniques
   Techniques to consider when forecasting seasonal data are the classic decomposition model, X-12 census, exponential smoothing winters, time series multiple regression, and the ARIMA model.
4. Techniques for forecasting cyclical data
   Techniques to consider when forecasting cyclical data consist of classical decomposition, economic indicators, econometric models, multiple regression, and ARIMA models.

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2.3 Autoregressive Integrated Moving Average (ARIMA) Method

The Autoregressive Integrated Moving Average (ARIMA) method or commonly referred to as the Box-Jenkins method is a method that was intensively developed by George Box and Gwilym Jenkins in 1970 (Iriawan, *et al.*, 2006). The ARIMA method is a type of linear model that can represent stationary and non-stationary time series. In generating forecasts, this method does not include independent variables in its formation, this method uses information in the series itself. For example, for monthly sales, the ARIMA model will project historical sales patterns to forecast next month's sales (Hanke, *et al.*, 2001).

The group of time series models included in this method include autoregressive (AR), moving average (MA), autoregressive-moving average (ARMA), and autoregressive integrated moving average (ARIMA):

1. Autoregressive (AR) Model
   This model assumes that the current period data is influenced by the data in the previous period. The autoregressive model with order p is abbreviated as AR (p) or ARIMA (p,0,0) and is formulated as follows (Deviana, et al., 2021):
   $$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t \quad \ldots\ldots\ldots\ldots \ (1)$$
   Where:
   Y_t = data in t-period, where t = 1,2, ... , n
   $Y_{t-1,-2}, \ldots, Y_p$ = past value of the data in question
   ϕ_0 = average constant
   $\phi_1, \phi_2 \ldots \phi_p$ = autoregressive coefficient parameters
   e_t = error
2. Moving Average (MA) Model
   Moving Average (MA) is the value of time series data at time t which is influenced by the error element in the current period and the weighted error element in the past. The moving average model with order q is abbreviated as MA (q) or ARIMA (0,0,q) and is formulated as follows (Deviana, et al., 2021):
   $$Y_t = \theta_0 + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \ \ldots\ldots\ldots\ldots \ (2)$$
   Where:
   Y_t = data in t-period
   e_t = error
   θ_0 = constanta
   $\theta_1, \theta_2, \ldots \theta_q$= Moving Average coefficient parameter
3. Autoregressive-Moving Average (ARMA) Model
   The AR (p) and MA (q) models can be unified into a model known as Autoregressive-Moving Average (ARMA), so it has the assumption that the current period data is influenced by data in the previous period and the error value in the previous period. The ARMA model with p and q sequences is written ARMA (p,q) or ARIMA (p,0,q) which has the following formulation (Deviana, et al., 2021):
   $$Y_t = \phi_0 + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} + \theta_2 e_{t-1} \ldots + \theta_q e_{t-q} \quad \ldots\ldots\ldots\ldots \ (3)$$
   Where:
   Y_t = data in the t-period
   $Y_{t-1}, \ldots, _{-p}$ = past value of the series concerned
   $e_{t-1,\ldots,-q}$ = error
   e_t = forecasting error
   ϕ_0 = constanta
   $\phi_1, \phi_2 \ldots \phi_p$ = Autoregressive coefficient parameters
   $\theta_1, \theta_2, \ldots \theta_q$ = Moving Average coefficient parameters
4. Autoregressive Integrated Moving Average (ARIMA) Model
   The Autoregressive Integrated Moving Average (ARIMA) model involves an AR process, a differentiation process (I), and MA. It is said that non-stationarity data is added to the ARMA process, then the ARIMA (p,d,q) model is obtained as follows (Deviana, et al., 2021):
   $$\phi_p (B) (1-B)^d Y_t = \theta_q (B)_{et} \quad \ldots\ldots\ldots\ldots (4)$$
   Where:
   e_t = error in t-period
   $(1 - B)^d$ = d-order differencing process
   ϕ_p (B) = $(1-\phi_1 B - \phi_2 B^2 - \cdots -)$ which is the backward step operator for AR(p)
   θ_q (B) = $(1 - \theta_1 B - \theta_2 B^2 - \cdots -)$ which is the backward step operator for MA (q)

2.4 Steps of the ARIMA Approach

According to Makridakis, *et al.* (1999) the basis of the ARIMA approach consists of several steps, namely:

1. Time Series Model Identification
   An important first step in choosing a time series model is to consider the type of data pattern, so that the most appropriate method with the pattern can be tested.
2. Parameter Estimation
   In general, the estimation of ARIMA models can be done using several methods such as Moment method, Least Square method, Maximum Likelihood method and so on.
3. Diagnostic Checking
   Diagnostic checking can be divided into two parts, namely parameter significance test and model fit test (including white noise and normal distribution assumption test).
   a. Parameter Significance Test
      In general, suppose θ is a parameter in the ARIMA model and θ is the estimated value of the parameter, and SE (θ) is the standard error of the estimated

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value of θ, then the parameter significance test can be carried out in the following stages:

- Hypothesis:
  $H_0 : \theta = 0$ (Model parameters are not significant)
  $H_1 : \theta \neq 0$ (Model parameters are significant)
- Test Statistic:
  $$t = \frac{\theta}{SE\ (\theta)} \quad \text{……………………. (5)}$$
- Rejection Region:

Reject H_0 if $|t| \geq t_{\frac{a}{2};df=n-np}$, where: np = number of parameters, or you can also use the P-Value, which rejects H_0 if the P-Value $\leq \alpha$.

b. Model Fit Test

This test includes a normal residual assumption test using the Kolmogorov-Smirnov test and a white noise residual test using the Ljung-Box test.

1. Normal Distributed Residual Assumption Test
   Residual normality is tested using the Kolmogorov-Smirnov test.
   - Hypothesis:
     H_0 : Residual data is not normally distributed
     H_1 : Residual data is normally distributed
   - Test Statistic:
     $$D = \text{Sup}_x |F^*(x) - S(X)| \quad \text{……………..(6)}$$
     Where:
     $F^*(x)$= Normal cumulative probability value
     $S(x)$=Empirical cumulative probability value
     D = Kolmogorov-Smirnov test value
   - Rejection Area:
     H_0 is rejected if $D \geq D_{(n;1-\alpha)}$or P-Value $\geq \alpha$
2. White Noise Residual Test
   In summary, the white noise residual test can be written as follows:
   - Hypothesis:
     H_0: residuals do not fulfill white noise
     H_1: distributed residuals fulfill white noise
   - Test Statistic:
     $$Q = n(n+2)\sum_{k=1}^{K}\frac{\rho_k^2}{(n-k)} \quad \text{…………..(7)}$$
   - Rejection Area
     Reject H_0 if $Q \geq X^2_{(\alpha\ ;\ df=K-m)}$where K means K lags and m is the number of parameters estimated in the model, or it can also use the P-Value which rejects H_0 if the P-Value $\geq \alpha$.

4. Selection of the Best Model

In determining the best model from several models that meet these requirements, you can use the Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) criteria, which is a criterion for selecting the best model based on the results of its forecasting residuals, MSE and MAPE can be estimated as in the following equation:

$$MSE = \frac{1}{N}\Sigma^{N}_{t=1}\ a_t^2 \quad \text{……………………………………………(8)}$$

Where:

at = estimated residual on forecasting

N = number of residuals

$$MAPE : \left(\frac{1}{M}\sum_{i=1}^{M}\left|\frac{ei}{Zi+1}\right|\right)100\% \quad \text{…………….(9)}$$

Where:

ei = residual

i = 1,2,...,M

M = number of observations to be predicted (out-sample)

III. RESEARCH METHODS

This research was conducted at PT. XYZ which is located in Denpasar City, Bali. The implementation of the research was carried out by means of a preliminary survey through field studies by coming directly to the company to conduct interviews, direct observations related to company management in the company and literature study. The data collected are general company data, data on products provided, sales data for body scrub products per month for the last five years.

Determination of the forecasting method is done by plotting past sales data using Minitab Software, determining the body scrub product data pattern, then determining the selected ARIMA method or model that can be used to forecast body scrub products at PT. XYZ. Demand forecasting is done by using monthly body scrub product sales data for the last five years which is entered the selected ARIMA model and processed through Minitab Software or can use the following formula (Deviana, *et al.*, 2021):

$$\phi_p\ (B)\ (1-B)^d\ Y_t = \theta_q\ (B)e_t \quad \text{…………...(10)}$$

Where:

e_t = error in t-period

$(1 - B)^d$ = d-order differencing process

ϕ_p (B) = $(1-\phi_1 B - \phi_2 B^2 - \cdots -)$ which is the backward step operator for AR(p)

θ_q (B) = $(1 - \theta_1 B - \theta_2 B^2 - \cdots -)$ which is the backward step operator for MA(q)

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IV. RESULTS AND DISCUSSION

4.1 Body Scrub Sales Data Pattern

Based on observations of PT. XYZ body scrub sales for the last 5 years, from 2019 – 2023, it shows up and down movements. In 2020 it decreased by 27% or 1,114 kg. In 2021, there was a decrease in sales of 21% or 613 kg from 2020. The next year, which is 2022, experienced an increase of 32% and in 2023 by 18%. This is due to the return of industrial activities after the Covid-19 pandemic, making it easier for people to mobilize in carrying out activities outside. This is supported by Sanjaya (2023) entering 2022, pandemic conditions are getting better with the arrival of domestic and foreign tourists to Bali which can help restore the state of the industry after the pandemic, especially in Bali. The results of the PT. XYZ body scrub sales data plot output is presented in Figure 2.

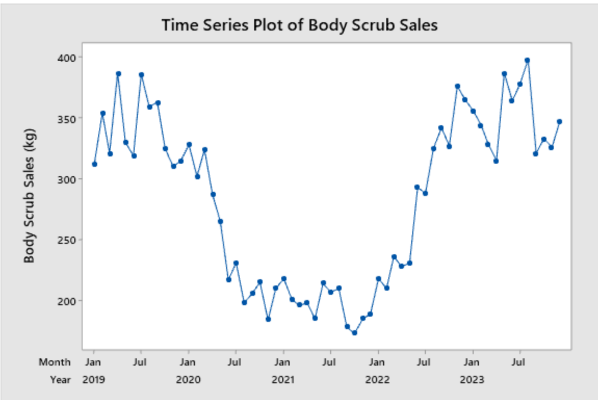

Figure 2: Plot of body scrub sales data of PT. XYZ in 2019 – 2023

4.2 Identification of Body Scrub Sales Data Patterns

The data patterns obtained at this stage are presented in the form of graphs that have been processed using Minitab 19 software to determine the Box-Cox plot of body scrub sales data, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF). These results are used to determine the elements contained in the body scrub sales data so that it can be determined whether the data is stationary or not, has a trend element or not, seasonal elements or not.

4.2.1 Box-Cox Plot of Body Scrub Sales Data

The results of the first Box-Cox plot graph output of body scrub sales data, namely the data is not yet stationary in variance or variety because the rounded value is 0.00 < 1. In stationary data, it is necessary to transform. Based on the rounded value, the transformation formula is InZt, which means that all data for each year of monthly body scrub sales are integrated (Laia, 2019). The transformed data can be seen the rounded value = 1 in Figure 3.

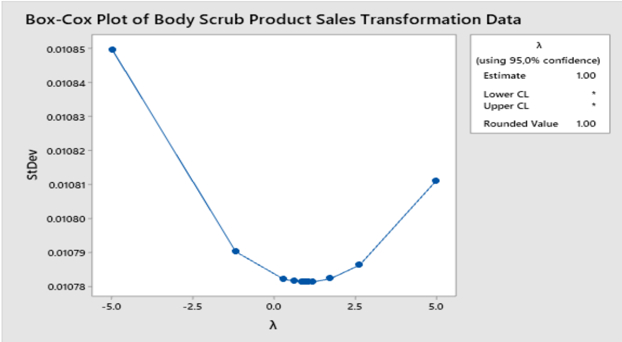

Figure 3: Box-cox plot of body scrub product sales transformation data

4.2.2 Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) Patterns

The first ACF data pattern output results in data that is not yet stationary in average or mean. Therefore, differencing is performed where a new time series is constructed by taking the difference of consecutive values. The results can be seen in Figure 4. and Figure 5.

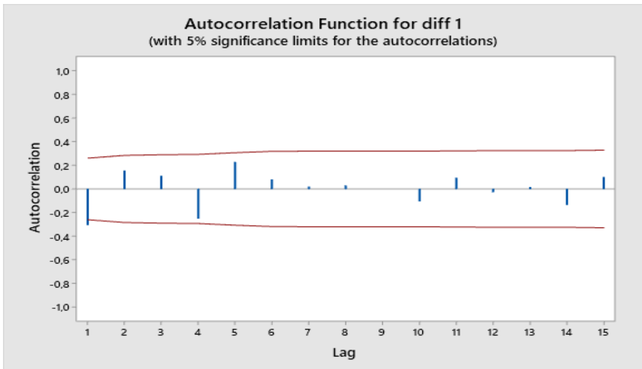

Figure 4: Autocorrelation function (ACF) pattern

Based on Figure 4 the ACF pattern lag 1 crosses the red line which is the lower confidence limit or lower significant limit which means that the ACF pattern of the first differencing results (d = 1) is significant at lag 1. It can be concluded that there is a moving average (MA) pattern and forms an MA (1) model.

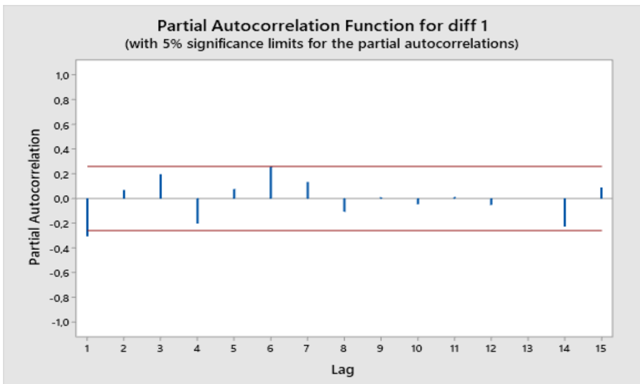

Figure 5: Partial autocorrelation function (PACF) pattern

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Based on Figure 5 the PACF pattern lag 1 passes the lower confidence limit or lower significant limit, which means that the PACF pattern of the first differencing results (d = 1) is significant at lag 1. It can be concluded that there is an autoregressive (AR) pattern and forms an AR (1) model.

Based on the results of the analysis on the ACF pattern, namely the significant graph at lag 1 and the significant PACF at lag 1 as well, the data from the first differencing results concluded that the data is stationary and a temporary model can be determined, namely ARIMA (1,1,1), ARIMA (0,1,1), and ARIMA (1,1,0).

4.3 Diagnostic Checking

4.3.1 Parameter Significance Test

The results of parameter estimation on PT. XYZ body scrub sales data show that the model with all parameters contained is significant is the ARIMA (1,1,0) model and the ARIMA (0,1,1) model which is stated with a P-value ≤ α, namely 0.05. This is supported by Mulyati, *et.al.*, (2019) which states that the estimated parameters are significant if the P-value of the parameter coefficient ≤ α = 5%. This parameter estimate will be used in modeling provided that the residuals meet the assumptions. The results of parameter estimation on PT. XYZ body scrub sales data are presented in Table 1.

Table 1: Estimation and significance test of ARIMA model parameters

Variable	Model	Parameter	Estimation	P-value	Significance
Sales of Body Scrub at PT. XYZ	ARIMA (1,1,1)	ϕ_1	-0.391	0.250	Not Significant
		θ_1	-0.032	0.931	Not Significant
	ARIMA (1,1,0)	ϕ_1	-0.363	0.005	Significant
	ARIMA (0,1,1)	θ_1	0.294	0.023	Significant

4.3.2 Model Fit Test

4.3.2.1 Normal Distributed Residual Assumption Test

The results of the normal distributed residual assumption test show a p-value = 0.150 ≥ 0.05 so that H0 is rejected or it can be said that the residuals in the data have met the assumption of normality. The results of the normal distribution residual assumption test are presented in Table 2.

Table 2: Test results of normal distribution residual assumptions

Variable	Model	P-value	Description
Sales of Body Scrub at PT. XYZ	ARIMA (1,1,0)	0.150	Normal
	ARIMA (0,1,1)	0.150	Normal

4.3.2.2 White Noise Residual Test

The residual white noise test results show the p-value of each parameter ≥ 0.05 so that H0 is rejected or it can be concluded that the model has met the white noise test requirements, which means that the model can be used for forecasting. The white noise residual test results are presented in Table 3.

Table 3: Residual white noise test results

Variable	Model	White Noise		Description
		Up to Lag	P-value	
Sales of Body Scrub at PT. XYZ	ARIMA (1,1,0)	12	0.456	White Noise
		24	0.470	White Noise
		36	0.431	White Noise
		48	0.109	White Noise
	ARIMA (0,1,1)	12	0.379	White Noise
		24	0.489	White Noise
		36	0.480	White Noise
		48	0.169	White Noise

4.4 Best Model Selection

The best model selection is done when all assumptions have been met, namely normal distribution and white noise where the p-value of each parameter ≥ 0.05. The best model selection is performed on variables that have two model estimates presented in Table 4.

Table 4: MSE and MAPE values

Variable	Model	MSE	MAPE
Sales of Body Scrub at PT. XYZ	ARIMA (1,1,0)	745.46	7.40
	ARIMA (0,1,1)	761.28	7.51

Table 4 shows that the MSE and MAPE values in the ARIMA (1,1,0) model are smaller than the ARIMA (0,1,1) model so that the model to be used for forecasting is the

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ARIMA (1,1,0) model. This is supported by Fauzi (2015) research on the best model selection criteria obtained using the MSE and MAPE values. The model that has the smallest MSE and MAPE values is the best model.

4.5 Body Scrub Forecasting Results

Based on the ARIMA model obtained, namely ARIMA (1,1,0), forecasting is carried out with the help of Minitab 19 and the results obtained can be seen in Table 5.Table 5. shows the results of forecasting the demand for body scrubs at PT. XYZ for the next 12 months has increased every month with an average sales of 343.4 kg per month. The highest forecasting results are in December 2024. This may be due to the beauty trend in maintaining healthy skin in the midst of rampant skin damage due to free radicals from direct sun exposure. This is in line with the research of Iskandar, *et.al.*, (2023) who said that body scrub is one of the promising choices as a cosmetic that can remove and reduce dead skin cells.

Table 5: The results of body scrub demand forecasting at PT. XYZ for the period January - December 2024

Period	Forecasting Results (kg)
January	339.8
February	342.8
March	342.1
April	342.8
May	343.0
June	343.3
July	343.6
August	343.9
September	344.3
October	344.6
November	344.9
December	345.2
Average	343.4

The best ARIMA forecasting model obtained, namely ARIMA (1,1,0), is then applied to the January - June 2024 period and compared with the actual data presented in Table 6.

Table 6: Forecasting error of body scrub demand at PT. XYZ for the period January - June 2024

Period	Forecasting Results (kg)	Actual Data (kg)	*Residual Error*	*SE*	*APE (%)*
January	339.8	348	8.2	67.24	2.36
February	342.8	356	13.2	164.24	3.71
March	342.1	334	-8.1	65.61	2.43
April	342.8	346	3.2	10.24	0.92
May	343.0	351	8.0	64.00	2.28
June	343.3	354	10.7	114.49	3.03
Average	342.3	348	5.9	82.64	2.45

The error in forecasting body scrub demand at PT. XYZ using the ARIMA (1,1,0) model is shown in Table 6. This error calculation is done by comparing the forecasting results with the actual data for 6 months, namely January - June 2024. The results of the error in this forecasting are measured using (Mean Square Error) MSE and (Mean Absolute Percentage Error) MAPE with MSE results of 82.64 and MAPE of 2.45%, which means the accuracy of forecasting in 6 months reaches 97.55%.

The accuracy of a forecasting method is the suitability of a method that shows how far the forecasting model can forecast actual data. The value of the forecasting results will always be different from the actual data. The difference between the forecasting value and the actual value is called the error or forecasting error. Therefore, in choosing a forecasting method, it will be determined by the smallest error which can be calculated through MSE or MAPE.

V. CONCLUSION

5.1 Conclusions

Based on the research that has been done, it can be concluded as follows:

1. The best ARIMA model obtained for forecasting body scrub products at PT. XYZ, namely using the ARIMA (1,1,0) model which has an MSE value = 745.46 and MAPE = 7.40%.
2. The results of forecasting the demand for body scrub products at PT. XYZ for the period January 2024 to December 2024 using the ARIMA (1,1,0) model experienced an average demand of 343.4 kg with an increase every month. The error obtained by comparing the forecasting results with the actual sales data for 6 months, namely January - June 2024 of 2.45%, which means that the accuracy of forecasting in 6 months reaches 97.55%.

5.2 Recommendation

Further research is recommended that researchers use different forecasting methods, so that they can compare the results between the ARIMA method and other methods in PT. XYZ body scrub forecasting.

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ISSN (online): 2581-3048
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ISSN (online): 2581-3048
Volume 8, Issue 8, pp 17-25, August-2024
https://doi.org/10.47001/IRJIET/2024.808003

Citation of this Article:

Ni Wayan Mutriani, I Ketut Satriawan, & I Made Mahaputra Wijaya. (2024). Demand Forecasting Analysis of Body Scrub Product at PT. XYZ Using Autoregressive Integrated Moving Average (ARIMA) Method. *International Research Journal of Innovations in Engineering and Technology - IRJIET*, 8(8), 17-25. Article DOI https://doi.org/10.47001/IRJIET/2024.808003

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