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Comparison of ARIMA and Winters Methods on Sales Forecasting of Furniture Companies at UD Podomoro Asahan

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ABSTRACT

Indonesia's economic growth has an impact on the demand for household furniture. Because of the increased demand, customers must wait a long time for the desired furniture. As a result of consumer disappointment, which results in cancellation of requests, sales are not optimized. The goal of this research is to determine the optimal sales development and create a production schedule based on the forecasting results. This study's data are window sales at UD. Podomoro Asahan from July 2016 to July 2021. The data was processed using the ARIMA and Winters methods, and the results were compared. The ARIMA method was used in the study's results, specifically the ARIMA model (0,1,1) with an error value of MPE -0.079772% and MAPE 16.592778%. The Winters method was used in the study, with the smoothing constants =0.546225; =0.259846; =0.116178; and MPE error value -0.397855% and MAPE 39.78471%.

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1. INTRODUCTION

Industry is an economic field whose main activities are the processing of raw materials in factories and distribution. PDK Podomoro Asahan is a Tanjung Balai-based furniture company that was founded in 2010. The number of furniture sales at UD. Podomoro Asahan has increased since the increase in the number of furniture requests in 2015. However, as the level of demand rises, consumers must wait a long time for the furniture they desire. As a result, it frequently disappoints customers and even cancels requests. This increases UD sales, but Podomoro is not optimal. With an increase in sales, UD. Podomoro must forecast sales in order to maintain an optimal level of sales.

The number of furniture sales at UD. Podomoro Asahan shows a trend pattern based on sales data. ARIMA and Winters are the two methods with the lowest error values and are commonly used in forecasting quantitative data. They are also suitable for forecasting trend-patterned data. Every forecasting method will inevitably result in an error. Mean Percentage Error (MPE) and Mean Absolute Pencentage Error (MAPE) are measuring instruments used to calculate forecasting error. If the MPE and MAPE values are small, forecasting is said to be accurate. The forecasting results are used as a reference in creating a Master Production Schedule (MPS), which is used to regulate the production process and the company's resources so that it can meet furniture needs based on the forecasting results.

The formulation of the problem in this study is how to determine the appropriate forecasting to project furniture sales on UD. Podomoro Asahan. The benefit of this research is that it can be used as a reference in producing furniture for the next one year. The results of the study can be used to look at the possible increases and decreases in furniur sales over the next one year.

2. RESEARCH METHODE

This type of research includes observational research, also known as non-experimental quantitative research, because the data is gathered through observations or without the need for treatment. This is classified as applied research because it attempts to apply forecasting methods in the field of industry, specifically the sale of furniture products.

The type of data used in this study is secondary data in the form of monthly furniture sales data. The data used in this study was obtained from data on furniture sales at UD. Podomoro Asahan from July 2016 to June 2021. (there are 60 sales data whichjhereinafter referred to 60 pointsnhistorical data). In this case, the variable nused is the window.

The processing of data that isused in forecasting this, both with the ARIMA method and with then winters method is carried out with the help of application Minitab and Ms. Excel.

1) Explore Data
2) Stage ARIMA Method
   The data that has is processed through five stages that according to with the forecasting ARIMA, namely:
   - Plotting Data
   - Temporary Model
   - Model Parameters
   - Diagnostic Examination
   - Use Model for Forecasting
3) Stages Method Winters
   The data five stages, including:
   - Identifying the Model
   - Determining Initial Value of Parameter
   - Determining Value of Constant Smoothing
   - Calculating Forecast Value Original Data
   - Forecasting Future Periods
4) Comparing Error Value Forecasting
   At this stage, acomparison of error values is carried out using tests MAPE (Mean Absolute Percentage Error) and MPE (Mean Percentage Error) to find out which forecasting.

Prosedur carried out in the implementation of research starts from initial stage formulation problem and goal setting to the final stage conclusions and suggestions. The stages that used in this study can seen in block diagram ***Figure 3.1***.

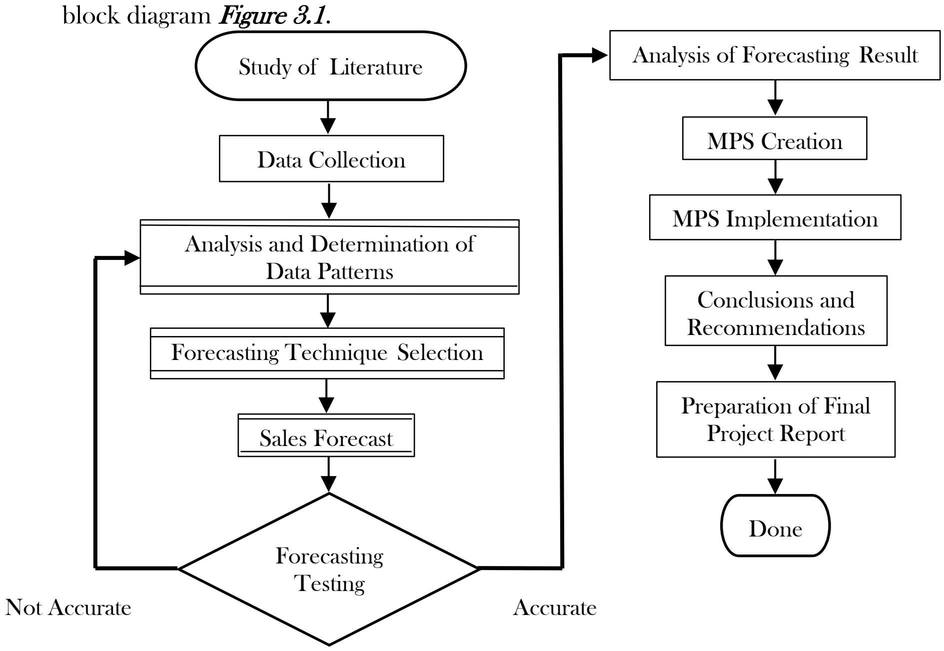

Figure 3.1 Block Diagram of Research Procedure

3. RESULT AND ANALYSIS

Sales data of windows recorded in UD. Podomoro Asahan from July 2016 to June 2021 as shown in the table below:

Table 3.1 Sales Data

Year	Month to month												S
	7	8	9	10	11	12	1	2	3	4	5	6s	
2016-2017	142	146	135	139	133	140	158	147	114	121	168	194	1737
2017-2018	183	187	153	181	174	139	144	112	140	123	154	157	1847
2018-2019	111	178	198	147	209	152	167	119	145	148	194	109	1877
2019-2020	129	167	170	214	175	127	176	131	183	211	145	221	2049
2020-2021	176	158	137	194	207	222	187	168	136	145	197	132	2059

3.1. Forecasting with ARIMA Method

3.1.1. Data Stationaryity Check

Plot trend analysis of window sales data in UD. Podomoro Asahan for the period of July 2016 to June 2021 as shown in the figure below.

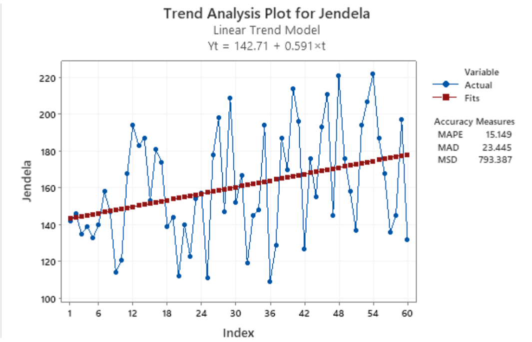

Figure 3.1 Window Analysis Trend Plot

Figure 3.1 shows that the data pattern indicates an uptrend and that the spread of data points is not constant, implying that the window sales data in UD. Podomoro Asahan from July 2016 to June 2021 is not stationary. It can be demonstrated by calculating the average value of Window sales:

$$\bar{Y} = \frac{\sum_{t=1}^{N} Y_t}{N}$$

$$\bar{Y} = \frac{142 + 146 + \cdots + 132}{60}$$

$$\bar{Y} = \frac{9569}{60} = 159{,}4833$$

$$X_{(transformasi)} = X^{\lambda}$$

With

$X_{(transformation)}$ = variable already changed

X = variables to change

l = exponent of the variable to be changed

The data shows no fluctuations around the value of 159.4833, but rather continues to rise and exhibits a trend pattern. The following Box-Cox plot shows window sales data from July 2016 to June 2021.

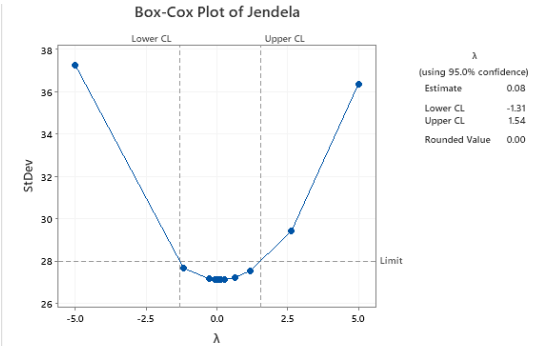

Figure 3.2 Box-Cox Plot of Window

A data is said to be stationary in *variance* if the value of l is worth 1 or passes 1 (Aritonang, 2009). Because the *lambda* value (l) is 0.00, it must first be transformed so that the data becomes stationary in *variance*.

The results of the transformation with the Box-Cox Plot method using the minitab application are shown in Figure 3.3 below.

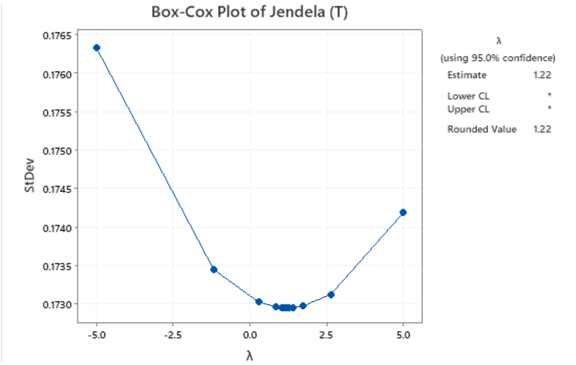

Figure 3.3 Box-Cox Transformation Plot of Windows

In Figure 4.3 shows that the *rounded value* (L) is 1.22 with a 95% confidence interval. Because the acquisition of the *lambda* value (l) has passed 1, it indicates that the data is already stationary in *variance*.

Further more,an examination of the accuracy of the data in *means* is carried out by creating ACF and PACF plots. Performed using the minitab application.

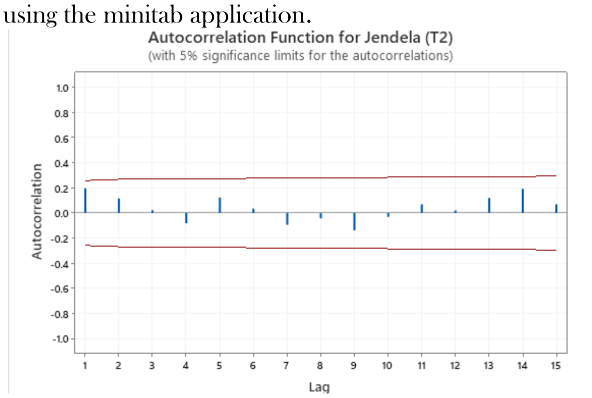

Figure 3.4 Plot ACF of Windows (T2)

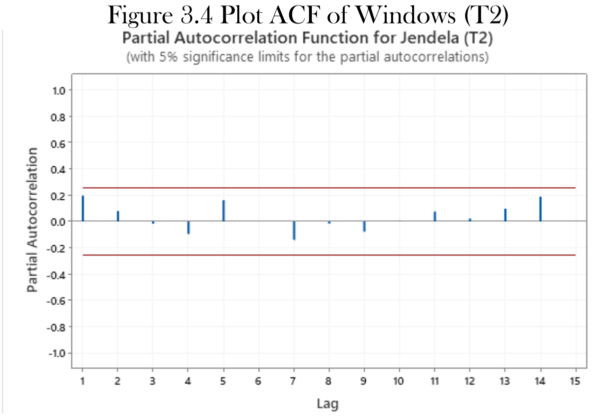

Figure 3.5 Plot PACF Windows (T2)

Analyze the ACF plot by the formula:

$$r_k = \frac{\sum_{t=1}^{n-k}(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2}$$

$$r_1 = \frac{(142 - 159{,}4833)(146 - 159{,}4833) + \cdots + (197 - 159{,}4833)(132 - 159{,}4833)}{(142 - 159{,}4833)^2 + (146 - 159{,}4833)^2 + \cdots + (132 - 159{,}4833)^2} = 0{,}124775$$

$$r_2 = \frac{(142 - 159{,}4833)(135 - 159{,}4833) + \cdots + (145 - 159{,}4833)(132 - 159{,}4833)}{(142 - 159{,}4833)^2 + (146 - 159{,}4833)^2 + \cdots + (132 - 159{,}4833)^2} = 0{,}093712$$

Analyze the PACF plot by the formula:

$$11 = r_1 = 0{,}124775$$

$$22 = \frac{r_2 - r_1^2}{1 - r_1^2} = \frac{0{,}093712 - (0{,}14775)^2}{1 - (0{,}14775)^2} = 0{,}073486$$

Because neither the ACF nor the PACF plots in Figures 4.4 and 4.5 show any cuts off or dies down, the periodic series data of window sales are not stationary in terms of means. To illustrate, look at the Trend Analysis Plot below.

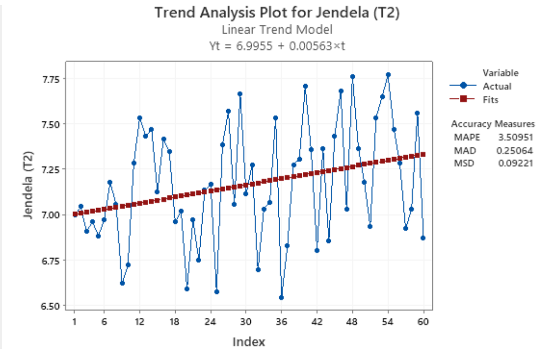

Figure 3.6 Window Analysis Trend Plot (T2)

From the trend analysis plot above, it can be seen that the data still tends to have trend patterns. Therefore, the data must be differentiated at the first order. The results of first-order differentiation are as shown in Figure 3.7 and Figure 3.8.

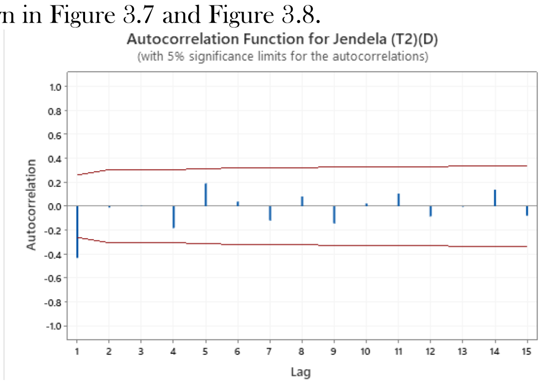

Figure 3.7 Plot ACF Windows (T2)(D)

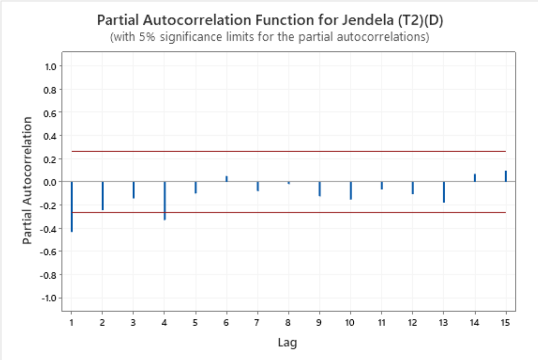

Figure 3.8 Plot PACF Windows (T2)(D)

The ACF plot in Figure 3.7 shows cuts off at *lag* 1, while in Figure 3.8 the PACF plot shows *cuts off* at *lags* 1 and 4. Therefore, the periodic series data of window sales are already stationary after first-order differentiation. Data differentiation can also be calculated manually by using the formula:

$$Y_t' = Y_t - Y_{t-1}$$

For t_1=0

t = 2, 3, 4, ..., 60 obtained:

$$Y_2' = Y_2 - Y_{2-1} = 7{,}04336 - 6{,}99567 = 0{,}047688$$

$$Y_3' = Y_3 - Y_{3-1} = 6{,}90904 - 7{,}04336 = -0{,}134322$$

$$\vdots$$

$$Y_{60}' = Y_{60} - Y_{60-1} = 6{,}87059 - 7{,}56126 = -0{,}690672$$

$$Y_t' = \frac{\sum_{t=2}^{N} Y_t'}{N-1} = \frac{-0{,}12508}{59} = -0{,}00212$$

The data shows fluctuations at -0.00212 as shown in Figure 3.9. With this the data is declared stationary because there are no more trend patterns.

The differencing value is used to determine the value of I (*integrated*) in the ARIMA model (Aritonang, 2009). If:

1) *Differencing* is done 1 time, then the value of I is equal to 1
2) *Differencing* is done 2 times, then the value of I is equal to 2, and so on.

But in general, data that is not yet stationary will become stationary with a process of *differencing* 2 times. If the data is stationary without *any differencing* process, then the value of I is equal to zero, and the *Box-Jenkins* model that can be formed is AR, MA, or ARMA.

Here is Figure 3.9 which is a *trend analysis plot* which shows that the data from the results of the first level of differentiation do not represent any trends.

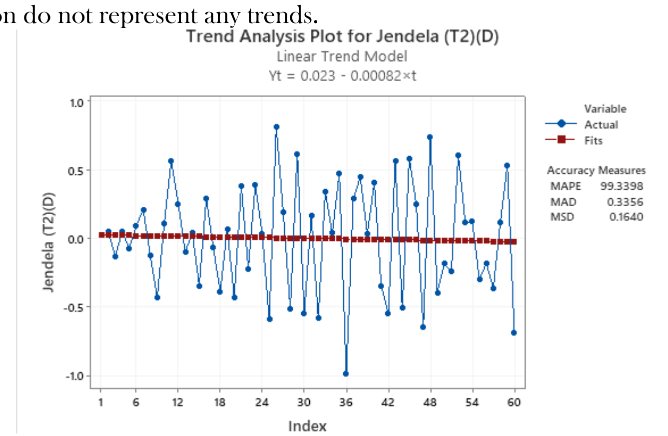

Figure 3.9 Trend Analysis Plot of Windows (T2)(D)

3.1.2. Temporary Model Identification (*Tentative*)

After differentiating on the first order, the window sales data becomes stationary, so the value of d is automatically 1, indicating that the temporary ARIMA model, i.e. (p,1,q). The AR (Autoregressionve) or p and MA (Moving Average or q orders are then determined using ACF and PACF values from stationary periodic series data.

From the ACF plot in Figure 4.8, it can be seen that the *cuts off* are located at *lag* 1, which can form a temporary model with an MA aspect. While from the PACF plot in Figure 4.9, it can be seen that *the cuts off* are located at *lags* 1 and 4, which can form a temporary model with an AR aspect.

Thus, the provisional ARIMA models obtained are: ARIMA (1,1,0); ARIMA (4,1,0); ARIMA (0,1,1); ARIMA (1,1,1); and ARIMA (4,1,1).

3.1.3. Estimation of Model Parameters

1) ARIMA (1,1,0)

The estimated output of the ARIMA model (1,1,0) is as follows.

Table 3.2 Estimated ARIMA Model Parameters (1,1,0)

Final Estimates of Parameters

Type	Coef SE	Coef	T-Value	P-Value
AR 1	-0.455	0.122	-3.74	0.000
Constant	0.0019	0.0481	0.04	0.969

From Table 3.2 it can be seen that:

a) AR value 1

Found *T-value*= -3.74. Since |-3.74|>2.145 then the parameter φ_1 = -0.455 is significant at *a*5%.

b) *Constant* Value

Found *T-Value* = 0.04. Due to |0.04| <2.145 then the *constant* parameter = 0.0019 is insignificant at *a* 5%.

The *constant* value is insignificant at *a* 5%, so the ARIMA equation (1,1,0) is parameter φ_1.

2) ARIMA (4,1,0)

The estimated output of the ARIMA model (4,1,0) is as follows.

Table 3.3 ARIMA Model Parameter Estimation (4,1,0)

Final Estimates of Parameters

Type	Coef SE	Coef	T-Value	P-Value
AR 1	-0.644	0.129	-4.99	0.000
AR 2	-0.431	0.149	-2.89	0.006
AR 3	-0.342	0.150	-2.28	0.027
AR 4	-0.360	0.132	-2.72	0.009
Constant	0.0070	0.0445	0.16	0.876

From Table 3.3 it can be seen that the *constant* value is insignificant at *a* 5%, so the ARIMA equation (4,1,0) is *the* parameters φ_1, $\varphi_2 \varphi_3$, and φ_4.

3) ARIMA (0,1,1)

The estimated output of the ARIMA model (0,1,1) is as follows.

Table 3.4 ARIMA Model Parameter Estimation (0,1,1)

Final Estimates of Parameters

Type	Coef SE	Coef	T-Value	P-Value
MA 1	-0.9704	0.0851	11.40	0.000
Constant	0.00562	0.00370	1.52	0.134

From Table 3.4 it can be seen that the *constant* value is insignificant at *a* 5%, so the ARIMA equation (0,1,1) is parameter q_1.

4) ARIMA (1,1,1)

ARIMA model estimation output (1,1,1) as follows.

Table 3.5 ARIMA Model Parameter Estimation (1,1,1)

Final Estimates of Parameters

Type	Coef SE	Coef	T-Value	P-Value
AR 1	0.100	0.150	0.67	0.508
MA 1	0.967	0.102	9.50	0.000
Constant	0.00508	0.00378	1.34	0.184

From Table 3.5 it can be seen that the AR value of 1and *the constant* value is insignificant at *a* 5%, so the ARIMA equation (1,1,1) is parameter q_1.

5) ARIMA (4,1,1)

The estimated output of the ARIMA model (4,1,1) is as follows.

Table 3.6 Estimated ARIMA Model Parameters (4,1,1)

Final Estimates of Parameters

Type	Coef SE	Coef	T-Value	P-Value

AR 1	0.105	0.144	0.73	0.468
AR 2	0.044	0.142	0.31	0.757
AR 3	-0.081	0.144	-0.56	0.577
AR 4	-0.166	0.151	-1.10	0.277
MA 1	1.0091	0.0638	15.82	0.000
Constant	0.00564	0.00189	2.99	0.004

From Table 3.6 it can be seen that the values of AR 1, AR 2, AR 3, and AR 4are not significant at *a* 5%, so the ARIMA equation (4,1,1) is the parameter $q_1$and *the constant* parameter.

3.1.4. Diagnostic Examination

At this stage, it is divided into 3 stages, namely: test the significance of the model parameters, test white *noise*on residual and test normality.

1) ARIMA Model (1,1,0)

a) Parameter Significance Test

Table 3.7 Estimated parameters of the ARIMA model (1,1,0) without constants

Final Estimates of Parameters

Type	Coef SE	Coef	T-Value	P-Value
AR 1	-0.455	0.121	-3.77	0.000

Differencing: 1 regular difference

Number of observations: Original series 60, after differencing 59

Residual Sums of Squares

DF	SS	MS 58	7.777190.134090

Back forecasts excluded

From Table 3.7 it can be seen that the P-Value of the AR parameter 1 = 0.000 which means that the *P-Value*<*a*(0.05) so *that* H_0 is accepted, signifying the parameter has been significant against *the* model.

b) *White Noise*

Table 3.8 ARIMA Ljung-Box Modifications (1,1,0)

Modified Box-Pierce (Ljung-Box) Chi-Sqaure Statistic

Lag	12	24	36	48
Chi-Sqaure	13.62	23.99	33.44	43.80
DF	11	23	35	47
P-Value	0.255	0.405	0.544	0.606

From Table 3.8 it can be seen that *P-Value*>*a*(0,05) so H 0 is accepted, indicating residual *white noise* in ARIMA (1,1,0).

c) Normality Test

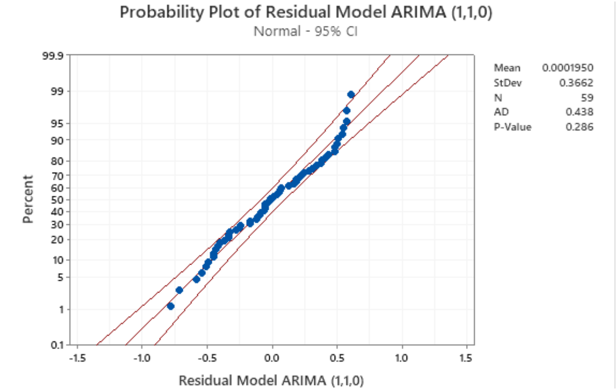

Figure 3.10 ARIMA Residual Probability Plot (1,1,0)

From Figure 3.10 it can be seen that the P-Value on the ARIMA residual probability plot (1,1,0) = 0.286 which means that *P-Value*>a(0.05) signifies *a* normally distributed residual.

Similar was done to ARIMA (4,1,0); ARIMA (0,1,1); ARIMA (1,1,1); and ARIMA (4,1,1) so summarized in Table 3.9.

Table 3.9 Summary of Diagnostic Examination Results

Type	Significant	White Noise	Normality	Conclusion
ARIMA (1,1,0)	Significant to the model	Residual *white noise*	Normally distributed residuals	All fulfilled
ARIMA (4,1,0)	Significant to the model	Residual *white noise*	Normally distributed residuals	All fulfilled
ARIMA (0,1,1)	Significant to the model	Residual *white noise*	Normally distributed residuals	All fulfilled
ARIMA (1,1,1)	Insignificant to the model	Residual *white noise*	Normally distributed residuals	Unfulfilled
ARIMA (4,1,1)	Insignificant to the model	Residual *white noise*	Normally distributed residuals	Unfulfilled

The following is a comparison of the *Mean Squared Error* (MSE) summarized from the results of the model parameter significance test *output* with the Minitab application to get the best model.

Table 3.10 Comparison of MSE Values of Each Model

Type	MSE Value	Conclusion
ARIMA (1,1,0)	0,134090	
ARIMA (4,1,0)	0,114800	
ARIMA (0,1,1)	0,104522	Smallest MSE vlue
ARIMA (1,1,1)	0,104000	Did not pass
ARIMA (4,1,1)	0,131852	diagnostic test

According to the summary of diagnostic examination results in Table 3.9, the ARIMA models that pass the three tests are: ARIMA (1,1,0); ARIMA (4,1,0); and ARIMA (5,1,0). (0,1,1). Meanwhile, ARIMA (0,1,1) has the lowest MSE value of the three ARIMA models that pass the three tests, as shown in Table 3.10. In other words, the ARIMA model is best for forecasting UD window sales. Podomoro Asahan is a model for ARIMA (0,1,1).

3.1.5. Best Models for Forecasting

Table 3.11 Window Sales Forecasting Results with ARIMA (0,1,1)

Year	Month	Forecast Result	Lower Confidence Level (LCL)	Upper Confidence Level (UCL)
2021	July	176,809	119,541	234,077
	August	177,366	120,070	234,662
	September	177,923	120,599	235,247
	October	178,480	121,129	235,832
	November	179,037	121,658	236,417
	December	179,595	122,188	237,001
2022	January	180,152	122,717	237,586
	February	180,709	123,247	238,171
	March	181,266	123,776	238,756
	April	181,823	124,306	239,341
	May	182,380	124,835	239,925
	June	182,937	125,365	240,510

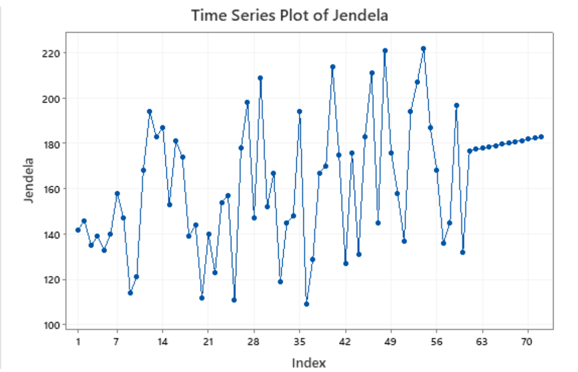

Figure 3.11 Plot of Window Sales Original Data and Forecasting Results

The forecasting results in Table 3.11 are evaluated to determine the average error in percent using Mean Percentage Error (MPE) and *Mean Absolute Percentage Error* (MAPE). The data used to get MPE and MAPE is the last 1 year data, namely July 2020-June 2021.

Table 3.12 Evaluation of Window Sales Forecasting Results with ARIMA Model (0,1,1)

Month	Forecast Result	Lower Confidence Level (LCL)	Upper Confidence Level (UCL)	Original Data 2020-2021	PE (%)	APE (%)
7	176,809	119,541	234,077	176	-0,00459659	0,459659
8	177,366	120,070	234,662	158	-0,12256962	12,256962
9	177,923	120,599	235,247	137	-0,29870803	29,870803
10	178,480	121,129	235,832	194	0,8000000	8,000000
11	179,037	121,658	236,417	207	0,13508696	13,508696
12	179,595	122,188	237,001	222	0,19101351	19,101351
1	180,152	122,717	237,586	187	0,03662032	3,662032
2	180,709	123,247	238,171	168	-0,07564881	7,564881
3	181,266	123,776	238,756	136	-0,33283824	33,283824
4	181,823	124,306	239,341	145	-0,25395172	25,395172
5	182,380	124,835	239,925	197	0,07421320	7,421320
6	182,937	125,365	240,510	132	-0,38588636	38,588636
MPE					-0,07977212	
MAPE						16,592778

From the evaluation table of forecasting results with ARIMA (0,1,1) above, it can be seen that the MPE value is -0.07977212% and the MAPE value is 16.592778%.

3.2. Forecasting by the Winters Method

3.2.1. Model Identification

By looking at Figure 4.1, it is known that window sales data in July 2016 – June 2021 has a trend pattern that tends to increase and has a seasonal pattern. From the pattern of ups and downs in sales data, it is concluded that the seasonal effect is seasonal additives.

3.2.2. Determine the Initial Estimated Value

The level value is obtained by calculating the average value of the sales results of the first 1 year. The trend value in the first 1 year is still zero. Meanwhile, the *seasonal* value is obtained from the results of reducing seat sales data by level. From the calculation, the level, trend, and *seasonal* values below.

$$L_s = \frac{1}{12}(142+146+135+139+133+140+158+147+114+121+168+194) = 144{,}75$$

$$T_1, T_2, \cdots, T_{12} = 0$$

$$S_1 = Y_1 - L_s = 142 - 144{,}75 = -2{,}75$$

$$S_2 = Y_2 - L_s = 146 - 144{,}75 = 1{,}25$$

$$S_3 = Y_3 - L_s = 135 - 144{,}75 = -9{,}75$$

$$S_4 = Y_4 - L_s = 139 - 144{,}75 = -5{,}75$$

$$S_5 = Y_5 - L_s = 133 - 144{,}75 = -11{,}75$$

$$S_6 = Y_6 - L_s = 140 - 144{,}75 = -4{,}75$$
$$S_7 = Y_7 - L_s = 158 - 144{,}75 = 13{,}25$$
$$S_8 = Y_8 - L_s = 147 - 144{,}75 = 2{,}25$$
$$S_9 = Y_9 - L_s = 114 - 144{,}75 = -30{,}75$$
$$S_{10} = Y_{10} - L_s = 121 - 144{,}75 = -23{,}75$$

3.2.3. Calculating the Forecast Value of the Original Data

$$S_{11} = Y_{11} - L_s = 168 - 144{,}75 = 23{,}25$$
$$S_{12} = Y_{12} - L_s = 194 - 144{,}75 = 49{,}25$$
$$L_{13} = Y_{13} - S_1 = 183 - (-2{,}75) = 185{,}75$$
$$T_{13} = L_{13} - Y_{12} - S_{12} = 185{,}75 - 194 - 49{,}25 = -57{,}5$$
$$L_t = \alpha(Y_t - S_{t-m}) + (1-\alpha)(L_{t-1} + T_{t-1})$$
$$L_{14} = 0{,}1(187 - 1{,}25) + (1 - 0{,}1)(185{,}75 + (-57{,}5)) = 134$$
$$L_{15} = 0{,}1(153 - (-9{,}75)) + (1 - 0{,}1)(134 + (-56{,}925)) = 85{,}6425$$
$$\vdots$$
$$L_{60} = 0{,}1(132 - 84{,}17144) + (1 - 0{,}1)(166{,}9291 + 5{,}367084) = 159{,}8494$$

3.2.4. Defining the Smoothing Constant

The value of the smoothing constant is determined by the rule of each value smaller than 1 and greater than 0. At this stage, it is done using the *solver* in Ms. Excel. Based on the *solver* results, *alpha*, *beta* and *gamma* values were obtained as well as low MPE and MAPE values as shown in the table below.

Table 3.13 Window Forecasting Smoothing Constants

Alpha	Beta	Gamma	MPE (%)	MAPE (%)
0,546224906	0,259845963	0,116178246	0,012762869	25,14094169

3.2.5. Forecasting the Upcoming Period

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$
$$T_{14} = 0{,}1(134 - 185{,}75) + (1 - 0{,}1)(-57{,}5) = -56{,}925$$
$$T_{15} = 0{,}1(85{,}6425 - 134) + (1 - 0{,}1)(-56{,}925) = -56{,}0683$$
$$\vdots$$
$$T_{60} = 0{,}1(159{,}8494 - 166{,}9291) + (1 - 0{,}1)(5{,}367048) = 4{,}122371$$
$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-m}$$
$$S_{13} = 0{,}1(183 - 185{,}75) + (1 - 0{,}1)(-2{,}75) = -2{,}75$$
$$S_{14} = 0{,}1(187 - 134) + (1 - 0{,}1)(1{,}25) = 6{,}425$$
$$\vdots$$
$$S_{60} = 0{,}1(132 - 159{,}8494) + (1 - 0{,}1)(84{,}17144) = 72{,}96935$$
$$F_{t+1} = L_t + T_t + S_{t-m+1}$$
$$F_{14} = 185{,}75 + (-57{,}5) + 1{,}25 = 129{,}5$$
$$F_{15} = 134 + (-56{,}925) + (-9{,}75) = 67{,}325$$
$$\vdots$$
$$F_{60} = 166{,}9291 + 5{,}367048 + 84{,}17144 = 256{,}4676$$

$$MPE = \frac{1}{n}\sum_{t=1}^{n}\frac{Y_t - \hat{Y}_t}{Y_t}$$

$$MPE = \frac{1}{59}\left[\left(\frac{187-129{,}5}{187}\right)+\left(\frac{153-67{,}325}{153}\right)+\cdots+\left(\frac{132-256{,}4676}{132}\right)\right] = 0{,}84823$$

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

$$MAPE = \frac{1}{59}\left[\begin{array}{l}\left(\frac{|187-19{,}5|}{187}\times 100\%\right)+\left(\frac{|153-67{,}325|}{153}\times 100\%\right)+\\ \cdots+\left(\frac{|132-256{,}4676|}{132}\times 100\%\right)\end{array}\right] = 97{,}99761\%$$

Then optimization is carried out with solver on Ms. Excel. This section is not explained in the study because this section only focuses on the *winters* method. Next is sought forecasting for the next 12 months.

$$F_{t+k} = L_t + k\times T_t + S_{t-M+k}$$

$$F_{61} = 159{,}8494 + 1\times 4{,}122371 + 38{,}34449 = 202{,}3163$$

$$F_{62} = 159{,}8494 + 2\times 4{,}122371 + 50.04618 = 218{,}1403$$

$$\vdots$$

$$F_{72} = 159{,}8494 + 12\times 4{,}122371 + 72{,}96935 = 282{,}2872$$

Table 3.14 Window Forecasting Results Accuracy Test

Month	Forecast Result	Original Data 2020-2021	PE (%)	APE (%)
7	202,3163	176	-0,14952	14,95243
8	218,1403	158	-0,38064	38,06351
9	213,5139	137	-0,5585	55,84958
10	227,9104	194	-0,1748	17,4796
11	229,6985	207	-0,10965	10,96546
12	228,3288	222	-0,02851	2,850822
1	246,6835	187	-0,31916	31,9163
2	231,743	168	-0,37942	37,94225
3	218,4996	136	-0,60661	60,66149
4	227,979	145	-0,57227	57,22686
5	267,2388	197	-0,35654	35,65422
6	282,2872	132	-1,13854	113,854
	MPE			-0,39785
	MAPE			39,78471

From the evaluation table of forecasting results with *winters* above, it can be seen that the MPE value is -0.39785% and the MAPE value is 39.78471,,%

Table 3.15 Comparison of Furniture Sales Forecasting Results with ARIMA and *Winters* method

Month to month	ARIMA	*Winters*
1	177	202
2	177	218
3	178	214
4	178	228
5	179	230
6	180	228
7	180	247

8	181	232
9	181	218
10	182	228
11	182	267
12	183	282
.MPE	-0,079772	-0,39785
MAPE	16,592778	39,78471

4. CONCLUSIOON

After forecasting with the ARIMA method and the Winters smoothing method, it is possible to conclude that the ARIMA method is a suitable forecasting method for sales forecasting. ARIMA models are appropriate for forecasting window sales (0,1,1) Forecasting projections for the sale of windows using the ARIMA method tend to rise from the beginning to the end of the period.

Because the ARIMA method has a lower error value than the Winters method, the development of the Master Production Schedule (MPS) follows the forecasting results.

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