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Analysis of Forecasting Demand for Wheel Loader Unit Rental Using the Arima Method to Determine Safety Stock Inventory and Service Level at PT Petrokopindo Cipta Selaras

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Abstract: *PT XYZ is a company engaged in the rental of heavy equipment such as excavators, forklifts, bulldozers, and Wheel Loaders. The problem faced is unpreparedness in dealing with fluctuations in demand, so there is often a backlog or excess inventory. This research aims to improve the accuracy of demand forecasting and determine safety stocks to anticipate these uncertainties. The research was conducted using historical data on Wheel Loader rental requests from September to November 2024. The data was processed using the ARIMA (Autoregressive Integrated Moving Average) method through several stages, namely stationarity testing, identification of ACF and PACF, model estimation, parameter testing, white noise test, and selection of the best model. The resulting significant model was ARIMA (3,1,1), with a MAPE error value of 21% (79% accuracy), an increase of 9% compared to the previous method with an error of 30%. The results of the calculation of safety stock to deal with fluctuations in demand at various service levels show that the need for 2,688 units at the 90% level, increased to 3,444 units at the 95% level, and reached 3,900 units at the 97% level. This study shows that the ARIMA method is able to improve the accuracy of forecasting and provide a better basis for determining safety stock in managing fluctuations in heavy equipment rental demand.*

Keyword: *ARIMA, Forecast, Safety Stock, Service Level, White Noise*

INTRODUCTION

PT XYZ is a company engaged in the rental and supply of heavy equipment. The company provides various types of heavy equipment for the needs of industry, construction, and other projects. In addition, PT XYZ also offers heavy equipment rental services with a wide selection of units, such as *excavators, forklifts, bulldozers, Wheel Loaders* and others. Currently, the problem faced is a lack of preparation in dealing with uncertain demand fluctuations from customers. This causes companies to often face *backlog* problems, namely the inability to meet rental demand, as well as a large amount of unused Wheel Loader inventory. Therefore, steps and strategies are needed to anticipate these unexpected events.

Forecasting is the process of predicting or forecasting future conditions or events based on the analysis of historical data and existing trends. The goal is not only to be as accurate as possible, but also to know the difference between the plan and the actual data that can help improve which engineering forecasting is better (Ivanov et al., 2021). ARIMA (*Autoregressive Integrated Moving average*), is a forecasting model that predicts the historical value of various variables to ensure correlations or statistical relationships between these variables (Rahma & Dahda, 2024). The ARIMA model predicts future projections. The ARIMA model is a viable alternative that gives satisfactory results in terms of predictive kin (Qodri et al., 2024). In forecasting, the ARIMA model ignores independent variables (because it relies on Historical data) (Saumi & Amalia, 2020). ARIMA generates precise short-period forecasts by using old and current data from dependent variables to generate short-period forecasts with small error values (Dadhich et al., 2021). If the model *Time Series* interdependent (*dependent*), then the ARIMA model is still suitable for use (Rahma & Dahda, 2024).

The ARIMA model consists of three main components: *Autoregressive* (AR), Moving Average (MA), and Integrated (I). These three elements can be modified to build a new forecasting model. ARIMA (p,d,q) is a common form of this model, where p indicates the *order of the Autoregressive* (AR) model, d indicates the order of *differencing*, and q indicates the order of the Moving Average (MA) model. This research was conducted to forecast future rental demand, in order to anticipate the uncertainty of demand. To reduce the risk of forecasting errors, the amount of *Safety Stock* is specified as a backup stock so that the company can meet unexpected Wheel Loader demands.

Problem Formulation

1. How do I choose the most appropriate ARIMA model to forecast demand using stationarity testing, ACF and PACF analysis, and white noise testing?
2. How do I calculate the optimal amount of Safety Stock at different Service Levels to cope with fluctuations in demand and avoid understocking or overstocking?
3. How do I find out the accuracy of forecasting Wheel Loader requests using the ARIMA model?

Purpose

1. To determine the most appropriate ARIMA model in forecasting demand, through stationarity testing, ACF and PACF analysis, and white noise tests on various ARIMA models formed.
2. To determine the number of Safety Stock Wheel Loaders required at various Service Levels to deal with fluctuations in demand and prevent unavailability.
3. To determine the accuracy of the Arima Model forecasting through MAPE (Mean Absolute Percentage Error) Values

METHOD

Types and Data Sources

The data used is data collected from the company's data reports. The Company provides historical demand data for Wheel *Loader* Units from September 2024 to November 2024 as one of the secondary data sets. Below are the steps using the ARIMA sales forecasting model, which was carried out (Wulandari et al., 2021) using *Minitab* software.

Research Object

The object of research is the main element that is the focus of a research, namely a certain thing, phenomenon, or entity that is analyzed. Research objectives can be individual, group, organization, process, system, or product, depending on the field of study and research objectives. Wheel Loader heavy equipment rental request data

Type of Research

The type of research used in this activity is quantitative research with descriptive and analytical approaches. Quantitative research is used to analyze numerical data related to heavy equipment rental demand patterns using statistical models such as ARIMA. The Descriptive Approach aims to describe the operational conditions of heavy equipment rental at PT XYZ. The analytical approach is carried out through statistical data processing to identify optimal solutions related to safety *stock* management and service levels.

Research Data Sources

The data sources in this study consist of primary data and secondary data:

1. Primary data, is data obtained directly from original sources through interaction or direct observation of the research object. In this study, primary data was obtained through direct observation in the field and interviews. The data taken is as follows:
   a) Unit Rental Daily Report Data
   b) Unit Inventory Data
   c) Unit Rental History Data
2. Secondary, is data obtained from pre-existing documents or sources. The data obtained is as follows:
   a) Company Profile
   b) Company History
   c) Company Vision and Mission

Defining the Model

The following are the steps to determine the model:

1. Plotting the monthly data (t) as the x-axis on the Wheel Loader Unit request as the y-axis. Determine whether the variance and *Mean* data are stationary.
   a) Determining the station by the Box-Cox method. In terms of variance, the data is said to be stationary if the rounding value is 1.00. On the other hand, Box-Cox transforms can be applied if the data is not stationary.
   b) Use the Autocorelation Function (ACF) graph and the data plot to determine if the data is stationary. Differencing should be done on the original data if it is still not stationary in the Mean.
2. Select a temporary ARIMA model with parameters (p,d,q) by looking at the ACF and PACF plots. If on the chart the ACF gradually drops past the significance limit, it shows an MA with a lag (q). In the PACF graph, if it goes down gradually, then the process of passing the significance shows AR with lag (p).
3. Results of the ARIMA Model Coefficient (p, d, q).
   The model can be obtained through parameter calculation and then continued with Diagnostic checks

Model Fit Test and Parameter Significance Test

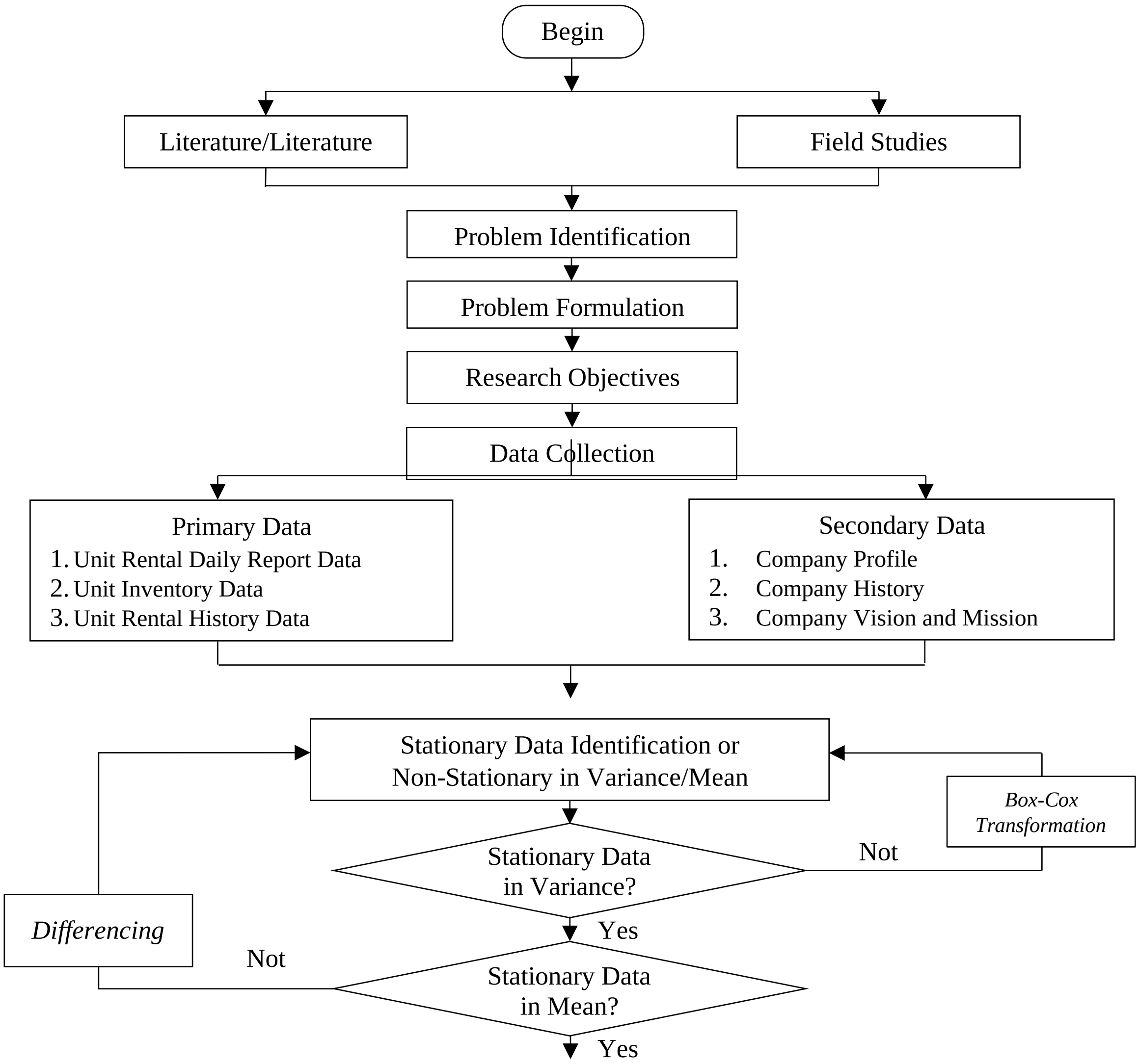
This test is a two-part diagnostic check:

1. Parameter Signification Test
   The hypothesis model used in the test is intended to assess the level of significance of parameters in a model as follows:
   H0 : Insignificant parameters
   H1 : Significant parameters
   H0 is rejected if the value of $|tcal|$ > T table, or H0 is not accepted if the value $p < \alpha(0.05)$.
2. White Noise Test
   This test aims to determine whether the residual is random, specifically by comparing *the Chi-Square* Distribution and *the Ljung-Box* value.
   H0 : residual meets condition *white noise* ($\rho 1 = \rho_2$,,,= $\rho_k = 0$)

H1 : residual no *white noise* ($\rho_j \neq 0$)
Reject H0 if the p-value is <α (0.05). If H0 is rejected or not accepted, then the ARIMA model (p,d,q) cannot be used.

Data Processing Stage

The data processing method used in this study is a *descriptive quantitative* method. The data processing process will be further elaborated in the flowchart below



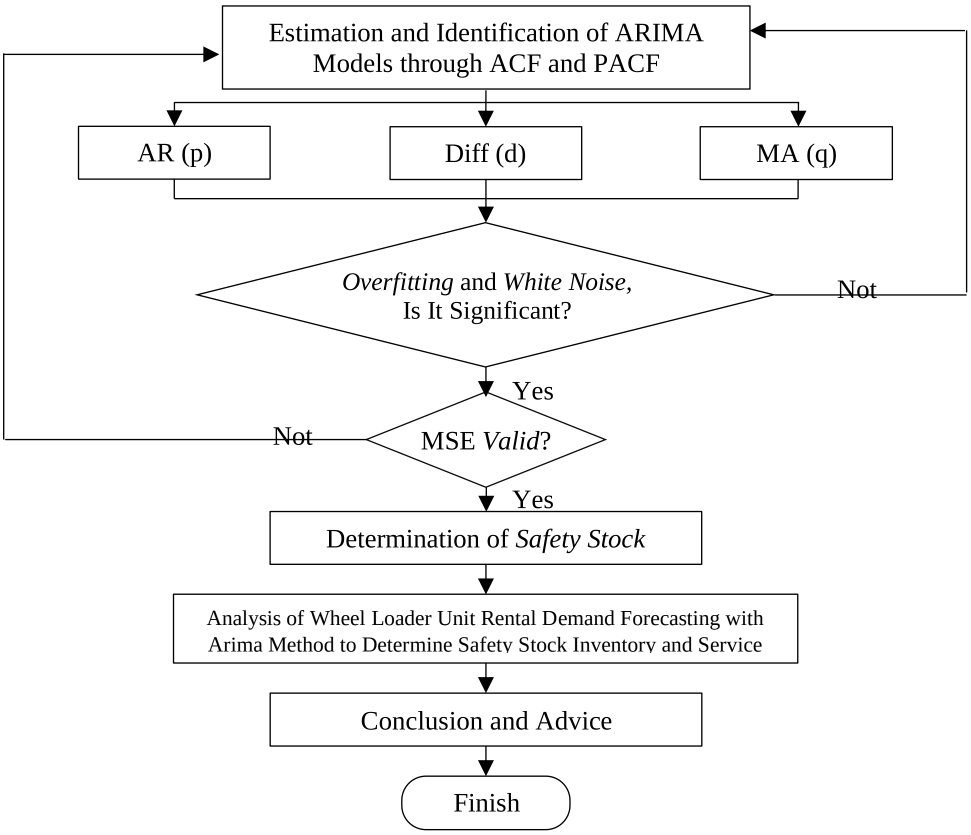


Figure 1. Data Processing Procedure

RESULTS AND DISCUSSION

Data Collection

Based on the results of interviews and data analysis, Wheel Loader was chosen as a representation to describe the pattern of heavy equipment rental in the company because it has a higher rental frequency compared to other units, flexibility of use in various areas, and more complete supporting data.

Table 1. Unit Rental Data

It	Date	Used Units	It	Date	Used Units
1	15/08/2024	5	1	01/10/2024	6
2	16/08/2024	3	2	02/10/2024	9
3	17/08/2024	5	3	03/10/2024	5
4	18/08/2024	6	4	04/10/2024	8
5	19/08/2024	7	5	05/10/2024	7
6	20/08/2024	7	6	06/10/2024	8
7	21/08/2024	8	7	07/10/2024	9
8	22/08/2024	2	8	08/10/2024	9
9	23/08/2024	3	9	09/10/2024	6
10	24/08/2024	3	10	10/10/2024	5
11	25/08/2024	3	11	11/10/2024	5
12	26/08/2024	5	12	12/10/2024	5
13	27/08/2024	3	13	13/10/2024	9
14	28/08/2024	4	14	14/10/2024	8
15	29/08/2024	6	15	15/10/2024	8
16	30/08/2024	8	16	16/10/2024	9
17	31/08/2024	4	17	17/10/2024	8
18	01/09/2024	2	18	18/10/2024	10

19	02/09/2024	8	19	19/10/2024	9
20	03/09/2024	9	20	20/10/2024	10
21	04/09/2024	6	21	21/10/2024	8
22	05/09/2024	4	22	22/10/2024	8
23	06/09/2024	4	23	23/10/2024	5
24	07/09/2024	4	24	24/10/2024	7
25	08/09/2024	4	25	25/10/2024	9
26	09/09/2024	10	26	26/10/2024	9
27	10/09/2024	6	27	27/10/2024	4
28	11/09/2024	8	28	28/10/2024	5
29	12/09/2024	5	29	29/10/2024	5
30	13/09/2024	4	30	30/10/2024	9
31	14/09/2024	4	31	31/10/2024	9
32	15/09/2024	8	32	01/11/2024	10
33	16/09/2024	9	33	02/11/2024	11
34	17/09/2024	6	34	03/11/2024	10
35	18/09/2024	6	35	04/11/2024	10
36	19/09/2024	9	36	05/11/2024	8
37	20/09/2024	4	37	06/11/2024	9
38	21/09/2024	4	38	07/11/2024	7
39	22/09/2024	4	39	08/11/2024	6
40	23/09/2024	5	40	09/11/2024	7
41	24/09/2024	9	41	10/11/2024	8
42	25/09/2024	9	42	11/11/2024	11
43	26/09/2024	9	43	12/11/2024	8
44	27/09/2024	6	44	13/11/2024	10
45	28/09/2024	6	45	14/11/2024	11
46	29/09/2024	6	46	15/11/2024	10
47	30/09/2024	5	47	16/11/2024	11
Average2			7		
Total			643		

Data Processing

1. Plot Creation *Time series* Unit Rental Data

   The first step in forecasting in this research is to create a *time series plot* to see the pattern of Unit Rental Data. For data plots, minitab software is used . After plotting using *Minitab* software, the *output* obtained is as shown in Figure 2. which shows that the data is not stationary because it shows a trend that continues to increase, so it must be stationed. To further ensure that the data is not stationary, it is necessary to autocorrelate and partial autocorrelation.

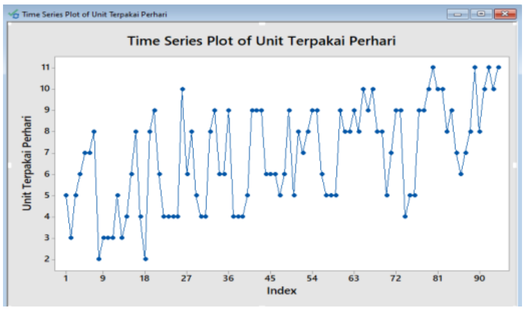


Figure 2. Graphs *Plotting* Data

2. Data station identification and examination
   a) Test of Data Susceptibility in Variance (Box Test – cox)

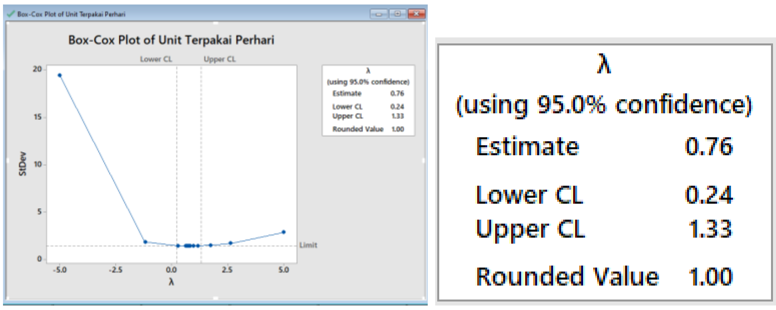


Figure 3. Test box – cox Original Data

Based on *the Box-Cox test*, *the* plot data has been stationary for variance because the rounded *value* has shown a figure of 1.00. Furthermore, the stationarity of the data against the average value will be seen. When there is no visible trend on the time series plot and the Autocorrelation Function (ACF) plot of the data is not decreasing gradually, then the stationery requirement is met. The plot of ACF is shown below.

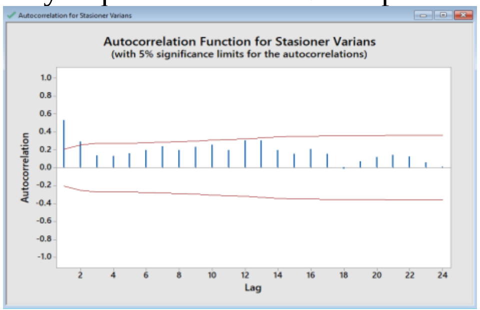


Figure 4. ***Autocorrelation Function***

The ACF (*Autocorrelation Function*) graph shows that there is an outgoing lag in lag 1 and lag 2 so that it shows that the data is not stationary to the average, so a Level 1 defensive is needed

b) Data Accuracy Test in Average (Differencing Test)

Differencing Test Level 1

The data that is done defensively is Stationary Variance data. Here are

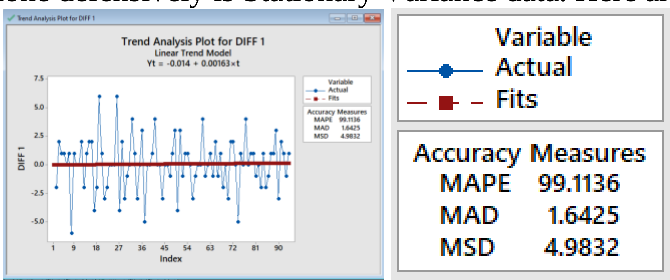


Figure 5. Results Graph *Differencing*

The image above shows that there is no trend on the chart, the trendline is already horizontal which indicates that the data has been stationary in the mean so that the data can be used to create an ARIMA model. The next step in the process of forming a model using the ACF and PACF pattern patterns is as follows:

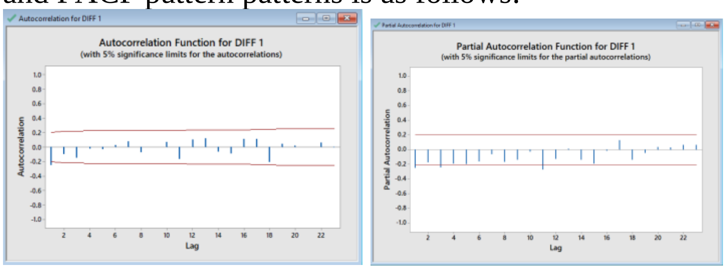


Figure 6. ACF and PACF charts

The ACF chart is already stationary as it shows rapid *decay* towards zero after a few lags. And there are no systematic patterns or trends in autocorrelation; Significant lines only appear in the early lag, with most of them being within the *confidence interval* limit. Meanwhile, the PACF graph shows **a significant spike** that crosses the interval *convicence* limit, namely lag 1; lag3 and lag8. There is no strong trend between the lags, so there is no indication that the data still contains non-stationary elements. Thus, the data has met the stationery requirements and does not require *an additional* differencing *process (Level* 2).

3. Identification of ARIMA Models

Autocorrelation correlogram (ACF) and partial autocorrelation (PACF) in Figure 6, *differencing Level 1 was performed* , which resulted in a value of order **d = 1**. In the ACF plot, it can be seen that the data is not significant in one lag, namely lag 1, so it is suspected that the data follows *the Moving average* (MA) model with the order **q = 1** or MA(1). Meanwhile, in the PACF plot, the partial autocorrelation was not significant in three lags, namely lags 1, 3, and 8, indicating that the data followed an *Autoregressive* (AR) model with the order **p = 3** or AR(3). Thus, the temporarily identified Arima model is **ARIMA (3,1,1).**

From the initial model, it can be assumed that there is also another model, namely by trial *and error* as a numerical estimation that is close to the initial model, although it is possible that other ARIMA models are formed. Possible ARIMA models are Arima (3,1,1), Arima (3,1,0), Arima (2,1,1), Arima (2,1,0), Arima (1,1,1), Arima (1,1,0) and Arima (0,1,1) are possible ARIMA (p,d,q) models.

4. *Overfitting* Testing Parameters of the formed ARIMA Model

The next stage is to estimate the parameters using a significance test. The parameter is considered significant if the probability (P) < 0.05 (α); if P > 0.05, the parameter is rejected and cannot be used for forecasting. In addition, the parameter can also be said to be significant if the statistical value of T – is < t-table = (α/2; df) where for the value of t = (0.05/2; 94 – 1) = 1.98580

Table 2. ARIMA Model Significance Test

Type	Test Results					Significance	
	Type	Coef	SE Coef	T-Value	P-Value	T	P
Arima (3,1,1)	AR 1	-1.252	0.213	-5.88	0.000	Significant	Not
	AR 2	-0.438	0.172	-2.55	0.013		
	AR 3	-0.160	0.112	-1.43	0.157		
	MA 1	-0.969	0.214	-4.52	0.000		
Arima (3,1,0)	AR 1	-0.337	0.102	-3.30	0.001	Significant	Significant
	AR 2	-0.247	0.105	-2.35	0.021		
	AR 3	-0.248	0.102	-2.43	0.017		
Arima (2,1,1)	AR 1	-1.230	0.102	-12.01	0.000	Significant	Significant
	AR 2	-0.256	0.103	-2.49	0.015		
	MA 1	-0.97927	0.00854	-114.63	0.000		
Arima (2,1,0)	AR 1	-0.295	0.103	-2.86	0.005	Significant	Not
	AR 2	-0.176	0.103	-1.70	0.093		
Arima (1,1,1)	AR 1	0.5481	0.0970	5.65	0.000	Not	Significant
	MA 1	0.98138	0.00881	111.36	0.000		
Arima (1,1,0)	AR 1	-0.253	0.101	-2.50	0.014	Significant	Significant
Arima (0,1,1)	MA 1	0.8741	0.0525	16.66	0.000	Not	Significant

Based on Table 2, the test was carried out by observing the p-value value of the parameter. If the p-value < 0.05 (α), the parameter is considered significant. Conversely, if the p-value > 0.05, the parameter is rejected, so the model cannot be used for forecasting. Significant models have been obtained, but they cannot be used because of the need for *white noise* testing. Feasibility is assessed by testing the *white noise assumption* (if the p-value is > α then the *white noise* assumption is met)

5. *White Noise*

Table 3. Ljung Box Test Results

Type	Test Results					Significant
Arima (3,1,0)	Lag	12	24	36	48	*White Noise*
	Chi-Square	13.35	24.36	40.21	51.27	
	DF	9	21	33	45	
	P-Value	0.147	0.276	0.181	0.241	
Arima (2,1,1)	Lag	12	24	36	48	*White Noise*
	Chi-Square	14.68	27.83	38.60	47.04	
	DF	9	21	33	45	
	P-Value	0.100	0.145	0.231	0.389	
Arima (1,1,0)	Lag	12	24	36	48	*White Noise*
	Chi-Square	14.42	28.11	39.00	47.43	
	DF	11	23	35	47	
	P-Value	0.211	0.212	0.295	0.455	

Table 3 shows the results of residual testing on ARIMA (3,1,0); (2,1,1) and (1,1,0). The hypothesis from the Ljung-Box test can be written:

H0 = ρ1 = ρ2 = ρ3 = ⋯ = 0 (*white noise*)

H1 = at least one ρk ≠ 0 (no *white noise*)

Result: Reject H0 if the P-value < a significant level of α = 0.05. It can be seen that there is a p-value of all models and the lag is more than α>0.05, so the model is *white noise* and is suitable for forecasting demand.

6. Selection of the Best Arima Models

After the parameter estimation process is carried out, significant models can be determined. The next stage is to choose the best model from these significant models. The selection was carried out by evaluating the measure of forecasting accuracy using the *Mean Square Error* (MSE) value. The MSE values generated through the *Minitab software output* in table 4. will be used as the basis for determining the best model.

Table 4. Recapitulation of MSE Value AR Model

Type	Residual Sums of Squares Test Results			MSE Values
	DF	SS	MS	
Arima (3,1,0)	90	395.872	4.39857	4.39857
Arima (2,1,1)	90	432.788	4.80876	4.80876
Arima (1,1,0)	92	434.445	4.72223	4.72223

Based on Table 4, the model with the smallest *Mean Square Error* (MSE) value is **ARIMA (3,1,0),** with an MSE of **4.39857**, so this model was chosen as the best. In **the ARIMA(3,1,0) model**, the p-values for the regression coefficients AR(1), AR(2), and AR(3) are all below α = 0.05. This shows that the regression model is significant and can be used to make predictions in the next period.

7. Forecasting Using ARIMA's Best Models

After diagnostic checks and tests show that the model is suitable, the formed ARIMA model can be used for forecasting. Forecasting is done to project demand over the next 50 periods. The following are the projected results for the next 50 periods.

Table 5. Forecasting Values with the ARIMA Method (3,1,0)

		95% Limits		
Period	*Forecast*	*Lower*	*Upper*	*Actual*
95	10.8972	6.6311	15.1632	
96	10.7478	5.4986	15.997	
97	10.8201	4.9161	16.7241	
98	10.8114	4.1909	17.4319	
99	10.8145	3.5553	18.0737	
100	10.8029	2.9752	18.6306	
101	10.8175	2.452	19.1829	
102	10.8038	1.9343	19.6733	
103	10.8164	1.4692	20.1635	
104	10.8043	1.0043	20.6043	
105	10.8161	0.5815	21.0507	
106	10.8046	0.1547	21.4545	
107	10.8158	-0.2352	21.8667	
108	10.8049	-0.6318	22.2416	
109	10.8155	-0.9956	22.6265	
110	10.8052	-1.3676	22.978	
111	10.8152	-1.71	23.3403	
112	10.8055	-2.0613	23.6723	
113	10.8149	-2.3858	24.0155	
114	10.8058	-2.7195	24.3311	
115	10.8146	-3.0286	24.6578	
116	10.8061	-3.3471	24.9592	
117	10.8144	-3.6429	25.2716	
118	10.8063	-3.948	25.5606	
119	10.8141	-4.2321	25.8604	
120	10.8065	-4.5254	26.1385	
121	10.8139	-4.7991	26.4269	
122	10.8067	-5.0818	26.6953	
123	10.8137	-5.3463	26.9737	
124	10.8069	-5.6194	27.2333	
125	10.8135	-5.8755	27.5025	
126	10.8071	-6.1399	27.7542	
127	10.8133	-6.3884	28.0151	
128	10.8073	-6.6449	28.2596	
129	10.8131	-6.8865	28.5128	
130	10.8075	-7.1357	28.7507	
131	10.813	-7.371	28.9969	
132	10.8077	-7.6135	29.2288	
133	10.8128	-7.8428	29.4685	
134	10.8078	-8.0791	29.6947	
135	10.8127	-8.3031	29.9284	
136	10.8079	-8.5336	30.1494	
137	10.8125	-8.7525	30.3775	
138	10.8081	-8.9776	30.5937	
139	10.8124	-9.1918	30.8166	
140	10.8082	-9.4118	31.0282	
141	10.8123	-9.6216	31.2462	
142	10.8083	-9.837	31.4536	
143	10.8122	-10.0426	31.6669	

		95% Limits		
Period	*Forecast*	*Lower*	*Upper*	*Actual*
144	10.8084	-10.2535	31.8704	

Based on forecast results, the total demand for *Wheel Loader* rentals at PT XYZ is projected to reach **541 units** by the end of 2024, with an average rental of **11 units per day**. With a MAPE score of 21,287%, which means that the forecast accuracy is around 78,717%.

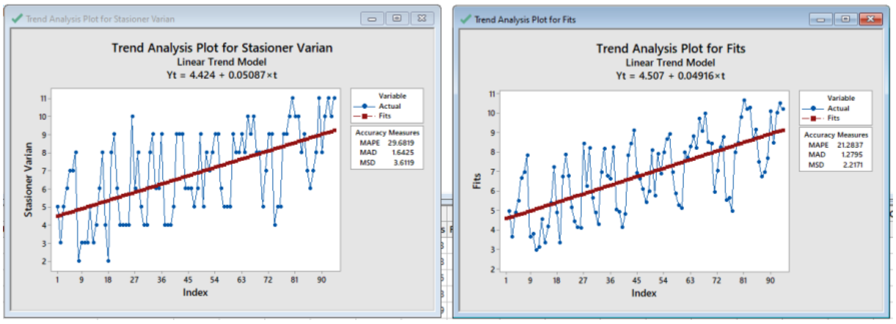


Figure 7. Comparing MAPE Values on Secondary Data with ARIMA Results (3.1.1)

8. Determination of *Service Level* and *Safety Stock*

a) *Service Level*

The safety factor is obtained from the level of *Service Level* (probability) which is calculated as 100%−α (0.05). Thus, the value of *the Safety factor*, which is the ratio of the level of safety, can be determined.

Table 6. Value *Safety* Factors on Several Levels *Service Level*

Service Level	*Service* Factor
50.00%	0.00
60.00%	0.25
70.00%	0.52
75.00%	0.67
80.00%	0.84
85.00%	1.04
90.00%	1.28
92.00%	1.41
95.00%	1.64
96.00%	1.75
98.00%	2.05
99.00%	2.33
99.50%	2.58
99.80%	2.88
99.99%	3.72

b) Determination of *Safety Stock*

Forecast errors, which are calculated as forecast *errors*, use RMSE (*Root Mean Square Error*) values. This value is important because it will determine the number of *Safety Stock* in units. Based on the ARIMA Model (3.1.1) the RMSE value $\sqrt{4.39857} = 2.1$ units. The following is the number of *Safety Stock* for various Service Level levels.

$$Safety\ Stock = SL \times FE \times \sqrt{LT}$$

Table 7. Sum *Safety Stock* In a variety of *Level*

Service Level		90%	92%	93%	94%	95%	96%	97%
Safety Factor		1.28	1.41	1.48	1.55	1.64	1.75	1.88
Lead Time (Days)	*Push*	1	1	1	1	1	1	1
Forecast Error (Daily)	*Daily*	2.1	2.1	2.1	2.1	2.1	2.1	2.1
Safety Stock (Units)	*Units*	2.688	2.961	3.108	3.255	3.444	3.675	3.948

Based on the table, the number of *Safety Stock* increased along with the increase in *Service Level*. The higher the service level, the greater the safety supply required to anticipate demand uncertainty or unavailability. At *90%* Service Level, *the required Safety Stock* is 2,688 units, increasing to 3,444 units at 95% *Service Level*, and reaching 3.9 units at *97% Service* Level.

CONCLUSION

Based on *the variables* in the ARIMA model, namely ARIMA (3,1,1); (3,1,0); (2,1,1); (2,1,0); (1,1,1); (1,1,0) and (0,1,1) after going through various and average stationary tests, ACF and PACF identification, parameter testing, and *white noise tests* , a significant model was obtained which is ARIMA (3,1,1); (2,1,1); (1,1,0).

Based on the deviation from the ARIMA Method (3.1.1), the RSME result was obtained of 2.1 units and the number of *Safety Stock* was made to overcome fluctuations in demand that always existed. The following is the number of *Safety Stock* at various *Service Levels,* from the calculation for each period obtained to determine the amount of *Safety Stock*, it is obtained at *90%* Service Level, the *required Safety Stock* is 2,688 units, increased to 3,444 units at 95% *Service Level,* and reached 3.9 units at *97% Service* Level

Forecasting errors with the ARIMA method (3,1,1) measured by MAPE (*Mean Absolute Percentage Error*) are the average percentage of errors which is 21,283 21% means that the accuracy of forecasting is around 78,717 ≈≈ 79%. When compared with the value of the forecast error made by the previous forecast in table 2 with the result in figure 7 the MSE value was obtained at 29.681 ≈ 30%, forecasting with this method resulted in a better calculation, namely the accuracy increased by 9%.

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