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Forecast Analysis of Single-Phase Prepaid KWh Meter Demand at PT PLN (Persero) UP3 Surakarta Using the ARIMA Method

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ABSTRACT

This study analyzes the causes of overstocking and implements a more accurate forecasting method for planning the inventory of single-phase prepaid kWh meters at PT PLN (Persero) UP3 Surakarta. The primary issue is the discrepancy between demand forecasting and actual purchases, which is attributed to ineffective forecasting methods and a lack of adaptation to dynamic economic conditions. To overcome this problem, this study uses two methods, namely interviews and ARIMA forecasting. The interview results, which are summarized and visualized in a fishbone diagram, identify the main root causes of the problem as two factors: human and method. From the human side, the lack of communication and coordination between staff and departments is a crucial factor. Meanwhile, from the method side, the use of ineffective forecasting methods and the lack of optimal utilization of historical data resulted in inaccuracies in demand planning. To overcome the method problem, this study applied the ARIMA method to historical data. The analysis results show that the ARIMA (1,0,0) model is the most accurate forecasting model, proven to be significant because it produces a p-value of 0.001 with an error rate below 10% and produces the lowest AIC value. This high accuracy indicates that the model can predict future demand very well. This recommendation provides a significant contribution to PT PLN (Persero) UP3 Surakarta in making more accurate procurement decisions, optimizing inventory management, and minimizing ongoing financial losses.

Keywords: ARIMA, KWh meter, overstock, forecasting

Introduction

PT PLN (Persero), as the main electricity provider in Indonesia, plays a crucial role in meeting the community's energy needs. One important aspect of its operations is material inventory management, including single-phase prepaid kWh meters. The effectiveness of this inventory management greatly determines cost efficiency and smooth service [1]. However, this study identified serious challenges related to inventory management at PT PLN (Persero) UP3 Surakarta, particularly in dealing with overstock events.

The kWh meter overstock incident that occurred in August 2024 was the primary focus of this study. While this incident was incidental, preliminary investigations indicated that the overstock was not a random occurrence but rather an indication of fundamental inconsistencies in the inventory management system.

Based on the results of interviews with internal parties, two main root causes of overstock were identified: a mismatch between demand forecasts and actual purchases. Internal parties stated that "There is a mismatch between demand and purchases." This indicates a misalignment between actual needs in the field and the procurement process and an inaccurate forecasting system. It was found that "Forecasts or forecasting systems span several years but do not take into account current economic conditions. This indicates that the previously used forecasting method (demand needs obtained from the average usage of the previous month) was not robust enough or unable to adapt to dynamic market conditions.

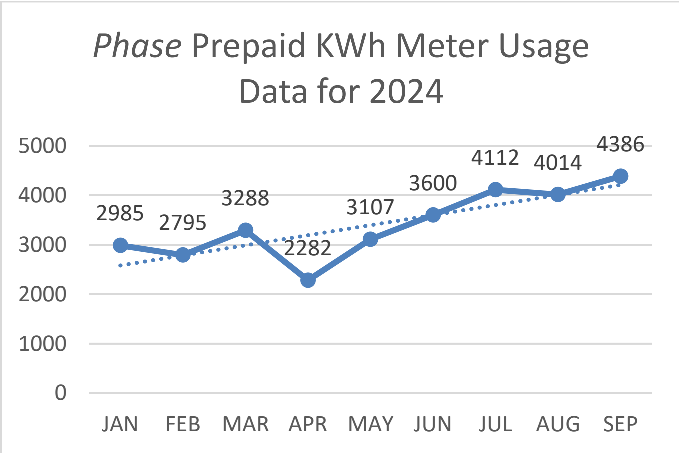

Figure 1. KWh Meter Usage Data

Figures 1 and 2 show a graph of the use of single-phase prepaid kWh meters and inventory stock data for the period from January to September 2024, where the average monthly need for single-phase prepaid kWh meters to meet new installations and changes in customer power is 3397 units.

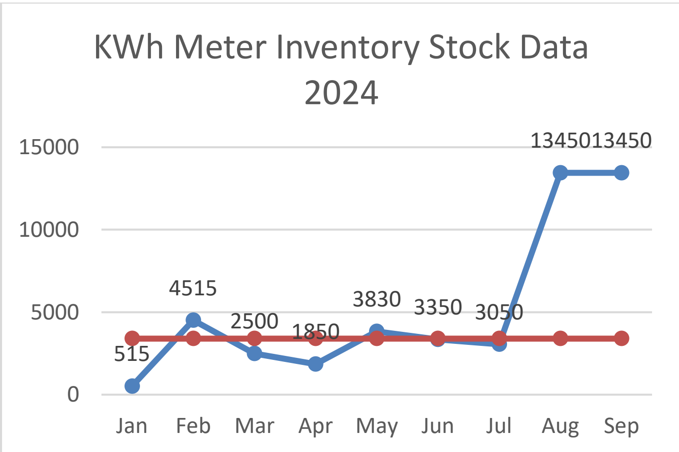

Figure 2. KWh Meter Stock Data

One of the problems faced by PT PLN (Persero) UP3 Surakarta is that if you look at the picture above in August the stock of kWh meters is very high, each stock is 13450, so there is a buildup of material (overstock) in the warehouse of PT PLN (Persero) UP3 Surakarta. The overstock problem is very clear in August and September. The stock of inventory reached 13450 units, which far exceeds the average usage of 3397 units. The stock spike was very drastic from 3050 units in July to 13450 units in August, even though the average monthly need is far below that figure. If you look at the overstock percentage, the incoming kWh meters of 13450 divided by the average usage of 3397 then multiplied by 100% produces a 395.9% overstock percentage. This indicates that there is an order or procurement of materials in very large quantities.

As for previous research conducted by [2] with the title "Forecasting Model of Automobile Spare Parts Production Quantity at PT. Showa Katou Indonesia with ARIMA Method" the results obtained from the study were that the ARIMA method showed significant forecasting accuracy for forecasting the number of spare parts production using more test data. And in this study there are differences with previous research, because previous research only focused on forecasting product or spare part needs in various industries, without identifying overstock problems.

Therefore, this study specifically focuses on forecasting the supply demand of single-phase prepaid kWh meters, which has not been widely studied in the context of the electricity industry. This study also aims not only to predict supply needs but also to identify the factors causing overstock in single-phase prepaid kWh meters specifically at PT PLN (Persero) UP3 Surakarta.

Therefore, this study has two main objectives that are mutually continuous, namely identifying the factors causing overstock using Fishbone Diagram and providing proactive solutions through the application of ARIMA (Autoregressive Integrated Moving Average) forecasting method. This method was chosen because of its ability to model time series data to predict future inventory needs more accurately and scientifically proven, so that companies can reduce the risk of overstock in the warehouse by using appropriate forecasting techniques [3].

Thus, this study not only focuses on the problems that have occurred, but also aims to provide valid and applicable recommendations for PT PLN (Persero) UP3 Surakarta to improve inventory management efficiency.

Method

This research was conducted at PT PLN (Persero) UP3 Surakarta with the object of research being single-phase prepaid kWh meters. The research at PT PLN (Persero) UP3 Surakarta aims to identify the causes of overstock in single-phase prepaid kWh meter materials and forecast future demand to optimize stock management. In this study, the researcher conducted interviews with five employees working in the PT PLN (Persero) UP3 Surakarta warehouse who had the criteria of 5 years of experience working in the logistics warehouse sector and were directly involved in warehouse inventory stock management, as well as handling documentation and reporting related to management and inventory [4]. Interviews with these informants were conducted to identify the causes of overstock in kWh meter materials. The results of the interviews were then visualized in a Fishbone diagram to map the causal factors more clearly.

In addition, forecasting analysis using the ARIMA (Autoregressive Integrated Moving Average) method is also used to predict demand. The data used is secondary data in the form of demand for changes in prepaid kWh meter power for 36 months (January 2022 to December 2024). The ARIMA analysis stage includes creating a data plot to check for stationarity in the variance using the Box Cox Plot Transformation, which is said to be stationary if the Rounded Value = 1 [5] and stationary in the average is done by looking at the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots, it is said to be stationary if there is no lag that goes outside the red line on the ACF and PACF plots [6], determining the most significant ARIMA model with P-Value < 0.05 [7], and finally making a forecast for the next 12 periods (January to December 2025).

Results and Discussion

Interview Results

Interviews with employees in the warehouse of PT PLN (Persero) UP3 Surakarta were analyzed to identify factors causing overstock. A summary of the interview findings is presented in the following table, which then served as the basis for constructing the diagram.

Table 1. Interview Results

Fishbone Category	Key Statements from the Interview (Paraphrase)	Identified issues
Man	"There are rarely meetings or COC (Code of Conduct) between departments and superiors." "The implementation of material purchasing is at UID, UP3 only makes proposals."	Lack of communication between management and staff or teams and departments. Lack of understanding of material needs.
Method	"In carrying out procurement, we still use a simulation system of average usage over several years." “The need for prepaid kWh meter materials fluctuates because demand is unpredictable.”	Inaccurate forecasting methods. Unanticipated fluctuations in demand.
Material	“Purchase of materials from UID is more than needed.” “Stacking of materials in the warehouse.”	Excessive purchase of materials. Mismatch of ordered materials and actual requirements.
Environment	"The economic level of customers is decreasing, and population density is at its maximum."	Customer economic downturn

Fishbone Diagram

Cause-and-effect diagrams, commonly known as fishbone diagrams, are one of the analytical techniques used to identify the root causes of a problem [8]. In this study, fishbone diagrams were used to visualize the factors causing overstock that had been identified through in-depth interviews with employees directly involved in inventory management. After conducting the interviews, the researchers conducted content analysis to group the various statements and views expressed by the informants. Based on the themes that emerged, the answers were categorized into five main factors according to the structure of the fishbone diagram. This grouping ensures that each point in the diagram (Man, Method, Material, Environment) has a strong basis from field data. The following is a visualization of the results of the analysis:

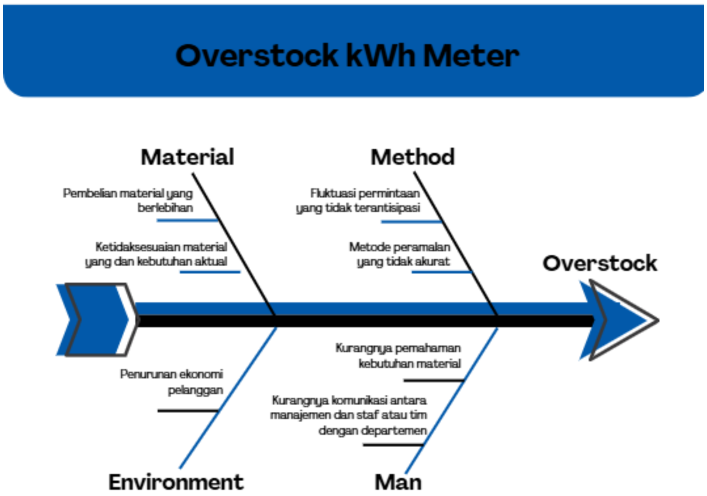

Figure 3. Fishbone Diagram of KWh Meter

a) Man

Based on the results of the interviews, errors that occurred from the "Man" aspect were a lack of understanding of material needs and a lack of communication between management and staff or teams with departments. A lack of understanding of customer needs can lead to inappropriate procurement, and a lack of coordination between teams and departments can result in unsynchronized procurement decisions. This finding is in line with research [9], which also emphasizes the importance of understanding and coordination in the sustainable procurement process to avoid operational errors.

b) Method

Based on the results of the interview, the errors that occurred in terms of "Method" were fluctuations in kWh meter demand and inaccurate forecasting methods. Uncertainty in market demand can trigger companies to make more purchases than necessary, which can lead to overstock. This is supported by research [10], which shows that the use of ineffective forecasting methods is the main cause of overstock problems and the need for the implementation of more accurate forecasting methods such as ARIMA for precise predictions.

c) Materials

Based on the results of the interview, errors that occurred in terms of "Materials" were the purchase of materials that were inaccurate or exceeded actual needs. Purchasing materials that exceed actual needs can lead to stock buildup, and if the material is not used for a long time, it is at risk of damage and reduces the value of the inventory. This finding is supported by research [11] which analyzed inventory control and found that purchases that do not meet needs can lead to excess stock.

d) Environment

Based on the interview results, the error that occurred in terms of the "Environment" was a decline in the customer's economy. Poor economic conditions can affect demand, causing fluctuations that are difficult to predict. This is in accordance with a study [12] that examined the influence of demand and supply on basic needs, where economic conditions can be an important factor influencing demand patterns.

Forecasting Method

Forecasting using time series analysis data for 36 months to forecast the demand for kWh meter supplies in 2020 requires data on customer demand for changes in kWh meter power at PT PLN (Persero) UP3 Surakarta for the period January 2022 to December 2024. The total data is 36 months.

Table 2. KWh Meter Data

Year	Month	KWh Meter Data
2022	January	1000
	February	4000
	March	1000
	April	700
	May	300
	June	900
	July	1000
	August	1640
	September	2655
	October	1910
	November	720
	December	315
2023	January	300
	February	500
	March	6000
	April	2200
	May	5000
	June	3000
	July	5519
	August	1150
	September	6000
	October	941
	November	941
	December	1000
2024	January	515
	February	4515
	March	2500
	April	1850
	May	3830
	June	3350
	July	3050
	August	13450
	September	13450
	October	7950
	November	6950
	December	3450

From Table 1, it is known that the data obtained is customer demand data for changes in kWh meter power for 36 months, from the period January 2022 to December 2024 with an average demand of 1039.

1. Identify Data Plots

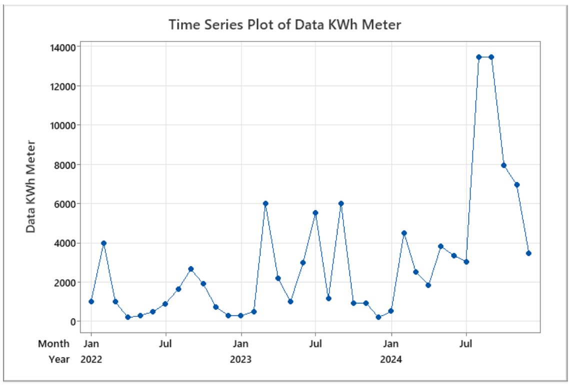

Figure 4. KWh Meter Data Plot

Figure 4 shows a plot of kWh meter data for the period January 2022 to December 2024 with a total of 36 months. The graph shows significant fluctuations, which means the data is not stationary with respect to the mean or variance. In some months there are significant increases and decreases, this is influenced by customer demand. So the data must be tested for stationary variance. This is a common problem in time series data and must be addressed before applying the ARIMA model. If the data is not stationary, the resulting forecast can be inaccurate [13], Therefore the next step is to conduct a stationary test.

2. Stationary Test in Variance

Examination of stationary data in variance can use Box Cox Plot Transformation in Minitab Software.

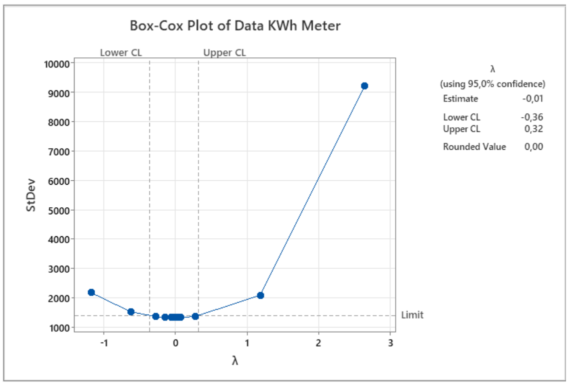

Figure 5. Stationary Graph against Variance

Stationary in the variant looks at the Rounded Value or lambda value [14]. From the output obtained in Figure 5, the value is 0.00, meaning that the data is not stationary in the variant because the data can be said to be stationary in the variant if the Rounded Value = 1. Because the data is not stationary in the variant, it is necessary to carry out data transformation [15].

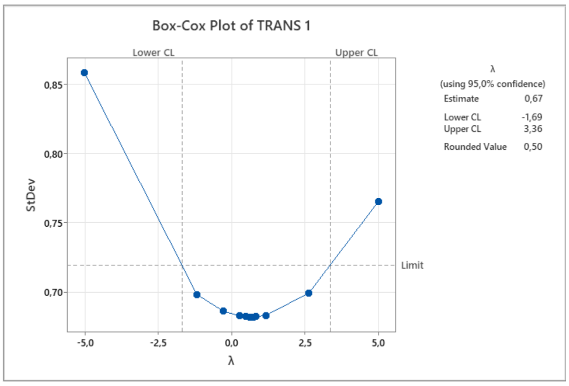

Figure 6. Data Transformation Graph

Rounded Value value can be seen in Figure 6 above = 0.50. It can be said that the data is not stationary in variance, therefore the data must be transformed secondly so that the data becomes stationary. Box Cox transformation helps stabilize data variance, so that fluctuations in the data become more uniform over time [16]. Because the ARIMA model assumes a constant variance.

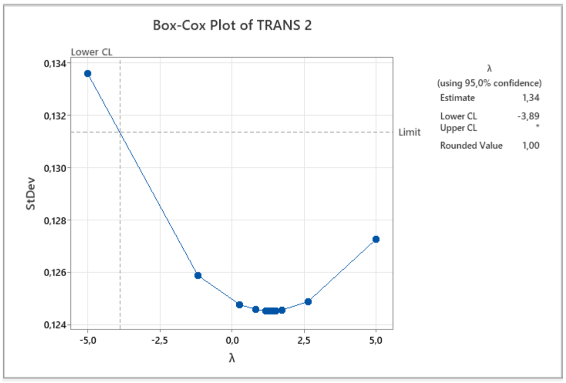

Figure 7. Data Transformation Graph

After the data has been transformed again, the Rounded Value can be seen again. Figure 7 shows that the data has become stationary in its variance because it shows a Rounded Value value of 1 [17] . Thus, this second transformed data can be used for the next analysis stage in the ARIMA method.

3. Stationary Test in Mean

Next, we examine the stationary data in the mean by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) data plots. In the ARIMA method, the data must be stationary in the mean, meaning the average value does not change significantly over time. The following Autocorrelation Function (ACF) graph is used to determine the Moving Average or q-order in the ARIMA model. The red one is called the Confidence Interval, while the blue one is called the lag.

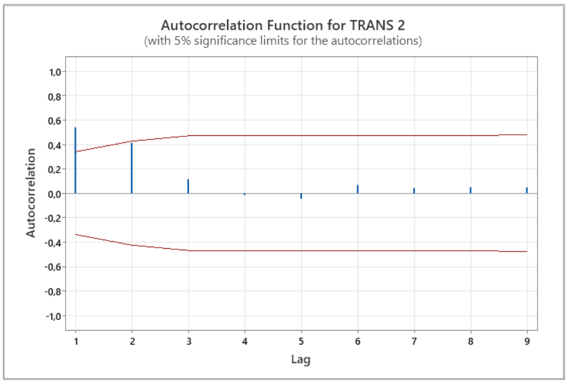

Figure 8. Autocorrelation Function Graph

Based on Figure 8 in the ACF graph above, it can be seen that the data is stationary. The data can be said to be stationary if there are no initial 3 lags that are outside the confidence interval (red line) [18]. In addition, the data is also said to be stationary if the data experiences a rapid decline approaching zero. If the data has been transformed but is still not stationary with respect to the mean, differentiation is necessary. But if the data is stationary, differentiation is not necessary. Next, test the PACF data plot to determine the Autoregressive (AR) component, or order p in the ARIMA model.

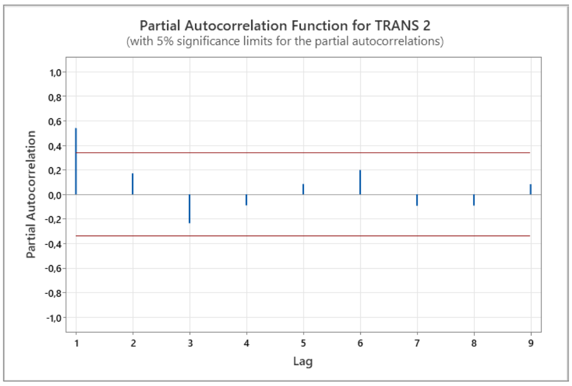

Figure 9. Partial Autocorrelation Function Graph

Based on the PACF data plot in Figure 9 above, it can be seen that there is only one lag outside the confidence interval. From this, we can obtain the p-order value, or a combination for the ARIMA model, which can use p=1 or p=0. Once we know the lags outside the ACF and PACF, as well as their differentiation, we can determine several ARIMA model estimates.

Based on the PACF value, there is 1 lag that comes out, meaning the order p = 1 or 0. There is no differencing, meaning the order d = 0. And the ACF value, there is also 1 lag that comes out, the order q = 1 or 0. So, here are the combinations of ARIMA models (1,0,1) , (1,0,0), and (0,0,1).

4. Determining the ARIMA Model

Before forecasting, the next step is to estimate the ARIMA model and select the best model by observing the P-Value <0.05, which will then be used for forecasting. After identifying a suitable tentative model, the next step is to assess the significance of the parameters in the model. To determine the best ARIMA model, here is a comparison of several ARIMA models that have been tested:

Table 3. Comparison of ARIMA Models

ARIMA Model	P-Value		AIC value	Information
	AR	MA		
1,0,1	0.008	0.581	678,385	Not Significant
1,0,0	0.001	-	676,857	Significant
0,0,1	-	0.029	681,557	Significant

Based on Table 3, several ARIMA model coefficients show varying p-values. Several p-values can be used to measure statistical significance:

- If the p-value < 0.05: The result is said to be significant. This means that the probability that the result obtained occurred by chance (randomly) is very small, namely less than 5%. In other words, it can be believed that there is a real relationship between the parameter and the model. As explained in the study [19], a result is said to be significant if the p-value is below the specified threshold (usually 0.05), which indicates that the result has a probability of less than 5% of occurring by chance.
- If the p-value > 0.05: The result is said to be insignificant. This means that the probability that this finding occurred due to chance is quite high, namely more than 5%. Therefore, we cannot be sure that the parameter has a real influence in the model. This is explained by previous research [20], namely when a coefficient has a p-value greater than 0.05, it indicates that the coefficient is not statistically significant, meaning that its influence is not large enough to accurately predict information.

Although some parameters in the ARIMA model show significance, the ARIMA (1,0,0) model is still selected as the best model. This selection is based on the overall model accuracy criteria, such as the smallest AIC value, as explained by previous research [21], the selection of the best ARIMA model is not only based on the significance of the parameters, but also on the goodness of fit of other models, such as AIC and MAPE which show the highest forecasting accuracy [22].

Table 4. ARIMA Model Parameters

Type	Coef	SE Coef	T-Value	P-Value
AR 1	0.551	0.144	3.82	0.001

It can be seen in Table 4 above after testing the ARIMA (1, 0, 0) model, the final results produced by AR produced a P-Value of 0.001, this indicates that the ARIMA (1,0,0) model is accepted because it is significant and can be used for estimation.

5. Forecasting

Next, forecasting was performed using the ARIMA (1,0,0) model for the next 12 periods. Based on Table 5, the forecast results for kWh meter material demand for the 12 periods from January to December 2025 tended to decrease, although not significantly.

Table 5. Forecast Results

		95% Limits		
Period	**Forecast**	**Lower**	**Upper**	**Actual**
37	3292.42	- 2098.55	8683.39	
38	3204.46	- 2969.57	9378.48	
39	3155.35	- 3243.12	9553.82	
40	3127.94	- 3338.87	9594.76	
41	3112.64	- 3375.32	9600.61	
42	3104.10	- 3390.44	9598.64	
43	3099.33	- 3397.26	9595.92	
44	3096.67	- 3400.56	9593.90	
45	3095.19	- 3402.24	9592.61	
46	3094.36	- 3403.13	9591.85	
47	3093.89	- 3403.61	9591.40	
48	3093.64	- 3403.88	9591.15	

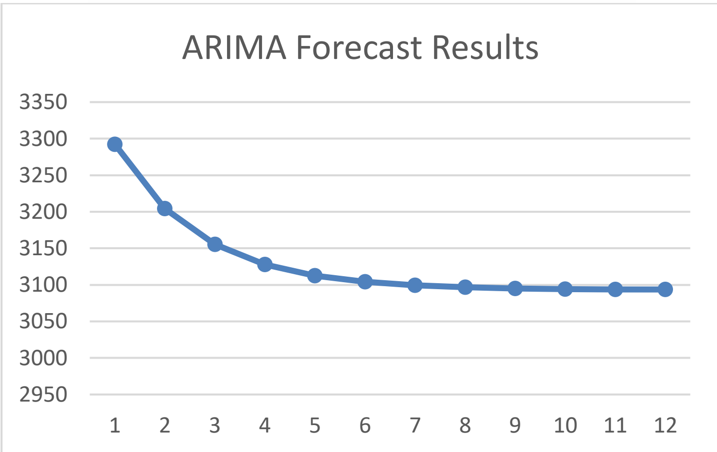

Figure 9. Forecast Chart

With more accurate forecasting, PT PLN (Persero) UP3 Surakarta can plan material procurement more precisely, avoid excessive purchases that cause overstock, and ultimately reduce financial losses due to material accumulation. Better forecasting also supports operational efficiency and inventory management optimization, ensuring material availability according to customer needs [23].

Table 6. Forecast Data

No	Month	Forecast
1	January	3292

2	February	3204
3	March	3155
4	April	3128
5	May	3113
6	June	3104
7	July	3099
8	August	3097
9	September	3095
10	October	3094
11	November	3094
12	December	3094

5. Calculation of Mean Absolute Percentage Error (MAPE)

One way to measure how accurate a prediction is is to use MAPE. This indicator measures forecast accuracy by dividing the absolute or average percentage error by the total percentage error [24]. The following table calculates the MAPE value:

Table 7. MAPE Results

Month	KWh Meter Data	Prediction Value (Fit)	Absolute Value	Percentage Error Value
January	515	1925	2.737467	0.531547048
February	4515	4654	0.0308	0.000682171
March	2500	3887	0.554767	0.022190663
April	1850	2762	0.493036	0.026650578
May	3830	3599	0.060241	0.00157287
June	3350	3505	0.046131	0.001377056
July	3050	3237	0.06118	0.002005887
August	13450	9069	0.325715	0.002421673
September	13450	8875	0.340182	0.002529233
October	7950	8875	0.116296	0.001462845
November	6950	7804	0.122932	0.002371761
December	3450	4246	0.230773	0.015090666
MAPE (Mean Absolute Percentage Error)				0.050075
MAPE (In %)				5%

Based on Table 7, it explains that the results obtained by calculating MAPE or the average error in this study were 5%. The lower the MAPE value, the better the ability of the forecasting model used can be said to be [25]. When looking at the overstock percentage after forecasting with ARIMA, there was no overstock percentage exceeding 100%. For example, in December, the incoming kWh of 3450 divided by the ARIMA prediction value of 4246 then multiplied by 100% resulted in an overstock percentage of 81%. This shows that after implementing the ARIMA model, the overstock percentage dropped from a very high figure (almost 400%) to a much lower figure of 81%.

Table 8. MAPE Range

MAPE Range	Information
< 10%	Forecasting Model Competence Very Good
10 – 20%	Good Forecasting Model Competence
20 – 50%	Forecasting Model Competence Sufficient
> 50%	Poor Forecasting Model Competence

(source: [26])

For MAPE, there is a range of values that can be used to assess how well the forecasting model works. This range of values can be seen in Table 8. Therefore, it can be said that the MAPE results have very good forecasting model capabilities because the MAPE results obtained are <10%, namely 5% [27].

Conclusion

Based on the analysis conducted, the researchers successfully identified and visualized the factors causing overstocking of single-phase prepaid kWh meters at PT PLN (Persero) UP3 Surakarta and proposed preventative solutions. The conclusions of this study can be summarized as follows:

1. Analysis using a fishbone diagram based on interview results shows that the main root cause of overstock stems from man and method. From the man side, a lack of understanding and communication between departments is the main factor. Meanwhile, from the method side, the use of ineffective forecasting methods is another important cause.

2. Historical data analysis using the ARIMA (Autoregressive Integrated Moving Average) method has proven effective as a more accurate forecasting tool. Before implementing the ARIMA method, the company experienced an overstock of almost 400%. After using the ARIMA method, the overstock in December 2024 was successfully reduced to 81%, demonstrating the efficiency of the ARIMA method in predicting future kWh meter inventory needs. It can be said that this study successfully used the ARIMA method to forecast kWh meter inventory.

This research provides a concrete solution for prevention. The proposed ARIMA forecasting model can be used by PT PLN (Persero) UP3 Surakarta to make more informed procurement decisions in the future. Thus, this research not only identifies overstock issues but also provides a measurable tool to reduce the risk of overstock and the potential for ongoing financial losses.

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