Intechno Journal :
Information Technology Journal
Vol. 8 No. 1 July 2026
Homepage: https://jurnal.amikom.ac.id/index.php/intechno

INTECHNO Journal
INFORMATION TECHNOLOGY JOURNAL
e-ISSN: 2655-1438
p-ISSN: 2655-1632

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Comparing ARIMA and Single Exponential Smoothing for Spare-Part Demand Forecasting: A Case Study at PT XYZ

Angger Styo Yuniarti[1], Muhammad Arif Kurniawan[2]
[1,2]Universitas Insan Pembangunan Indonesia, Jl. Raya Serang KM 10 Bitung, Tangerang 15810 Indonesia

Article Info

Article history:

Received: 29 June 2026
Revised: 10 July 2026
Accepted: 14 July 2026
Published: 31 July 2026

Keywords:

ARIMA
Forecasting
Single exponential smoothing
Spare-parts
Time series Analysis

ABSTRACT

Purpose: This study aims to compare the forecasting performance of the Autoregressive Integrated Moving Average (ARIMA) and Single Exponential Smoothing (SES) methods using Battery DYC spare-part demand data from PT XYZ as an industrial case study to identify the most appropriate forecasting approach for inventory planning.
Methods: Monthly sales data from January 2020 to May 2026 were analyzed using a quantitative time-series approach. The dataset was divided into training data (65 observations) and testing data (12 observations). The ARIMA model was developed according to the Box-Jenkins procedure, while the SES model used the optimal smoothing parameter estimated by SPSS. The forecast performance was assessed in terms of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).
Result/Findings: The results show that ARIMA (0,0,1) model has RMSE of 3.8370, MAE of 2.8925 and MAPE of 53.21%. SES (α=0.052) has RMSE of 3.8336, MAE of 3.0000 and MAPE of 55.19%. SES is slightly better than ARIMA in terms of RMSE but ARIMA is better in MAE and MAPE, thus ARIMA is more robust overall.
Novelty/Originality/Value: The study provides empirical evidence from an industrial case study that forecasting performance is dependent on demand characteristics, rather than on the universal superiority of one method over another. The findings offer practical guidance for spare-part inventory planning and provide a basis for future comparisons with specialized intermittent demand forecasting methods.

Corresponding Author:

Angger Styo Yuniarti
Email: anggeryuniarti06@gmail.com

1. INTRODUCTION

The timely availability of spare parts in proportionate quantities is critical to the operational sustainability of after-sales service-based industries. Companies engaged in the distribution of material-handling products, such as turbine ventilators and caster wheels, are highly dependent on service centers' ability to ensure the availability of replacement components for customers. The inability to meet spare part requests in a timely manner not only impacts customer satisfaction but can also cause significant financial losses due to stockouts and excessive storage costs. Therefore, inventory planning based on accurate demand forecasting is essential for companies in this industry [1].

However, spare-part demand is often volatile, irregular, and characterized by intermittent patterns, making it difficult to forecast using conventional time-series techniques. Although methods such as Single

Exponential Smoothing (SES) and Autoregressive Integrated Moving Average (ARIMA) are widely used in industry as they rely on historical data to predict future demand [2], no single forecasting method can perform better than the others under all demand patterns as the accuracy of the forecast depends on the statistical properties of the data [3].

PT XYZ is a material-handling distribution company founded in 1992, managing 1186 spare parts. One of the spare parts is the Battery for Stacker Semi Electric DYC (Battery DYC), of which a total of 192 units have been sold from January 2020 to May 2026. The monthly demand for Battery DYC exhibits large fluctuations with no obvious trend or seasonality, creating a difficulty in choosing a proper forecasting method. Therefore, PT XYZ is employed as an industrial case study to represent a real-world inventory forecasting problem. Few previous studies have compared ARIMA and SES for spare-part demand in the material-handling sector. Many studies have only analyzed one forecasting method without systematically comparing forecasting accuracy using multiple performance indicators such as RMSE, MAE, and MAPE [3],[2]. The gap points to the necessity of a more thorough comparative evaluation under actual industrial settings.

This study compares the practical applicability of ARIMA and SES using actual monthly Battery DYC demand data from PT XYZ. The novelty lies in comparing the ARIMA (0,0,1) model, identified through the Box–Jenkins procedure, with the SES model ($\alpha = 0.052$) to determine the forecasting approach most suitable for the operational characteristics of Battery DYC demand. ARIMA and SES were selected because they represent two widely used yet fundamentally different forecasting approaches, whereas Croston's method, although widely recognized for intermittent demand forecasting, was beyond the scope of this study and is proposed for future research. The findings provide empirical evidence that both methods produce comparable forecasting performance but different error characteristics for fluctuating demand without strong trend or seasonality, offering practical guidance for inventory planning while demonstrating that forecasting performance should be interpreted within the operational context rather than as evidence of a universally superior method [4], [5].

Based on this background, the research addresses three questions: (1) How does the ARIMA method forecast Battery DYC spare-part demand? (2) How does the SES method forecast Battery DYC spare-part demand? And (3) which method provides better forecasting performance based on RMSE, MAE, and MAPE? Therefore, this research is intended to analyze the forecasts of ARIMA and SES to compare the performance of the two methods and to find the most suitable method for Battery DYC inventory planning at PT XYZ. The study contributes to demand forecasting and inventory management by providing empirical evidence from an industrial case study and practical guidance for selecting forecasting methods under fluctuating demand conditions, while encouraging future research to evaluate more adaptive forecasting approaches.

2. METHOD

This study employs a quantitative research design with a time series forecasting approach to compare the forecasting performance of Autoregressive Integrated Moving Average (ARIMA) and Single Exponential Smoothing (SES) methods using Battery DYC spare-part demand data from PT XYZ as an industrial case study. The aim was not to produce a better forecasting model for all situations, but to assess the feasibility of both approaches under real operating conditions.

The study utilized secondary data on monthly sales extracted from the company's service center records for the period January 2020 to May 2026, with 77 observations. The hold-out validation approach was used to divide the dataset into 65 observations (84.4%) for model training (January 2020–May 2025) and 12 observations (15.6%) for model testing (June 2025–May 2026). The ARIMA and SES models were constructed on the training dataset, and the testing dataset was used to assess the forecasting performance by employing Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Since the study was conducted on one industrial dataset, the results should be interpreted in the context of the operational setting of PT XYZ and provide practical insights for similar spare-part inventory management problems.

The ARIMA analysis method is performed using the four procedural stages of Box-Jenkins, namely model identification, parameter estimation, diagnostic testing, and forecasting. In the identification stage, data stationarity is measured by the time series plot, Autocorrelation Function (ACF) graph, and Partial Autocorrelation Function (PACF) graph. The differencing value (d) is determined based on the data transformation needs to achieve stationarity, while the autoregressive order (p) and moving average (q) are determined based on the cut-off pattern on the PACF and ACF graphs. In addition, several ARIMA model candidates are tested and compared based on the smallest Normalized Bayesian Information Criterion (N-BIC) value and the results of the Ljung-Box test to confirm that the residuals are white noise. The significance of the AR and MA parameters is also evaluated as an additional selection criterion, so the ARIMA (0,0,1) model is selected as the best model, with a training data RMSE of 1.916 and a Ljung-Box P-value of 0.178.

The SES method is implemented by determining the best alpha (α) smoothing parameter value through trial-and-error procedures in the range of values from 0 to 1. The α value that produces the smallest error measure is chosen as the best parameter. The optimal parameter value of $\alpha = 0.052$ is obtained, which implies that the model gives more weight to older historical data, consistent with the characteristics of data that do not have a dominant trend or seasonal pattern. Both models are then used to generate forecast values for the testing period, and their performance is assessed using three complementary error indicators, namely Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). Data processing is carried out using RStudio software as a verification tool for the calculation results. The method that yields the lowest RMSE and MAE values is selected as the best method because both measures reflect the closeness of the forecast values to the actual data as a whole [6].

3. RESULTS

3.1 Characteristics of Sales Data Spare Part Battery

Table 1. Spare part Battery DYC sales data

Period	2020	2021	2022	2023	2024	2025	2026
January	3	1	2	2	3	1	3
February	5	2	1	5	0	3	1
March	2	6	4	5	0	5	4
April	0	3	2	6	1	4	6
May	0	2	3	10	5	0	8
June	0	1	1	4	1	0	-
July	0	0	1	2	2	2	-
August	0	2	4	5	6	0	-
September	1	1	0	1	3	7	-
October	4	2	3	0	3	12	-
November	4	3	6	3	3	1	-
December	0	2	2	3	0	0	-

The sales data for DYC Battery spare parts (Battery for DYC Semi Electric Stacker) used in this study cover 77 monthly observations from January 2020 to May 2026. Based on the time series plot visualization, the data series shows no consistent trend or strong seasonal pattern. Fluctuations in sales values move randomly around the average, with one possible mild outlier identified in October 2025 with a sales value of 12 units. This condition indicates that the data behaves close to a horizontal pattern with irregular variance, thus becoming the basis for consideration in selecting a time series approach that does not rely on trend or seasonal components.

3.2 ARIMA Modeling Results

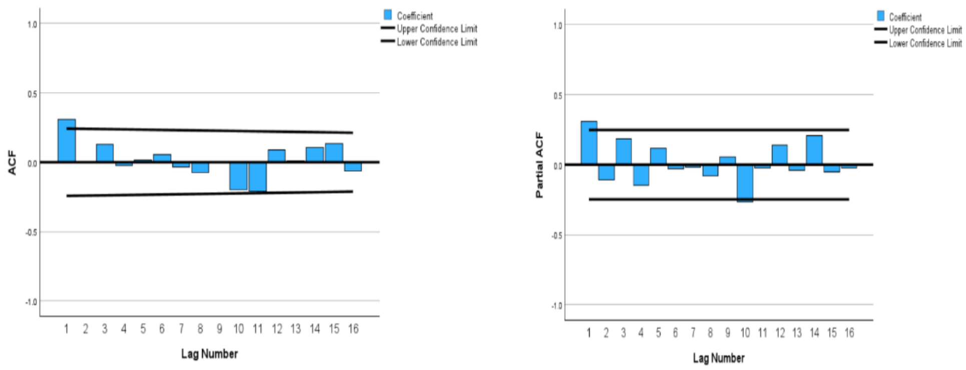

Figure 1. ACF and PACF plots of the time series data

After checking the stationarity of the training data (January 2020–May 2025), the ACF and PACF graphs show that the data is stationary at differencing $d = 0$, meaning no difference transformation is required. A total of 15 ARIMA model candidates were systematically tested by considering RMSE, MAPE, MAE, N-BIC values, the Ljung-Box test results, and the significance of the AR and MA parameters. A summary of the comparison of all model candidates is shown in Table 2.

Table 2. Comparison Results of Candidates' ARIMA Model on Training Data

Model	Error				Ljung Box Q Test		Significant	
	RMSE	MAPE	MAE	N-Bic	P Value	White Noise	AR	MA
ARIMA (0,0,0)	2,047	56,385	1,633	1,497	0.399	Yes	-	-
ARIMA (0,0,1)	**1,916**	**56,538**	**1,532**	**1,429**	**0.178**	**Yes**	**-**	**Yes**
ARIMA (0,0,2)	1,908	58,297	1,511	1,484	0.406	Yes	-	No
ARIMA (0,1,0)	2,400	79,826	1,871	1,816	0.001	No	-	-
ARIMA (0,1,1)	2,112	53,372	1,600	1,625	0.314	Yes	-	No
ARIMA (0,1,2)	1,984	58,911	1,566	1,566	0.159	Yes	-	No
ARIMA (0,1,3)	1,974	60,502	1,536	1,620	0.388	Yes	-	No
ARIMA (0,2,3)	2,177	74,315	1,694	1,819	0.111	Yes	-	No
ARIMA (1,0,0)	1,958	53,654	1,555	1,472	0.268	Yes	No	-
ARIMA (1,0,1)	1,897	57,039	1,496	1,474	0.588	Yes	No	Yes
ARIMA (1,0,2)	1,912	56,651	1,495	1,553	0.506	Yes	No	No
ARIMA (1,1,0)	2,336	71,467	1,850	1,827	0.12	Yes	No	-
ARIMA (1,1,1)	2,028	53,865	1,573	1,609	0.248	Yes	No	No
ARIMA (2,0,0)	1,960	53,855	1,533	1,538	0.162	Yes	No	-
ARIMA (2,0,1)	1,912	56,855	1,494	1,553	0.503	Yes	No	Yes

Based on the multicriteria evaluation, the ARIMA (0,0,1) model was determined as the best model. This model has the smallest N-BIC value of 1.429, white-noise residuals (Ljung-Box P-Value = 0.178 > 0.05), and significant MA parameters, although its training RMSE value of 1.916 is not the lowest in absolute terms. This selection considers the balance between model simplicity (parsimony), diagnostic validity, and parameter stability.

3.3 Results on ARIMA (0,0,1) Forecasting

The ARIMA (0,0,1) model was then applied to forecast 12 testing periods (June 2025–May 2026). The resulting forecast value remained constant after the first period, at 2.42 units per month. A comparison of the actual values and the ARIMA forecast results is presented in Table 3.

Table 3. ARIMA (0,0,1) Forecasting Results in the Testing Period

Period	Actual	*Forecast*	*Sq. Error*
Jun-25	0	1.13	1.28
Jul-25	2	2.42	0.18
Aug-25	0	2.42	5.86
Sep-25	7	2.42	20.98
Oct-25	12	2.42	91.78
Nov-25	1	2.42	2.02
Dec-25	0	2.42	5.86
Jan-26	3	2.42	0.34
Feb-26	1	2.42	2.02
Mar-26	4	2.42	2.50
Apr-26	6	2.42	12.82
May 26	8	2.42	31.14
	Total		**176.78**

Based on the data in Table 3, the MSE is 14.7225, the RMSE is 3.8370, the MAE is 2.8925, and the MAPE is 53.21%

3.4 Results on SES Forecasting

In the Single Exponential Smoothing (SES) method, the optimal alpha (α) parameter is determined through an automated search procedure, and the best parameter is α = 0.052 with a training RMSE of 2.061 and a Ljung-Box P-Value of 0.313. This very small α value indicates that the model places more weight on long-term historical data than on the most recent observations, consistent with the data's random pattern without a trend. The forecast value generated by SES remains constant throughout the testing period at 2.59 units per month. A comparison of the actual and forecast SES values is shown in Table 4.

Table 4. SES Forecasting Results (α = 0.052) in the Testing Period

Period	Current	*Forecast*	*Sq. Error*
Jun-25	0	2.59	6.71
Jul-25	2	2.59	0.35
Aug-25	0	2.59	6.71

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Sep-25	7	2.59	19.45
Oct-25	12	2.59	88.55
Nov-25	1	2.59	2.53
Dec-25	0	2.59	6.71
Jan-26	3	2.59	0.17
Feb-26	1	2.59	2.53
Mar-26	4	2.59	1.99
Apr-26	6	2.59	11.63
May 26	8	2.59	29.27
	Total		**176.60**

Based on Table 4, the MSE value is 14.6968; RMSE is 3.8336; MAE is 3.0000; and MAPE is 55.19%

3.5 Comparison of ARIMA and SES Accuracy

To obtain a comprehensive comparative picture, all error indicators of both methods are summarized in Table 5.

Table 5. Comparison of ARIMA and SES Accuracy

Indicator	ARIMA (0,0,1)	SES (α = 0.052)	Best
MSE	14.7225	14,6968	SES
RMSE	3,8370	3.8336	SES
MAE	2.8925	3,0000	ARIMA
MAPE	53.21%	55.19%	ARIMA

Table 5 shows that both methods produce very close numerical forecasting performance. SES excels in the MSE and RMSE indicators by a very small margin (MSE: 14.6968 vs. 14.7225; RMSE: 3.8336 vs. 3.8370), while ARIMA produces lower MAE and MAPE values (MAE: 2.8925 vs. 3.0000; MAPE: 53.21% vs. 55.19%). Verification results in RStudio confirm these findings: RMSE_ARIMA is recorded at 3.83772, and RMSE_SES is 3.83598, with an insubstantial difference. Referring to the MAE indicator, which is a more robust measure against extreme values (outliers), the ARIMA (0,0,1) method shows superiority in minimizing the average absolute deviation between forecasts and actual values.

4. DISCUSSIONS

4.1 Results of Forecasting Using the ARIMA Method

The model identification results indicate that differencing d = 0 makes the Battery DYC spare part sales data stationary; therefore, the Box-Jenkins method requires no additional differencing. This result matches the data characteristics, which, as previously described in the results of the research, did not have a pronounced trend or seasonality. Among the 15 candidate models, the selected model is ARIMA (0,0,1), based on white-noise residuals (P-value of the Ljung-Box test = 0.178) and the minimum Normalized Bayesian Information Criterion (N-BIC) of 1.429. The selection of this model, based on the combination of information criteria and diagnostic tests, follows the principle of parsimony in the Box-Jenkins methodology, which prefers models that have fewer parameters and are more straightforward, while still being statistically valid, compared to more complex models [7].

Testing period forecasts project that ARIMA (0,0,1) will generate a relatively constant predicted value of 2.42 units per month. It is common for ARIMA models with a zero order of autoregression to express a long-run value that is the average of the historical data. The model's performance is illustrated with an RMSE of 3.8370, an MAE of 2.8925, and a MAPE of 53.21%. It is worth noting that the MAPE is relatively high and consistent with what was reported in the previous study [8]. It was reported that applying ARIMA to highly volatile time series yields statistically significant results, but higher error percentages than to time series with lower volatility. The large MAPE in this case was mainly driven by the October 2025 demand spike of 12 units, leading to 1 squared error of 91.78 that was much larger than all other squared errors in all other time periods. This further confirms the presence of mild outliers noted during the exploratory data analysis.

Demand for DYC Battery spare parts is so volatile that choosing the simple ARIMA model (0,0,1) with no autoregressive component makes sense, even on its own. This model may better account for the characteristics of the demand pattern for DYC Battery parts. As noted in reference [9], demand for many industrial spare parts is irregular and, at times, sudden, which requires the modification of typical forecasting techniques in order to accommodate the irregular demand patterns. Reference [10] also indicates that, in forecasting retail product sales, demand patterns learned from historical data tend to provide more stable forecasts than the simple moving average technique. This also applies to the use of the low-order ARIMA technique for DYC Battery data. For all the above reasons, the ARIMA technique used in this study is the best tool for forecasting demand and estimating the long-term average demand for DYC Battery spare parts, even though the model is, to some extent, inadequate for forecasting unanticipated spikes in demand.

4.2 Results of Forecasting Using the Single Exponential Smoothing (SES) Method

The application of the SES method to Battery DYC spare part sales data resulted in an optimal smoothing parameter alpha (α) of 0.052, which is a relatively small value approaching zero. The small α value suggests that the model favors long historical data over recent observations, a common feature for data with fluctuating patterns and no trend. This result is consistent with the findings of research [11], which reported an optimal α parameter of 0.0645 for cement sales forecasting in the context of fluctuating demand patterns. They showed a similar tendency that data without significant trends generally produce small α values, so the smoothing was more robust to random noise.

The SES forecasting results for the testing period produced a constant value of 2.59 units per month for all 12 periods, with an RMSE of 3.8336, an MAE of 3.0000, and a MAPE of 55.19%. The MAPE value generated by SES in this study is in the less accurate category when referring to conventional MAPE interpretation standards, and this condition is comparable to the findings [12] reported a MAPE value of 39.04% for carbon black demand forecasting using SES with parameter $\alpha = 0.3$, where the method remains the best method despite its relatively high error value compared to cases with more stable data patterns. This confirms that the MAPE value is very much influenced by the volatility characteristics of the data under analysis and not only by the weaknesses of the method.

As expected, the SES forecast value was constant during the testing period, since the single exponential smoothing method produces a single forecast value for the entire forecast horizon and does not consider periodic changes. This contrasts with the study in [13], which analyzes SES and Double Exponential Smoothing (DES) with regard to Bali domestic tourist visits, where DES provides the flexibility to accommodate trend components that SES cannot. In the present study, the absence of a trend for the Battery DYC data makes SES a conceptually better choice since the model does not have to accommodate a trend that is not present in the data. The appropriateness of the SES model is further corroborated by the study in [10], which demonstrates that the smoothing method that uses historical weight yields the lowest accuracy for data that has a high level of fluctuation, as demonstrated by the MAPE Weighted Moving Average of 17.35% in their study, which, although it is low compared to MAPE SES in this study, illustrates the general tendency regarding the simple smoothing methods that are applied to data that do not exhibit sufficient stability.

4.3 Comparison of ARIMA and SES Accuracy

The accuracy comparison shows that both methods achieved very similar forecasting performance, with SES producing a slightly lower RMSE (3.8336 vs. 3.8370), whereas ARIMA achieved a lower MAE (2.8925 vs. 3.0000) and MAPE (53.21% vs. 55.19%). This pattern is consistent with previous studies, where SES may outperform ARIMA in RMSE while ARIMA provides better MAPE performance depending on the evaluation criterion [8]. Similarly, research [14] reported that SES performs slightly better on stable data, although this advantage diminishes for highly fluctuating demand, such as spare parts. Considering MAE as a more robust measure of average forecasting error, ARIMA (0,0,1) can be regarded as relatively more effective in minimizing forecasting deviations, which is consistent with the findings of [7]. But the difference in RMSE is very small (0.0034), showing that both models are adapted similarly to the Battery DYC demand.

ARIMA outperformed SES in MAE and MAPE, but both models produced MAPE values above 50%, indicating poor forecasting accuracy. The main reasons are the intermittent characteristics of Battery DYC demand, including frequent periods of zero demand, irregular demand intervals, and a large demand surge in October 2025. Such conditions inflate percentage-based error measures because small absolute errors become large percentage errors when actual demand approaches zero. Consequently, the forecasting results should be interpreted as decision-support information rather than precise demand estimates. ARIMA performed relatively better because it captures autocorrelation and stochastic dependencies after stationarity is achieved, whereas SES assumes a relatively constant demand level and is therefore better suited to stable, non-seasonal demand than to intermittent demand.

These results confirm that there is no one forecasting method that is better than the others, as the forecasting performance is based on the statistical characteristics of the demand data and the operational objectives of the inventory management. For PT XYZ, ARIMA (0,0,1) is recommended for the routine Battery DYC inventory planning due to the lower values of MAE and MAPE, although the forecasting should be complemented with safety-stock policies and periodic forecast reviews to reduce the risks of

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stock shortages and overstocking. Similar conclusions were reported by [15], where the adaptive forecasting approaches beat the conventional smoothing methods for fluctuating demand. However, because both ARIMA and SES were originally developed for relatively continuous demand, neither method is fully suitable for intermittent demand. Therefore, specialized forecasting methods such as Croston's method and its variants should be investigated in future studies. Since this research was conducted as a single industrial case study, the findings should be interpreted within the operational context of Battery DYC demand rather than generalized to all time-series data. Future research is also encouraged to validate these results using benchmark datasets and additional industrial case studies with different demand characteristics.

5. CONCLUSION

The results and discussion lead to some conclusions about the comparative performance of ARIMA and Single Exponential Smoothing (SES) in the forecasting of Battery DYC spare-part demand. First, the Box–Jenkins method finds ARIMA (0,0,1) to be the most suitable model with a constant forecast of 2.42 units per month with values of RMSE, MAE and MAPE of 3.8370, 2.8925 and 53.21%, respectively. The relatively high MAPE is due to the intermittent nature of Battery DYC demand, including irregular demand intervals, frequent zero-demand periods and an extreme demand surge in October 2025, which in turn reduced the accuracy of the forecast.

The SES model with the optimal smoothing parameter ($\alpha = 0.052$) resulted in a constant forecast of 2.59 units per month, with the RMSE, MAE, and MAPE being 3.8336, 3.0000, and 55.19%, respectively. The small alpha value indicates that SES pays more attention to long-term historical observations, making it suitable for demand that is relatively stable without significant trend or seasonality. Overall, SES achieved a slightly lower RMSE, while ARIMA performed better than SES in MAE and MAPE. Considering MAE as a more robust measure of forecasting error, ARIMA (0,0,1) is relatively more appropriate for Battery DYC demand forecasting, although the performance difference between the two methods is small.

These findings also confirm that no forecasting method is universally superior, as forecasting performance depends on the statistical characteristics of the demand data and the operational objectives of inventory management. Therefore, ARIMA is recommended to support Battery DYC inventory planning at PT XYZ, while forecasting results should be complemented with safety-stock policies and managerial judgment because both models produced MAPE values above 50%.

This study is limited to a single industrial case study and the evaluation of only two conventional forecasting methods. Therefore, the results should be interpreted in the context of the operational setting of the demand for Battery DYC and not generalized to other industries or demand patterns. Future research should validate these findings with benchmark data sets and other industrial case studies, while also evaluating the performance of specialized intermittent-demand forecasting methods (e.g., Croston's method and its variants, hybrid forecasting approaches) to improve the forecasting accuracy and the generalization potential of the results.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Author1: Generate research ideas, develop a conceptual framework, collect the data, utilize software, conduct the data processing, write the conclusion, and write the references. **Author2**: Writing of methodology, introduction, literature review sections, involved invalidating results, and writing discussion sections

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data will be made available on request.

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