MIKAILALSYS
Journal of Multidisciplinary Sciences

e-ISSN : 2987-2286
p-ISSN : 2987-3924
Index: Harvard, Boston, Sydney, Copernicus, Sinta 4, Scilit, Semantic, Google, etc

https://doi.org/10.58578/mikailalsys.v4i3.12126

Battery Sales Forecasting Using ARIMA at Store X for Monthly Data Based on Battery Brand

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Submitted:	Revised:	Accepted:	Published:
Aug 4, 2026	Sep 1, 2026	Sep 13, 2026	Sep 18, 2026

Abstract

Demand uncertainty poses a persistent challenge for sales planning and inventory management in retail businesses, particularly when products exhibit heterogeneous sales patterns across brands. This study aims to develop brand-specific vehicle battery sales forecasting models using the Autoregressive Integrated Moving Average (ARIMA) method. The study follows the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, comprising Business Understanding, Data Understanding, Data Preparation, Modeling, and Evaluation. Historical sales transaction data from Toko Aki Restu covering July 2016 to July 2026 were aggregated into monthly sales series for nine battery brands and divided into training and testing sets using an 80:20 ratio. Model development involved stationarity assessment using the Augmented Dickey-Fuller test, preliminary model identification through the Autocorrelation Function and Partial Autocorrelation Function, and parameter combination selection using Grid Search. Forecasting performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The findings indicate that the optimal ARIMA specification varies across battery brands, reflecting differences in their underlying sales patterns. GS ASTRA MF achieved the lowest MAE and RMSE, whereas AMARON recorded the lowest MAPE among the evaluated brands. The selected models were subsequently used to forecast monthly sales for a 12-month period from August 2026 to July 2027. These findings demonstrate that brand-specific ARIMA modeling can accommodate heterogeneous sales characteristics and provide differentiated forecasts for vehicle battery products. The study contributes a systematic forecasting approach that can support more informed sales planning and inventory management by aligning forecasting models with the time-series characteristics of individual brands.

Keywords: ARIMA; Battery Sales; Grid Search; Sales Forecasting; Time Series

INTRODUCTION

Sales forecasting is one of the important aspects in managing operational activities in retail businesses because forecasting results can be used as a basis for estimating product needs and supporting purchasing planning. Demand uncertainty can cause companies to face inventory conditions that do not match market needs. Excessive inventory can increase storage costs, while insufficient inventory can increase the risk of product shortages. Therefore, the ability to estimate sales based on historical patterns is one of the factors that can support decision-making in retail operations management. (Ramos et al., 2015) explain that sales forecasting plays an important role in various retail operational decisions, including purchasing planning and inventory management. In addition, the characteristics of sales data arranged sequentially over time make it suitable for analysis using a time series approach.

This problem is also found at Store X, which is engaged in vehicle battery sales. Demand for batteries from various brands changes over time, so the sales volume in a given period is not always the same. This condition can complicate the planning process if purchasing decisions are based solely on sales from the previous period without considering the overall historical pattern. The transaction data available for the period July 2016 to July 2026 shows sales data that can be utilized to build a forecasting model. In this study, the transaction data was then aggregated into monthly sales data based on brand in order to obtain a more structured time series that could be used in the modeling process. The brand-based aggregation approach was chosen because the study focuses on the demand patterns of each battery brand, rather than on individual product or battery type level(Kim et al., 2023).

One method that can be used to forecast time series data is the Autoregressive Integrated Moving Average (ARIMA). ARIMA is a method that utilizes the relationship between past observation values and forecasting errors to produce predictions for the next period. The use of ARIMA in sales forecasting has been applied in various business contexts. (Saputra, 2024), for example, used monthly sales data and applied the Augmented Dickey-

Fuller (ADF) test, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF) in the process of forming an ARIMA model. The results show that ARIMA can be used to model sales data based on time series characteristics. Research by (Ramos et al., 2015) also shows that ARIMA can be used to forecast retail sales and evaluate forecasting performance using error measures such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE)(Atesongun & Gulsen, 2024).

Nevertheless, the selection of ARIMA model parameters is an important part of producing an appropriate forecasting model. Parameter identification through ACF and PACF can provide an initial indication of the autoregressive (p) and moving average (q) orders, but the correlation patterns in time series data do not always provide a single parameter combination that can be directly established as the best model. Therefore, a systematic search approach can be used to compare several parameter combinations. (Hasanudin & Mujiyono, 2026) applied Grid Search to ARIMA modeling for monthly sales forecasting and used a combination of evaluation criteria in determining the appropriate model. This approach shows that systematic parameter search can help reduce subjectivity in model selection. Thus, the use of ACF and PACF as initial identification followed by Grid Search can provide a more systematic modeling process in determining ARIMA parameter combinations(Chen, 2023).

Based on the previous research above, some studies have applied ARIMA for sales forecasting and used prediction error-based evaluation, while other studies have developed systematic parameter search through Grid Search. However, the application of this approach specifically to battery sales data based on brand with a long historical period still has room for further study. In addition, the sales characteristics of each brand can differ, so using a single identical model for all brands may not necessarily produce an optimal level of accuracy. Therefore, a modeling process is needed that allows each brand to obtain an ARIMA configuration based on the characteristics of its own data(Kurnia et al., 2025; Kusuma et al., 2018).

The novelty of this study lies in the application of ARIMA modeling separately for each battery brand using monthly sales data for the period July 2016 to July 2026. The modeling process was carried out systematically through the stages of Augmented Dickey-Fuller to determine the level of stationarity, ACF and PACF to obtain initial parameter indications, and Grid Search to evaluate combinations of the p and q parameters(Syabrina, 2022). The resulting models were then evaluated using MAE, RMSE, and MAPE on the testing data, so that model selection was not only based on fit to the training data, but also considered the model's ability to produce predictions on data not used during the training process. This evaluation approach using out-of-sample data is also in line with the research of (Ramos et al., 2015), which evaluated ARIMA model performance based on out-of-sample data.

This study focuses on forecasting monthly battery sales based on nine brands, namely AMARON, BOSCH, BOSCHAGM, DELKOR, FURUKAWA BATTERY, GS ASTRA, GS ASTRA MF, RCA BATTERY, and SUPREME. The data consists of 121 monthly observations for each brand and is divided using a proportion of 80% training data and 20% testing data. The purpose of this study is to build an appropriate ARIMA model for each brand, evaluate model performance based on MAE, RMSE, and MAPE, and produce sales forecasts for the following period. The results of the study are expected to provide an overview of the ability of the ARIMA method to model battery sales patterns based on brand and serve as a basis of information for research and decision-making related to sales forecasting in the retail business.(Eşidir et al., 2022)

METHODS

This study uses a quantitative approach with a time series analysis method to forecast battery sales at Toko Aki Restu. The research framework refers to the Cross-Industry Standard Process for Data Mining (CRISP-DM), which consists of six stages: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment.(Wang et al., 2024) However, this study focuses on the stages up to the forecasting process and model evaluation, so the research results are directed toward obtaining the best ARIMA model for each battery brand.(Nagalakshmi et al., 2025)

The data used is battery sales transaction data from Toko Aki Restu for the period July 2016 to July 2026. The initial data consisted of transaction data containing battery sales information, which was then selected and cleaned to ensure consistency in brand naming. After the data preparation process, sales transactions were grouped by brand and aggregated into monthly sales data. Aggregation was carried out because the procurement and sales planning patterns of the research object are more relevant to analyze on a monthly basis. Based on the grouping results, the study uses nine battery brands, namely AMARON,

BOSCH, BOSCHAGM, DELKOR, FURUKAWA BATTERY, GS ASTRA, GS ASTRA MF, RCA BATTERY, and SUPREME. Each brand has 121 monthly observations, which are then used as a time series in the modeling process.(Maslim et al., 2020; Sumitra & Sidqi, 2024)

In the Data Preparation stage, the monthly data was divided into training data and testing data with an 80:20 ratio. This division resulted in 97 observations for training data and 24 observations for testing data for each brand. The training data was used to build and determine the ARIMA model parameters, while the testing data was used to determine the model's ability to produce predictions on data not used during the model formation process. The data division was carried out based on time order so that the time series characteristics were maintained and no mixing occurred between past data and data to be predicted.(Ensafi et al., 2022)

The Modeling stage was carried out using the Autoregressive Integrated Moving Average (ARIMA) method, represented in the form ARIMA(p,d,q). The parameter p indicates the autoregressive order, d indicates the level of differencing, while q indicates the moving average order. The value of d was determined through the Augmented Dickey-Fuller (ADF) test to test data stationarity. If the data was already stationary at the level, then $d = 0$ was used, while data that was not yet stationary required a differencing process. After the level of integration was determined, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were used as an initial analysis to identify possible p and q orders. The use of ACF and PACF provides an overview of the relationship between observations at several lags and helps determine appropriate candidate models.(Hidayatullah et al., 2025)

To obtain a more systematic parameter combination, the study then applied Grid Search to the values of p and q. Testing was carried out over a range of values from 0 to 15 for each parameter, while the value of d was set based on the ADF test results. Each parameter combination that met the modeling criteria was compared based on the Akaike Information Criterion (AIC) value and the forecasting error performance on the testing data. This approach was used to reduce subjectivity in parameter selection and obtain the model most suited to the characteristics of each brand(Syabrina, 2022).

The Evaluation stage was carried out by comparing the model's forecasting results with the actual values in the testing data. Three metrics were used to measure model performance: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE was used to measure the average absolute value of prediction errors, RMSE imposes a larger penalty on large prediction errors, while MAPE indicates the magnitude of prediction error as a percentage. The use of these three metrics allows evaluation to be carried out from both absolute and relative error perspectives. The best model for each brand was determined based on a combination of model selection results and forecasting error values on the testing data.(Nusamandiri & Rianto, 2025)

After the best model was obtained for each brand, the model was used to generate sales forecasts for the following period. The forecasting results were used as an estimate of the sales development of each brand based on the historical patterns learned by the model. Thus, the research stages produced the best ARIMA model for each brand, MAE, RMSE, and MAPE evaluation values, and sales forecasts for the upcoming period.

RESULTS

ARIMA Modeling Results

Based on the results of processing monthly sales data for the nine battery brands, all time series were tested for stationarity using the Augmented Dickey-Fuller (ADF) test. The test results show that the data for each brand was stationary at the level, so the differencing value used was $d = 0$. Next, initial identification of the autoregressive order (p) and moving average order (q) was carried out using ACF and PACF.

The candidate models obtained were then systematically tested using Grid Search with a range of p and q values from 0 to 15. The model search results produced different ARIMA combinations for each brand. This difference shows that the sales pattern characteristics are not entirely the same between brands, so using a single identical model for all brands was not the approach used in this study.

Table 1. Best ARIMA Model for Each Brand

Brand	ARIMA Model	AIC
AMARON	ARIMA(4,0,4)	655,908
BOSCH	ARIMA(0,0,3)	608,006
BOSCHAGM	ARIMA(2,0,2)	462,003
DELKOR	ARIMA(3,0,3)	573,018
FURUKAWA BATTERY	ARIMA(2,0,1)	610,301
GS ASTRA	ARIMA(0,0,2)	522,080

Brand	ARIMA Model	AIC
GS ASTRA MF	ARIMA(2,0,4)	494,019
RCA BATTERY	ARIMA(3,0,3)	622,604
SUPREME	ARIMA(1,0,9)	537,972

Table 1 best ARIMA model for each brand shows that the best model differs for each brand. The ARIMA(4,0,4) model was obtained for AMARON, while BOSCH produced ARIMA(0,0,3). BOSCHAGM used ARIMA(2,0,2), DELKOR and RCA BATTERY used ARIMA(3,0,3), while FURUKAWA BATTERY produced ARIMA(2,0,1). GS ASTRA produced ARIMA(0,0,2), GS ASTRA MF produced ARIMA(2,0,4), and SUPREME produced ARIMA(1,0,9).

Forecast Evaluation Results

The ARIMA models obtained were then evaluated using 24 observations from the testing data. Evaluation was carried out using MAE, RMSE, and MAPE to determine the level of prediction error for each model.

Table 2. ARIMA Model Evaluation Results

Brand	MAE	RMSE	MAPE
AMARON	5,50	6,74	13,26%
BOSCH	3,90	4,63	18,96%
BOSCHAGM	2,00	2,60	39,36%
DELKOR	3,60	4,14	30,97%
FURUKAWA BATTERY	4,50	5,75	15,53%
GS ASTRA	2,70	3,82	30,58%
GS ASTRA MF	1,90	2,31	41,24%
RCA BATTERY	4,50	5,00	16,59%
SUPREME	2,80	3,71	26,43%

Based on Table 2 ARIMA model evaluation results, GS ASTRA MF produced the lowest MAE and RMSE values, at 1.90 and 2.31 respectively. Meanwhile, AMARON produced the lowest MAPE value at 13.26%, followed by FURUKAWA BATTERY at 15.53% and RCA BATTERY at 16.59%. These results show that model performance can differ depending on whether it is viewed based on absolute or relative error measures.

As shown in Table 2 ARIMA model evaluation esults, the relatively high MAPE values for some brands, such as GS ASTRA MF at 41.24% and BOSCHAGM at 39.36%, do not directly indicate that their prediction errors are the largest in absolute terms. This can be seen from the RMSE value of GS ASTRA MF, which is in fact the lowest, at 2.31. This difference occurs because MAPE measures error relative to actual values, so it can produce a high percentage for data with relatively small sales values. Therefore, the interpretation of model performance in this study takes MAE, RMSE, and MAPE into account together.

Sales Forecasting Results

The best model for each brand was then used to generate sales forecasts for the next 12 periods, namely August 2026 to July 2027. The forecasting results provide an estimate of monthly sales volume for each brand based on the historical patterns learned by the ARIMA model.

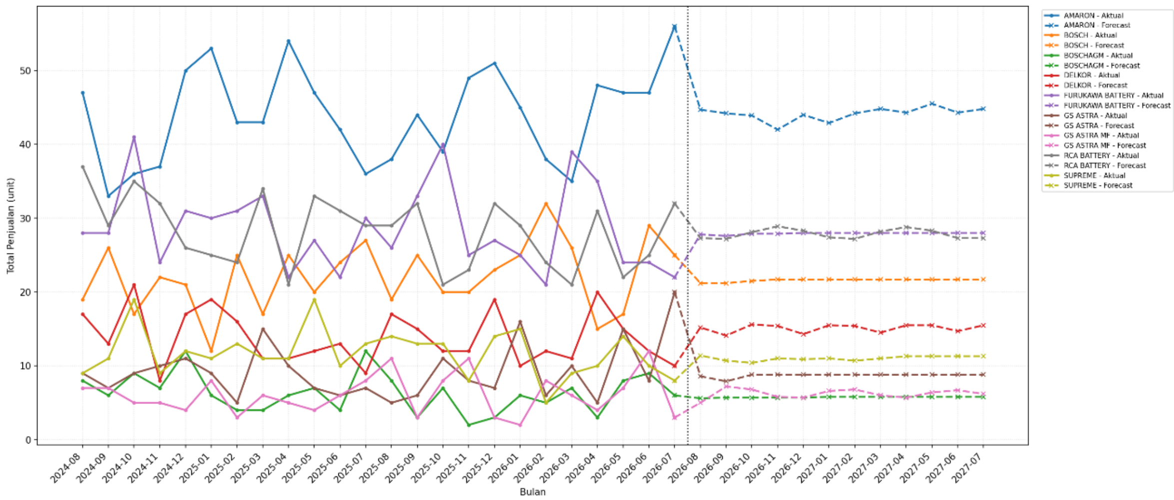

Figure 1. Results ARIMA Forecasting

Figure 1 results ARIMA forecasting illustrates the ARIMA forecasting results for the nine battery brands over the 12-month forecasting horizon from August 2026 to July 2027. The forecasts represent the expected monthly sales volumes generated from the best ARIMA model selected for each brand based on the preceding modeling and evaluation stages. The figure provides a comparative view of the predicted sales patterns across brands, allowing the variation in forecast levels and trends to be observed over the forecasting period. As an illustration, the AMARON model predicts sales of 44.7 units in August 2026, followed by 44.2 units in September, 43.9 units in October, and 42.0 units in November, indicating a relatively stable pattern with a gradual decline. Similar forecasts were generated for the other brands according to their respective ARIMA configurations, resulting in a total of 108 monthly predictions. These forecasting results indicate that the selected ARIMA models can be used to estimate future sales based on the historical characteristics of each brand, while the differences in forecast patterns further reflect the distinct sales behavior observed across the battery brands. The implications of these forecasting results are further discussed in the following section.

DISCUSSION

The results show that the ARIMA model obtained differs for each battery brand. This difference can be seen in the parameter combinations selected, namely AMARON using ARIMA(4,0,4), BOSCH ARIMA(0,0,3), BOSCHAGM ARIMA(2,0,2), DELKOR ARIMA(3,0,3), FURUKAWA BATTERY ARIMA(2,0,1), GS ASTRA ARIMA(0,0,2), GS ASTRA MF ARIMA(2,0,4), RCA BATTERY ARIMA(3,0,3), and SUPREME ARIMA(1,0,9). These differences in models show that sales pattern characteristics are not entirely the same across brands, so using a single ARIMA configuration for all brands is not appropriate. This finding is in line with research by (Suryawan et al., 2024), which shows that forecasting model performance can differ according to the characteristics of the sales data analyzed. That study also shows that ARIMA can provide good performance on certain sales data compared to other alternative methods.(Husein et al., 2021)

The model identification stage in this study began with stationarity testing using the Augmented Dickey-Fuller (ADF) test. The test results show that all nine brand sales series were stationary at the level, so the differencing value used was d=0. After that, ACF and PACF were used to obtain an initial overview of the possible autoregressive order (p) and moving average order (q). The use of ADF, ACF, and PACF in the ARIMA model identification process has also been used in previous sales research, particularly to determine differencing needs and identify initial model parameters (Simanungkalit, 2024). Thus, the identification stages used in this study are consistent with the general approach to ARIMA modeling of monthly sales data.

The initial identification results through ACF and PACF were then followed by Grid Search to obtain a more systematic combination of the p and q parameters. In this study, the values of p and q were tested over a range of 0 to 15, while the value of d was set based on the stationarity test results. This approach was used to reduce reliance on parameter selection based solely on visual interpretation of ACF and PACF. Grid Search allows a number of model combinations to be tested and compared based on predetermined criteria. The use of systematic parameter search has also been found in sales forecasting research that utilizes parameter search to obtain a model configuration with better performance (Hasanudin & Mujiyono, 2026).

Evaluation on the testing data shows differences in accuracy levels between brands. The GS ASTRA MF model produced an MAE of 1.90 and an RMSE of 2.31, which are the lowest values compared to other brands. Meanwhile, AMARON produced the lowest MAPE value at 13.26%. These differences in results show that there is no single error measure that comprehensively describes model performance across all brands. MAE and RMSE indicate the magnitude of prediction error in sales data units, while MAPE indicates error as a percentage. The simultaneous use of MAE, RMSE, and MAPE has also been used in ARIMA-based sales forecasting research to provide an overview of model performance from several evaluation perspectives (Simanungkalit, 2024; Suryawan et al., 2024).

One finding that needs attention is the relatively high MAPE value for some brands, even though their MAE and RMSE values are relatively low. GS ASTRA MF, for example, produced an MAE of 1.90 and an RMSE of 2.31, but had a MAPE of 41.24%. This condition shows that errors in unit terms may appear small, but when calculated relative to a low actual value, the resulting error percentage can become larger. Therefore, the interpretation of MAPE for data with relatively small sales values needs to be done carefully and should not be used as the sole basis for determining model quality. In contrast, AMARON had the lowest MAPE at 13.26%, but its RMSE of 6.74 was higher than that of GS ASTRA MF. These results show that different evaluation measures can provide different perspectives on model performance.

Differences in performance between brands also reinforce the importance of modeling separately at the brand level. The research data was not treated as a single overall sales series, but was formed into nine series based on brand. This approach allows the characteristics of each brand to be preserved during the identification and modeling process. This is relevant because previous research has shown that ARIMA performance can vary depending on the characteristics of the category or sales series used (Brykin, 2024). Thus, the results of this study support the use of ARIMA models tailored to the characteristics of each brand rather than applying a single identical model to all data.

The forecasting results for the next twelve months show that the resulting models can be used to generate sales estimates for each brand for the period August 2026 to July 2027. The use of these forecasting results can provide quantitative information on the demand trends of each brand, which can serve as a consideration in sales planning. Research by (Suryawan et al., 2024) also shows that sales forecasting results can be used to help companies anticipate changes in demand and support sales-related decision-making.

Although it provides results that can be used for forecasting, this study has several limitations. The ARIMA model used only utilizes historical sales patterns and does not yet incorporate external variables such as price, promotions, economic conditions, or changes in consumer preferences. In addition, the study was conducted at the brand level using data that had been aggregated monthly. This aggregation helps produce a more consistent time series, but causes sales variation at the individual type or product level not to be analyzed directly. Future research could consider the use of external variables through models such as ARIMAX or compare ARIMA with other methods, including LSTM, Prophet, or hybrid models. Research by Suryawan et al. (2024) and Brykin (2024) shows that comparing ARIMA with other methods can provide additional information on model suitability for different data characteristics.

CONCLUSION

This study successfully applied the Autoregressive Integrated Moving Average (ARIMA) method to forecast battery sales at the brand level at Toko Aki Restu using the CRISP-DM framework. Based on the stationarity test results, all sales data from the nine brands were stationary at the level, so the differencing value used was d=0. The ACF and PACF identification process, followed by Grid Search, produced different ARIMA models for each brand, namely ARIMA(4,0,4) for AMARON, ARIMA(0,0,3) for BOSCH, ARIMA(2,0,2) for BOSCHAGM, ARIMA(3,0,3) for DELKOR, ARIMA(2,0,1) for FURUKAWA BATTERY, ARIMA(0,0,2) for GS ASTRA, ARIMA(2,0,4) for GS ASTRA MF, ARIMA(3,0,3) for RCA BATTERY, and ARIMA(1,0,9) for SUPREME.

Evaluation results using the testing data show that model performance differs for each brand. The GS ASTRA MF model produced the lowest MAE and RMSE values, at 1.90 and 2.31 respectively, while the AMARON model produced the lowest MAPE at 13.26%. These results show that the ARIMA model is able to produce different levels of error according to the characteristics of each sales series. The resulting models were then used to generate sales forecasts for 12 months, namely the period from August 2026 to July 2027.(Ferdinansyah et al., 2026)

This study contributes by applying ARIMA modeling individually to nine battery brands using monthly sales data for the period July 2016 to July 2026. This approach allows the characteristics of each brand to be preserved during the modeling process and produces different models suited to the data patterns. The forecasting results can serve as supporting information for Toko Aki Restu in understanding the sales trends of each brand in the upcoming period.

Future research could develop the model by considering external variables that may affect sales, such as price, promotions, seasons, or economic conditions. In addition, future research could compare ARIMA with other forecasting methods or hybrid approaches to determine the method most suited to the characteristics of battery sales data. The use of data at the type or product level could also be considered if the number of observations and data consistency are sufficient.

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