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Article

Hybrid Approaches to Machine Learning for Improved Battery Sales Forecasting: A Case Study in Thailand

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Abstract. Battery sales forecasting is a critical component of demand planning in the automotive battery industry, directly influencing production, inventory management, and supply chain optimization. This study presents a comprehensive evaluation of traditional forecasting methods and machine learning techniques to predict monthly sales for a battery manufacturer in Thailand. Utilizing a dataset of monthly sales for the 10 best-selling products from January 2018 to December 2023, the research investigates the performance of traditional models such as Holt's Linear Trend, Holt-Winters Seasonal, ARIMA, SARIMA, and SARIMAX. Advanced machine learning approaches, including Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANN), are also explored. Additionally, hybrid models combining traditional and machine learning techniques are developed to leverage their respective strengths. The study integrates external factors such as economic indicators, industry-specific variables, and lagged data during feature selection to enhance predictive accuracy. Model performance is rigorously evaluated using Mean Absolute Percentage Error (MAPE). The results demonstrate that the hybrid ANN-LSTM model achieves the highest accuracy, with an average MAPE of 8.83%, significantly outperforming individual models, including the best-performing traditional model, ANN, at 9.43%. This research contributes to the field by providing a robust analytics framework that integrates traditional and advanced machine learning methodologies, offering actionable insights for battery sales forecasting and enhancing decision-making processes in the automotive industry.

Keywords: hybrid machine learning, battery sales forecasting, traditional forecasting methods, machine learning techniques.

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1. Introduction

The battery industry is a cornerstone of modern technology, powering everything from consumer electronics to automotive vehicles and industrial machinery. Among the various types of batteries, lead-acid batteries have been a stalwart, primarily due to their reliability, recyclability, and cost-efficiency. Despite the rising interest in electric vehicles (EVs) and associated battery technologies like lithium-ion, lead-acid batteries remain indispensable for conventional automotive applications, including starting, lighting, and ignition (SLI) systems in vehicles [1].

Thailand has become a pivotal player in the global automotive market, establishing itself as a significant manufacturing and export hub within Southeast Asia. This is clearly illustrated in Fig. 1., which depicts the Domestic Automotive Sales in Thailand from 2014 to 2023. As the graph shows, the country's lead-acid battery market has flourished alongside a vigorous automotive sector, which extensively utilizes these batteries for diverse applications ranging from vehicles to renewable energy storage systems [2]. The strategic emphasis on automotive production and exportation has not only carved a niche for Thailand as a prime location for battery manufacturing but has also drawn investments from international corporations, thereby nurturing a dynamic and competitive local industry [3].

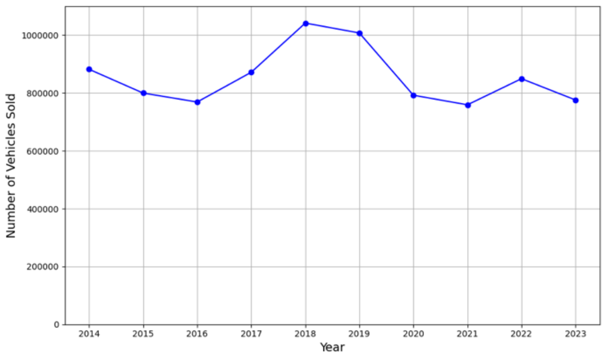

Fig. 1. Domestic automotive sales in Thailand from 2014 to 2023 from Thailand Automotive Institute.

In the rapidly evolving automotive market, effective demand planning and forecasting are crucial for manufacturers to maintain competitiveness and profitability. For the lead-acid battery industry, this entails accurately predicting market demand to optimize production schedules, manage inventory levels, and reduce operational costs. Demand planning also helps companies to anticipate shifts in consumer preferences and technological advancements, ensuring that they can adapt quickly to maintain their market position [4].

Forecasting methods are essential across industries, enabling organizations to predict future demand, trends, and challenges with notable accuracy [5]. These methods encompass a wide spectrum, from quantitative techniques such as time series analysis and regression models to qualitative approaches like expert judgment and market analysis. The integration of these methods provides organizations with a robust toolkit to navigate market uncertainties, optimize operations, and make informed decisions regarding production, inventory management, and strategic planning. Accurate forecasting helps minimize costs, enhance operational efficiency, and secure a competitive advantage in the market [6]. This understanding of forecasting methodologies forms a basis for examining specific demand forecasting techniques, their applications, and the benefits they bring to various sectors.

Demand forecasting is critical in numerous industries, each facing distinct challenges and opportunities in aligning operations with customer demand. In the retail sector, it supports inventory optimization and ensures adequate stock levels to meet consumer needs [7]. In manufacturing, accurate forecasts streamline production scheduling, resource allocation, and supply chain logistics [8]. In the energy sector, demand forecasting is essential for planning power generation, managing peak loads, and facilitating the transition to renewable energy sources.

In healthcare, forecasting aids in staffing, bed allocation, and medical supply management, enhancing operational efficiency and patient care [9]. Similarly, the pharmaceutical industry utilizes demand forecasting to predict drug consumption patterns, maintain inventory levels, and ensure medication availability [10].

In the automotive industry, demand forecasting helps manufacturers align production with market demand for various vehicle models and components [11]. In the food industry, it supports supply chain operations, reduces wastage, and aligns production with consumer preferences [12]. Additionally, the transportation and logistics sectors rely on demand forecasting to optimize route planning, fleet management, and cargo logistics, leading to reduced costs and improved delivery efficiency [13]. Overall, demand forecasting serves as a cornerstone for efficient resource allocation, strategic planning, and enhanced customer satisfaction across diverse industries.

This case-study company showcases an expansive selection of 129 stock keeping units (SKUs), illustrating its extensive reach within the battery market. Currently, they face challenges in forecasting automotive battery sales due to the lack of a structured, data-driven methodology, relying instead on subjective adjustments. Additionally, the company has not integrated external factors, such as economic and market indicators, into its forecasting framework. Thus, the primary objective of this research is to develop prediction models utilizing traditional time-series forecasting methods, machine learning techniques, and hybrid approaches to accurately forecast the monthly sales of automotive batteries for the company. Establishing a systematic, data-driven method that incorporates both internal and external factors is essential to enhance forecast precision, streamline production planning, and adapt to the dynamic demands of the automotive battery market.

By leveraging diverse modelling techniques, this study aims to identify the most effective predictive models tailored to various data patterns. Additionally, the research seeks to extract valuable insights from the most accurate model for each data pattern, providing a comprehensive understanding of sales dynamics and contributing to more informed decision-making processes within the automotive battery industry.

2. Literature Review

Extensive research has been conducted to explore different forecasting techniques, with particular attention to automotive sales forecasting, and highlighting gaps in knowledge that this study aims to address."

2.1. Traditional Time-series Forecasting

2.1.1. Holt's linear trend

Holt's linear trend method is an extension of simple exponential smoothing, developed by Holt in 1957, to forecast data with a trend. The method consists of three main equations: a forecast equation, a level equation, and a trend equation [14]. The forecast equation is given by:

$$\hat{y}_{t+h|t} = l_t + hb_t \,, \tag{1}$$

where:

- $\hat{y}_{t+h|t}$ is the forecast for time t+h based on information available at time t,
- l_t is the estimated level of the series at time t,
- b_t is the estimated trend (slope) of the series at time t,
- h is the number of periods ahead for the forecast.

2.1.2. Holt-Winters seasonal

Holt and Winters expanded Holt's method to incorporate seasonality, resulting in the Holt-Winters seasonal method. This method includes a forecast equation and three smoothing equations for the level (l_t), trend (b_t), and seasonal component (s_t), each with its own smoothing parameter (α, β^*, and γ). The seasonal frequency is denoted by m, representing the number of seasons in a year [15].

There are two variations of the Holt-Winters method: additive and multiplicative. The additive method is suitable when seasonal variations are approximately constant, while the multiplicative method is used when seasonal variations change proportionally to the series level. In the additive method, the seasonal component is in absolute terms, and the series is adjusted by subtracting the seasonal component. The seasonal component sums to approximately zero within each year. In the multiplicative method, the seasonal component is in relative terms (percentages), and the series is adjusted by dividing by the seasonal component, summing to approximately mm within each year.

Holt-Winters Additive Method:

The additive method's component form is:

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1} \,, \tag{2}$$

$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \,, \tag{3}$$

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1} \,, \tag{4}$$

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \,, \tag{5}$$

Holt-Winters Multiplicative Method:

The multiplicative method's component form is:

$$\hat{y}_{t+h|t} = (l_t + hb_t) + s_{t+h-m(k+1)} \,, \tag{6}$$

$$l_t = \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(l_{t-1} + b_{t-1}) \,, \tag{7}$$

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1} \,, \tag{8}$$

$$s_t = \gamma \frac{y_t}{l_{t-1} + b_{t-1}} + (1-\gamma)s_{t-m} \,, \tag{9}$$

2.1.3. ARIMA

Autoregressive Integrated Moving Average (ARIMA) model, which is a combination of the Autoregressive (AR) and Moving Average (MA) models. The ARIMA model is expressed as [16]:

$$\begin{aligned} Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} \\ + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots \\ - \theta_q \varepsilon_{t-q} \,, \end{aligned} \tag{10}$$

where:

- Y_t is the time series value at time t.
- $\phi_0, \phi_1, \dots, \phi_p$ are the coefficients of the autoregressive terms.
- $\varepsilon_t, \varepsilon_{t-1}, \dots, \varepsilon_{t-q}$ are the error terms.
- $\theta_1, \theta_2, \dots, \theta_q$ are the coefficients of the moving average terms.
- p is the order of the autoregressive part.
- q is the order of the moving average part.

In this model, analysts can utilize a mix of past values and past errors for forecasting. The model is typically denoted as ARIMA(p, d, q), where 'p' is the order of the AR part, 'd' is the degree of differencing, and 'q' is the order of the MA part. For instance, ARIMA(1, 0, 0) signifies an AR(1) model, while ARIMA(0, 0, 1) refers to an MA(1) model.

2.1.4. SARIMA

As a continuation from the discussion on the ARIMA model, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is an extension that specifically addresses the presence of seasonality in time series data. The SARIMA model combines both non-seasonal and seasonal factors in a multiplicative fashion to capture patterns that repeat at a fixed period. The SARIMA model is expressed as:

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$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} + \Phi_1 Y_{t-s} + \cdots + \Phi_P Y_{t-Ps} - \Theta_1 \varepsilon_{t-s} - \cdots - \Theta_Q \varepsilon_{t-Qs}, \quad (11)$$

where:

- $\Phi_1, \Phi_2, \ldots, \Phi_P$ are the coefficients of the seasonal autoregressive terms.
- $\Theta_1, \Theta_2, \ldots \Theta_Q$ are the coefficients of the seasonal moving average terms.
- P is the order of the seasonal autoregressive part.
- Q is the order of the seasonal moving average part.
- s is the seasonality period.

The model is typically denoted as SARIMA (p,d,q)(P,D,Q)$_s$, where (p,d,q) are the orders of the non-seasonal part and (P,D,Q) are the orders of the seasonal part, with s indicating the seasonality period.

2.1.5. SARIMAX

The SARIMAX model extends the SARIMA model by incorporating external factors (exogenous variables) that can influence the time series. This model is particularly useful when the time series is affected by factors outside of its own past values and seasonal components.

The SARIMAX model is expressed as [17]:

$$Y_t = \phi_0 + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{P} \Phi_k Y_{t-sk} - \sum_{l=1}^{Q} \Theta_l \varepsilon_{t-sl} + \sum_{m=1}^{M} \beta_m X_{m,t} + \varepsilon_t, \quad (12)$$

where:

- Y_t is the time series value at time t.
- $\phi_0, \phi_1, \ldots, \phi_p$ are the coefficients of the non-seasonal autoregressive terms.
- $\varepsilon_t, \varepsilon_{t-1}, \ldots, \varepsilon_{t-q}$ are the non-seasonal error terms.
- $\theta_1, \theta_2, \ldots, \theta_q$ are the coefficients of the non-seasonal moving average terms.
- $\Phi_1, \Phi_2, \ldots, \Phi_P$ are the coefficients of the seasonal autoregressive terms.
- $\Theta_1, \Theta_2, \ldots \Theta_Q$ are the coefficients of the seasonal moving average terms.
- $X_{m,t}$ represents the mth exogenous variable at time t.
- β_m is the coefficient for the mth exogenous variable.
- M is the number of exogenous variables included in the model.

The SARIMAX model is denoted as SARIMAX (p,d,q)(P,D,Q)$_s$ with exogenous variables. It allows for a more comprehensive analysis by considering the impact of external factors on the time series, making it a powerful tool for forecasting when such influences are significant.

2.2. Machine Learning

2.2.1. ANN

Artificial Neural Networks (ANNs) are computational models inspired by the human brain. They are used for various tasks, including classification, regression, and pattern recognition. ANNs consist of interconnected nodes or neurons, organized in layers [18]. The most basic components of an ANN are:

- Input Layer: This layer receives the input features for the network.
- Hidden Layers: These layers perform computations and feature transformations. The number of hidden layers and the number of neurons in each layer can vary.
- Output Layer: This layer produces the final output of the network.

The connections between neurons have associated weights, which are adjusted during the training process to minimize the error between the predicted and actual outputs.

Multilayer Perceptron (MLP) is a type of ANN that consists of one or more hidden layers. It is a feedforward network, meaning that the data flows from the input layer to the output layer without looping back. The neurons in MLP use nonlinear activation functions, which enable the network to learn complex patterns. The most common activation functions are the sigmoid, tanh, and ReLU (Rectified Linear Unit) [19].

The basic equation for a neuron in an MLP can be expressed as:

$$a = f\left(\sum_{i=1}^{n} w_i x_i + b\right), \quad (13)$$

where:

- a is the output of the neuron.
- f is the activation function.
- w_i are the weights associated with each input x_i.
- b is the bias term.
- n is the number of inputs to the neuron.

2.2.2. LSTM

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to address the limitations of traditional RNNs, particularly the vanishing gradient problem. This problem occurs when the gradients of the network's weights become very small during backpropagation, making it difficult for the network to learn long-term dependencies in the data.

LSTMs overcome this issue by introducing a memory cell and three gates (input, forget, and output gates) that control the flow of information through the network [20].

2.3. Hybrid Model Forecasting

Hybrid forecasting techniques integrate the strengths of multiple models to enhance predictive accuracy, recognizing that no single model can fully capture the complexities of real-world data. These approaches are classified into three categories: parallel, series, and parallel-series hybrid models [21].

Parallel hybrid models apply different models to the same dataset and combine their outputs for a final forecast. Series hybrid models use the output of one model as input for the next. Parallel-series models combine both approaches. Extensive research shows these hybrid structures outperform individual models in capturing complex data patterns [22].

Parallel hybrid models integrate the outputs of multiple forecasting models to achieve a consensus forecast, capitalizing on the different aspects of the data each model captures. The combination process can be linear, using methods like weighted averaging, or nonlinear, employing techniques like neural networks to dynamically adjust weights and capture complex interactions. Parallel hybrid models have shown success in applications such as financial forecasting, energy consumption prediction, and weather forecasting, proving their efficacy in handling diverse and complex datasets. Their flexibility and adaptability make them a preferred choice for high-accuracy forecasts in numerous real-world scenarios. The general structure of a parallel hybrid model, illustrating the integration of different models and the combination of their outputs, is depicted in Fig. 2. [21].

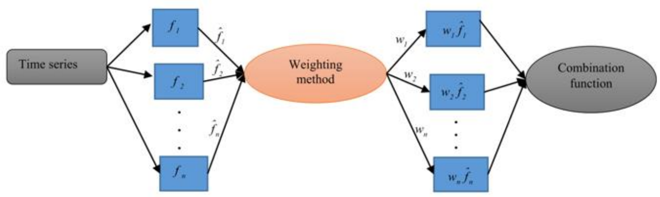


Fig. 2. The general framework of parallel hybrid structure.

2.4. Related Forecasting Research in Automotive Industry

Table 1 summarizes key studies on demand forecasting, including authors, data, error metrics, and models. For instance, Ibrahima et al. [23] developed an extensive hierarchical model for forecasting the demand for automotive components, emphasizing the importance of analyzing major factors affecting demand. Rožanec et al. [24] evaluated various algorithms for demand forecasting in the automotive industry, finding that global machine learning models achieved superior performance. Jain and Arora [25] conducted a study on time series forecasting techniques for the Indian automotive industry, demonstrating that the Holt's Linear Trend model was the most precise and accurate.

Gonçalves et al. [26] proposed a multivariate approach for multi-step demand forecasting in assembly industries, including automotive, showing that a multi-indicator approach can lead to lower inventory costs. Chandriah and Naraganahalli [27] presented a method for forecasting automobile spare parts demand using LSTM with a modified Adam optimizer, highlighting the efficiency and accuracy of the proposed technique. Addo and Sackey [28] developed a demand forecast model for Toyota Ghana, exceeding the accuracy of expert opinions and demonstrating the benefits of a more scientific approach to forecasting. Anwar et al. [29] optimized an LSTM model to accurately forecast Low-Cost Green Car (LCGC) sales in Indonesia. Oukassi et al. [30] found LSTM models outperformed ARIMA in forecasting automotive manufacturing demand.

Table 1. Related forecasting research in automotive industry.

Author	Year	Data	Error Metric	Demand Model
Ibrahima et al.	2021	Car sales	MAPE	Extensive hierarchical
Rožanec et al.	2021	Car sales	R^2, MASE	SVR, Voting, ARIMA, ES,
Jain	2021	Car sales	MAPE	MA, WMA, ES, Holt 's Linear Trend, Regression, ARMA, ARIMA
Gonçalves et al.	2021	Spare parts demand	MAE	MLP, RF, ARIMAX, Theta
Chandriah and Naraganahalli	2021	Spare parts demand	MSE	SES, Croston, SBA, TSB, LTSM
Addo and Sackey	2022	Car sales	MAD, MSE, MAPE	ES
Anwar et al.	2022	Car sales	MAE, MAPE	LSTM
Oukassi et al.	2023	Spare parts demand	MSE, RMSE	ARIMA, LSTM

The use of independent variables in forecasting automotive sales has been extensively studied, with a focus on economic, consumer-related, and product-specific factors. Johan [31] and Muhammad [32] emphasized macroeconomic indicators such as GDP, inflation rate, unemployment rate, and loan rate as key determinants, particularly in the ASEAN region. Kaya et al. [33] employed artificial neural networks in Turkey, highlighting the significance of exchange rates, income levels, and industrial production, reinforcing the role of economic variables in shaping demand.

Beyond economic factors, studies like Nawi et al. [34] and Rasheed et al. [35] expanded the scope to include CPI, fuel prices, and income levels. Wei [36] further identified car production, ownership, and oil consumption as critical predictors, alongside GDP. These findings validate the inclusion of diverse indicators, as summarized in Table 2, for comprehensive forecasting in the automotive industry.

The evolving landscape of demand forecasting in the automotive industry reflects a shift towards integrating traditional methods with advanced computational techniques like ANN and LSTM. Furthermore, recent studies emphasize incorporating external factors, such as economic indicators and product-specific factors, to enhance forecast performance while exploring the complex relationships between external factors and automotive sales, providing a more holistic understanding of demand dynamics.

2.5. Research Gap

While there has been extensive research on forecasting techniques and their application in various industries, including the automotive sector, there is a notable gap in the literature concerning the specific application of both traditional forecasting techniques and machine learning techniques for battery sales forecasting. Previous studies have primarily focused on the automotive industry as a whole or on specific components within the industry, such as automobile sales or spare parts demand. However, the battery segment, particularly for lead-acid batteries used in automotive applications, has received limited attention in terms of demand forecasting.

Furthermore, the integration of exogenous factors into forecasting models for battery sales has not been extensively explored. While some studies have considered external variables in forecasting models for automotive sales, there is a lack of research on how these factors specifically impact battery sales. This gap is significant given the critical role of batteries in the automotive industry and the potential influence of economic indicators and consumer behavior patterns on battery demand.

Additionally, the comparative analysis of traditional forecasting and machine learning techniques in the context of battery sales forecasting is underrepresented in the literature. Most studies tend to focus on one type of forecasting method, either traditional forecasting or machine learning, without a comprehensive comparison of their performance in predicting battery sales.

In summary, the research gap identified from the literature review includes:

1. Limited focus on battery sales forecasting within the automotive industry.
2. Insufficient comparative analysis of traditional forecasting techniques and machine learning techniques specifically for battery sales forecasting.
3. Lack of hybrid models for battery sales forecasting, and in the automotive industry, there is often no hybridization between univariate models and multivariate models.

Addressing this research gap is crucial for developing more accurate and reliable forecasting models that can aid battery manufacturers and suppliers in optimizing production planning, inventory management, and strategic decision-making.

3. Methodology

This study aims to forecast monthly battery product sales through the application of predictive models and an analysis of factors influencing sales. The methodology of this research is depicted in Fig. 3.

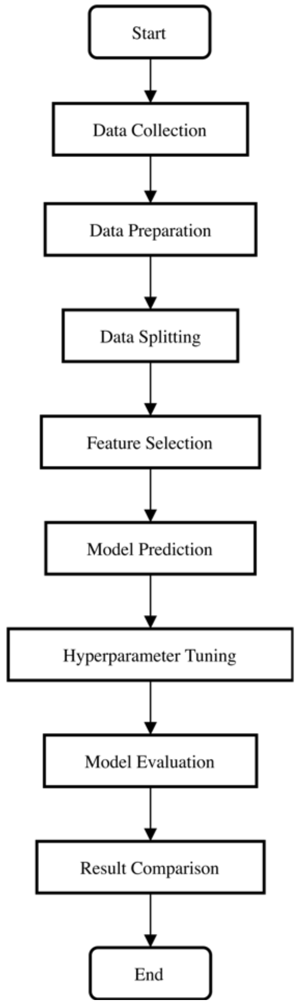


Fig. 3. Overview of the research's methodology.

3.1. Data Collection

The sales dataset employed in this study encompasses a 72-month period, ranging from January 2018 to December 2023. It incorporates monthly sales data for battery products sold by the manufacturer under investigation. To pinpoint the products exerting the most significant influence, the analysis will concentrate on the top 10 SKUs based on unit sales for the year 2022. These top-selling SKUs collectively account for 58.54% of the total units sold in 2022. Additional data and sources used as predictors will be described in detail in Table 2.

Table 2. Data description.

Data	Source
Gross Domestic Product (GDP)	National Economic and Social Development Council
Inflation Rate	Bank of Thailand
Unemployment Rate	Trading Economics
Loan Rate	Bank of Thailand
Consumer Price Index (CPI)	Trade Policy and Strategy Office
Exchange Rate USD/THB	Bank of Thailand
Growth of GDP	World Bank
Income Level	Trading Economics
Diesel Prices	Bank of Thailand
Gasoline Prices	Bank of Thailand
Gross National Income (GNI)	World Bank
Car Production	Thai Automotive Institute
Car Ownership	Thai Automotive Institute

3.2. Data Preparation

The dataset consists of 10 SKUs as rows and 26 features. During data preparation, no missing values or duplicate rows were identified, ensuring the dataset's integrity. Feature scaling was applied using Standardization, transforming the data to have a mean of 0 and a standard deviation of 1. The data types were verified for accuracy to ensure consistency and usability for analysis.

The study incorporates several independent variables grouped into categories based on their relevance:

- Economic Indicators: Gross Domestic Product (GDP), Inflation Rate, Unemployment Rate, Loan Rate, Consumer Price Index (CPI), Exchange Rate, Growth of GDP, Income Level, Gross National Income (GNI)
- Automotive Industry Specific: Car Production, Car Ownership, Lead Price
- Market Factors: Fuel Prices, Gasoline Prices
- Time-Related: Month
- Lagged Variables: Sales Lag 1 Month, Sales Lag 2 Months, Sales Lag 3 Months

3.3. Data Splitting

The study employs a monthly sales dataset spanning from January 2018 to December 2023, comprising 72 months of battery product sales data from a case study company in Thailand. Of these, 60 months are allocated for training prediction models, while the remaining 12 months are reserved for testing model performance.

3.4. Feature Selection

The feature selection process was streamlined by employing the stepwise regression method. This statistical technique iteratively adds or removes features based on their significance in explaining the variance in the target variable, Sales Quantity. The significance of each feature is determined using predefined criteria, with an entry alpha of 0.05 and a removal alpha of 0.05. This ensures that only features that contribute meaningfully to the model are retained.

3.5. Model Prediction

Various prediction models are explored, including Holt's Linear Trend, Holt-Winters Seasonal, ARIMA, SARIMA, SARIMAX, Univariate LSTM (U-LSTM), Multivariate LSTM (M-LSTM), ANN and hybrid model.

3.6. Hyperparameter Tuning

This research utilizes hold-out cross-validation for traditional forecasting techniques. Additionally, the 10-fold cross-validation method and grid search is employed for hyperparameter tuning in machine learning techniques.

Hyperparameter tuning for ARIMA/SARIMA/SARIMAX was performed using the Auto ARIMA algorithm, with the Akaike Information Criterion (AIC) serving as the selection criterion. The algorithm identifies the optimal model by exploring various parameter combinations to minimize the AIC. Holt and Holt-Winters methods were applied without hyperparameter tuning. Tables 3 and 4 present the hyperparameter tuning results for ANN, U-LSTM and M-LSTM models, respectively.

Table 3. Hyperparameters search grid of ANN model.

Hyperparameter	Value or Range
Number of Layers	[1, 2, 3]
Units in Hidden Layers	[50, 100]
Activation Functions	['relu', 'tanh', 'sigmoid']
Learning Rate	[0.01, 0.005, 0.0001]
Alpha (Regularization)	[0.0001, 0.001, 0.01]
Batch Size	[16, 32, 64]
Max Iterations	[200, 400, 600]

Table 4. Hyperparameters search grid of U-LSTM and M-LSTM model.

Hyperparameter	Value or Range
Number of Layers	[1, 2]
Units in Hidden Layers	[50, 100]
Activation Functions	['relu', 'tanh', 'sigmoid']
Learning Rate	[0.01, 0.005, 0.0001]
Alpha (Regularization)	[0.001, 0.01]
Batch Size	[16, 32]
Epoch	[50, 100]

3.7. Hybrid Models

Hybrid models have been shown to enhance the performance of forecasting or prediction, as evidenced by various prior studies. This research employs a parallel hybrid structure to improve forecasting accuracy through comprehensive pattern detection and modeling. The parallel hybrid model is implemented as described earlier. After training and making predictions with the selected individual models, the predictions from these models are used as input to train a linear regression model. Subsequently, the final predictions are made, evaluated, and the model's performance is compared. In this study, one model from the univariate category and two models from the multivariate category are chosen for the hybridization process.

3.8. Model Evaluation and Result Comparison

3.8.1. Model evaluation and selection

The performance of the models is evaluated using the Mean Absolute Percentage Error (MAPE). MAPE is used to assess the accuracy of the models, with a lower MAPE indicating higher accuracy. The model that achieves the lowest MAPE on the test set is selected as the best model for sales prediction of battery products.

3.8.2. Factor analysis

The factors influencing the sales of battery products can be identified and analyzed using SHAP values. SHAP values are used to interpret the influence of factors on the model's predictions, providing insights into the relationships between the factors and the dependent variable.

4. Results

4.1. Data Exploration Results

The analysis of sales data for each SKU involved identifying trend and seasonal components using the Seasonal and Trend decomposition using Loess (STL) method. This approach revealed strong trend and seasonal components, though high residuals indicated that the STL model might not fully capture the data's structure. Examination of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots found no distinct seasonal patterns, suggesting that sales are not significantly influenced by seasonal factors. Additionally, both Linear Regression and the Mann-Kendall Test confirmed the presence of a significant trend component, indicating consistent increases or decreases in sales over time. Overall, the analysis revealed a lack of discernible seasonality but a notable trend component across all SKUs.

4.2. Feature Selection Results

The application of stepwise regression for feature screening in linear regression models provided valuable insights into the predictive capabilities for different SKUs. The adjusted R-squared values varied significantly, with SKU1 showing a high predictability of 84.30% and SKU6 a low predictability of 14.60%. The average adjusted R-squared across all SKUs was 58.78%, indicating that the selected features explained more than half of the variance in sales data. The analysis highlighted the variable effectiveness of the linear regression models across SKUs, with some models showing strong predictability and others less so.

The selected factors influencing sales differed among SKUs, with economic indicators like the Unemployment Rate and Income Level being consistently significant, while specific month-related factors varied. SKU6 had unique predictors, such as a negative impact from the Exchange Rate, and SKU7 was notably influenced by seasonal adjustments. This variability underscores the importance of tailored forecasting models that consider both common and SKU-specific factors.

4.3. Univariate Model Prediction Results

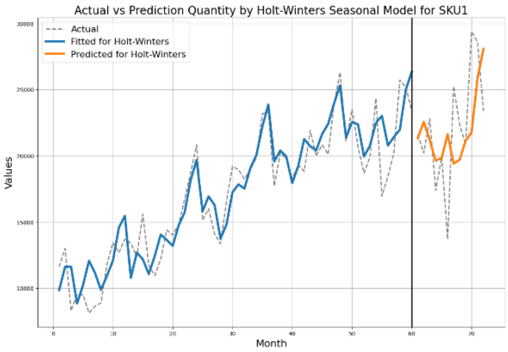
The overall performance of univariate models for each SKU reveals notable differences in forecasting accuracy, as summarized in Table 5. The Holt-Winters seasonal model consistently achieved low MAPE values across most SKUs, with SKU1 showing a MAPE of 15.25% and SKU3 achieving an outstanding 10.97%. The U-LSTM model also demonstrated strong performance, with SKU1 at 15.26% and SKU9 achieving a notably low MAPE of 4.21%. Conversely, the ARIMA model had higher MAPE values, particularly for SKU1 and SKU2, indicating less accuracy.

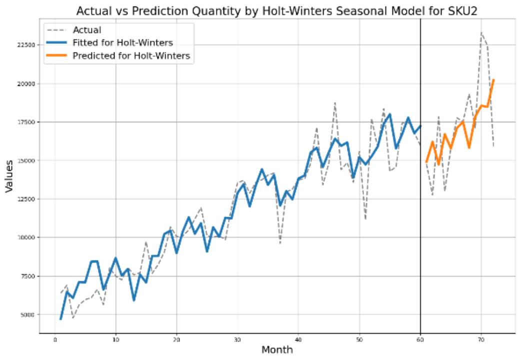
The average MAPEs across all models were as follows: Holt-Winters seasonal at 12.01%, U-LSTM at 13.61%, ARIMA at 14.87%, SARIMA at 15.44%, and Holt's at 13.99%. These results underscore the effectiveness of the Holt-Winters seasonal model in capturing both trend and seasonal components, with the U-LSTM model also showing strong performance. Despite the seasonal components in the data not being clearly discernible, the Holt-Winters seasonal and SARIMA models successfully adapted to and captured the underlying seasonal patterns.

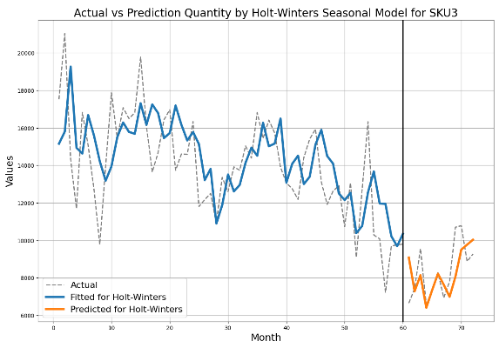
Figure 4 presents the actual versus forecast of SKU1-10 from Holt-Winters Seasonal model, which is the most accurate Univariate model from Table 4.

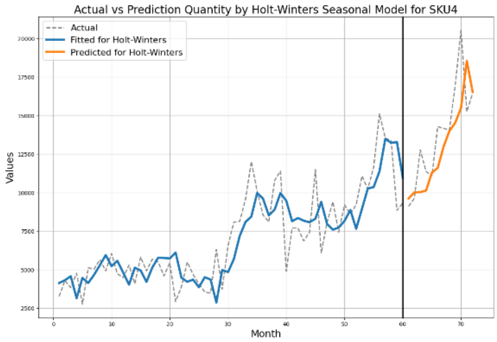
Table 5. Univariate model performance for each SKU.

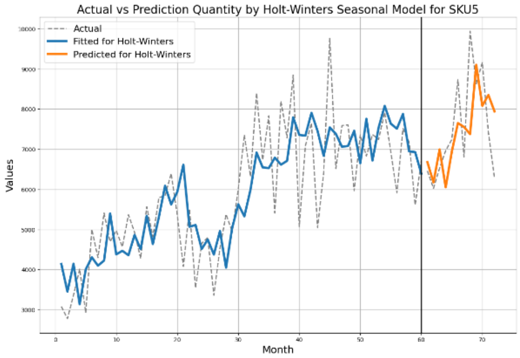
SKU	MAPE in Test Set (%)				
	Holts	Holt-Winter	ARIMA	SARIMA	U-LSTM
SKU1	17.53	15.25	18.07	18.02	15.26
SKU2	15.72	13.79	15.66	16.26	14.96
SKU3	15.76	10.97	15.67	19.32	15.61
SKU4	11.83	11.04	11.76	13.48	15.19
SKU5	12.91	11.31	12.94	12.94	12.71
SKU6	21.66	15.60	31.47	31.47	19.68
SKU7	16.77	15.21	16.49	16.22	15.90
SKU8	9.75	7.21	9.61	9.61	11.59
SKU9	6.28	8.21	5.36	5.36	4.21
SKU10	11.69	11.58	11.71	11.71	11.03
Average	13.99	12.02	14.88	15.44	13.61

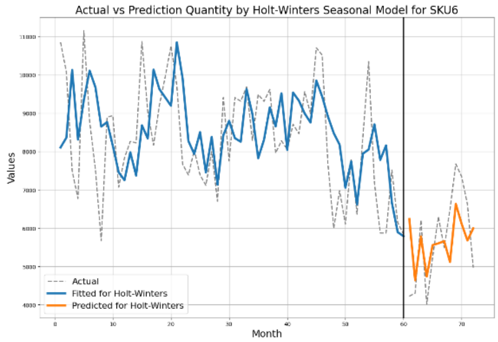


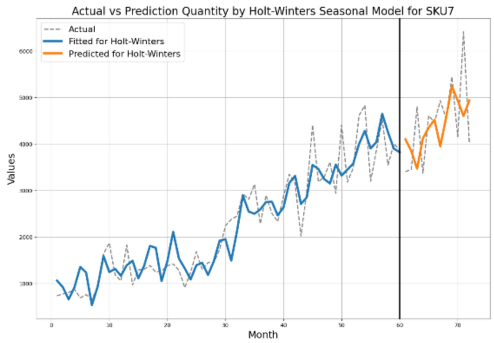


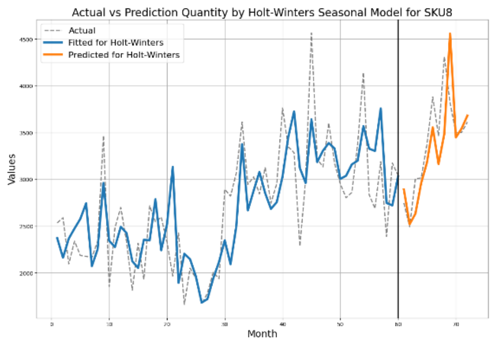












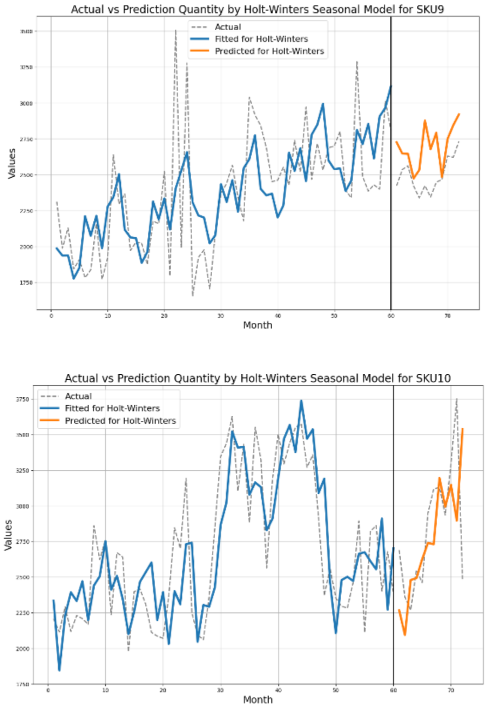


Fig. 4. The actual versus forecast of SKU1-10 from Holt-Winters Seasonal model.

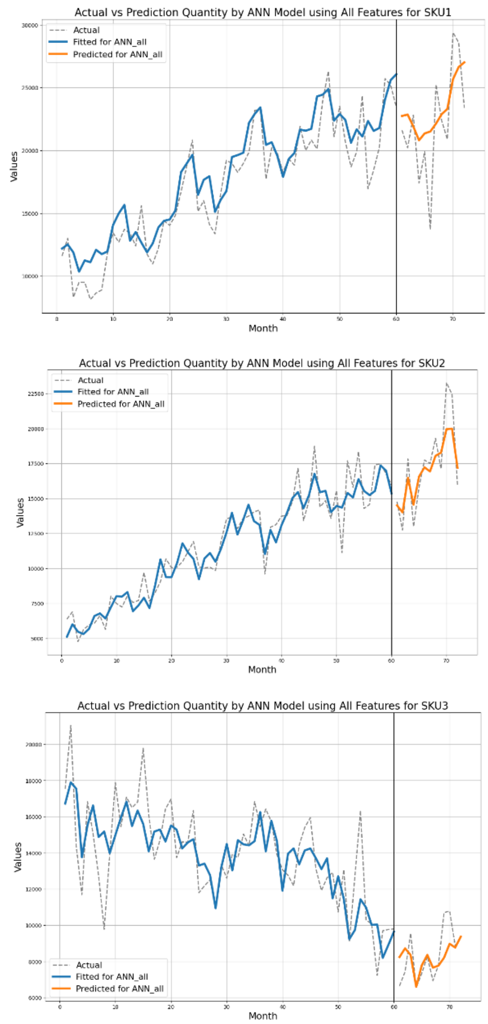
4.4. Result of Multivariate Model Prediction

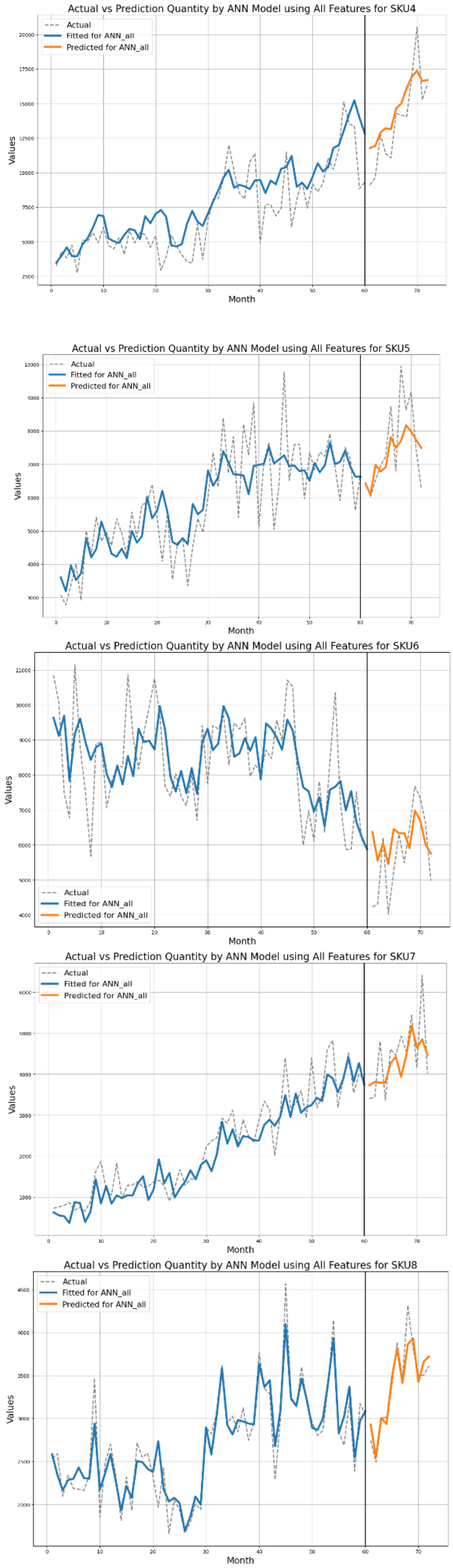
The performance of various multivariate models for each SKU, as detailed in Table 6, reveals notable differences in forecasting accuracy. The ANN model using all features generally outperformed the others, with the lowest average testing MAPE of 9.43%, indicating that incorporating all features enhanced prediction accuracy. For example, SKU2 and SKU9 achieved particularly low MAPEs of 7.4% and 2.72%, respectively, with this ANN model. The M-LSTM model using all features also performed well, especially for SKU1 and SKU2, with testing MAPEs of 10.51% and 9.25%, respectively, though it had a slightly higher average MAPE of 12.06% compared to the ANN model using selected features or significant features, which had a 12.50% average MAPE.

The SARIMAX model, with an average testing MAPE of 14.82%, showed less effectiveness compared to the neural network models. Overall, the ANN model using all features demonstrated the best performance, emphasizing the advantages of comprehensive data input for accurate forecasting. The M-LSTM model using all features also showed potential, particularly for SKUs with complex temporal patterns. These findings highlight the critical role of model and feature selection in improving forecasting accuracy across different SKUs. Figure 5 depicts the actual versus forecast of SKU1-10 from ANN (all features) model, which is the most accurate Multivariate model from Table 5.

Table 6. Multivariate model performance for each SKU.

SKU	MAPE in Test Set (%)				
	SARIMAX	ANN (Selected)	ANN (All)	M-LSTM (Selected)	M-LSTM (All)
SKU1	13.11	14.03	13.95	13.40	10.51
SKU2	17.36	14.06	7.40	12.49	9.25
SKU3	19.27	13.05	9.59	15.43	20.99
SKU4	12.39	11.58	11.52	14.31	11.17
SKU5	14.82	10.08	8.37	9.24	12.06
SKU6	28.01	20.34	17.41	19.19	22.84
SKU7	14.55	13.20	11.31	14.18	12.34
SKU8	12.96	10.02	3.38	8.26	7.51
SKU9	4.30	8.57	2.72	3.74	3.52
SKU10	11.46	10.14	8.69	8.77	10.36
Average	14.82	12.51	9.43	11.90	12.06





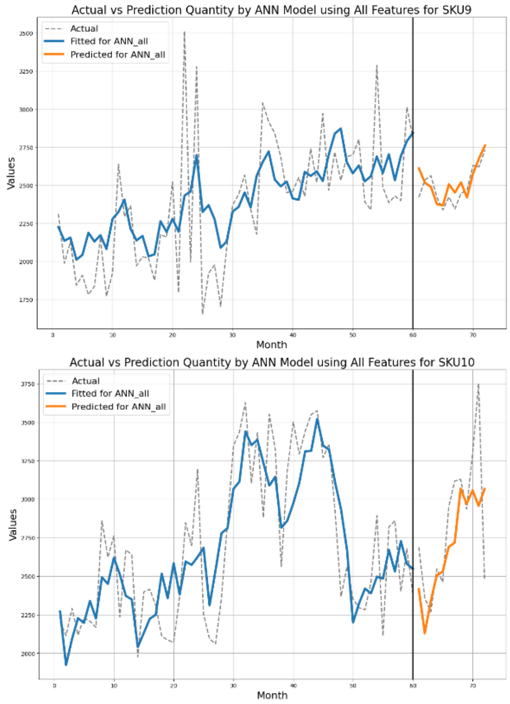


Fig. 5. The actual versus forecast of SKU1-10 from ANN (all features) model.

4.5. Result of Hybrid Models

In this study, one univariate model and two multivariate models are selected for hybridization. All possible permutations of these three models are evaluated to identify the optimal combination, enhancing forecasting accuracy by leveraging the strengths of each model type.

The performance of various hybrid models for each SKU, as detailed in Table 7, illustrates their enhanced forecasting accuracy. The hybrid models, which combine Holt-Winters, ANN using all features, and M-LSTM using all features, demonstrated improved predictive performance by integrating the strengths of different modeling approaches. Notably, the hybrid model combining ANN (All) and M-LSTM (All) achieved the lowest average testing MAPE of 8.83%, showcasing its effectiveness in capturing diverse data patterns.

The Holt-Winters + M-LSTM (All) model also performed admirably, with an average testing MAPE of 9.20%, followed by Holt-Winters + ANN (All) + M-LSTM (All) at 9.54%, and Holt-Winters + ANN (All) at 10.26%. Compared to multivariate models, hybrid models generally offered superior performance; for instance, the M-LSTM (All) + ANN (All) hybrid model outperformed the best multivariate model, ANN (All), which had a testing MAPE of 9.43%. This performance improvement highlights the hybrid models' ability to effectively capture trend, seasonality, and non-linear relationships by leveraging multiple modeling approaches. The findings underscore the robustness of hybrid modeling in enhancing forecasting accuracy and capturing complex data characteristics.

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Table 7. Hybrid model performance for each SKU.

SKU	MAPE in Test Set (%)			
	Holt-Winter + ANN (All)	Holt-Winter + M-LSTM (All)	M-LSTM (All) + ANN (All)	Holt-Winter + ANN (All) +M-LSTM (All)
SKU1	13.57	11.83	10.83	12.08
SKU2	7.54	10.75	7.48	7.50
SKU3	13.44	11.29	13.75	12.82
SKU4	9.14	9.02	8.78	9.00
SKU5	8.64	8.67	8.25	8.49
SKU6	19.01	16.88	17.35	19.91
SKU7	13.38	12.78	12.15	12.98
SKU8	4.05	4.15	3.43	4.07
SKU9	4.45	5.49	5.16	7.41
SKU10	9.35	1.15	1.12	1.16
Average	10.26	9.20	8.83	9.54

4.6. Model Evaluation and Selection

The evaluation and selection of prediction models, as detailed in Table 8. and Fig. 6., are crucial for accurate forecasting. The Holt-Winters seasonal model, with an average runtime of 0.48 seconds, is the fastest but has the highest average MAPE of 12.02%, indicating lower accuracy compared to other models. The ANN model using all features shows a significant improvement with an average MAPE of 9.43% and a runtime of 49.68 seconds, excelling in handling complex data patterns. The M-LSTM model, although the most computationally intensive with a runtime of 534.41 seconds, achieves an average MAPE of 11.90% and is suited for datasets with temporal dependencies. The hybrid model combining M-LSTM and ANN provides the best performance, with an average MAPE of 8.83% and a runtime of 575.10 seconds, effectively capturing both temporal and non-linear patterns. This hybrid approach demonstrates superior forecasting accuracy and efficiency. The recommended model, the hybrid of M-LSTM and ANN, integrates multiple techniques to achieve the lowest MAPE, highlighting its robustness in diverse data scenarios. Table 8 further details the best-performing model for each SKU based on test set performance.

Table 8. Hybrid model performance for each SKU.

Model	Average Runtime (Sec.)	Average MAPE in Test Set (%)
Holt-Winter	0.48	12.02
ANN (All)	49.68	9.43
M-LSTM(All)	534.41	11.90
M-LSTM (All) + ANN (All)	575.10	8.83

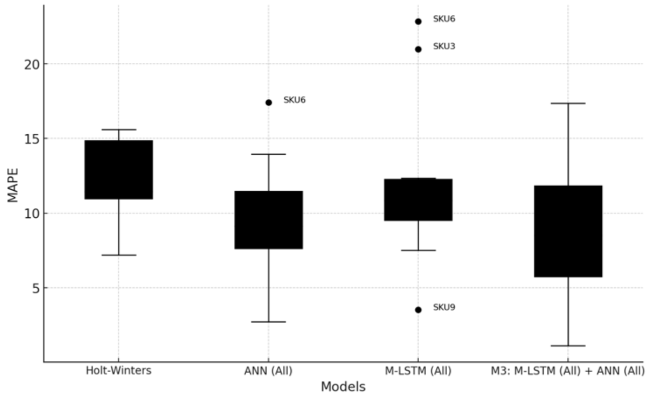

Fig. 6. Boxplot analysis for result comparison.

4.7. Model analysis based on data pattern

4.7.1. Observation I

To assess the volatility of a time series, one can employ a methodical approach. Initially, a trend line is fitted to the data to capture its inherent pattern. Subsequently, residuals are computed by subtracting the observed data points from those predicted by the trend line. The standard deviation of these residuals quantifies the extent of variability around the fitted trend. To normalize this measure, the average of the actual data points is calculated. Ultimately, the adapted coefficient of variation (Ad CV) is derived by dividing the standard deviation of residuals by this average. This ratio offers a comparative indicator of volatility, elucidating deviations from the typical behavior of the time series data as shown in Table 8.

The formula for the adapted coefficient of variation is:

$$Ad\ CV = \frac{\sigma_{residuals}}{\bar{x}}, \tag{14}$$

where:

- $\sigma_{residuals}$ is the standard deviation of the residuals.
- $\bar{x}$ is the mean of the actual data points

Traditional models like Holt-Winters Seasonal are particularly well-suited for stable data patterns, which can be identified through their lower coefficient of variations. In Table 9, the SKUs with adapted coefficient of variations ranging from 0.12 to 0.16 (SKU1 to SKU5 and SKU7) demonstrate this stability. These SKUs exhibit predictable environments, making them ideal candidates for traditional forecasting methods. The MAPE on the test set for these SKUs is acceptable and comparable to the performance of machine learning models, reinforcing the effectiveness of Holt-Winters Seasonal in these cases. The predictability of these SKUs is further illustrated in the time series plot Fig. 7. The associated Coefficient of variation results for these SKUs indicate a low level of fluctuation around the fitted trend line, confirming the stability of the data.

Table 9. Adapted Coefficient of variations (Ad CV) and MAPE results from each forecasting model for each SKU.

SKU	**Ad CV**	**Holt-Winters**	**ANN**	**M-LSTM**
SKU1	0.14	15.25	13.95	10.51
SKU2	0.12	13.79	7.4	9.25
SKU3	0.16	10.97	9.59	20.99
SKU4	0.14	11.04	11.52	11.17
SKU5	0.16	11.31	8.37	12.06
SKU6	0.18	15.6	17.41	22.84
SKU7	0.14	15.21	11.31	12.34
SKU8	0.19	7.21	3.38	7.51
SKU9	0.18	8.21	2.72	3.52
SKU10	0.21	11.58	8.69	10.36

4.7.2. Observation II

SKUs with higher adapted coefficient of variations (e.g., SKU6, SKU8, SKU9, SKU10) with values from 0.18 to 0.21, shown in Table 8., exhibit less predictable and more volatile patterns. For these SKUs, traditional models might struggle to capture the complexities and fluctuations in the data. Machine learning models, especially ANN, are better suited for these volatile conditions. ANN is capable of modeling intricate patterns and relationships in the data, making them effective in handling volatility and providing more accurate forecasts for such scenarios. For SKUs with lower adapted coefficient of variations, traditional models like Holt-Winters seasonal offer reliable performance, with MAPE values close to those of machine learning models, as they excel in stable and predictable environments. On the other hand, for SKUs with higher adapted coefficient of variations, machine learning models like ANNs are more suitable due to their ability to manage and predict complex, volatile data patterns effectively.

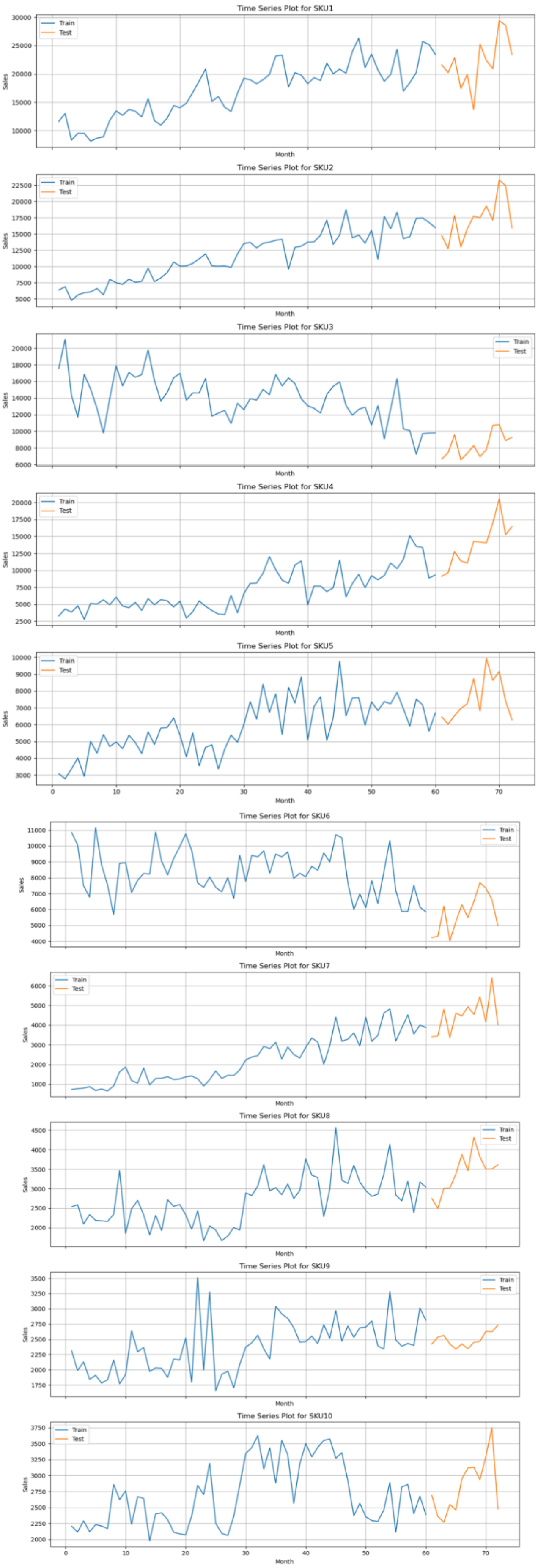

Fig. 7. Time-series plot for SKU1 – SKU10.

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4.7.3. Observation III

From time-series plot in Fig. 7, SKU3 and SKU6 display significant differences in data patterns between the training and testing sets, notably a noticeable downward shift. This discrepancy underscores the challenge of inconsistent temporal relationships and less predictable patterns in these SKUs. Despite the advanced capabilities of models like M-LSTM in capturing complex dependencies within time series data, these inconsistencies in temporal relationships present significant hurdles. The model may struggle to accurately forecast outcomes due to difficulties in discerning underlying trends amidst the volatility observed in the data. Furthermore, the results in Table 7 show that M-LSTM performs poorly compared to the ANN model. This disparity highlights the model's difficulty in effectively adapting to the unpredictable temporal dynamics of SKU3 and SKU6, where ANN, with its different learning approach, might handle the volatility and fluctuations more effectively.

To summarize, the challenges posed by inconsistent temporal relationships and volatility in SKU3 and SKU6 underscore the limitations that even advanced models like M-LSTM can encounter, especially when compared to more suitable models like ANN for handling such complex and fluctuating data patterns.

4.7.4. Observation IV

From Table 8., the comparative analysis of forecasting models reveals that Holt-Winters generally outperforms Holt's method, achieving better results in 9 out of 10 SKUs. This advantage is likely due to Holt-Winters' ability to model both trend and seasonal components, making it more adept at capturing complex data dynamics. However, Holt's method showed superior performance for one SKU, suggesting that its simpler approach may be advantageous in specific cases. In the comparison between ARIMA and SARIMA, ARIMA outperformed SARIMA in 3 SKUs, indicating its strength in handling autocorrelation and trend patterns without needing explicit seasonality adjustments. Both Holt-Winters and SARIMA, despite encountering unclear seasonality patterns, provided reliable forecasts, highlighting the adaptability of seasonal-based models. Overall, Holt-Winters excels in capturing trend and seasonality, while ARIMA effectively models autocorrelation, demonstrating the robustness of these models across diverse datasets.

4.8. Factor Analysis for Best Model

In this analysis, an ANN model was utilized, incorporating all features to determine the significant factors impacting the sales of various SKUs. The ANN model using all features was chosen due to its superior performance, achieving the lowest MAPE on the testing set compared to other single models, with the exception of the hybrid model. However, the hybrid model was excluded from this SHAP analysis due to its incompatibility with SHAP value computation. Below are the detailed insights for each SKU based on the SHAP analysis from the ANN model using all features.

The SHAP analysis figure for SKU1 indicates that several factors have a significant impact on its performance. Specifically, the Unemployment Rate, Income Level, Lead Price, and the months of November and December positively influence SKU1's sales. This suggests that higher unemployment rates and income levels, along with increased lead prices and sales during November and December, are associated with better performance for SKU1. On the other hand, the month of April has a negative impact, meaning that sales tend to be lower during this month (as shown in Fig. 8).

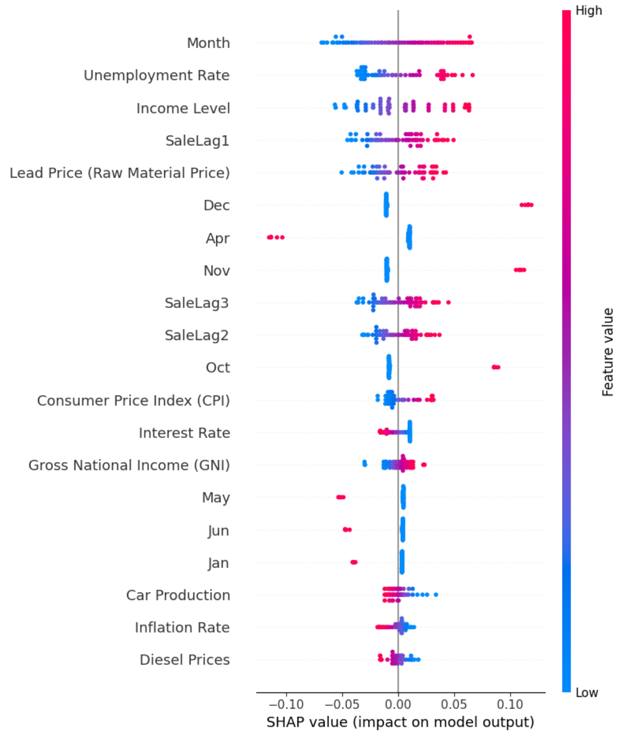

Fig. 8. Example of SHAP plot from SKU1.

In summary, the SHAP analysis as shown in Table 10 highlights the consistent positive impact of the Unemployment Rate across all SKUs, underscoring its importance as a key driver of sales. Unemployment Rate and Income Level play significant roles in forecasting nearly every SKU, aligning with the results from the majority of stepwise regression analyses. Other factors like Income Level, Lead Price, and specific months (e.g., November, December, September) also play significant roles for certain SKUs. Negative impacts, while less common, include factors such as Income Level, Gross National Income, and specific months like April and February. These insights provide a comprehensive understanding of the key drivers affecting each SKU's performance, enabling more informed decision-making to enhance sales strategies and achieve optimal results.

Table 10. The influencing factors to sales quantity of the 10 SKUs from SHAP.

Factors	Product Name									
	SKU 1	SKU 2	SKU 3	SKU 4	SKU 5	SKU 6	SKU 7	SKU 8	SKU 9	SKU 10
Inflation Rate										
Interest Rate										
Unemployment Rate	+(1)	+(1)	+(1)	+(2)	+(2)	+(1)	+(2)	+(1)	+(1)	+(2)
Exchange Rate										
Growth of GDP										
Income Level	+(2)		-(3)	+(1)	+(1)		+(1)	-(2)	+(2)	
Lead Price	+(3)									
Gasoline Price							+(3)			
Gross National Income			-(2)							
Jan										
Feb										-(1)
Mar										
Apr	-(5)		-(4)							
May										
Jun										
Jul										
Aug										
Sep						+(2)				
Oct										
Nov	+(6)									
Dec	+(4)								+(3)	

Note: (i) Highlight color: Orange - negative impact to the output, Green - positive impact to the output; (ii) The number shows the order of the important factors to the prediction (1 is the most important).

4. Conclusions

The performance of various predictive models for battery sales forecasting was evaluated. Among the univariate models, the Holt-Winters Seasonal model emerged as the best performer with the lowest average MAPE of 12.02%, demonstrating its effectiveness in capturing both trend and seasonal components. In the multivariate category, the ANN model using all features exhibited the highest accuracy, achieving an average testing MAPE of 9.43%, indicating that incorporating a comprehensive set of features significantly enhanced the model's predictive power. The hybrid model, particularly the M-LSTM using all features + ANN using all feature hybrid model, outperformed all other models with the lowest average MAPE of 8.83% on the test set, showcasing the advantages of integrating multiple modeling techniques for superior accuracy and efficiency.

Despite the absence of a clearly identifiable seasonal pattern in the sales data, models designed to capture seasonality, such as Holt-Winters seasonal and SARIMA, still performed well, indicating their inherent strengths in capturing underlying trends and patterns even without explicit seasonality. Traditional models like Holt-Winters seasonal are effective when the data exhibits low volatility and is relatively stable over time, leveraging well-established statistical methods to perform well in smooth and consistent datasets. On the other hand, machine learning models, particularly ANN excel in handling high volatility and complex data patterns, capturing non-linear relationships and adapting to sudden changes, as evidenced by their performance with SKUs showing highly fluctuating sales data.

Feature analysis using SHAP values provided insights into the key factors influencing battery sales. Factors such as the Unemployment Rate, Income Level, and specific months (e.g., November and December) consistently showed significant impact across multiple SKUs. However, the influence of these factors varied across different SKUs, underscoring the importance of tailored feature selection for each product. This analysis highlighted the necessity of understanding the unique characteristics of each SKU and incorporating relevant exogenous variables to enhance the model's predictive accuracy.

Based on the findings of this work, it is recommended that companies in the automotive battery industry adopt hybrid forecasting models, specifically the combination of M-LSTM and ANN models, to achieve the highest accuracy in sales predictions. The incorporation of a comprehensive set of features and the use of advanced machine learning techniques can enhance forecasting performance. Additionally, understanding the data patterns and key influencing factors specific to each SKU can further refine model accuracy.

This study differs from existing methods by providing a thorough analysis of data patterns, compiling and testing a wide range of popular forecasting models, and integrating almost all relevant features studied in the automotive industry into a single framework. It evaluates both univariate and multivariate models and explores diverse hybrid model combinations to determine the most effective approach. This comprehensive methodology ensures a more accurate and reliable prediction, making it particularly valuable for demand planning and decision-making in the automotive battery industry. The findings offer actionable insights that can improve inventory management and optimize supply chain operations, helping companies reduce costs and respond effectively to market demands.

One notable limitation of this study is the dataset's granularity and the lack of detailed exogenous variables such as price and promotion. While the current model uses monthly data, incorporating daily or weekly data could potentially capture more granular trends and seasonal effects, leading to more accurate forecasts. Furthermore, the absence of price and promotional data limits the model's ability to account for demand fluctuations due to marketing activities and price changes, which are critical factors in sales forecasting. Additionally, the study focuses on a limited number of products. Applying the model to a larger product portfolio could provide more comprehensive insights but also poses challenges in terms of model complexity and computational resources.

To address the identified limitations, future research should consider collecting and integrating more detailed data, such as daily or weekly sales figures and additional variables like selling price of our company, selling price of competitors and promotional activities. This enhancement could provide a more nuanced understanding of the sales dynamics and improve the model's predictive accuracy. Expanding the application of the forecasting model to a broader range of products within the company's portfolio could also yield valuable insights and increase the model's robustness. Additionally, exploring the use of hybrid models, particularly series-hybrid models, could be beneficial. These models, which combine different forecasting techniques in a sequential manner, have the potential to capture complex patterns and interactions in the data, further enhancing forecast accuracy. Finally, applying these advanced forecasting techniques to long-term forecasting could offer strategic benefits, enabling better resource allocation and strategic planning for the company.

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