PREDICTION SALES FORECASING OF PLUG-IN BOARD'S PRODUCT FACTORY BY USING LINEAR REGRESSION

BY

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Abstract

The aim of this study is to construct a sales forecasting model for Yaqi Factory's plug-in board products to optimize inventory management and improve operational efficiency. By collecting sales data over 31 months, a linear regression method was used to model and analyze the relationship between the sales volume of five best-selling products (B5220, B5330, B5320, UU4222, and UU4320) and key attributes such as price, inventory, and production volume. The results indicate that the linear regression model based on six months of data exhibits high predictive performance, with an R^2 value of 0.816, explaining approximately 81.6% of sales variations. The study also examined the impact of different time spans (three months vs. six months) on prediction accuracy. Comparisons show that as the data time span increases, the model's prediction error significantly decreases, demonstrating improved stability and accuracy. Specifically, the absolute error of the model trained on six months of data is 607, with a standard deviation of 646, outperforming the model trained on three months of data, which had an absolute error of 1,528. Additionally, the study visually assessed the model's accuracy by comparing moving average (MOA) sales with predicted sales. It was found that for products with significant fluctuations (such as B5330), the prediction results still require further optimization. This study provides valuable insights for Yaqi Enterprise in establishing reliable sales forecasting models, optimizing inventory management, and enhancing operational efficiency.

(Total 58 pages)

Keywords: Inventory Management, Plug-in Boards Sales Prediction, Linear Regression

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CHAPTER 1

INTRODUCTION

1.1 Background and Significance of the Problem

Hayes (2023) explain the inventory management refers to the process of ordering, storing, using, and selling a company's inventory. This includes raw materials, components, and finished products, as well as the warehousing and processing of these items. There are different methods of inventory management, each with their pros and cons, depending on a company's needs.

Also, the important of inventory management to facility operations, inventory represents products a company possesses on its premises or goods consigned to third parties. Inventory plays an important role in the smooth functioning of a company's business since it acts as a buffer between production and completion of customers' orders. Inventory represents a current asset since a company typically intends to sell its finished goods within a short amount of time, typically a year. Inventory has to be physically counted or measured before it can be put on a balance sheet. Companies typically maintain sophisticated inventory management systems capable of tracking real-time inventory levels. Inventory is accounted for using one of three methods: first-in-first-out (FIFO), last-in-first-out (LIFO), or weighted-average costing (Blokhin, 2022).

However, inventory management is a critical aspect in modern manufacturing that affects operational efficiency and corporate profitability. In any factory, inventory management is regarded as a critical aspect in cost reduction (Prachuabsupakij, 2019). Plug-in boards (also known as versatile socket boards or power socket extension boards) are commonly utilized in modern electrical equipment, particularly in homes, workplaces, and industrial settings. The rising popularity of smart home products has significantly increased demand for plug-in boards. With the rise of the Internet of Things (IoT), an increasing number of homes and organizations require plug-in boards that can manage many devices simultaneously (Wang, 2021).

Yaqi Factory produced plug-in boards for about six years. They had five types of plug-in boards for sale in China. They had some problems delivering those products to their customers on time. As the number of electrical items had grown and had the demand for more sockets to connect them, particularly smart plug boards with USB interfaces, overload protection, and independent control switches, which have witnessed a considerable growth in sales. Plug-in manufacturing companies face a significant issue in precisely predicting sales volume to maintain an appropriate inventory level. Wrong inventory management decisions can result in significant cost waste, such as excessive inventory levels and inventory shortages that prohibit timely delivery. Financial professionals typically use various ratios to judge whether a company has issues producing and promptly selling its inventory. Financial ratios can also raise potential red flags about accounting fraud or obsolescence. Investors and analysts typically look at a company's inventory ratios and peers within the same industry (Blokhin, 2022).

The purpose of this study is to apply a linear regression model to forecast future sales of plug-in goods and optimize inventory management tactics using this data. Linear regression, a traditional statistical analysis tool, can create a linear relationship between product sales volume and time or other variables by evaluating historical sales data and related factors that influence sales (Teja Reddy & Malathi, 2022). On this basis, businesses can better understand sales trends, develop reasonable production and inventory plans, and cut expenses associated with inventory surplus and shortage.

1.2 Research Objective

1.2.1 Determine a model of sales forecasting plugin-board product for Yaqi Factory.

1.2.2 Find out a correlation between the effects of seven factors of plug-in board product attributes on sales.

1.2.3 To create and execute optimal inventory management strategies, reduce inventory costs, and enhance operational efficiency.

1.3 Research Questions

This study aims at addressing the following major issues:

1.3.1 What's the model of sales forecasting plugin-board product?

1.3.2 What are the key factors that correlate between the effects of seven plug-in board product attributes on sales?

1.3. What strategies are effective in enhancing optimal inventory management, reducing inventory costs, and operational efficiency?

1.4 Research Framework

The research framework of this article is divided into five parts, including background and research significance, relevant theories and literature review, research methods, results and analysis, summary and limitations, as shown in Figure 1.1

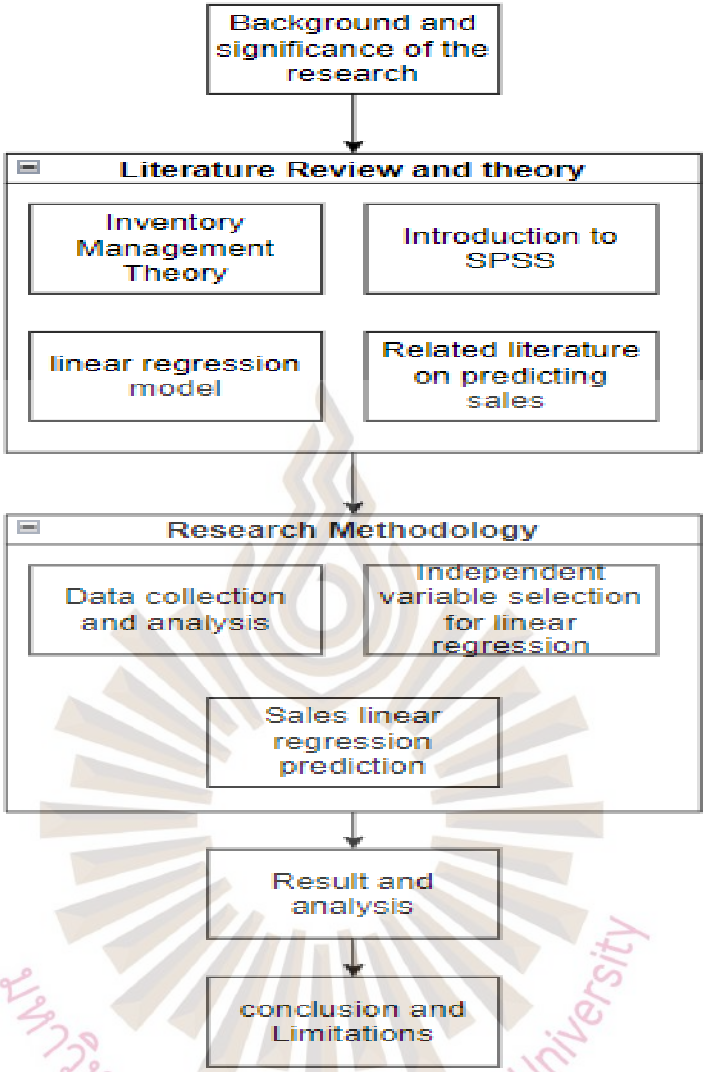

Figure 1.1 Research Framework

1.5 Definition of Terms

Sale Forecast: The estimate of expected sales revenue within a specific time frame, helps businesses plan and strategize their operations, make informed inventory and production decisions, and keep stakeholders aligned.

Product Code: A unique identifier is assigned to a product and is essential for inventory management, facilitating efficient tracking and stocking of products in various industries.

Product Model: The structure of products and services contributes to a common understanding of product specifications and requirements for customers.

Price: The product's value and market value are reflected in its price. Demand and sales forecasts are significantly impacted by a product’s pricing.

Month: a measure of time corresponding nearly to the period of the moon's revolution and amounting to approximately 4 weeks or 30 days or $^1/_{12}$ of a year.

Production: The tools and resources that enable the creation of products and services.

Initial Stock: Initial inventory: Initial inventory refers to the quantity of available plug-in boards or power boards at the beginning of each month. It serves as the baseline inventory level for sales and distribution activities.

Final Stock: Final inventory refers to the remaining quantity of plug-in boards or power boards at the end of each monthly time period. It is the result of subtracting sales and other allocations from the initial inventory.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction Inventory Management

Effective planning, control, and supervision of enterprise resources to meet production or sales needs while lowering costs and hazards constitute inventory management, a crucial component of supply chain management (Waters, 2020). Finding the ideal supply-demand balance is the aim of inventory management, which helps businesses continue to run effectively even in the face of shifting market conditions, supply chain interruptions, and demand swings. As a result, inventory management has a direct impact on business profitability in addition to product availability and customer service standards.

Businesses frequently utilize models like Safety Stock and Economic Order Quantity (EOQ) in traditional inventory management systems to establish appropriate ordering cycles and inventory levels. While safety stock is intended to handle supply or demand unpredictability and avoid inventory shortages, the economic order quantity model assists businesses in determining the ideal quantity for each order by balancing ordering and holding expenses (Wild, 2017). In settings with solid supply chains and high levels of predictability, these techniques can be somewhat successful. However, traditional inventory management techniques have steadily shown their limitations and are unable to handle the complex and constantly shifting market environment as a result of globalization and ongoing changes in market demand (Silver, Pyke, & Peterson, 2019).

Inventory management has seen significant changes in recent years due to the advancement of information technology. Businesses may make more accurate and dynamic inventory decisions by utilizing cutting-edge technology like data analysis, the Internet of Things (IoT), and machine learning. The advent of these technologies has transformed the conventional approaches to inventory replenishment and monitoring while also significantly raising the intelligence level of inventory management. Businesses may better forecast demand swings and optimize the timing and volume of replenishments by gathering and analyzing data in real-time. In addition to lowering inventory costs, this change increases the supply chain's adaptability and reactivity.

Additionally, using big data and machine learning technologies in inventory management enables businesses to identify trends in vast amounts of historical data and produce more precise demand projections (Zhang, 2021). It is noted that compared to traditional models, machine learning-based prediction models are more accurate in forecasting demand because they can manage more complicated variables like market trends, seasonal variations, and economic situations. Businesses can improve their ability to adapt to changes in the market and dynamically modify their inventory management methods by integrating these predictive models. Businesses can optimize inventory levels, lower the risk of inventory shortages and surpluses, and increase the overall effectiveness of the supply chain by combining forecasting with inventory control.

In conclusion, inventory management is an essential component of supply chain management, and as technology advances, supply chain complexity, and market demand change, so do its methods and strategies. In order to transition from static models to dynamic intelligence and increase the supply chain's efficiency and adaptability, modern inventory management uses technological tools including data analysis, the Internet of Things, and artificial intelligence.

2.2 Linear Regression Analysis in SPSS

SPSS (Statistical Package for the Social Sciences) is a data analysis software widely used in fields such as social sciences, business, and health. Developed by IBM, it features a user-friendly interface and powerful statistical analysis capabilities (Field, 2018). Since its launch in the 1960s, SPSS has become one of the mainstream data analysis tools in academic and business research due to its simplicity and ease of use. SPSS not only supports data management and cleaning but also performs various complex statistical analyses such as regression analysis, factor analysis, analysis of variance, etc. Drag and drop and selection allow users to complete complex analysis tasks, making it particularly suitable for researchers who lack programming experience (Pallant, 2020). SPSS provides multiple regression options, such as stepwise regression and hierarchical regression, allowing users to choose the appropriate method according to their research needs. SPSS can also output important statistics such as regression coefficients, R-squared values, and residual analysis, thereby helping researchers accurately explain the fit and predictive performance of the model (George & Malley, 2019). In addition, SPSS supports residual plots and diagnostic tests, which are particularly important for evaluating model hypotheses and identifying outliers. Overall, the linear regression function of SPSS enables researchers to effectively complete complex regression analysis tasks through an easy-to-use analysis process and rich output options.

2.3 Linear Regression

2.3.1 Linear Regression Introduction

Linear regression is a statistical technique commonly employed to examine the relationship between two or more variables. This model posits a linear correlation between the dependent variable (prediction target) and the independent variable (prediction factor), calculating the optimal regression coefficient via the least squares method to minimize the discrepancy between predicted and actual values (Montgomery, Peck, & Vining, 2021). Recently, the utilization of linear regression in data analysis and forecasting has proliferated, particularly within the domains of social sciences, business research, and engineering. It is appropriate for both exploratory examination of basic data and for significant contributions to more intricate predictive models (Seber & Lee, 2018).

2.3.2 Key Statistics and Their Explanations of Linear Regression Models

The linear regression model has several essential statistics and components that elucidate the model's fitting efficacy and the impact of independent variables on the dependent variable. The regression coefficient indicates the magnitude and direction of each independent variable's influence on the dependent variable, with positive values denoting a positive relationship and negative values indicating a negative relationship (Montgomery et al., 2021). Standardized regression coefficients facilitate the comparison of the relative influence of independent variables (Frost, 2020). The intercept represents the anticipated value of the dependent variable when the independent variable equals zero, typically requiring no more elucidation in practical contexts (James, Witten, Hastie, & Tibshirani, 2021). The goodness of fit index R^2 indicates the extent to which the model accounts for the variability of the dependent variable. A value near 1 signifies robust explanatory power of the model, yet it does not entirely represent predictive performance (James et al., 2021); the adjusted R^2 accounts for the effect of the number of independent variables, rendering it especially appropriate for multiple regression (Seber & Lee, 2018). However, a higher R^2 does not necessarily mean that the model is the optimal model. Researchers need to consider factors such as research objectives, model assumptions, and residual distribution comprehensively (Hayes, 2022). In recent years, with the increasing dimensionality of data and the growing importance of feature engineering, researchers have not only focused on model prediction accuracy, but also on model interpretability and simplicity (Wooldridge, 2020). During this process, Adjusted R^2 often interacts with AIC BIC, Cross validation error and other indicators are used in combination to assist in selecting the optimal feature combination: when certain variables only contribute minimally to R^2 and do not significantly improve Adjusted R^2, they can often be removed to obtain a more concise and robust regression model.

The p-value assesses the importance of regression coefficients. If it is below the significance threshold (often 0.05), the variable is seen to exert a significant influence on the dependent variable; a lower significance correlates with a higher confidence level (Field, 2018). The residual represents the discrepancy between anticipated and actual values, while residual analysis can evaluate model assumptions like linear connections, independence, and homoscedasticity, and assist in identifying systematic errors or outliers (Pallant, 2020). Through the analysis of these data and elements, researchers can enhance their comprehension of the model's applicability and accuracy, therefore facilitating a rational interpretation of the prediction results and refining the model.

2.3.3 Linear Regression Used in Inventory Management

Linear regression is extensively employed in logistics inventory management for demand forecasting, inventory optimization, cost control, and various other facets. It offers sound inventory management decision support for organizations by forecasting future demand and inventory consumption trends (Wang, J. & Wang, X., 2021). Linear regression enables firms to forecast future inventory requirements and mitigate stockouts and surplus inventory by examining previous sales and demand data (Silver et al. 2019). This approach enhances inventory management accuracy and decreases holding costs, resulting in more effective supply chain management (Zhu, Liu, & Zhang, 2020). In contexts characterized by substantial demand variability, linear regression can swiftly modify prediction models to accommodate shifts in market demand. In the retail sector, linear regression is employed to forecast demand variations influenced by seasonal shifts, holidays, and promotional events, facilitating the successful formulation of replenishment strategies (Taylor & Fawcett, 2019). Furthermore, linear regression can be employed to examine the demand patterns of various regions or customer segments, allowing the supply chain to judiciously allocate inventory resources according to regional demand features (Chen & Cai, 2022). To enhance prediction accuracy, logistics managers typically integrate numerous regression or advanced regression models, including time series analysis and machine learning algorithms. These models consider more intricate demand-influencing aspects, such as the economic climate and market competitiveness, to enhance predictive accuracy (Wang, J. & Wang, X., 2021). Moreover, automated inventory management systems frequently incorporate linear regression inside the system model to facilitate automatic replenishment decisions and enhance operational efficiency.

2.4 The Application of Moving Average in Prediction

The moving average method still plays an important role in short-term demand forecasting, especially when the data is relatively stable, and the time span is not long. The moving average can effectively smooth out random fluctuations and help enterprises or organizations more accurately grasp sales or load demand trends (Adeyemo & Olatunji, 2021). However, when there are sudden fluctuations or nonlinear changes in demand, traditional moving averages often suffer from prediction lag or insensitivity to outliers, requiring the introduction of improved methods such as dynamic weight adjustment and adaptive window length (Sharma, Rath, & Dash, 2020).

2.4.1 Combination of Moving Average and Linear Regression

A study used a mixed strategy of "moving average multiple linear regression" in manufacturing order demand forecasting, selecting different lengths of moving average windows for smoothing different seasonal and trend data, and then incorporating the smoothed values into the regression model along with other marketing factors (price, advertising investment, etc.), achieving high prediction accuracy (Sina, Secco, Blazevic, & Nazemi, 2023). However, if the window setting of the moving average is not appropriate, it may lead to lag effects or ignore short-term fluctuations; Linear regression itself is not well adapted to complex dynamic features such as nonlinearity and seasonality. Therefore, how to select appropriate moving average strategies based on data characteristics and incorporate necessary modifications or extensions into regression models has become a research hotspot in recent years. Sharma et al. (2020) preprocessed the demand data for perishable goods using weighted moving averages, and then combined linear regression analysis to examine the impact of external factors such as prices and promotions on sales volume. The results indicate that compared to directly regressing the raw data, moving averages have significant advantages in reducing high-frequency noise and highlighting seasonal trends.

2.4.2 The Challenge and Development Trend of Moving Average

Traditional moving averages mainly target relatively stable time series, and for demand and sales with strong seasonality or high volatility, it is often difficult to capture turning points in a timely manner, leading to lag. In the future, the characterization of seasons and trends can be strengthened through adaptive weighting or combined with time series methods such as seasonal adjustment models and ARIMA (Shakeel, Chong, & Wang, 2023).With the popularization of the Internet of Things and big data technology, mobile averaging plays an important role in real-time monitoring and online analysis. However, in large-scale data stream environments, it is necessary to further optimize the computational efficiency and memory usage of the moving average method at both the algorithm and system levels (Chevalier & Lavigne, 2023). In the context of the gradual integration of intelligent manufacturing and the Internet of Things (IoT), industrial equipment often requires real-time monitoring and rapid fault diagnosis to reduce downtime and maintenance costs. The author proposes a fault diagnosis method based on Moving Average and Support Vector Machine (SVM), and implements the collection and analysis of industrial equipment status data through the Internet of Things platform (Hui & Wu, 2012).

2.5 Related Literature Use Linear Regression to Predict Sales

By studying Zmart’s sales history from 2011 to 2013, Gopalakrishnan, Choudhary, and Prasad (2018) employed linear regression to forecast the retailer's sales for 2014. They discovered that the sales predicted by linear regression had an accuracy of 84% when compared to the actual sales in 2014. Zmart can enhance its inventory strategy and boost sales by forecasting sales.

By analyzing historical sales data and establishing the correlation between sales and other influencing variables, Xiong, Yu, and Li (2024) developed a sales forecasting model based on the linear regression (LR) algorithm with the goal of predicting future sales. In modeling the linear relationship between dependent variables (sales) and independent variables (pricing, promotion, and seasonal trends), this study highlights the ease of use and efficacy of the LR algorithm. According to the study's findings, linear regression is a trustworthy and understandable technique for sales forecasting. Platform profitability can be increased by using sales forecasting models to forecast product demand, improve inventory control, and efficiently schedule procurement.

The application of linear regression (LR) models to forecast home prices was investigated by Amaresh, Singh, Kamal, and Kulkarni (2022). The use of multiple linear regression techniques to forecast house prices based on a few variables, including location, property size, age, and neighborhood features, is the main topic of this article. The author highlights how useful the LR model is in the real estate sector and how precise forecasts may support policymaking, investment selection, and market analysis. The author comes to the conclusion that LR is still a useful and understandable tool for predicting home prices, particularly when paired with the right data pretreatment and analytic methods (Amaresh et al., 2022).

He (2023) investigated iPhone sales forecasting using Statista's sales data and a multiple linear regression (MLR) model. To forecast future sales trends, this article focuses on the relationship between iPhone sales and a number of independent variables, including pricing, consumer income, competition, and marketing expenditure. Both have a high degree of fitting, which can help anticipate sales, and the validation model's accuracy is as high as 82.4%. The study highlights the interpretability of the MLR model as one of its main benefits, which enables businesses to easily comprehend how each independent variable affects sales performance (He, 2023).

Long and Liu (2021) presented a study on the use of linear regression for sales forecasting in the new energy vehicle (NEV) sector. This paper examines the author's methodology for examining past sales data and pinpointing important variables influencing new energy vehicle sales. In modeling the linear relationship between dependent variables (sales) and independent factors (wheelbase, battery, lifespan, total motor power, maximum speed, width, height, vehicle mass, and price), this study highlights the ease of use and efficacy of the LR algorithm. R-Squared = 0.96 indicates that the model has a good fitting effect. The motor's price and total power have the most effects on sales, according to the sales forecasting model, which can offer the business optimization alternatives (Long & Liu, 2021). By integrating multidimensional influencing factors into a linear regression framework, the model improves both interpretability and prediction accuracy, especially when the enterprise has relatively complete sales history and external data (Wang, 2022).

2.6 Related Literature Uses Simple Moving Average (SMA) to Predict Sales

In the field of sales forecasting, Simple Moving Average (SMA) is a common time series analysis method, and recent studies have shown that combining SMA with other forecasting methods can improve accuracy. The calculation method of SMA is relatively simple. (Hasan, Kabir, Shuvro, & Das, 2022). The closing prices within a selected time range are added together and then divided by the number of days in that time period to obtain the average value (Investopedia, 2024).

Liu et al. (2024) proposed an LSTM model that combines spatial smoothing, and sequence generalized variational mode decomposition (GVMD) to improve the accuracy of time series prediction. This study found that SMA can be used to extract underlying trends and enhance the ability of LSTM to process sales data. Zhang, Wu, Gu, and Xie (2019) demonstrated the advantages of using SMA as one of the input variables, particularly in short-term sales forecasting, through random forest and feature engineering methods.

Swami, Shah, and Ray (2020) studied the performance of XGBoost and LSTM in predicting sales data of large retail enterprises. Research has shown that using SMA as a feature input can improve the performance of XGBoost in processing time series data. Saleti, Panchumarthi, Kallam, Parchuri, and Jitte (2024) further explored the combination of SMA and ARIMA-LSTM mixed models, and the results showed that the method was superior to the single model in terms of root mean square error (RMSE) and mean absolute percentage error (MAPE).

Overall, SMA, as a fundamental method for sales forecasting, can significantly improve prediction accuracy when combined with other models. Recent studies have shown that combining SMA with deep learning, machine learning, or statistical models is an important strategy for improving predictive performance.

CHAPTER 3

RESEARCH METHODOLOGY

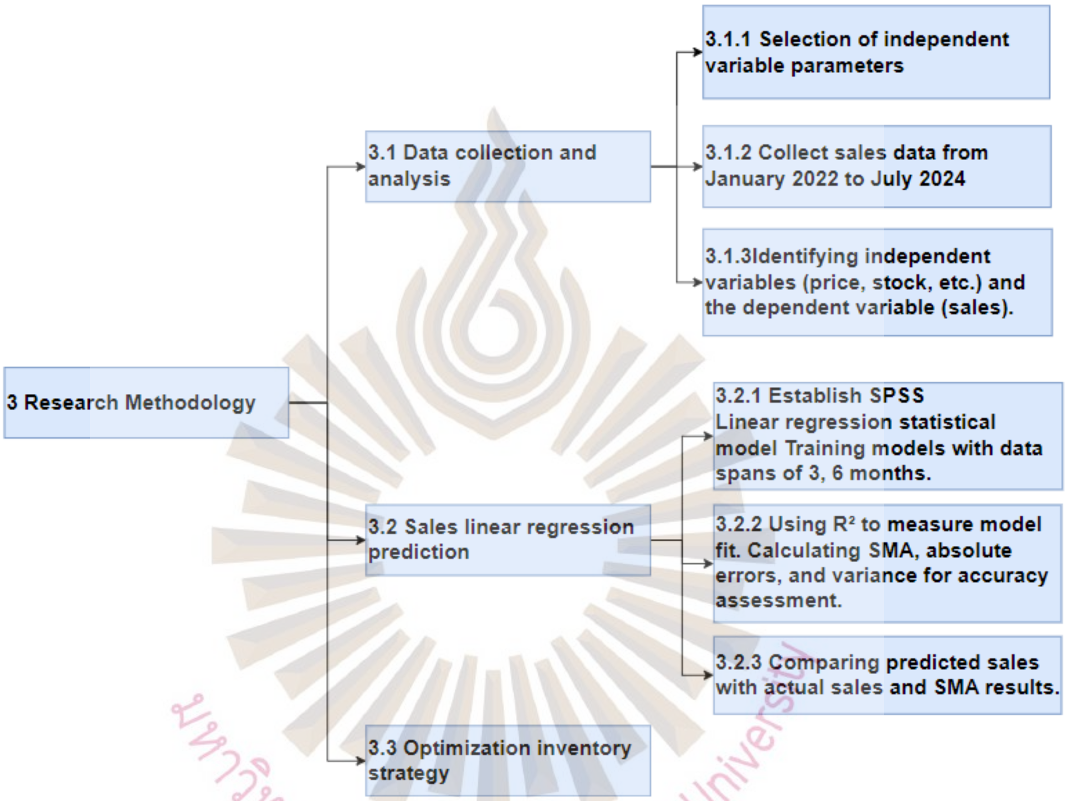

Figure 3.1 Research Methodology

3.1 Research Material

3.1.1 Factors Affecting the Sales of Plug-in Boards

The YaQi plug-in board factory's information system indicates that there are numerous packages of data monitoring packages pertaining to book sales. In this study, ten factors： including sales volume, product code, pricing, length of plug-in extension cable, safety certification, number of socket positions, maximum power, and number of promotions, Initial Stock, Final Stock that are closely associated with significant sales impacts were chosen based on the product parameters of the product itself, the years of sales experience of YaQi Plug-in Factory, and other pertinent literature. Ultimately, these variables were chosen as the pertinent variables for the YaQi plug-in manufacturing product sales linear regression prediction.

Create sample data to forecast the sales condition of YaQi plug-in board factories after filtering the plug-in board data, including these characteristics, plug-in board models, and sales revenue. The normal distribution analysis of the significance of the pertinent factors can be obtained after using IBM SPSS Statistics 26 software (henceforth referred to as SPSS software) for linear regression analysis and prediction. This can then be adjusted to determine whether to optimize and eliminate some factors that have little impact. Lastly, this model may be applied in real-world scenarios to forecast the sales of all previous data plug-in boards of YaQi plug-in board manufacturing products. The whole operation and management are more positively impacted by thorough statistical analysis.

Table 3.1 Linear Regression Dependent Variables

No.	Dependent Variables
1	Sales Forecasting

Table 3.2 Linear Regression Independent Variables

No.	Independent Variables
1	Product Model
2	Month
3	Price
4	Final Stock
5	Production

3.1.2 Data Used for Linear Regression

This study selected the top five best-selling products of YaQi Company as research objects, namely B5220, B5330, B5320, UU4422, and UU4320. The scope of data collection covers actual sales data from January 2022 to July 2024, with a total time span of 31 months.

The data includes the following indicators: month, product model, actual sales volume, selling price, extension cord length, number of sockets, maximum power, initial inventory, final inventory, and production volume. This detailed information provides a comprehensive feature set to support research on sales forecasting.

In the study, data were divided into different time windows of 3 months, 6 months and linear regression models were used to predict sales, aiming to explore the impact of different time spans on prediction accuracy. By designing experiments within the aforementioned time range, the performance of linear regression models in short-term, medium-term, and long-term predictions can be more accurately evaluated.

The detailed analysis of these data provides a solid foundation for optimizing inventory management and improving the accuracy of production planning, while also providing high-quality support for the validation of the sales forecasting model in this study.

3.2 Research Instruments

This study will employ linear regression analysis as the principal research instrument to determine the correlations between the independent variables (product features) and the dependent variable (sales performance). The variables included in the regression model comprise product code, price, length of the plug-in extension cable, security certification, number of socket positions, maximum power, and number of promotions, Initial Stock, Final Stock.

Furthermore, data gathering instruments such as spreadsheets or statistical software (e.g., SPSS, R) will be utilized to enhance data organization and analysis. These instruments will facilitate the effective management of extensive datasets, permitting the researcher to perform exploratory data analysis and evaluate the model's fit and predictive efficacy. This quantitative methodology guarantees that the research outcomes are based on statistical data.

3.3 Data Collection

The data collection for this study will be based on historical sales records from the plugin board factory from 31 months ago. I will obtain this data from the factory's sales records for a specific period, ensuring that we have a comprehensive dataset that includes various product attributes. The collection process will prioritize obtaining accurate and complete data regarding each product attribute and its corresponding sales figures.

3.4 Data Analysis

The data analysis in this study mainly needs to find out the best forecasting formula used to evaluate linear regression techniques and compare it with SMA (Simple Moving Average) as the core evaluation metric to measure the deviation between predicted sales and actual sales in 3 and 6 months.

First, a linear regression model will be used to evaluate how well selected product attributes predict sales performance. Each independent variable will be assessed based on its contribution and statistical significance within the model. Key indicators, such as regression coefficients and R^2 values, will measure the model's explanatory power and the degree of correlation between the variables.

Second, the Simple Moving Average (SMA) will be introduced as the primary metric to assess the difference between predicted sales and actual sales. SMA will be calculated quarterly, enabling a comparison between predicted sales volume and the actual sales volume obtained through the Method of Averages (SMA). This analysis will provide insights into the accuracy and stability of the model's predictions. Additionally, the predicted sales for the next 3 and 6 months will be compared with the actual sales data for 2023 to calculate the prediction error, absolute error, and variance, thereby evaluating the model's predictive performance.

3.5 Result Analysis Methodology

3.5.1 Linear Regression Formula Model

$$y = \beta_0 + \beta_{1x_1} + \beta_{2x_2} + \ldots + \beta_{nx_n} + \epsilon \quad (3\text{-}1)$$

y: Is the dependent variable (or response variable)

$x_{1\ldots n}$: It is an independent variable (or predictor variable)

β_0: It is intercept

$\beta_{1\ldots n}$: It is the coefficients of the respective variables

ϵ: It is an error term

3.5.2 R ² (Coefficient of Determination) Formula

R^2 is used to measure the explanatory power of a model on actual data, ranging from 0 to 1.

y_i: Actual value

$\hat{y}_i$: Prediction value

$\bar{y}$: The average of actual values

$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$: Residual sum of squares

$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$: Total sum of squares

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3-2}$$

3.5.3 The Simple Moving Average (SMA)

A simple moving average (SMA) is calculated by taking the arithmetic means of a given set of values over a specified period. A set of numbers, or prices of stocks, are added together and then divided by the number of prices in the set. The formula for calculating the simple moving average of a security is as follows:

$$SMA = \frac{A1+A2+\ldots+An}{N} \tag{3-3}$$

where: A = Average in period
n = Number of times periods

3.5.4 Error Formula

Error is the difference between the actual value and the predicted value.

$$Error = y_i - \hat{y}_i \tag{3-4}$$

3.5.5 Absolute Error Formula

Absolute error is the absolute value of the error

$$Absolute\ Error\ Formula = |y_i - \hat{y}_i| \tag{3-5}$$

3.5.6 Variance Formula

Variance is used to measure the volatility of prediction errors.

n: The number of data points

y_i: Actual value

$\hat{y}_i$: Prediction value

$$\text{Variance} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{3-6}$$

CHAPTER 4

RESEARCH RESULTS

4.1 R^2 Result and Analysis Use Linear Regression

This section presents the results of R^2 values in linear regression analysis, used to evaluate the predictive performance of the model at different time spans (3 months, 6 months). The analysis targets the top five products in terms of sales in the dataset, namely B5220, B5330, B5320, UU4422, and UU4320.

The data scope of this study covers 31 months of actual sales data from January 2022 to July 2024. By dividing the data into different time spans, this study aims to evaluate the explanatory power of linear regression models in different prediction scenarios. The R^2 value for each period can reflect the effectiveness of the model in capturing the relationship between product attributes and sales performance.

Table 4.1 Regression Summary Table for Different Time Spans

Time Span (Months)	R	R^2	Adjusted R^2
3	0.801	0.642	0.499
6	0.903	0.816	0.786

Table 4.1 shows that the R^2 value gradually increases with the increase of time span, from 0.642 at 3 months to 0.816 at 6 months. This indicates that as the time span increases, linear regression models can better explain the changing trends of sales data and have higher explanatory power. The 6-month time span has the highest R^2 value (0.816) and adjusted R^2 value (0.786), indicating that the model performs very stably in long-term data and can capture the relationship between sales performance and product attributes well.

4.2 Using a Three-month Data Linear Regression Model

4.2.1 Comparison between Three-month SMA Sales Value and Three-month Linear Regression Prediction Sales

The following equation was the equation obtained from applying the linear regression to predict sales:

$$PredictedSalesValue = 3578.579+(Price*18.925) + (Initial\ Stock*0.409) + (Final\ Stock *-0.613) + (Production*0.414) \tag{4-1}$$

Table 4.2 shows the results of using a linear regression model based on 3-month data predicting sales of B5220 product and compares it with actual sales and SMA (Simple Moving Average) Sales. The linear regression model is trained on 3-month data with an R^2 value of 0.642, indicating that the model can explain approximately 64.2% of sales changes and has a certain explanatory power.

From the results, it can be seen that the predicted values of the model are close to the actual sales in some months, especially in months with small sales fluctuations (such as April 2024), where the prediction error is small, only -167, demonstrating the good performance of the model in stable periods. However, due to the limited amount of training data for the model, it is unable to fully capture long-term trends and seasonal fluctuations, resulting in significant prediction biases during sales peaks and valleys. For example, in July 2024, the model's prediction deviation reached -1872, while the SMA error was 1533, indicating that the model failed to effectively predict sales peaks.

Table 4.2 Comparison of Actual Sales, 3-Month SMA, and Forecasted Sales for Product B5220

Product Model: B5220					
Month	Actual Sales	Predict Sales	Error	SMA 3 Months	Error
2022-04	5600	5411	-189	4470	1130
2022-05	6100	5720	-380	4810	1290
2022-06	5500	5245	-255	5500	0
2022-07	6400	5353	-1047	5733	667
2022-08	6400	5083	-1317	6000	400
2022-09	5600	4870	-730	6100	-500
2022-10	5300	4850	-450	6133	-833
2022-11	7000	5257	-1743	5767	1233
2022-12	7000	5257	-1743	5967	1033
2023-01	3800	4013	213	6433	-2633
2023-02	4600	4425	-175	5933	-1333
2023-03	4100	4286	186	5133	-1033
2023-04	6410	5359	-1051	4167	2243
2023-05	5800	5222	-578	5037	763
2023-06	6200	5116	-1084	5437	763
2023-07	7000	5196	-1804	6137	863
2023-08	6500	4985	-1515	6333	167
2023-09	6200	4989	-1211	6567	-367
2023-10	5200	4675	-525	6567	-1367
2023-11	7000	5176	-1824	5967	1033
2023-12	7000	5181	-1819	6133	867
2024-01	4900	4410	-490	6400	-1500
2024-02	4000	4112	112	6300	-2300
2024-03	5500	4828	-672	5300	200
2024-04	4800	4633	-167	4800	0
2024-05	6000	5239	-761	4767	1233
2024-06	5600	4835	-765	5433	167
2024-07	7000	5128	-1872	5467	1533

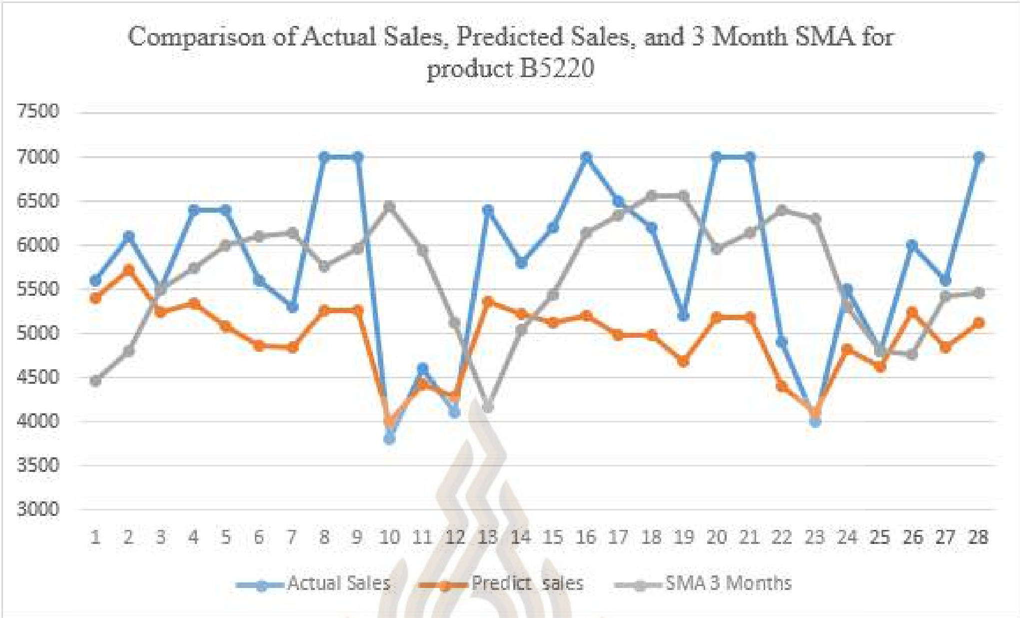

Figure 4.1 Comparison of Actual Sales, Predicted Sales and 3 Months SMA for B5220

Figure 4.1 shows a comparison chart of sales predicted by a linear regression model using 3-month data and SMA sales. The horizontal axis represents the sales distribution of B5220 product in 28 months, while the vertical axis represents the sales value. The sales line predicted by the model is close to the actual sales line in some months. The predicted sales revenue of B5220 product in the 22nd month is significantly lower than the actual sales revenue, showing a significant deviation. In most cases, the sales line of SMA falls between actual sales and forecasted sales, and in some months with significant sales fluctuations, the gap between SMA sales and actual sales remains large.

Table 4.3 shows the results of using a linear regression model based on 3-month data to predict sales of B5330 product, and compares it with actual sales and SMA (Simple Moving Average) Sales. The linear regression model is trained on 3-month data with an R^2 value of 0.642, indicating that the model can explain approximately 64.2% of sales changes and has a certain explanatory power.

From the results, the predicted values of the model are close to the actual sales in some months, especially in months with small sales fluctuations (such as May 2024), with a small prediction error of only -30, demonstrating the good performance of the model during relatively stable sales periods. However, due to limited training data for the model, it cannot fully capture long-term trends and seasonal fluctuations, resulting in significant prediction biases during sales peaks and valleys. For example, in August 2023, the model's prediction deviation was as high as -6500, while the SMA error was 1920, indicating that the model failed to effectively predict sales trends during peak sales periods.

Table 4.3 Comparison of Actual Sales, 3-Month SMA, and Forecasted Sales for Product B5330

Product Model: B5330					
Month	Actual Sales	Predict Sales	Error	SMA 3 Months	Error
2022-04	4600	3571	-1029	4273	327
2022-05	3600	2620	-980	3900	-300
2022-06	3640	1679	-1961	3933	-293
2022-07	3900	891	-3009	3947	-47
2022-08	7000	1896	-5104	3713	3287
2022-09	6900	1984	-4916	4847	2053
2022-10	6800	2081	-4719	5933	867
2022-11	6400	1506	-4894	6900	-500
2022-12	5660	795	-4865	6700	-1040
2023-01	5417	817	-4600	6287	-870
2023-02	5464	945	-4519	5826	-362
2023-03	5488	1064	-4424	5514	-26
2023-04	6790	1732	-5058	5456	1334
2023-05	6890	1890	-5000	5914	976
2023-06	6590	1395	-5195	6389	201
2023-07	5960	649	-5311	6757	-797
2023-08	8400	1900	-6500	6480	1920
2023-09	8621	2458	-6163	6983	1638

Table 4.3 Comparison of Actual Sales, 3-Month SMA, and Forecasted Sales for Product B5330 (Cont.)

Product Model: B5330					
Month	Actual Sales	Predict Sales	Error	SMA 3 Months	Error
2023-11	8620	3247	-5373	8884	-264
2023-12	7110	2650	-4460	8957	-1847
2024-01	6980	3092	-3888	8453	-1473
2024-02	6420	3227	-3193	7570	-1150
2024-03	7530	3982	-3548	6837	693
2024-04	8400	5063	-3337	6977	1423
2024-05	7420	4873	-2547	7450	-30
2024-06	6900	4349	-2551	7783	-883
2024-07	7820	4614	-3206	7573	247

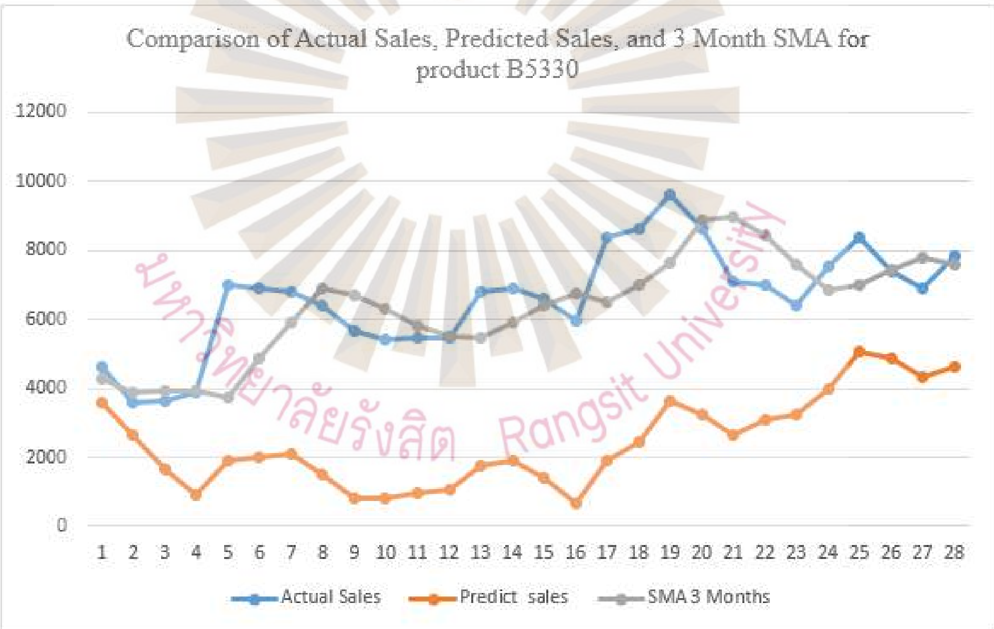

Figure 4.2 Comparison of Actual Sales, Predicted Sales and 3 Months SMA for B5330

Figure 4.2 shows the results of predicting the sales of B5330 product using a linear regression model based on a 3-month data range and compares them with actual sales and SMA (Simple Moving Average) Sales. The horizontal axis of the chart represents the sales distribution of B5330 products in 28 months, while the vertical axis represents the sales value. From the graph, the sales predicted by the model are relatively close to the actual sales in some months. There is a significant deviation between the predicted value and the actual sales revenue, especially in the 22nd month, showing a large deviation. SMA sales are located between actual sales and predicted sales, reflecting the model's stability in balancing prediction errors. In months with significant sales fluctuations, the gap between SMA sales and actual sales remains large.

Table 4.4 shows the predicted sales of B5320 product using a linear regression model based on 3-month data and compares it with actual sales and SMA (Simple Moving Average) Sales. The linear regression model is trained on 3-month data, with an R^2 value of 0.642, indicating that the model can explain approximately 64.2% of sales changes and has a certain explanatory power.

From the results, the model's predicted values are close to actual sales in certain months, especially in months with less sales fluctuations (such as April 2024), with a prediction error of only 151, demonstrating the model's good predictive performance during stable sales periods. However, due to the limited amount of training data for the model, it is unable to fully capture long-term trends and seasonal fluctuations, resulting in significant prediction biases during sales peaks and valleys. For example, in December 2023, the model's prediction deviation reached -1821, while the SMA error was 2183, indicating that the model failed to effectively predict the sales peak for that month.

Table 4.4 Comparison of Actual Sales, 3-Month SMA, and Forecasted Sales for Product B5320

Product Model: B5320					
Month	Actual Sales	Predict Sales	Error	SMA 3 Months	Error
2022-04	3900	4996	1096	5673	-1773
2022-05	5420	5782	362	4907	513
2022-06	4730	5302	572	5013	-283
2022-07	3640	4391	751	4683	-1043

Table 4.4 Comparison of Actual Sales, 3-Month SMA, and Forecasted Sales for Product B5320 (Cont.)

Product Model: B5320					
Month	Actual Sales	Predict Sales	Error	SMA 3 Months	Error
2022-08	4500	4581	81	4597	-97
2022-09	4600	4740	140	4290	310
2022-10	4750	4916	166	4247	503
2022-11	6800	5441	-1359	4617	2183
2022-12	7000	5531	-1469	5383	1617
2023-01	3300	4102	802	6183	-2883
2023-02	3820	4390	570	5700	-1880
2023-03	3650	4373	723	4707	-1057
2023-04	3860	4536	676	3590	270
2023-05	4580	4921	341	3777	803
2023-06	4760	4797	37	4030	730
2023-07	5600	4982	-618	4400	1200
2023-08	5290	4859	-431	4980	310
2023-09	5000	4804	-196	5217	-217
2023-10	4300	4603	303	5297	-997
2023-11	5600	4652	-948	4863	737
2023-12	7150	5329	-1821	4967	2183
2024-01	3950	4099	149	5683	-1733
2024-02	3200	3857	657	5567	-2367
2024-03	3810	4181	371	4767	-957
2024-04	4300	4451	151	3653	647
2024-05	4800	4737	-63	3770	1030
2024-06	5500	4798	-702	4303	1197
2024-07	5200	4476	-724	4867	333

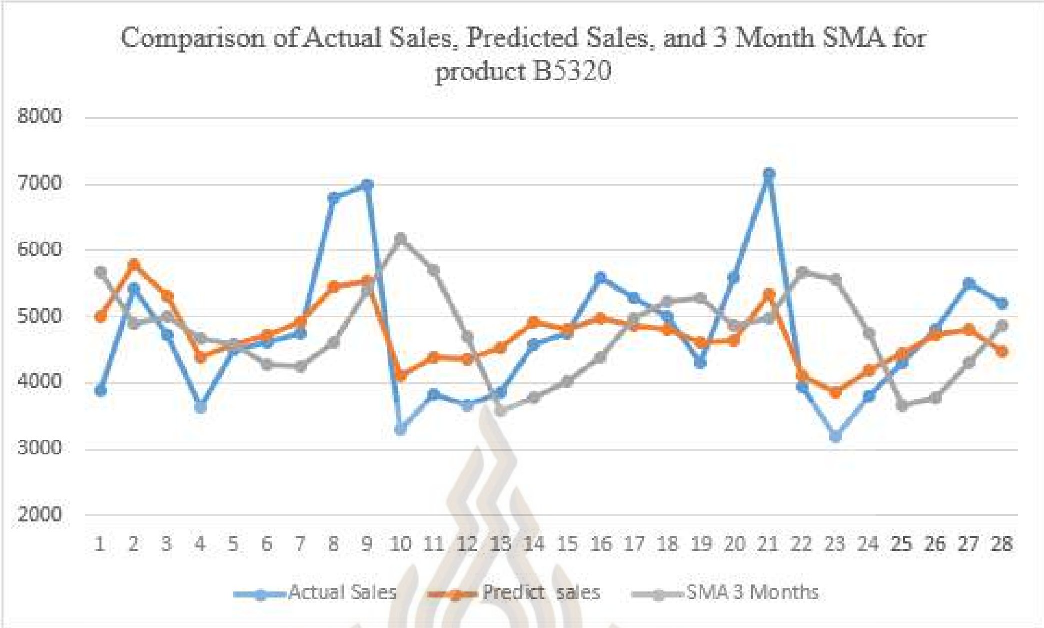

Figure 4.3 Comparison of Actual sales, Predicted sales and 3 months SMA for B5320

Figure 4.3 shows a comparison of sales predicted using a linear regression model with 3-month data and SMA sales. The horizontal axis represents the sales distribution of B5220 product in 28 months, and the vertical axis represents the sales value. The sales line predicted by the model approaches the actual sales line in certain months. The expected sales revenue of B5220 product in the 22nd month is significantly lower than the actual sales revenue, showing a significant deviation. In most cases, the sales line of SMA falls between actual sales and forecasted sales, and in some months with significant sales fluctuations, the gap between SMA sales and actual sales remains significant.

Table 4.5 shows the prediction results of UU4222 product sales based on a linear regression model using 3-month data and compares them with actual sales and SMA (Simple Moving Average) Sales. The linear regression model is trained on 3-month data, with an R^2 value of 0.642, indicating that the model can explain approximately 64.2% of sales changes and has a certain explanatory power.

The model’s predicted values are close to actual sales in certain months, especially in months with less sales fluctuations (such as April 2024), with a prediction error of only -1506. However, due to the limited amount of training data for the model, it is unable to fully capture long-term trends and seasonal fluctuations, resulting in significant prediction biases during sales peaks and valleys. For example, in May 2024, the model's prediction deviation reached -2214, while the SMA error was 1471, indicating that the model failed to effectively predict the sales peak for that month.

Table 4.5 Comparison of Actual Sales, 3-Month SMA, and Forecasted Sales for Product UU4222

Product Model: UU4222					
Month	Actual Sales	Predict Sales	Error	SMA 3 Months	Error
2022-04	5900	5813	-87	5533	367
2022-05	7000	6410	-590	5867	1133
2022-06	6850	6029	-821	6467	383
2022-07	6530	5524	-1006	6583	-53
2022-08	6600	5313	-1287	6793	-193
2022-09	5200	4860	-340	6660	-1460
2022-10	6310	5431	-879	6110	200
2022-11	5900	4750	-1150	6037	-137
2022-12	4600	3678	-922	5803	-1203
2023-01	5400	4140	-1260	5603	-203
2023-02	4600	3903	-697	5300	-700
2023-03	6030	4609	-1421	4867	1163
2023-04	6900	5112	-1788	5343	1557
2023-05	6770	5192	-1578	5843	927
2023-06	7140	5083	-2057	6567	573
2023-07	6210	4479	-1731	6937	-727
2023-08	6300	4310	-1990	6707	-407
2023-09	6410	4507	-1903	6550	-140

Table 4.5 Comparison of Actual Sales, 3-Month SMA, and Forecasted Sales for Product UU4222 (Cont.)

Product Model: UU4222					
Month	Actual Sales	Predict Sales	Error	SMA 3 Months	Error
2023-10	5370	4205	-1165	6307	-937
2023-11	6420	4276	-2144	6027	393
2023-12	5120	3370	-1750	6067	-947
2024-01	5200	3517	-1683	5637	-437
2024-02	4470	3307	-1163	5580	-1110
2024-03	6350	4214	-2136	4930	1420
2024-04	5467	3961	-1506	5340	127
2024-05	6900	4686	-2214	5429	1471
2024-06	5400	3457	-1943	6239	-839
2024-07	4200	2124	-2076	5922	-1722

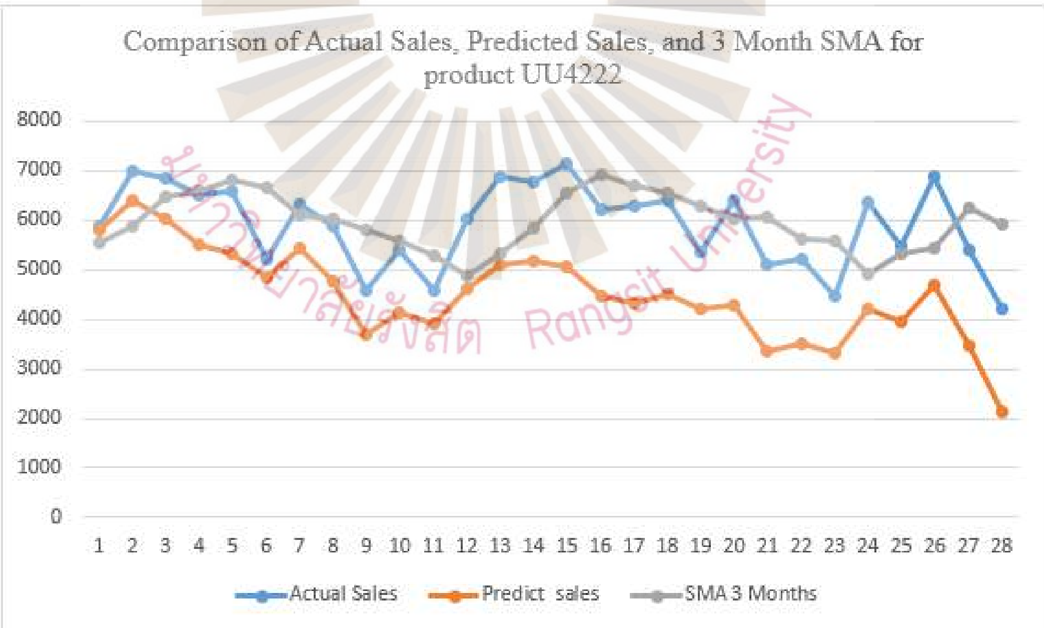

Figure 4.4 Comparison of Actual sales, Predicted Sales and 3 Months SMA for UU4222

Figure 4.4 shows a comparison of sales predicted using a linear regression model with 3-month data and SMA sales. The horizontal axis represents the sales distribution of UU4222 product in 28 months, and the vertical axis represents the sales value. The sales line predicted by the model approaches the actual sales line in certain months. The expected sales revenue of UU4222 product in the 28th month is significantly lower than the actual sales revenue, showing a significant deviation. In most cases, the sales line of SMA falls between actual sales and forecasted sales, and in some months with significant sales fluctuations, the gap between SMA sales and actual sales remains significant.

Table 4.6 Comparison of Actual Sales, 3-Month SMA, and Forecasted Sales for Product UU4320

Product Model: UU4320					
Month	Actual Sales	Predict Sales	Error	SMA 3 Months	Error
2022-04	5810	5859	49	4960	850
2022-05	5850	5991	141	5437	413
2022-06	7000	6173	-827	5753	1247
2022-07	7000	5895	-1105	6220	780
2022-08	6500	5422	-1078	6617	-117
2022-09	6250	5453	-797	6833	-583
2022-10	5700	5342	-358	6583	-883
2022-11	7000	5615	-1385	6150	850
2022-12	6930	5578	-1352	6317	613
2023-01	4200	4573	373	6543	-2343
2023-02	4600	4850	250	6043	-1443
2023-03	5070	5142	72	5243	-173
2023-04	4830	5152	322	4623	207
2023-05	5700	5679	-21	4833	867
2023-06	6500	5669	-831	5200	1300
2023-07	7000	5677	-1323	5677	1323

Table 4.6 Comparison of Actual Sales, 3-Month SMA, and Forecasted Sales for Product UU4320 (Cont.)

Product Model: UU4320					
Month	Actual Sales	Predict Sales	Error	SMA 3 Months	Error
2023-08	6030	5286	-744	6400	-370
2023-09	6030	5409	-621	6510	-480
2023-10	5930	5491	-439	6353	-423
2023-11	6950	5651	-1299	5997	953
2023-12	6870	5598	-1272	6303	567
2024-01	5020	4944	-76	6583	-1563
2024-02	4020	4614	594	6280	-2260
2024-03	5040	5133	93	5303	-263
2024-04	6000	5657	-343	4693	1307
2024-05	6100	5818	-282	5020	1080
2024-06	6530	5994	-536	5713	817
2024-07	6320	5642	-678	6210	110

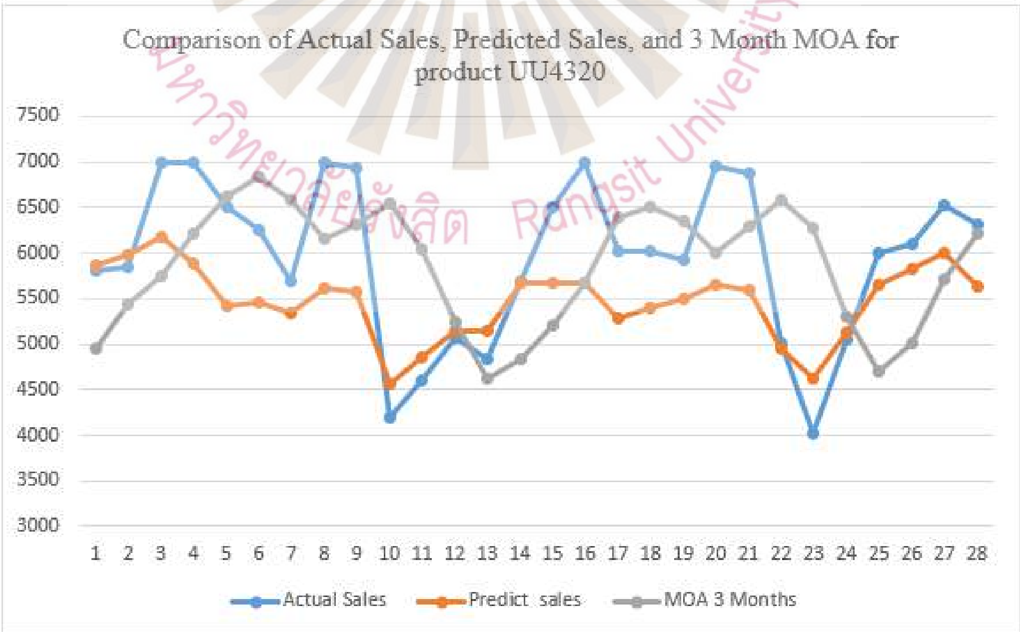

Figure 4.5 Comparison of Actual Sales, Predicted Sales and 3 Months SMA for UU4320

Figure 4.5 shows a comparison of predicted sales using a linear regression model with 3-month data and SMA sales. The horizontal axis represents the sales distribution of UU4320 product in 28 months, and the vertical axis represents the sales value. The sales line predicted by the model approaches the actual sales line in certain months. The expected sales revenue of UU4320 product in the 22nd month is significantly lower than the actual sales revenue, showing a significant deviation. In most cases, the sales line of SMA falls between actual sales and forecasted sales, and in some months with significant sales fluctuations, the gap between SMA sales and actual sales remains significant.

4.2.2 Comparison between Sales Forecast Based on 3-month Data and Actual Sales in 2023

Table 4.7 presents the error analysis results of sales forecasting for five products (B5220, B5330, B5320, UU4222, and UU4320) using a linear regression model. The model is trained based on sales data from 3 months (January to March 2022) and compared with actual sales data from 28 months in 2022-4 to 2024-7 using predicted values to evaluate the predictive performance of the model on different products.

The overall absolute error is 1528, indicating the average deviation level of the model across all products. The prediction error of B5330 is the largest, with an absolute error of 4156 and a standard deviation of 1453, indicating that the sales data of this product fluctuates greatly and the model is difficult to accurately capture its trend.

The prediction performance of B5320 is the best, with an absolute error of only 581 and a standard deviation of 456, indicating that the model's sales trend prediction for this product is relatively stable and accurate.

The errors and absolute errors of B5320 and UU4320 are relatively small, indicating that the model's predictions on these products have a certain level of reliability.

Table 4.7 Linear Regression Prediction Error Analysis Based on Sales Data of Five Products in Three Months

Product Model	Error	Absolute Error	Standard Deviation
B5220	-845	881	614
B5330	-4156	4156	1453
B5320	-14	581	456
UU4222	-1403	1403	581
UU4320	-481	616	458
All Models	-1380	1528	1564

4.3 Using a Six-month Data Linear Regression Model

4.3.1 Comparison between Six-month SMA Sales Value and Three-month Linear Regression Prediction Sales

The following equation was the equation obtained from applying the linear regression to predict sales:

$$PredictedSalesValue = 1537.726+(Price*16.199)+(InitialStock*0.626)+(FinalStock*0.7)+(Production*0.706) \quad (4\text{-}2)$$

Table 4.8 shows the results of using a linear regression model based on 6-month data to predict the sales of B5220 product and compares the predicted sales with actual sales and SMA (Simple Moving Average) Sales. The training of the linear regression model is based on 6 months of sales data, with an R^2 value of 0.816, indicating that the model can explain approximately 81.6% of sales changes and has strong explanatory power and certain predictive reliability.

From the table, in some months, the predicted sales revenue of the model is relatively close to the actual sales revenue, especially in months with small sales fluctuations, such as April 2024, where the prediction error is only -75, indicating the good predictive performance of the model in stable periods. However, in months with significant sales fluctuations, there is still a certain deviation between predicted values and actual sales. For example, in July 2023, the model's predicted sales deviation reached -708, while the corresponding SMA error was -1848, indicating that the model's predictive ability in dealing with sales peaks still needs to be improved.

Table 4.8 Comparison of Actual Sales, 6-Month SMA, and Forecasted Sales for Product B5220

Product Model: B5220					
Month	Actual Sales	Predict Sales	Error	SMA 6 Months	Error
2022-07	6400	6023	-377	5102	-1298
2022-08	6400	5927	-473	5405	-995
2022-09	5600	5251	-349	5800	200
2022-10	5300	5078	-222	5933	633
2022-11	7000	6328	-672	5883	-1117
2022-12	7000	6216	-784	6033	-967
2023-01	3800	3952	152	6283	2483
2023-02	4600	4540	-60	5850	1250
2023-03	4100	4219	119	5550	1450
2023-04	6410	5872	-538	5300	-1110
2023-05	5800	5489	-311	5485	-315
2023-06	6200	5825	-375	5285	-915
2023-07	7000	6292	-708	5152	-1848
2023-08	6500	5840	-660	5685	-815
2023-09	6200	5620	-580	6002	-198
2023-10	5200	4960	-240	6352	1152
2023-11	7000	6277	-723	6150	-850
2023-12	7000	6185	-815	6350	-650
2024-01	4900	4700	-200	6483	1583
2024-02	4000	4097	97	6133	2133
2024-03	5500	5181	-319	5717	217

Table 4.8 Comparison of Actual Sales, 6-Month SMA, and Forecasted Sales for Product B5220 (Cont.)

Product Model: B5220					
Month	Actual Sales	Predict Sales	Error	SMA 6 Months	Error
2024-04	4800	4725	-75	5600	800
2024-05	6000	5606	-394	5533	-467
2024-06	5600	5376	-224	5367	-233
2024-07	7000	6280	-720	5133	-1867

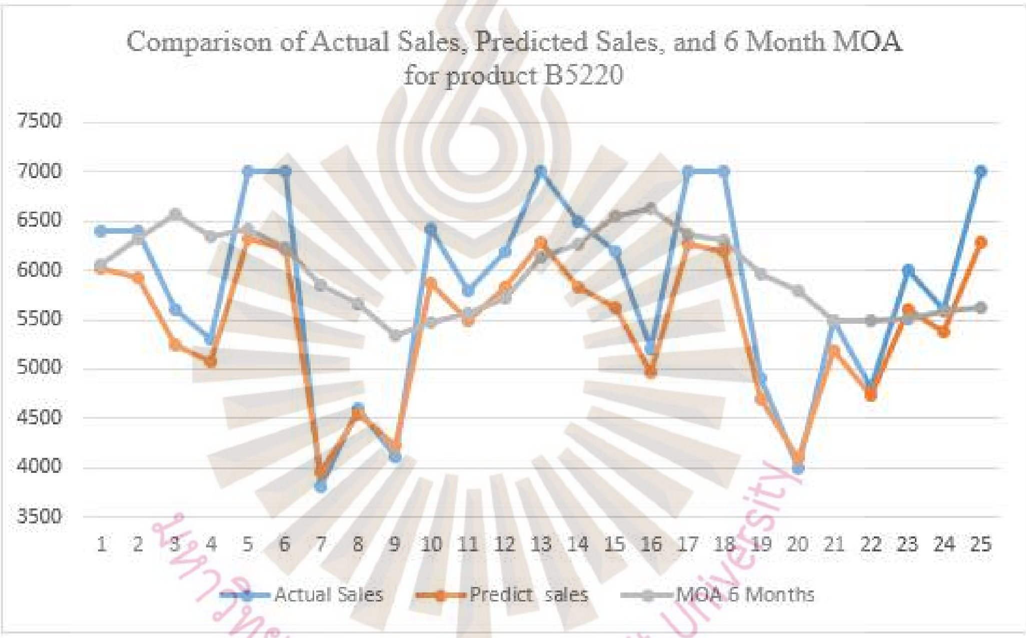

Figure 4.6 Comparison of Actual Sales, Predicted Sales and 6 Months SMA for B5220

Figure 4.6 shows the results of using linear regression to predict sales revenue, actual sales revenue, and SMA based on 6-month sales data. The obtained R2 value is 0.816, indicating that the model explains 81.6% of the data variation. The horizontal axis represents the sales distribution of B5220 product within 25 months, and the vertical axis represents the sales volume.

Table 4.9 shows the results of using a linear regression model based on 6-month data to predict the sales of B5330 product, and compares the predicted sales with actual sales and SMA (Simple Moving Average) Sales. The training of the linear regression model is based on 6 months of sales data, with an R^2 value of 0.816, indicating that the model can explain approximately 81.6% of sales changes and has good explanatory power.

From the table, it can be seen that in some months, the predicted sales revenue of the model is close to the actual sales revenue, especially in months with small sales fluctuations, such as May 2024, where the prediction error is only -1135, indicating the good performance of the model in a relatively stable sales environment. However, in months with significant sales fluctuations, the accuracy of the model's predictions is somewhat affected. For example, in August 2022, the predicted sales deviation of B5330 reached -1849, while the corresponding SMA error was -3193, indicating that the model's predictive ability still needs to be improved in dealing with sales peaks or drastic fluctuations.

Table 4.9 Comparison of Actual Sales, 6-Month SMA, and Forecasted Sales for Product B5330

Product Model: B5330					
Month	Actual Sales	Predict Sales	Error	SMA 6 Months	Error
2022-07	3900	3314	-586	4110	210
2022-08	7000	5151	-1849	3807	-3193
2022-09	6900	4965	-1935	4390	-2510
2022-10	6800	4938	-1862	4940	-1860
2022-11	6400	4723	-1677	5307	-1093
2022-12	5660	4053	-1607	5773	113
2023-01	5417	3714	-1703	6110	693
2023-02	5464	3788	-1676	6363	899
2023-03	5488	3845	-1643	6107	619
2023-04	6790	4804	-1986	5872	-919
2023-05	6890	4925	-1965	5870	-1020
2023-06	6590	4772	-1818	5952	-639

Table 4.9 Comparison of Actual Sales, 6-Month SMA, and Forecasted Sales for Product B5330 (Cont.)

Product Model: B5330					
Month	Actual Sales	Predict Sales	Error	SMA 6 Months	Error
2023-07	5960	4197	-1763	6107	147
2023-08	8400	5717	-2683	6197	-2203
2023-09	8621	5954	-2667	6686	-1935
2023-10	9630	6829	-2801	7209	-2422
2023-11	8620	6415	-2205	7682	-938
2023-12	7110	5369	-1741	7970	860
2024-01	6980	5272	-1708	8057	1077
2024-02	6420	5059	-1361	8227	1807
2024-03	7530	5982	-1548	7897	367
2024-04	8400	6696	-1704	7715	-685
2024-05	7420	6285	-1135	7510	90
2024-06	6900	6016	-884	7310	410
2024-07	7820	6549	-1271	7275	-545

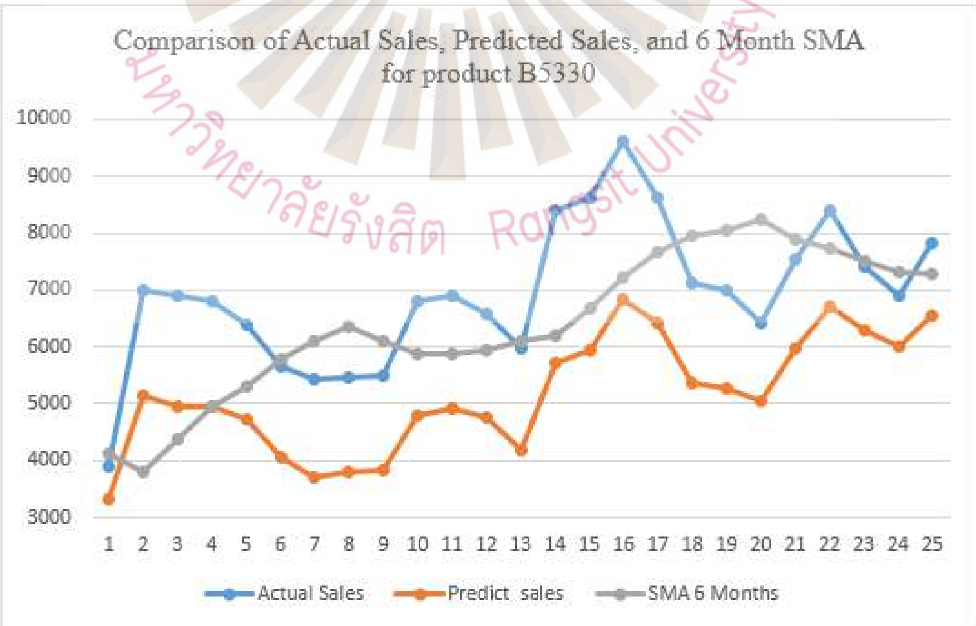

Figure 4.7 Comparison of Actual Sales, Predicted Sales and 6 Months SMA for B5330

Figure 4.7 shows the results of using linear regression to predict sales revenue, actual sales revenue, and SMA based on 6-month sales data. The obtained R2 value is 0.816, indicating that the model explains 81.6% of the data variation. The horizontal axis represents the sales distribution of B5330 product within 25 months, and the vertical axis represents the sales volume.

Table 4.10 shows the results of using a linear regression model based on 6-month data to predict the sales of B5320 product, and compares the predicted sales with actual sales and SMA (Simple Moving Average) Sales. The training of the linear regression model is based on 6 months of sales data, with an R^2 value of 0.816, indicating that the model can explain approximately 81.6% of sales changes and has strong explanatory power.

From the table, it can be seen that in some months, the predicted sales revenue of the model is close to the actual sales revenue, especially in months with small sales fluctuations, such as May 2024, where the prediction error is only -9, indicating that the model has good prediction performance under stable sales conditions. However, in months with significant sales fluctuations, the predictive accuracy of the model is somewhat affected. For example, the predicted sales deviation for November 2022 is -482, while the SMA error is as high as -2193, indicating that the model still needs to improve its predictive ability in dealing with sales peaks or drastic fluctuations.

Table 4.10 Comparison of Actual Sales, 6-Month SMA, and Forecasted Sales for Product B5320

Product Model: B5320					
Month	Actual Sales	Predict Sales	Error	SMA 6 Months	Error
2022-07	3640	4242	602	5178	1538
2022-08	4500	4670	170	4752	252
2022-09	4600	4669	69	4652	52
2022-10	4750	4816	66	4465	-285
2022-11	6800	6318	-482	4607	-2193

Table 4.10 Comparison of Actual Sales, 6-Month SMA, and Forecasted Sales for Product B5320 (Cont.)

Product Model: B5320					
Month	Actual Sales	Predict Sales	Error	SMA 6 Months	Error
2022-12	7000	6338	-662	4837	-2163
2023-01	3300	3723	423	5215	1915
2023-02	3820	4121	301	5158	1338
2023-03	3650	4030	380	5045	1395
2023-04	3860	4197	337	4887	1027
2023-05	4580	4734	154	4738	158
2023-06	4760	4903	143	4368	-392
2023-07	5600	5424	-176	3995	-1605
2023-08	5290	5141	-149	4378	-912
2023-09	5000	4934	-66	4623	-377
2023-10	4300	4463	163	4848	548
2023-11	5600	5428	-172	4922	-678
2023-12	7150	6334	-816	5092	-2058
2024-01	3950	4084	134	5490	1540
2024-02	3200	3584	384	5215	2015
2024-03	3810	4039	229	4867	1057
2024-04	4300	4412	112	4668	368
2024-05	4800	4791	-9	4668	-132
2024-06	5500	5324	-176	4535	-965
2024-07	5200	5031	-169	4260	-940

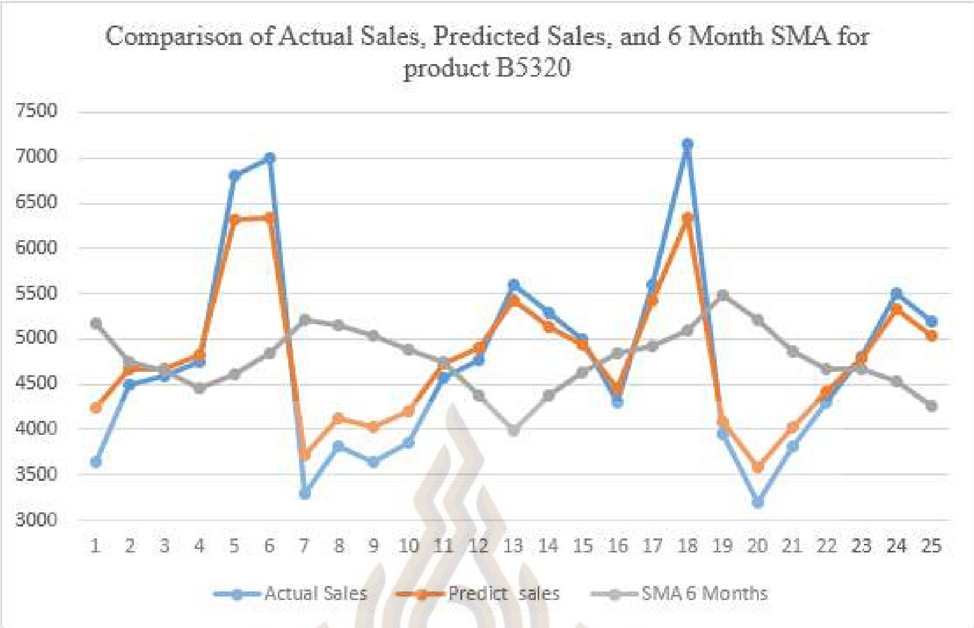

Figure 4.8 Comparison of Actual Sales, Predicted Sales and 6 Months SMA for B5320

Figure 4.8 shows the results of using linear regression to predict sales revenue, actual sales revenue, and SMA based on 6-month sales data. The obtained R2 value is 0.816, indicating that the model explains 81.6% of the data variation. The horizontal axis represents the sales distribution of B5320 product within 25 months, and the vertical axis represents the sales volume.

Table 4.11 shows the results of using a linear regression model based on 6-month data to predict the sales of UU4222 product, and compares the predicted sales with actual sales and SMA (Simple Moving Average) Sales. The training of the linear regression model is based on 6 months of sales data, with an R^2 value of 0.816, indicating that the model can explain approximately 81.6% of sales changes and has strong explanatory power.

From the table, it can be seen that the predicted results of the model are close to the actual sales in some months, especially in months with small sales fluctuations, such as September 2022, where the prediction error is only 6, demonstrating the good predictive ability of the model in a stable sales environment. However, in months with significant sales fluctuations, there is a certain deviation in the accuracy of the model's predictions. For example, the predicted sales deviation for July 2024 is -176, and the SMA error is as high as 1431, indicating that the model's predictive ability still needs to be improved in dealing with severe fluctuations or abnormal sales trends

Table 4.11 Comparison of Actual Sales, 6-Month SMA, and Forecasted Sales for Product UU4222

Product Model: UU4222					
Month	Actual Sales	Predict Sales	Error	SMA 6 Months	Error
2022-07	6530	6389	-141	6058	-472
2022-08	6600	6296	-304	6330	-270
2022-09	5200	5206	6	6563	1363
2022-10	6310	6031	-279	6347	37
2022-11	5900	5803	-97	6415	515
2022-12	4600	4702	102	6232	1632
2023-01	5400	5046	-354	5857	457
2023-02	4600	4526	-74	5668	1068
2023-03	6030	5569	-461	5335	-695
2023-04	6900	6227	-673	5473	-1427
2023-05	6770	6190	-580	5572	-1198
2023-06	7140	6513	-627	5717	-1423
2023-07	6210	5762	-448	6140	-70
2023-08	6300	5742	-558	6275	-25
2023-09	6410	5732	-678	6558	148
2023-10	5370	5052	-318	6622	1252
2023-11	6420	5853	-567	6367	-53
2023-12	5120	4807	-313	6308	1188
2024-01	5200	4710	-490	5972	772
2024-02	4470	4233	-237	5803	1333
2024-03	6350	5592	-758	5498	-852
2024-04	5467	5021	-446	5488	21
2024-05	6900	6072	-828	5505	-1396
2024-06	5400	5086	-314	5585	185
2024-07	4200	4024	-176	5631	1431

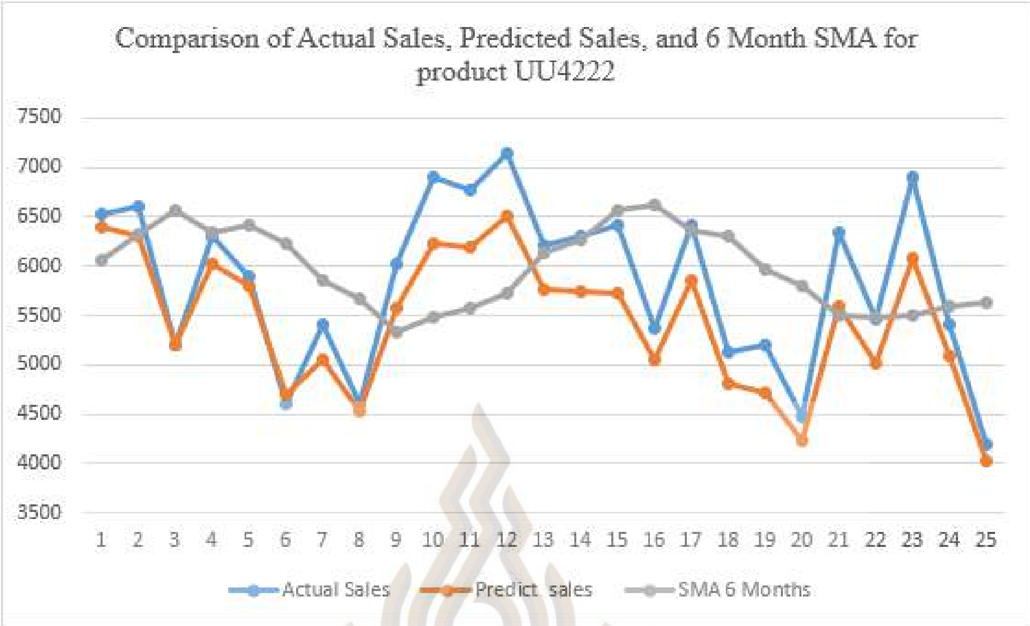

Figure 4.9 Comparison of Actual Sales, Predicted Sales and 6 Months SMA for UU4222

Figure 4.9 shows the results of using linear regression to predict sales revenue, actual sales revenue, and SMA based on 6-month sales data. The obtained R2 value is 0.816, indicating that the model explains 81.6% of the data variation. The horizontal axis represents the sales distribution of UU4222 product within 25 months, and the vertical axis represents the sales volume.

Table 4.12 shows the results of using a linear regression model based on 6-month data to predict the sales of UU4320 product and compares the predicted sales with actual sales and SMA (Simple Moving Average) Sales. The training of the linear regression model is based on 6 months of sales data, with an R^2 value of 0.816, indicating that the model can explain approximately 81.6% of sales changes and has strong explanatory power.

From the table, it can be seen that the predicted results of the model are relatively close to the actual sales in some months, especially in months with small sales fluctuations, such as May 2024, where the prediction error is only -61, indicating the good predictive ability of the model in a stable sales environment. However, in months with significant sales fluctuations, there is a certain deviation in the accuracy of the model's predictions. For example, the predicted sales deviation for July 2023 is -383, and the SMA error is as high as 1850, indicating that the model's predictive ability still needs to be improved in dealing with severe fluctuations or abnormal sales trends.

Table 4.12 Comparison of Actual Sales, 6-Month SMA, and Forecasted Sales for Product UU4320

Product Model: UU4320					
Month	Actual Sales	Predict Sales	Error	SMA 6 Months	Error
2022-07	7000	6730	-270	5590	-1410
2022-08	6500	6273	-227	6027	-473
2022-09	6250	5985	-265	6293	43
2022-10	5700	5643	-57	6402	702
2022-11	7000	6614	-386	6383	-617
2022-12	6930	6465	-465	6575	-355
2023-01	4200	4528	328	6563	2363
2023-02	4600	4851	251	6097	1497
2023-03	5070	5225	155	5780	710
2023-04	4830	5093	263	5583	753
2023-05	5700	5745	45	5438	-262
2023-06	6500	6388	-112	5222	-1278
2023-07	7000	6617	-383	5150	-1850
2023-08	6030	5851	-179	5617	-413
2023-09	6030	5848	-182	5855	-175
2023-10	5930	5822	-108	6015	85
2023-11	6950	6599	-351	6198	-752
2023-12	6870	6444	-426	6407	-463
2024-01	5020	5124	104	6468	1448

Table 4.12 Comparison of Actual Sales, 6-Month SMA, and Forecasted Sales for Product UU4320

Product Model: UU4320					
Month	Actual Sales	Predict Sales	Error	SMA 6 Months	Error
2024-02	4020	4456	436	6138	2118
2024-03	5040	5205	165	5803	763
2024-04	6000	5919	-81	5638	-362
2024-05	6100	6039	-61	5650	-450
2024-06	6530	6391	-139	5508	-1022
2024-07	6320	6252	-68	5452	-868

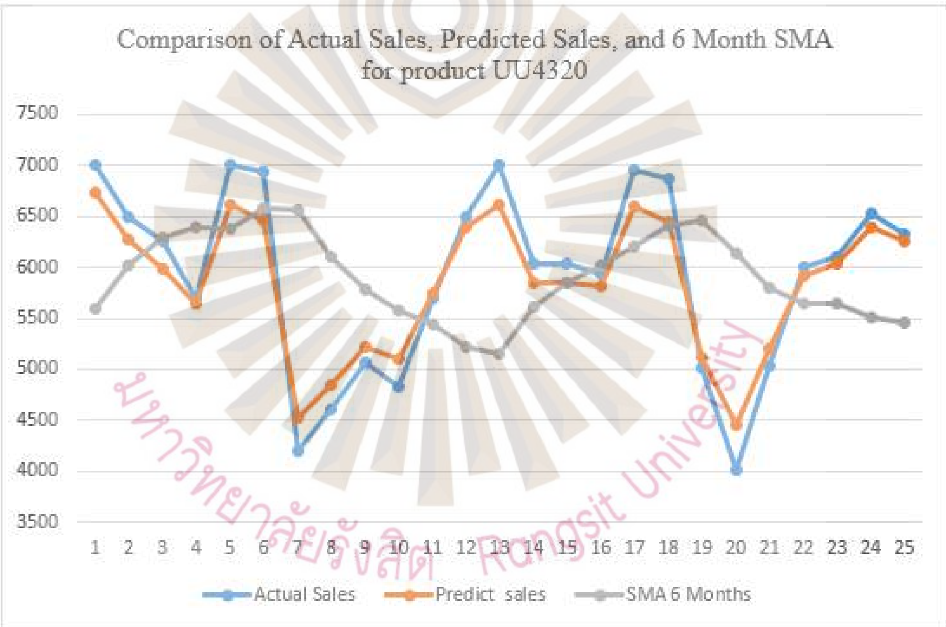

Figure 4.10 Comparison of Actual sales, Predicted Sales and 6 Months SMA for UU4320

Figure 4.10 shows the results of using linear regression to predict sales revenue, actual sales revenue, and SMA based on 6-month sales data. The obtained R2 value is 0.816, indicating that the model explains 81.6% of the data variation. The horizontal axis represents the sales distribution of UU4222 product within 25 months, and the vertical axis represents the sales volume.

4.3.2 Comparison between Sales Forecast Based on 6-month Data and Actual Sales in 2023

Table 4.13 shows the error analysis results of using a linear regression model for sales forecasting of five products (B5220, B5330, B5320, UU4222, and UU4320). The model is trained based on sales data from 6 months (January to June 2022) and compared with actual sales data from 28 months in 2022-4 to 2024-7. The overall absolute error of the model is 607, indicating the average deviation level of the model on all products. The prediction error of B5330 is the largest, with an absolute error of 1751 and a standard deviation of 506, indicating that the sales data of this product fluctuates greatly and the model is difficult to accurately capture its trend.

Compared to others, UU4320 has the best predictive performance with an absolute error of only 220 and a standard deviation of 132, indicating that the model's prediction of the product's sales trend is relatively stable and accurate. The errors and absolute errors of B5320 and UU4222 are relatively small, although the model's predictions for some products (such as B5330) still need improvement

Table 4.13 Linear Regression Prediction Error Analysis Based on Sales Data of Five Products in Six Months

Product Model	Error	Absolute Error	Standard Deviation
B5220	-378	407	243
B5330	-1751	1751	506
B5320	32	262	204
UU4222	-384	393	228
UU4320	-81	220	132
All Models	-513	607	646

4.4 Summary of Results

The R^2 value significantly increases with the increase of time span: from 0.642 at 3 months to 0.816 at 6 months. This indicates that as the training data span extends, the model's explanatory power for sales changes significantly increases. The overall absolute error decreased from 1528 at 3 months to 607 at 6 months, indicating that the model became more accurate as the amount of data increased. For products with good stability, such as UU4320 and B5220, the prediction error significantly decreases with an increase in time span. For example: The absolute error of UU4320 decreased from 458 in 3 months to 132 in 6 months. The absolute error of UU4222 decreased from 1403 at 3 months to 393 at 6 months.

For products with high volatility (such as B5330), although the error is still large, it has decreased from 4156 at 3 months to 1751 at 6 months, indicating that the model has improved in capturing complex trends. The overall standard deviation has also decreased from 1453 at 3 months to 506 at 6 months, indicating a gradual reduction in the volatility of the predicted results.

As the time span increases, the predictive performance and stability of linear regression models significantly improve. The model based on 6 months of data has the highest R^2 value and the lowest error, making it suitable for long-term sales forecasting. For products with high volatility (such as B5330), although the prediction error has been reduced, there is still some deviation, and further optimization of the model or introduction of more variables is needed to improve the prediction accuracy.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study established a sales forecasting model for patch panel products applicable to YaQi factory and revealed the impact mechanism of product attributes on sales through data analysis. The research results have important practical application value in improving inventory management efficiency, reducing inventory costs, and optimizing enterprise operations. In the future, the model can be further optimized.

By using a linear regression model and combining sales data of power strip products, the impact of various time spans (3 months, 6 months) on the prediction results was studied. The model based on 6 months of data performs the best, with an R^2 value of 0.816, which can explain approximately 81.6% of sales changes. This indicates that with the extension of data time span, the predictive accuracy and stability of the model significantly improve, providing a reliable tool for formulating long-term sales strategies and inventory planning.

Using SPSS software, a correlation analysis was conducted between seven key attributes of power strip products (such as price, initial inventory, final inventory, production volume, etc.) and sales data. The research results indicate that these variables have a statistically significant impact on sales, providing data support for optimizing prediction models and inventory management strategies in the future. By comparing sales forecasts with actual sales data, the model's prediction errors (such as absolute error and standard deviation) were quantified, and the performance of models with different time spans was evaluated.

Research has shown that models based on 6 months of data can effectively reduce prediction errors (with an overall absolute error of 607), improve inventory management accuracy, and avoid inventory surplus or shortage. At the same time, a visual evaluation of the accuracy of the forecast results was conducted in conjunction with SMA sales, which helps to develop more targeted inventory replenishment and production strategies.

5.2 Discussion

The results indicate that the linear regression model based on six months of data exhibits high predictive performance, with an R value of 0.816, explaining approximately 81.6% of sales variations. According to Long and Liu's (2021) was found that the training data time span increases, the explanatory power and prediction accuracy of the model significantly improve. Specifically, the R^2 value increased from 0.642 at 3 months to 0.816 at 6 months, indicating a significant enhancement in the explanatory power of the model for sales changes, according to Xiong et al. (2024) was found that, the study's findings, linear regression is a trustworthy and understandable technique for sales forecasting. Platform profitability can be increased by using sales forecasting models to forecast product demand, improve inventory control, and efficiently schedule procurement, and according to Gopalakrishnan T. et al. (2018) found that the sales predicted by linear regression had an accuracy of 84% when compared to the actual sales in 2014. Zmart can enhance its inventory strategy and boost sales by forecasting sales.

Meanwhile, the overall absolute error decreased from 1528 at 3 months to 607 at 6 months, further demonstrating the accuracy improvement of the model with increasing data volume.

5.3 Recommendations

5.3.1 Limitations

Although this study has achieved certain results in sales forecasting and inventory management optimization, there are still some limitations The data only covers the sales records of five best-selling plug-in board products from YaQi factory, without considering the sales data of other product lines or potential new products, which may limit the universality of the model. Although the model shows high accuracy (R^2 value of 0.816), there is still some deviation in the prediction of products with high volatility (such as B5330), indicating that the model has weak adaptability to high volatility sales data. This study mainly relied on SPSS software for regression analysis and did not compare with more complex machine learning methods such as support vector machines, neural networks, etc., which may not have fully explored the potential of the data

5.3.2 Future Outlook

In future research, more product line data and cross industry sales records should be included to enhance the universality and applicability of the model.

Extend the time frame for data collection and analyze the impact of special market conditions (such as major holiday promotions or force majeure events) on sales to improve the predictive ability of the model. On the basis of existing linear regression models, nonlinear prediction models (such as support vector regression, random forest, deep learning, etc.) can be introduced to better capture complex sales trends and fluctuations. By collaborating with the supply chain management system, improve the response speed and efficiency of the entire supply chain.

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