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Forecasting Inventory Demand Under Volatile Sales Patterns Using the Prophet Algorithm

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Keywords

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Abstract

Inventory availability is a critical factor for companies to maintain operational continuity and customer satisfaction. However, many organizations still face challenges in forecasting demand, particularly when sales patterns are highly volatile and irregular. Although the Prophet forecasting algorithm has been widely used for time-series prediction, its behavior and robustness under unstable sales patterns remain insufficiently examined in practical inventory contexts. This study aims to evaluate the ability of the Prophet algorithm to forecast inventory demand using historical sales data characterized by fluctuating patterns. A quantitative time-series forecasting approach was applied using one year of secondary sales data obtained from PT XYZ. The data were cleaned to address missing values and aggregated into weekly time intervals to reduce noise. Five products with the highest transaction frequency were selected as case studies. Forecasting performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The results show that Prophet is capable of generating reasonably accurate forecasts even under volatile demand conditions. The evaluation results indicate RMSE values ranging from 5.41 to 52.78 and MAPE values ranging from 5% to 23.46% across the five analyzed products. These findings provide empirical evidence that the Prophet algorithm can maintain forecasting robustness despite irregular demand patterns. However, the absence of comparisons with alternative forecasting models limits the strength of conclusions regarding its relative performance. This study contributes by providing empirical insight into the application of Prophet for inventory forecasting under volatile sales conditions and offers practical implications for improving inventory planning in data-driven decision-making environments.

1. Introduction

In the business world, the availability of stock is very important to help companies ensure operational continuity and customer satisfaction. Therefore, stock prediction is very important for companies to anticipate dynamic situations, such as changes in consumer demand and market instability [1]. This is particularly relevant to the role of HACH as a distributor of water parameter testing products. Although not a direct user, HACH plays a vital role in ensuring product availability. Given the high dependence of this sector on equipment and reagents such as pH meters, iron reagents, and chlorine, maintaining inventory availability is essential to avoid eroding customer trust and disrupting operations.

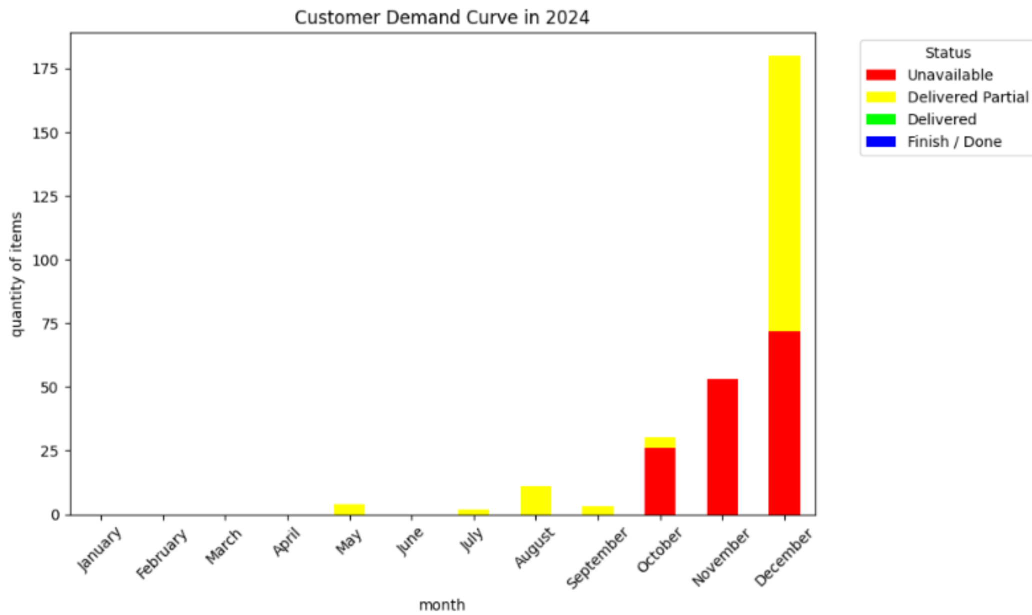

Figure 1. Customer Demand Curve at PT XYZ

Based on Figure 1, the graph shows the number of unfulfilled customer requests over the course of a year. It can be seen that in the last three months, the company has still been unable to cover all requests. Analysis based on company data sources shows that the company is still experiencing difficulties in fulfilling customer requests in a timely manner. Therefore, a solution is needed to fulfill these requests. In this situation, time series forecasting is one of the most common approaches to predicting stock levels [2]. By using this method, the company can identify patterns and trends from their historical data, enabling them to make accurate estimates for future stock requirements [3].

This study will use Prophet as the main predictive method for forecasting stock levels. Prophet is a forecasting library developed by Facebook (Meta) to predict time series data [4]. This method uses an additive approach by dividing data into three main components: trend, seasonal, and irregular components, enabling it to adapt to unexpected changes in trends [3]. Compared to other methods, Prophet excels at managing fluctuating data and handling missing data [5]. Therefore, the Prophet algorithm is the best choice for improving the accuracy of inventory forecasting in this study.

Like previous research [6] that discussed product demand forecasting using the Prophet method. The results of this study show that the Prophet model is useful for understanding sales patterns and making short- and long-term predictions. Something similar was found in research [5], which conducted a forecasts of supermarket sales data using the Prophet method. The results of this study state that the Prophet method is superior with a MAPE value of 8.3% compared to the additive and Autoregressive Integrated Moving Average (ARIMA) methods. Another study by [7] also showed that the Prophet algorithm can produce accurate forecasts, especially for products with stable and regular demand. In addition, [8] showed that Prophet excels in forecasting food prices in Bandung City by considering holidays and is able to handle volatile data better than ARIMA and LSTM, although it has not discussed the impact of variations in training data on prediction results.

Previous studies have shown that Prophet works well with stable data. However, there is still unclear literature on how this algorithm can be adapted to handle volatile data. This study focuses on how the Prophet algorithm can be used to analyze historical sales data that is volatile. Additionally, this study aims to develop methods that can assist practitioners in handling irregular or volatile sales data. Thus, this study not only contributes to the development of forecasting theory but also offers practical solutions to help companies make better decisions.

The main contribution of this research is to provide empirical evidence regarding the robustness of the Prophet algorithm when applied to inventory forecasting with volatile demand patterns. Unlike many previous studies that focus on relatively stable time-series data, this study investigates Prophet's ability to model fluctuating sales behavior and evaluates its forecasting accuracy in a real-world inventory dataset. The findings offer practical insights for companies seeking forecasting approaches capable of handling irregular demand conditions [9].

Although the Prophet algorithm has been widely applied in various forecasting studies, most previous research primarily focuses on datasets with relatively stable demand patterns [10]. Several studies have demonstrated that Prophet performs well in predicting supermarket sales, food prices, and general time-series data with consistent seasonal characteristics. However, its performance under highly volatile sales conditions—where demand fluctuates significantly and irregularly—has not been extensively examined.

Therefore, there is still limited empirical evidence regarding how robust the Prophet model is when applied to unstable sales data, particularly in the context of inventory forecasting [11]. Addressing this gap is important because many real-world business environments experience irregular demand patterns due to market dynamics, customer behavior, and supply chain disruptions [12].

Based on the identified research gap, this study aims to investigate the robustness of the Prophet algorithm when applied to inventory forecasting with highly volatile sales data. Specifically, this study addresses the following research question: *How effective is the Prophet forecasting model in predicting inventory demand when the historical sales data exhibit unstable and irregular patterns?* By answering this question, the study provides empirical insights into the practical applicability of Prophet for handling volatile demand conditions in real-world inventory management.

2. Research Method

In predicting inventory, Prophet is used as a predictive method. This method uses an additive approach by dividing data into three main components: trend, seasonal, and irregular components, so that this method can adapt to unexpected changes in trends. The Prophet algorithm formulation is presented in equation (1), [13].

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \qquad (1)$$

The predicted value at time t is denoted as $y(t)$, which is the sum of several main components. $g(t)$ shows the trend or direction of data growth over time. $s(t)$ describes the recurring seasonal patterns in the data. $h(t)$ describes the effect of holidays. The trend component in Prophet is designed to capture long-term changes in the data. Prophet divides trends into two main types: Logistic growth model (non-linear) Piece-wise linear model (linear). For non-linear functions, the formula is expressed in equation (2).

$$g(t) = \frac{C}{1 + \exp(-k(t - m))} \qquad (2)$$

In the logistic growth model for time series forecasting, there are several important parameters that determine the shape of the growth curve. C represents capacity or maximum limit, which is the maximum value that can be achieved by the trend at a given time. The parameter k indicates the initial growth rate, which controls how quickly the trend increases in the early stages of growth. The parameter m is the offset parameter or midpoint of growth, which indicates the time when the trend reaches half of its maximum capacity. In its application, the non-linear model is designed to capture unstable growth patterns because it is more flexible in adapting to changes in growth rates over time. Meanwhile, the linear model is formulated in equation (3).

$$g(t) = (k + a(t)^T\delta)t + (m + a(t)^T\gamma) \qquad (3)$$

k is the growth rate or initial growth rate, which determines how quickly the data increases in the early stages. δ (delta) is the adjustment rate, which is a parameter that regulates how flexible the model is in adjusting to changes in the growth rate over time. m is the offset parameter that determines the midpoint of the data growth curve. A linear model is used when the data shows a stable and consistent trend, where there is no maximum limit affecting growth, so that the data graph tends to form a straight line.

In modeling the seasonal component, Prophet uses a Fourier series approach to capture periodically recurring patterns in the data, such as weekly, monthly, or annual patterns. This approach is used because the Fourier series is able to represent complex seasonal patterns in the form of a combination of sine and cosine functions, which is very effective in describing periodic fluctuations. For the seasonal function in this prophet, it can be formulated in equation (4).

$$s(t) = \sum_{n-1}^{N}\left[a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)\right] \qquad (4)$$

t represents time, which can be days, weeks, or other time units according to the data used. P is the seasonal period, which is the length of one seasonal cycle. n represents the number of Fourier components used in the model. The larger the value of n, the more complex the seasonal pattern that can be captured by the model. The ($a_n$and b_n) are Fourier coefficients that must be calculated through linear regression, where these values determine how much each sine and cosine function contributes to the overall seasonal pattern.

Prophet also provides arguments for including holiday effects in the model, but the holiday component h(t) is not used because there are no sales on holidays and red dates. As a result, there is no data on those dates, and Prophet automatically ignores them in the calculation. To predict inventory at PT XYZ using the Prophet model, this study applied the Knowledge Discovery in Databases (KDD) method[14], which consists of five main stages, namely:

2.1 Data Collection

Data collection is the process of gathering information or data from various sources with the aim of gaining an understanding that is relevant to the research problem. In this study, the data used is secondary data obtained from PT XYZ. The following is an example of historical sales data for 2024 with 5,161 rows and 18 attributes, which will be displayed in Figure 2:

	TGL	NO. SO	CUSTOMER	SALES	KODE ITEM	NAMA BARANG	QTY	Harga Satuan	Sub Total	PPN	TOTAL	Status	
0	2024-12-31	SAMS/SO/2024/12/01352	PT. LABORATORIUM SOLUSI INDONESIA	Hendro	2105569	DPD FREE CHLORINE RGT PP, 10 ML, PK/100	13	565000.0	7345000.0	807950.0	8152950.0	Finish / Done	SAMS/DO
1	2024-12-31	SAMS/SO/2024/12/01352	PT. LABORATORIUM SOLUSI INDONESIA	Hendro	2122326	ALKALINE CYANIDE RGT, 50ML SCDB	7	674000.0	4718000.0	518980.0	5236980.0	Finish / Done	SAMS/DO
2	2024-12-31	SAMS/SO/2024/12/01352	PT. LABORATORIUM SOLUSI INDONESIA	Hendro	2606945	RGT SET, TNT AMVER HR 50 TESTS	8	3590000.0	28720000.0	3159200.0	31879200.0	Finish / Done	SAMS/DO
3	2024-12-31	SAMS/SO/2024/12/01352	PT. LABORATORIUM SOLUSI INDONESIA	Hendro	2241732	ALKALI SOLUTION, 100ML MDB	4	701000.0	2804000.0	308440.0	3112440.0	Finish / Done	SAMS/DO
4	2024-12-31	SAMS/SO/2024/12/01352	PT. LABORATORIUM SOLUSI INDONESIA	Hendro	1457799	ASCORBIC ACID PWD PLWS PK/100	1	680000.0	680000.0	74800.0	754800.0	Finish / Done	SAMS/DO

Figure 2. Example of Dataset Display
Source : Secondary data from PT XYZ

2.2 Data Preparation

The data preparation stage is an important step in the KDD process, which aims to prepare raw data so that it is ready for use in the modeling process. Handling missing data and aggregation processes may influence forecasting accuracy. Filling missing values using default placeholders and product catalog references helps maintain dataset completeness, but it may introduce minor inconsistencies if the original transaction records contain reporting delays. Furthermore, aggregating daily sales data into weekly intervals reduces short-term noise and improves pattern detection, but it may also smooth extreme fluctuations that occur within shorter time periods [15]. Consequently, while aggregation helps stabilize the forecasting model, it may slightly reduce sensitivity to sudden demand spikes. Several main processes are carried out at this stage, namely:

2.2.1 Data Cleaning

Data cleaning aims to ensure that the data to be used in the model is clean and suitable for analysis. In this study, preparations were made to handle missing data in columns No. SO, No. DO, Tgl DO, Tgl Delivery, Qty Delivery, Tgl DO Balik, and Nama Barang. Columns with missing values must be handled so that the data can be used optimally in the analysis. To handle NaN values, columns with empty values are filled with appropriate default values. For example, the No. SO, No. DO, Tgl DO, Tgl Delivery, Qty Delivered, and Tgl DO Balik columns are filled with N/A, as empty values in these columns indicate that the transaction or delivery stage has not been recorded. To handle missing values in the Nama Barang column, they are taken from the product catalog reference by linking the item code to the corresponding product name. Thus, NaN values in the Nama Barang column will be replaced with the corresponding product name based on the item code.

2.2.2 Data Transformation

Data transformation aims to convert the data type in the Tgl DO, Tgl Delivery, and Tgl DO Balik columns from object data type to datetime data type. After the data type has been successfully converted, the data transformation process is carried out by changing the time scale from daily to weekly. This is done by adding a new column that represents the weekly period based on the transaction date. Weekly grouping aims to reduce random daily fluctuations (noise) and facilitate the identification of more consistent seasonal patterns and medium-term trends. Next, the data is grouped based on the TGL and KODE ITEM columns. This aggregation process calculates the total sales (quantity) of each product for each week.

2.2.3 Data Sellection

Data selection aims to select relevant data for modeling purposes. At this stage, only the columns required for the forecasting process are selected, namely date, item name, and quantity. These three columns are then renamed to match the input format required by the model, namely: the date column is renamed to *ds* and quantity to *y*. From a research perspective, focusing on the five most frequently purchased products allows the study to analyze items with the highest demand variability and operational impact on inventory management. High-transaction products typically exhibit more dynamic demand fluctuations compared to low-frequency items, making them suitable for evaluating the robustness of forecasting models under volatile conditions [16].

Furthermore, analyzing the most demanded products ensures that forecasting accuracy directly contributes to improving inventory planning and reducing the risk of stockouts.

In addition, the five products with the highest purchase frequency by customers were also selected from a total of 841 product types recorded in historical sales data throughout 2024. The reason for selecting these five products is that this approach focuses the analysis on the products most frequently purchased by customers, thereby making the modeling results more impactful for inventory control efforts and overall customer satisfaction. By prioritizing products with the highest transaction volumes, the company can optimize the availability of products most at risk of stockouts. The bar chart in Figure 3 displays the top five products based on the highest number of sales transactions.

The dataset used in this study covers one full year of sales transactions. A one-year observation period is considered sufficient to capture the primary seasonal patterns commonly found in inventory demand, including monthly and quarterly fluctuations. In time-series forecasting, a full annual cycle allows models such as Prophet to learn repeating seasonal behavior across weeks and months. With weekly aggregation, the dataset provides approximately 52 observations, which is adequate for identifying medium-term seasonal trends while minimizing short-term noise [17].

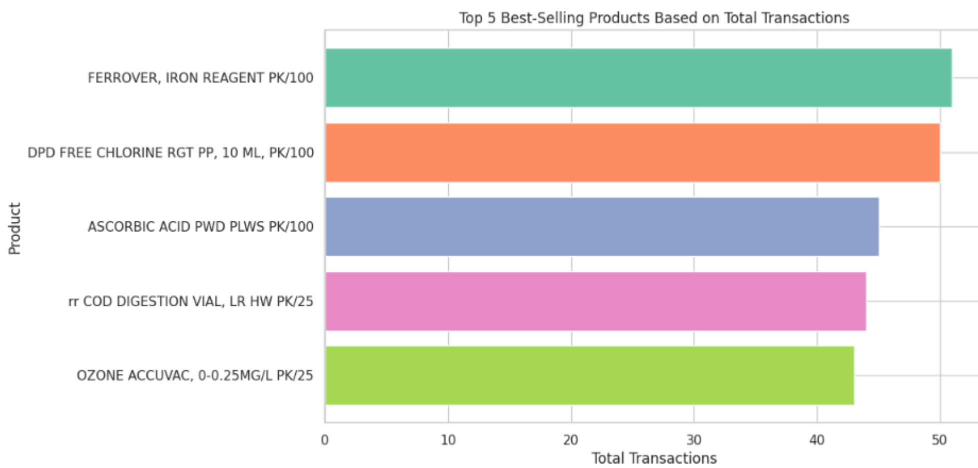

Figure 3. Top 5 Best-Selling Products Based on Total Transactions

2.3 Data Mining, Evaluation, Knowledge

At this stage, the Prophet model was used to forecast or predict the inventory for the five products with the highest sales transaction volumes. The selection of these top five products was based on a previous analysis that showed that these five products had the highest sales frequency, making them the most important to monitor in terms of availability. The Prophet model was then applied individually to each product, using historical sales data as input to establish trend and seasonal patterns. Model evaluation aims to assess how well the model performs in making predictions using two metrics, namely RMSE (Root Mean Squared Error) and MAPE (Mean Absolute Percentage Error). Knowledge is the process of combining analysis results into strategic information for use in decision making. At this stage, predictions about inventory levels are presented. This information can be used to prevent stock shortages during periods of high demand or overstocking.

3. Result and Discussions

This section thoroughly explains the results of the research conducted in an effort to predict inventory quantities using the Prophet algorithm. The research focus is directed at the top five products selected based on the highest number of sales transactions during the observation period. The selection of these five products aims to ensure that the analysis process is carried out on products that have high demand and have a considerable influence on inventory management in the company.

To verify that the dataset represents volatile demand conditions, descriptive statistics were calculated for the weekly sales data. The results show a high level of variability, where the standard deviation of weekly sales exceeds 40% of the mean for several products. Additionally, the coefficient of variation (CV) ranges between 0.42 and 0.71 across the analyzed products, indicating significant fluctuations in demand. These statistics confirm that the dataset contains unstable sales patterns, making it suitable for evaluating the robustness of forecasting models under volatile conditions.

Before making predictions, several stages are carried out, namely data preparation, data mining, model evaluation, and knowledge. After data preparation is carried out, then apply the prediction model by implementing prophet using two main approaches, namely:

3.1 Prophet Method Calculation

In this research, the prophet model uses a logistic growth approach. This model considers the maximum sales limit (C) which is determined based on the highest sales value. The trend estimation process involves two main parameters of the logistic function, namely k (growth rate) and m (midpoint of the curve). Both are calculated using a numerical optimization approach as this model is a type of non-linear regression. The L-BFGS-B method from the scipy.optimize library is used to find the values of k and m by minimizing the error (MSE). The initial values used are k = 0.1 and m = 5. Then the trend parameters for the product Ferrover, Iron Reagent pk/100 are obtained as follows C = 100, k = -0.0114 and m = -9.2046.

These three parameters are used in the 5 trend logistic growth. As an example of calculating the trend component in week 1. Next, prophet uses the Fourier Series approach to capture the seasonal component. With a year's worth of weekly data (52 weeks), an order of N = 12 is used to capture monthly fluctuations. The Fourier coefficients are obtained from linear regression, resulting in 12 pairs of sine and cosine parameters. The final prediction component is calculated as the combination of the logistic trend g(t) and seasonality s(t).

Instead of presenting detailed manual calculations, the Prophet model decomposes the time series into three main components: trend, seasonality, and irregular variations. The trend component can be modeled using either a piecewise linear or logistic growth function depending on the characteristics of the data [18]. In this research, the logistic growth model was used to capture potential changes in demand growth patterns over time. Seasonality is modeled using Fourier series to represent periodic patterns in the data, such as weekly or monthly sales cycles. Prophet automatically estimates the corresponding coefficients through optimization during the model training process. This approach enables the model to flexibly adapt to changing sales patterns while maintaining computational efficiency [18].

The result shows that the sales prediction in week 0 is 48 units. This value represents Prophet's prediction results based on a combination of trend and seasonality without clearly considering the error. Furthermore, calculations to generate sales predictions will be carried out from week 1 to week n. Then to evaluate the performance of the model, calculations are carried out. Then to evaluate the performance of the model, RMSE and MAPE calculations are performed on all weeks of observation. In addition, parameter variation experiments were conducted to test the sensitivity of the model to changes in k and m. Three variations of k and m combinations show that:

Table 1. Parameter Variations k and m on Ferrover Products, Iron Reagent pk/100

Variation	k	m	Description
1	-0.0114	-9.2046	Optimization results (baseline model)
2	0.001	-5	Slightly faster growth
3	-0.005	-12	Very slow growth

To facilitate the analysis, the prediction results are visualized in the form of a graph which can be seen in Figure 4. This graph shows the comparison between the predicted value and the actual value at each time.

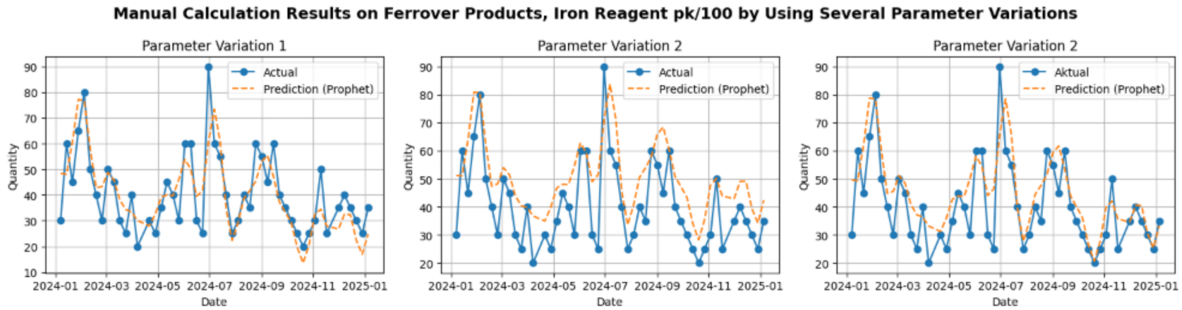

Figure 4. Graph of Calculation Results on Ferrover Products, Iron Reagent pk/100 by Using Several Parameter Variations

These results show that variations in the value of parameters k and m have a significant effect on the shape and direction of the trend curve in the logistic model. Parameter k plays a role in regulating the rate of growth or decline of the trend curve. And the parameter m plays an important role in determining the time of the most significant change in the trend rate in the logistic curve.

After the calculation is done manually, the next step is to evaluate the accuracy of the prediction results using two metrics [19], namely RMSE is used to measure the average error between the actual value and the predicted value with the original data unit. The RMSE formula can be written in equation (8). For example on Ferrover products, Iron Reagent pk/100, where n = 51, y_i= actual value, and $y(t)_i$= prediction results.

$$RMSE = \sqrt{\frac{[(y_0 - y(t)_0)^2 + (y_1 - y(t)_1)^2 + \cdots + (y_n - y(t)_n)^2]}{n}} \tag{5}$$

$$= \sqrt{\frac{[(30 - 48.4341)^2 + (60 - 48.0327)^2 + \cdots + (35 - 24.7445)^2]}{51}} = 9.56$$

MAPE is used to measure the average absolute error as a percentage of the actual value. The MAPE formula can be written in equation (9). For example on Ferrover products, Iron Reagent pk/100.

$$MAPE = \frac{1}{n}\left(\frac{|y_0 - y(t)_0|}{y_0} + \frac{|y_1 - y(t)_1|}{y_1} + \cdots + \frac{|y_n - y(t)_n|}{y_n}\right) \times 100\% \tag{6}$$

$$= \frac{1}{51}\left(\frac{|30 - 48.4341|}{30} + \frac{|60 - 48.0327|}{60} + \cdots + \frac{|35 - 24.7445|}{35}\right) \times 100\% = 20.46\%$$

Table 2. RMSE and MAPE Evaluation Results from Manual Calculation

Product	k	m	RMSE	MAPE (%)
Ferrover, Iron Reagent pk/100	-0.0114	-9.2046	9.56	20.46
	0.001	-5	13.35	33.95
	-0.005	-12	10.07	21.52
DPD Free Chlorine Rgt Pp, 10 mL, pk/100	-0.0208	27.4824	8.75	23.08
	0.012	9	15.86	32.68
	-0.001	14	16.65	34.41
Ascorbic Acid Pwd Plws pk/100	-0.0167	-4.8744	6.17	24.68
	0.001	-2	8.53	43.61
	-0.009	12	7.57	34.66
rr COD Digestion Vial, Lr Hw pk/25	-0.0168	15.3499	6.12	22.34
	0.003	-5	7.24	31.56
	-0.006	7	6.35	24.91
Ozone Accuvac, 0-0.25mg/L pk/25	-0.0324	7.2652	55.13	24.28
	-0.006	23	79.85	72.81
	-0.004	-12	72.81	42.94

Table 2 shows the evaluation results of calculations based on the RMSE and MAPE values of five products using three variations of logistic parameters, namely different combinations of k and m values. From the comparison results, it can be seen that the baseline model obtained through the iterative numerical approach produces better evaluation values than the other two variations. This shows that parameter determination using the numerical optimization method is more effective and efficient because it does not require a manual trial process. Therefore, the numerical optimization method is suggested as a more effective and accurate way of applying the logistic function to the Prophet model.

Furthermore, the same approach was applied to DPD Free Chlorine Rgt Pp, 10 mL, pk/100; Ascorbic Acid Pwd Plws pk/100; rr COD Digestion Vial, Lr Hw pk/25; and Ozone Accuvac, 0-0.25mg/L pk/25. Each product has a different data pattern, so the parameter values k, m, and fourier coefficients (a_n dan b_n) are calculated according to the characteristics of the data pattern. The calculation results will be attached in the appendix and for the prediction result graph for each product will be shown in figure 5:

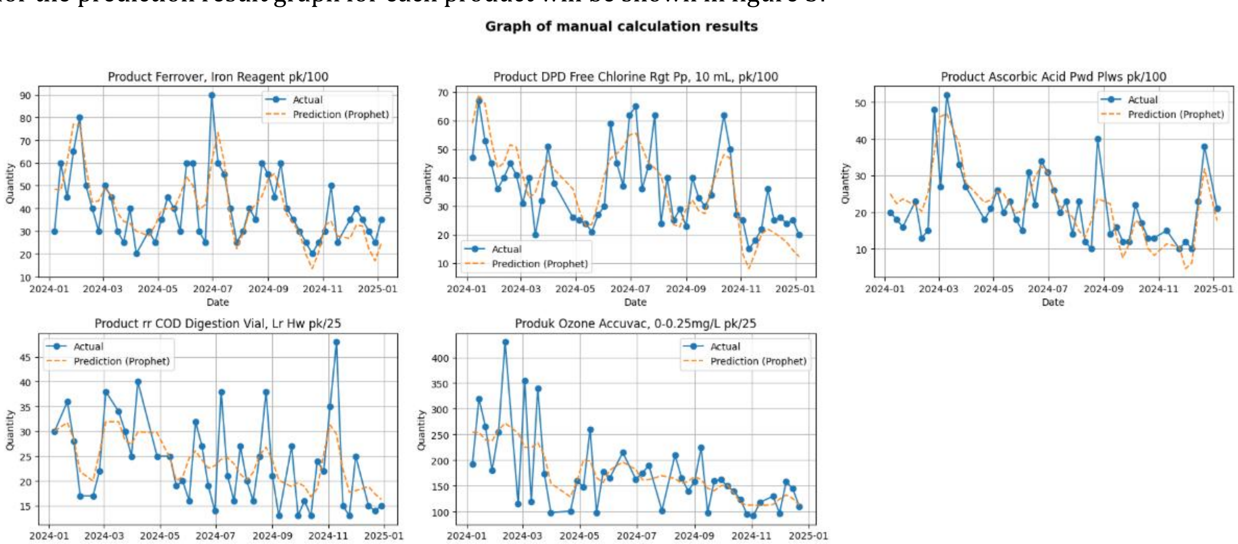

Figure 5. Graph of Manual Calculation Results

3.2 Prophet Model Implementation

After manual calculations, Prophet model training is then carried out using Python to facilitate prediction. The computation process is carried out in the following stages:

- Model initialization: The Prophet model is configured to enable annual and weekly seasonal components.
- Model training: The model is trained with actual sales data of the product, where the date (ds) and sales amount (y) columns are used.
- Prediction of product inventory for 52 weeks: Future data is created to forecast the inventory needs of goods for the next 52 weeks with a weekly frequency.
- Calculate the accuracy value of the prediction results against the actual data.

These steps were applied to each product to produce the results that can be seen in Figure 6.

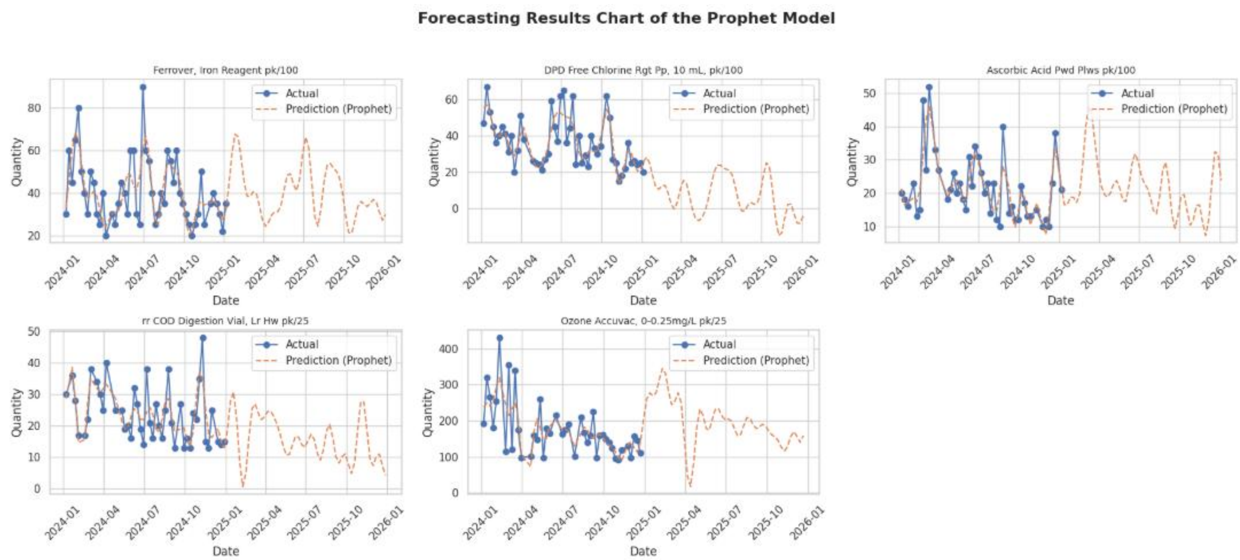

Figure 6. Forecasting Results Chart of the Prophet Model

Furthermore, model evaluation is carried out to measure the accuracy of the Prophet model forecasting results, which can be seen in table 3.

Table 3. RMSE and MAPE Evaluation Results of the Prophet Forecasting Model

Product	RMSE	MAPE (%)
Ferrover, Iron Reagent pk/100	9.51	18.58
DPD Free Chlorine Rgt Pp, 10 mL, pk/100	7.29	16.05
Ascorbic Acid Pwd Plws pk/100	5.41	19.93
rr COD Digestion Vial, Lr Hw pk/25	5.70	20.91
Ozone Accuvac, 0-0.25mg/L pk/25	52.78	23.46

The forecasting performance varies across products due to differences in demand patterns. Prophet performs better for products with relatively consistent seasonal structures, such as DPD Free Chlorine Rgt Pp and Ascorbic Acid Pwd Plws. These products show clearer trend and seasonal signals, which can be effectively captured by Prophet's additive decomposition model.

On the other hand, products such as Ozone Accuvac exhibit higher forecasting errors because their demand patterns are more irregular and contain sudden spikes that are difficult to model accurately. Similar findings have been reported in previous studies [5], [7], which indicate that Prophet performs best when time-series data contain identifiable trend and seasonal components but may struggle when demand patterns are highly sporadic.

Modeling was done with two approaches: Manual Prophet and automated Prophet using Python. In the manual approach, the trend component was calculated using a logistic growth function, while the seasonality used a Fourier series. Parameters such as growth rate (k), offset (m), and seasonal coefficients (a_n dan b_n) are determined based on historical pattern analysis, without automatic optimization, so the results tend to be simpler. Meanwhile, the Python-based Prophet is able to optimize parameters automatically, making it more adaptive to fluctuating seasonal patterns. The results of the comparison between the two approaches can be seen in figure 7.

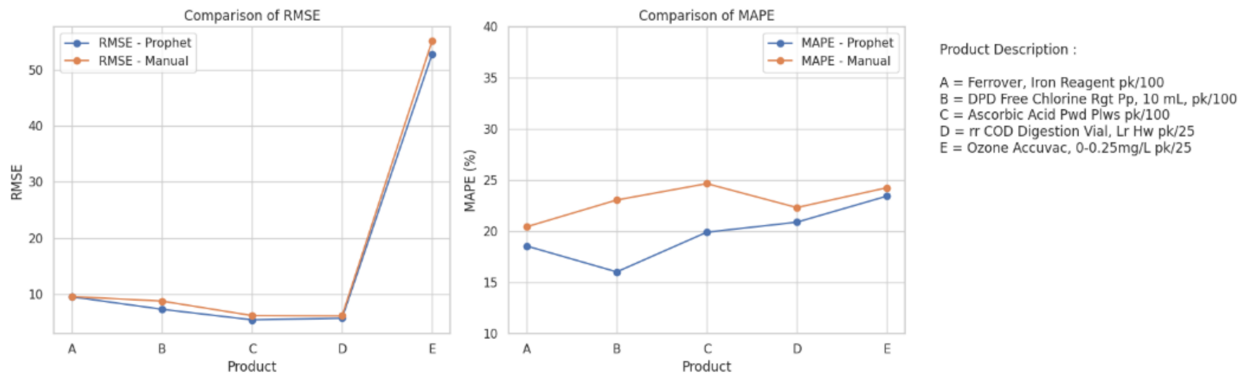

Figure 7. Comparison Chart of RMSE and MAPE Evaluation between Prophet Model and Manual Calculation

The evaluation results show that the automatic model provides more accurate predictions, especially for products DPD Free Chlorine Rgt Pp, 10 mL, pk/100 and Ascorbic Acid Pwd Plws pk/100. For products Ferrover, Iron Reagent pk/100, rr COD Digestion Vial, Lr Hw pk/25, and Ozone Accuvac, 0-0.25mg/L pk/25, the difference is not significant. Overall, Prophet Python excels in flexibility, accuracy, and efficiency, although the manual approach is still quite feasible.

These findings are consistent with the results reported that demonstrated how Prophet performs well for retail sales forecasting with clear seasonal behavior. Similarly, Žunić et al.[11] showed that Prophet can generate accurate predictions for structured sales datasets. However, unlike previous studies that mostly analyze relatively stable datasets, this research provides empirical evidence that Prophet can still maintain acceptable forecasting performance even when applied to volatile demand conditions.

4. Conclusions and Future Works

Based on the research results, it can be concluded that stock requirements in the coming period can be predicted more measurably using historical sales data. The Prophet model is able to identify trends and seasonal patterns in weekly sales data, thus providing more realistic demand projections, especially for products with stable seasonal characteristics. Evaluation using RMSE and MAPE metrics shows a good level of accuracy, so Prophet can be an effective tool in inventory planning and data-driven decision making.

Despite the promising forecasting results, this study has several limitations. The research only evaluates the Prophet model without comparing it with other forecasting algorithms such as ARIMA, SARIMA, or machine learning-based approaches. Consequently, the findings cannot conclusively demonstrate whether Prophet provides superior performance relative to alternative methods. Future research should include comparative experiments to provide stronger evidence regarding the effectiveness of Prophet in volatile demand forecasting scenarios.

This study provides empirical evidence that the Prophet algorithm is capable of producing reliable forecasts even when applied to sales data with unstable and fluctuating patterns. The findings highlight Prophet's ability to capture trend and seasonal structures in volatile time-series data, making it a practical tool for inventory planning [20]. By demonstrating the model's robustness under irregular demand conditions, this research contributes to the practical understanding of Prophet's applicability in real-world inventory management scenarios.

However, this research is still limited to the use of one forecasting method without comparison with other algorithms. For this reason, it is recommended that future research involve other methods such as ARIMA, Exponential Smoothing, or machine learning algorithms to obtain more comprehensive results. Despite the promising results, several limitations should be acknowledged. First, this study only analyzes data from a single company, which may limit the generalizability of the findings to other industries. Second, the observation period is limited to one year of historical data, which may not fully capture long-term demand patterns. Third, the study evaluates only one forecasting method, namely Prophet, without conducting comparative experiments with other time-series models. These limitations should be considered when interpreting the results.

Future research should address these limitations by incorporating longer observation periods and datasets from multiple companies to improve generalizability. Additionally, comparative experiments involving other forecasting models such as ARIMA, SARIMA, LSTM, or hybrid machine learning approaches could provide a more comprehensive evaluation of forecasting performance under volatile demand conditions.

5. References

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