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Article

Demand Forecasting and Ordering Policy of Fast-Moving Consumer Goods with Promotional Sales in a Small Trading Firm

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Abstract. This research focuses on enhancing inventory management for fast-moving consumer goods (FMCGs) with promotional sales in a small trading company, particularly high-end items with fluctuating demand patterns. The analysis revealed that promotional campaigns led to an average demand increase of 60.44% for WM 85ML, and 161.76% for SW 85ML, highlighting the importance of including these variables in demand forecasting models. The research aims to determine an effective forecasting method for the company and develop an improved purchasing strategy. The methodology encompasses a comprehensive review of the existing system, problem investigation, solution proposal, and result analysis. Quantitative time-series forecasting methodologies specifically tailored to such luxury FMCGs were introduced including Exponential Smoothing and Holt-Winters's Additive and Multiplicative forecasting. The application of these methods has led to a significant enhancement in forecast accuracy, with an approximate 90% improvement. The research's pivotal contribution is the development of a hybrid order policy named "Periodic Review with Safety Stocks and Reorder Point," which merges a fixed-order quantity model with a fixed-time period model. This hybrid approach has practical implications for maintaining efficient inventory levels, enabling continuous promotional activities, and potentially reducing the company's inventory costs by approximately 30%.

Keywords: Luxury products, niche fast-moving consumer goods (FMCGs), demand forecasting, hybrid ordering policy, promotional sales.

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1. Introduction

1.1. Company Introduction

The case study focuses on a small but distinct company, specializing in the import, distribution, and sale of an Italian brand of toothpaste in Thailand. Unlike conventional toothpaste primarily valued for its functional use [1], the case study's products stand out as a niche commodity. Its appeal lies not in its teeth-cleaning capabilities, but in its unique packaging and exotic flavours, e.g., ginger mint, Amareli liquorice, cinnamon, flower tea, and Earl Grey tea. Catering to a high-income demographic, the product commands a premium price of 425 Thai Baht (£9.85) per 75ML, compared to the typical 34 Thai Baht (£0.79) per 100ML for regular toothpaste. Positioned in the upper right corner of the Puttick Grid, indicating excessive uncertainty and low complexity [2], the product demands a responsive supply chain and timely operations [3]. The atypical demand pattern, heavily influenced by product promotions, deviates from the smooth sales trajectory of standard functional products, emphasising the need for the specific inventory management strategies discovered in this research.

1.2. Problem Statement

Figure 1 displays the company inventory level vs inventory capacity from 2021 to 2022. The company faces significant inventory management challenges, exhibiting through two primary issues: over-flowing inventory and inventory shortages. In 2021, the storage capacity was exceeded by 50% for six months. Despite expanding the inventory capacity by 200% in April 2022 (period 16), the problem of excess inventory continued as displayed. Additionally, there is also evidence of inventory shortages, e.g., periods 15 and 19.

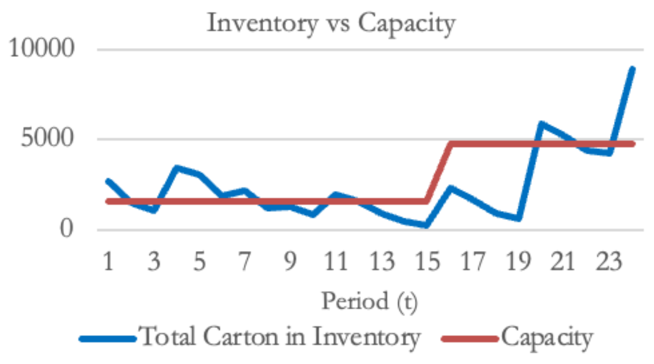

Fig. 1. The Inventory vs Capacity, Year 2021 – 2022.

This overstocking primarily stems from faulty demand forecasting, leading to an accumulation of unsold goods. Regarding demand forecasting, the company's reliance on a simplistic 3–6-month average demand projection, without responsive revisions, has led to substantial forecast errors [4]. Table 1 displays the forecast error of selected items in this research. The existing approach fails to account for demand variations and contradicts the need for a responsive supply chain as required for the company product category [5].

Table 1. Existing System Forecast Accuracy, year 2021-2022.

	WM	SW	AM2	CSM
ME	-1088	-687	-714	-788
MAE	1130	726	744	812
MSE	1947873	700059	668348	796818
MAPE	1707%	1654%	449%	989%

In terms of purchasing, the company's purchasing is based on these faulty forecasts, plus a 20% safety stock, which has led to a significant disconnect between the orders placed to the supplier and the actual demand from buyers. This discrepancy can result in a supply chain bullwhip effect [6], where misinterpreted demand signals cause overproduction, inconsistent inventories, and various other operational inefficiencies [7]. Generally, the company places orders in January, April, July, and October, but this schedule is not strictly followed. Figure 2 illustrates the mismatch between demand, forecast, and inventory levels for the company's toothpaste, WM in an 85ML tube. In April 2021, corresponding to period 4, no order was placed with the supplier, which is an abnormality from the general ordering pattern. Subsequently, a large order was made in July, i.e., period 7. This erratic ordering behaviour led to a stock shortage in the following period, indicating that the supplier was unable to meet the sudden spike in demand with a single order. Consequently, the company faced continuous stock shortages over several periods, thereafter, exemplifying the repercussions of poor inventory planning and the lack of a robust ordering system.

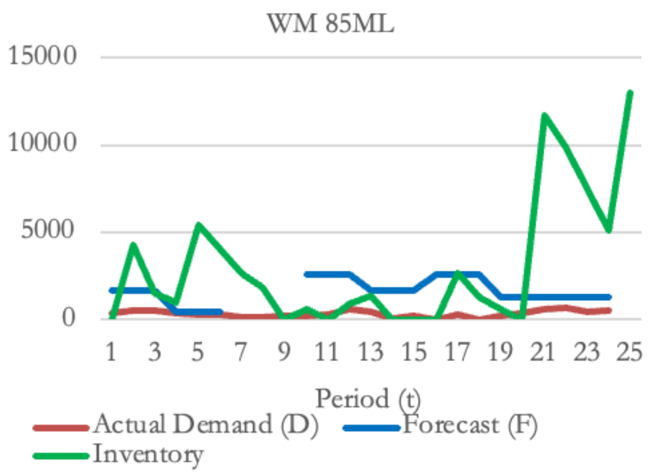

Fig. 2. Demand, Forecast, and Inventory Level of WM 85ML, Year 2021-2022.

Thus, the company's inventory management issues are excessive stock resulting from inadequate demand forecasting and occasional stock shortages due to suboptimal purchasing practices. These challenges underline the need for a more sophisticated approach to inventory management that can address both aspects of this problem.

1.3. Research Objective

The objective of the research is to improve the inventory management of the case study company.

1.4. Research Question

(1) What is the suitable forecast method for the company?
(2) How to improve purchasing strategy for the company?

1.5. Research Scope

This study is the design and application of an optimal forecasting method and ordering policy specifically for Class A and Class B items within the company's product range. Class A item is WM 85ML, and Class B items are SM85ML, AM2 85ML, and CSM 85ML. The investigation utilizes two years of historical data spanning from 2021 to 2022, encompassing actual sales figures, demand forecasts, and inventory levels. Additionally, the first six months of 2023 serve as a validation period for the developed models.

The remaining sections are presented as follows. Section 2 presents a comprehensive literature review, covering relevant tools and techniques, while Section 3 describes the research methods applied. Results and in-depth analysis are presented in Section 4, leading to the conclusions and recommendations in Section 5.

2. Literature Survey

2.1. Forecasting

A definition of forecasting is the process of predicting the future as correctly as possible given all available information, including past data and information on any potential events that may affect the projections [8]. Another definition that is relevant to forecasting is the forecasting horizon. These commonly range from short-term (less than three months) to long-term (more than two years). There are 3 established terms for forecasting [8] i.e., long-term, medium-term, and short-term forecast. The three vary from the necessity and complexity of the industry. Long-term predictions are required for strategic planning to "take into consideration market possibilities, environmental concerns, and internal resources,". Medium-term projections are needed to "purchase essential materials, recruit personnel, or purchase equipment and machinery. Finally, short-term projections are required "for the scheduling of staff, manufacturing, and transportation". Inarguably, no matter how much data is available, the forecast will be wrong [5]. The longer the predicted horizon, the greater the forecast inaccuracy, Fig. 3.

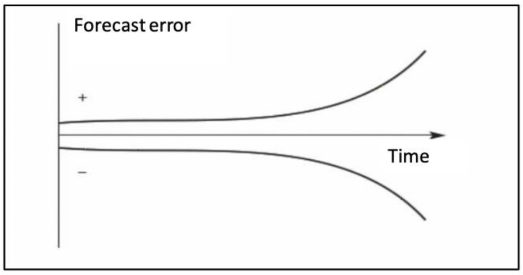

Fig. 3. Forecast error and planning horizons [5].

2.1.1. Accuracy Measurement

The forecasts are compared to the actual demand data [5], [9]. This would enable the authors to evaluate the model and, ultimately, pick among various models. The forecast error may also be stated as a percentage of the actual (or trending) value. The prediction error analysis aids in the assessment of a forecasting model [9]. Some of the accuracy measurements are as follows:

Mean Error (ME), Eq. (1): Aids in determining if a model regularly overestimates (negative bias) or underestimates (positive bias).

$$ME = \left(\frac{1}{n}\right)\sum_{i=1}^{n} e_i \tag{1}$$

Mean Absolute Error (MAE), Eq. (2): The average absolute difference between expected and observed values. Suitable for: When the average magnitude of errors regardless of their direction needs to be understood.

$$MAE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}|x - x_i| \tag{2}$$

Mean Squared Error (MSE), Eq. (3): The sum of the squared discrepancies between projected and actual values. It punishes greater mistakes more severely than minor ones. Suitable for: When large errors are particularly undesirable.

$$MSE = \left(\frac{1}{n}\right)\sum_{i=1}^{n} e_i^2 \tag{3}$$

Mean Absolute Percentage Error (MAPE), Eq. (4): This represents the average percentage difference between the forecasted and actual values. Often expressed as a percentage, providing a simple and intuitive measure of forecast accuracy.

$$MAPE = \frac{\left(\frac{1}{n}\right)\sum_{i=1}^{n}|e_i|}{\left(\frac{1}{n}\right)\sum_{i=1}^{n}|D_i|} * 100 \tag{4}$$

2.1.2. Forecasting Methods

2.1.2.1. Exponential Smoothing

The introduction to Exponential Smoothing in this section is referenced from a published book by Hyndman [8]. Exponential Smoothing is a time series forecasting approach that is extensively used to anticipate future data points based on a time series' past values. It is especially beneficial when dealing with data that has a pattern or is seasonal. The approach provides weights to prior data in an exponentially reducing order, with more recent observations getting larger weights than older ones. The primary principle underlying Exponential Smoothing is to emphasize current data points while progressively diminishing the value of older data points. This is accomplished by giving a weight (a smoothing parameter) to each observation, with the weights decreasing exponentially as time passes. The equation for Exponential Smoothing referred from [8] and [9] is listed as, Eq. (5):

$$\mathrm{Ft} + 1 = \alpha\mathrm{Dt} + (1 - \alpha)\mathrm{Ft} \tag{5}$$

where
Ft + 1 = Forecast of the next period
Dt = Actual demand at period t
Ft = Forecast of Previous period (t)
α = Alpha Smoothing Constant

It should be noted that Canela [9] provided the equation in the same calculation logic but in different lettering.

Smoothing constant ranges from 0 to 1. The value decides how much weight the most recent observation is given. In general, the value is chosen by applying it to historical data and picking the value that minimizes the error [8]. A bigger α weights recent data heavily, making the prediction more sensitive to fluctuations. A lower value, on the other hand, leads to a smoother prediction that is less subject to short-term volatility. Figure 4. illustrates the effect of changing α. The dashed line denotes Exponential Smoothing. On the left side, using = 0.2 produces a smoother trend since the trend is less sensitive to variations in the current observation. The trend on the right side, with = 0.7, captures a great deal of variance in the series [9].

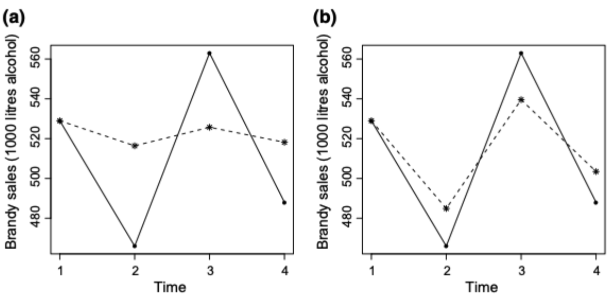

Fig. 4. (a) α=0.2, and (b) α=0.7 [9].

The forecasting steps in Excel are as follows:

1. Data Preparation.
2. Enter historical data of actual demand in column A.
3. Input the first forecast manually using the actual demand data of the first period.
4. Apply the Exponential Smoothing formula to the rest of column B using cell function = (α * Dt) +((1-α) * Ft). For example, the input function in a cell with actual demand in row 2 and forecasted demand in row 3 will be equal to (0.5*B2) +((1-0.5) *B3), given that α = 0.5.

2.1.2.2. Holt-Winter's Multiplicative and Additive

The Holt-Winters Method, occasionally known as the triple Exponential Smoothing (ETS) [9], is an established time series forecasting approach created in the early 1960s by Charles C. Holt and Peter G. Winters. This technique was created primarily for handling time series data with seasonality and trend patterns [9]. In practicality, the authors of the book "Quantitative Methods for Management" suggest that it is not necessary to understand the entire equation of how ETS is formulated, rather, users should focus more on understanding the concept of the method [9]. The three components could be explained according to [9] and collogue as follows:

Trend (Level - L): A time series' underlying, non-seasonal component representing the data's long-term average or trend. The Holt-Winters trend is commonly referred to as a level.

Slope (Growth Factor - T): The direction in which the data is progressing, whether rising or falling over time, is taken into consideration.

Seasonality (Seasonal Factor - S): Seasonality refers to reoccurring patterns or cycles in time series data that occur at regular intervals. Retail sales, for example, may see seasonal surges during the holidays.

The Holt-Winters approach may be divided into two variations:

1. **Holt-Winters Multiplicative:** When the seasonal fluctuations vary proportionately with the amount of data (i.e., the seasonal pattern is Multiplicative), the three components are multiplied (i.e., Forecast = L * T * S).
2. **Holt-Winters Additive:** When the seasonal changes have a constant amplitude (i.e., the seasonal variation is Additive), the three components are added together (i.e., Forecast = L+T+S).

Depending on the nature of the data, either the Additive or Multiplicative variation of the approach could be adopted. Whichever the variation, smoothing parameters are involved. These parameters, represented by α, β and γ are known as the smoothing parameters. A smoothing parameter for each component (L, T, and S) is utilized to weigh the new observation.

Smoothing Parameters Values: A number around 1 indicates that recent observations are given greater weight, making the prediction more sensitive to recent developments. On the other hand, a number near 0 indicates that earlier data are given greater weight, making the prediction less sensitive to current changes.

α (Alpha) - Level Smoothing Parameter: Oversees the smoothing of the series level.

β (Beta) - Trend Smoothing Parameter: Overseas the smoothing of the trend component.

γ (Gamma) - Seasonal Smoothing Parameter: Overseas the smoothing of seasonal components.

2.2. Inventory Management

Christopher [5] defines an inventory as "the stock of any item or resource used in an organization.". Another two terms worth clarification are item and unit. Waters offers a useful definition: "An item is a distinct product which is kept in stock: it is one entry in the inventory." [10]. "A unit is the standard size or quantity of a stock item" [5]. Finally, a common word used in retail settings is a 'Stock Keeping Unit or SKU'.

According to Stevenson [11], inventory management is viewed as a structure used by businesses to handle their inventory holdings. It entails documenting and monitoring stock levels, projecting future demand, and deciding when and how to get things organized. Deveshwar and Dhawal added that inventory management is a process implemented by businesses to arrange, store, and replace inventory to maintain an appropriate supply of items while reducing costs [12]. Inventory must be properly controlled to avoid excessive or insufficient levels [12].

2.2.1. ABC Categorization

The 80/20 rule is credited to quality control pioneer Joseph Juran [13]. This concept of 80/20 allows activities to be prioritized; attentively controlling 20% of inventory items affords control over 80% of the investment. The 'population' is generally divided into three groups labelled A, B, and C. Using the cumulative yearly cost and the cumulative amount of inventory items, applying Pareto to inventory, the curve shown in Fig. 5. is obtained, Thai Baht is used in this research instead of a dollar. The 'population' is generally divided into three groups called A, B, and C, with Class A products accounting for 20% of the population and 80% of the money, Class B products accounting for 30% of the population and 15% of the money, and Class C products accounting for 50% and 5% of the money, respectively [14].

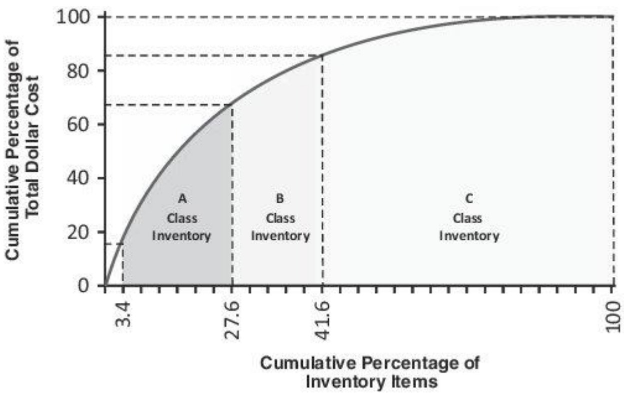

Fig. 5. The Pareto Chart of ABC Classification [15].

2.2.2. Demand Classification

Operational criteria for product classification are a critical component of inventory systems. They enable the proper amount of supervisory attention, as well as the necessary forecasting and stock control procedures, to be employed on the relevant items [16], [17]. Based on the mean inter-demand interval and the coefficient of variation, a theoretical coherent demand categorization system is developed, Fig. 6. below.

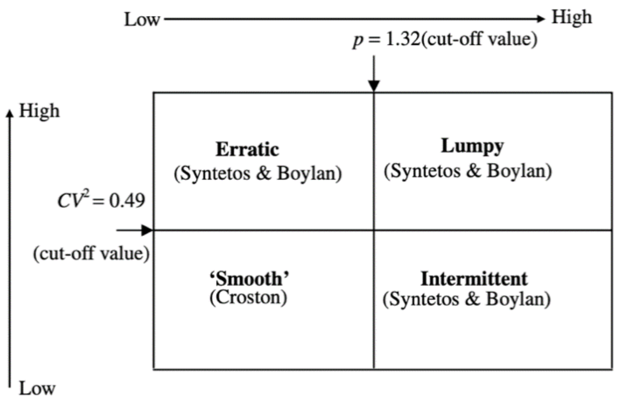

Fig. 6. Demand-Based Categorization for Forecasting [16].

Forecasting and stock-control strategies are often chosen based on the classified demand type of the items [16], e.g., erratic, lumpy, and intermittent demand could be more difficult to forecast and manage than items classified as smooth. Additionally, erratic, lumpy, and intermittent demand might need a more complex forecasting method than smooth demand.

2.2.3. Inventory Costs

Holding cost is the cost for storage facilities, handling, insurance, pilferage, breakage, obsolescence, depreciation, taxes, and the opportunity cost of capital [14]. Given that the holding cost is calculated by multiplying the inventory holding cost percentage (i) with the cost of the product per unit (C) (i.e., **$H=iC$**). Examining the list of different costs, it is not surprising to find that inventory holding costs can only be an estimate of the likely value. Waters (2003) gives 20% as the average. As of 2020, common holding expenses often account for 12-35% of the inventory holding costs [18], increasing the longer an item is kept before being sold.

Set up cost (S), or ordering cost, is an administrative and clerical expenditure associated with preparing the purchase or manufacturing order [14].

2.3. Order Policy

The primary goal of inventory analysis in manufacturing, distribution, retail, or services is to determine 2 questions (1) when should order be placed, and (2) how much should be ordered [14].

2.3.1. When to Order

Figure 7 demonstrates multiple systems of supply chain inventory that might exist in a make-to-stock scenario, particularly for consumer-facing commodities. Inventory is often held at the higher levels of the supply chain, which are supply points nearer to the client so that an item can be supplied swiftly when a customer's demand arises. According to Jacobs and Chase the models that could be best suited to the case study company's upper-tier inventories (retail and warehouse), are the single-point model, the fixed-order quantity model, and the fixed-time period model [14].

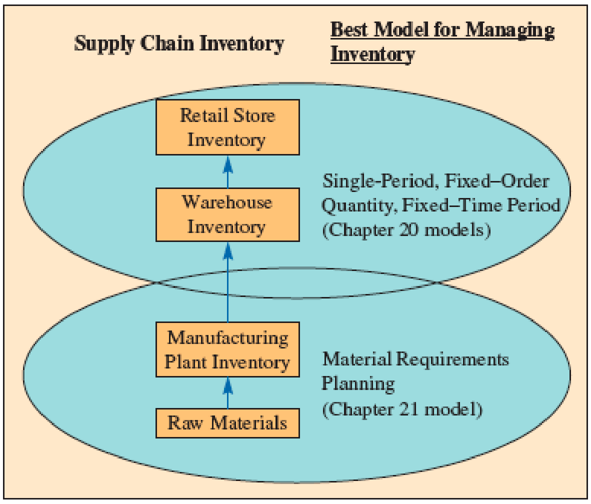

Fig. 7. "Supply Chain Inventories—Make-to-Stock Environment" [14].

The Single-Period Model. Although the single-point model is useful for goods with a short selling season and high worth that depreciates quickly (such as holiday-specific items) [19], it could be less appropriate to the FMCG industry, where demand is continuous, and products have a longer life before their value depreciates.

Fixed Order Quantity Model. A significant approach in inventory management is the fixed-order quantity model, often known as the Economic Order Quantity (EOQ) model [14]. The model assumes that demand is constant and that lead time, holding cost, stockout cost, and unit price are all known and fixed variables. This model is utilized when the company wishes to keep an item "in stock," The item's inventory is monitored until it reaches a point where the likelihood of running out is high enough that the company is obligated to place an order.

While the fixed-order quantity model may be applied to the FMCG sector, particularly for items with consistent demand and non-perishable nature, it may not be the ideal match for all FMCG products, particularly those with significant demand fluctuation or short shelf life.

Fixed-Time Period Model. The fixed-time period model, also known as the periodic review system [14], is an inventory management strategy in which orders are made at the end of a set interval, such as weekly or monthly. This technique entails periodically assessing the inventory level and making an order to bring it back up to a predefined level. This approach, like the fixed-order quantity model, is utilized when the item should be in stock and available for purchase. In this situation, rather than monitoring inventory levels and ordering when they reach a critical level, the item is ordered at regular periods [14].

While the fixed-time period model may be appropriate for FMCG in certain scenarios, particularly when demand is steady and predictable, it may not be the greatest match in situations when demand is volatile, the market is tremendously competitive, or the items are highly perishable. Companies should carefully analyze these issues.

2.3.2. How Much to Order?

Figure 8 demonstrates what occurs when the two concepts are used to create an operating system. The fixed-order quantity method concentrates on order amounts and reorder points. Procedurally, when a unit is removed from stock, the withdrawal is recorded, and the quantity left in inventory is instantly matched to the reorder point. If it has reached this level, an order for Q products is made. If it has not, the system will stay inactive until the next withdrawal. The decision to place an order in the fixed-time period method is made after the stock has been measured or assessed. The inventory level at the review period determines how much the order needs to be placed or whether an order should be placed.

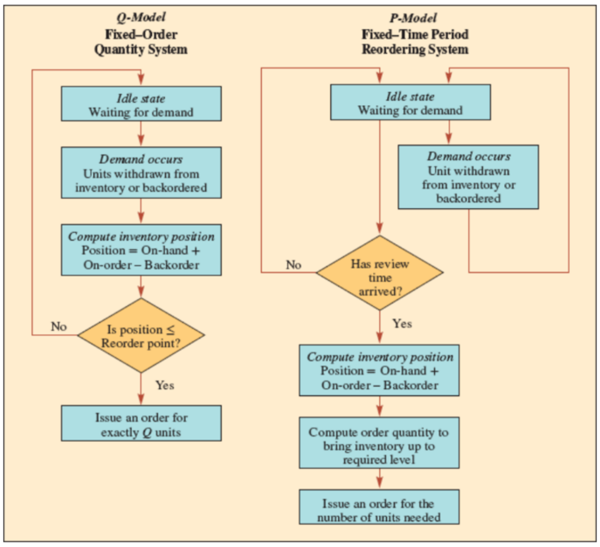

Fig. 8. "Comparison of Fixed-Order Quantity and Fixed-Time Period Reordering Inventory Systems" [14].

Fixed-order quantity models aim to predict the period, R, at which an order will need to be placed, as well as the amount of that order, Q. R, the order point, is always a fixed number of units. When the inventory available (now in stock and on order) reaches point R, an order of size Q is placed [14]. For example, the order policy could be, when the inventory drops to 100 units; R, place an order of 120 units; Q. Because we are concerned with cost in this example, according to Jacob and Chase, Eq. (6): "Total Annual Cost" [14].

$$\mathrm{TC} = \mathrm{DC} + \frac{\mathrm{D}}{\mathrm{Q}}\mathrm{S} + \frac{\mathrm{Q}}{2}\mathrm{H} \qquad (6)$$

where
TC = Total annual cost
D = Annual demand
C = Cost per unit
Q = Quantity to be ordered (the optimal amount is called EOQ or Qopt)
S = Set up cost or cost of placing an order
H = Annual holding and storage cost per unit of average inventory (often used as a percent carrying cost i; **H = iC**)

In the second step, after all the above variables are known, the optimal order quantity (Qotp) can be calculated using the following equation, Eq. (7): Optimal Order Quantity (Qotp) [14].

$$\mathrm{Qopt} = \sqrt{\frac{2\mathrm{DS}}{\mathrm{H}}} \qquad (7)$$

Considering this basic model assumes continuous demand and lead time, the reorder point, R, is readily defined as, Eq. (8): Reorder Point (R) [14].

$$\mathrm{R} = \bar{\mathrm{d}}\mathrm{L} \qquad (8)$$

where
$\bar{d}$ = Average Demand (constant)
L = Lead time (constant)

This approach implied continuous and knowing demand. However, in some cases, demand is not steady and changes from day to day [20]. To give some amount of protection against shortages, **safety stock** should be considered [14]. However, it should be noted that this method simply analyzes the possibility of running out of stock, not the number of units short. Companies employing this strategy frequently set the chance of not running out at 95 percent. That implies that the company would have a **Z value** of 1.64 [14]. The z value could also be calculated in Excel with the NORMSINV function. While waiting for the replenishment order, safety stock guarantees that there is a buffer against fluctuations in demand and lead time. Safety Stock could be computed using the following formula, Eq. (9): Safety Stock of Fixed-order Quantity Model [14].

$$\mathrm{SS} = Z\sigma_{\mathrm{L}} \qquad (9)$$

where
Z = Number of standard deviations for a specified service probability
σL = Standard deviation during lead time

Taking the uncertainty element into account, the reorder point would become, Eq. (10): Reorder Point with Safety Stock [14].

$$\mathrm{R} = \bar{\mathrm{d}}\mathrm{L} + Z\sigma_{\mathrm{L}} \qquad (10)$$

where
R = Reorder point in units
$\bar{d}$ = Average Demand
L = Lead time (constant)
Z = Number of standard deviations for a specified service probability
σL = Standard deviation during lead time

An estimate or forecast could be used when considering $\bar{d}$, L and σL. It could be as simple as using the previous year's demand or summation from the forecast of expected demand over the lead time [14].

The fixed-order quantity models require continuous inventory tracking, with an order made instantaneously once the reorder point is reached. In contrast, fixed-time period models consider that inventory is only measured at the point of review. There is a possibility of shortages that could occur in between review periods. Because of that, safety stock plays a crucial role in the fixed-time period model. Reorders are placed at the time of review (T) in a fixed-time period system, and the safety stock that must be ordered is, Eq. (11): Safety Stocks, Fixed-Time Period Model [14].

$$\mathrm{SS} = Z\sigma_{\mathrm{T+L}} \qquad (11)$$

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where
Z = Number of standard deviations for a specified service probability
$\sigma T+L$ = Standard deviation of demand over the review period and lead time

The quantity (q), thus, becomes order quantity equals average demand over the vulnerable period plus safety stock minus inventory position, Eq. (12): Order Quantity (q), Fixed-Time Period Model [14].

$$q = \bar{d}(T + L) + Z\sigma_{T+L} - I \tag{12}$$

where
q = Quantity to be ordered
$\bar{d}$ = Average monthly demand
T = Time number of days/months between reviews
L = Lead time between placing an order and receiving
Z = Number of standard deviations for a specified service probability
$\sigma T+L$ = Standard deviation of demand over the review period and lead time
I = Current inventory position

2.4. Forrester Effect

Forrester [6] produced the most notable research on the challenges this causes. The 'Forrester effect' coined after Jay Forrester, is also referred to as the 'bullwhip effect' since this graph, illustrated in Fig. 9, looks like a 'bullwhip'. This is caused by a combination of variables such as failure to share information between supply chain members, delays in sharing information due to inefficient operations, delays in ordering caused by placing a larger volume order and forecast error [6].

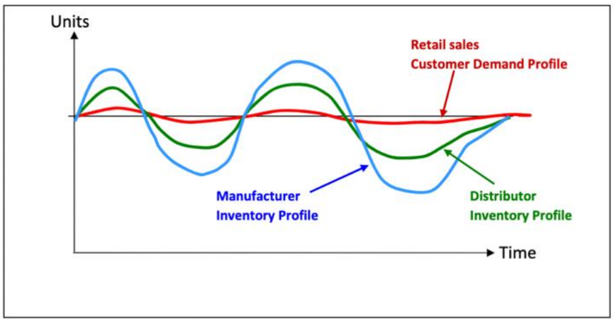

Fig. 9. Supply Chain Bull-whip Effect [6].

The bullwhip effect in FMCG industries causes inventory inaccuracy [21]. When the Forrester Effect is considered, the relatively consistent demand results in a very volatile inventory profile for the distributor and producer above in the production chain.

2.5. Identification of Research Gap

Demand Forecasting for Luxury FMCGs: There is an absence of research addressing demand forecasting for luxury FMCGs, which behave differently from mass-market competitors.

The impacts of various **Promotional Activities** on inventory levels in small trading organizations are not well-documented in extant research. More study is required to understand how various promotional strategies affect customer demand and supply chain dynamics.

The creation and efficacy of **hybrid order policies** that contain components of both fixed-order quantity and fixed-time period models are not well documented in the literature. There is an opportunity to investigate the effectiveness of such policies for a small trading company.

Bullwhip Effect in Niche Markets: The bullwhip effect is a well-known phenomenon in supply chain management, but its expression and mitigation in niche markets, particularly for luxury FMCGs, need more exploration.

In contrast to previous research on demand forecasting and inventory management, which primarily focuses on broad strategies applicable across various sectors, our study addresses the complexities of forecasting and ordering policies for luxury Fast-Moving Consumer Goods (FMCGs), with a strong emphasis on promotional sales impacts. Unlike the study by Farizal et al. (2021) [4] that applies multi-linear regression in a generalized FMCG context, our study introduces a combination of Exponential Smoothing and Holt-Winters's Additive forecasting within the niche market of luxury FMCGs in Thailand, offering new insights into demand fluctuations driven by high-end promotions. Furthermore, while Christopher (2016) [5] explored inventory management principles broadly, it did not account for the unique challenges posed by luxury FMCGs' promotional activities, which our study addresses by developing a hybrid order policy named "Periodic Review with Safety Stocks and Reorder Point." This differentiation not only advances the academic discussion on inventory management and demand forecasting but also provides practical/managerial implications, underscoring the significance of tailoring inventory strategies to accommodate promotional sales impacts.

3. Research Methodology

The research methodology employed in this study is tailored to the context of the case study company—a small-scale enterprise. Data relevant to the company's operations were collected from a set of standard office software, including Microsoft Excel, Word, and PowerPoint. For this research, all relevant operational data were obtained from these platforms, with calculations conducted using Microsoft Excel. The research methodology is divided into four key steps. The procedural steps of the methodological approach are illustrated in Fig. 10.

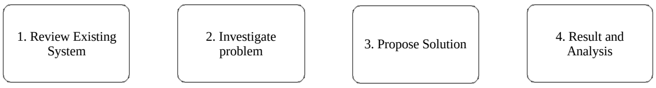

Fig. 10. Research Methodological Approach.

The first two steps, 'Review Existing System' and 'Investigate Problem,' will be briefly explained to provide the necessary background and context for the issues at hand. The third step, 'Solution Proposal,' will outline the devised strategies to tackle the identified problems. However, the focus of the discussion will be dedicated to the fourth step, 'Results and Analysis,' where the results of the proposed solutions will be detailed expansively. This focus ensures a comprehensive understanding of the research findings and their implications for the field.

3.1. Review Existing System

The methodology adopted for assessing the company's inventory system incorporates an analysis of the storage capacity, demand forecasting techniques, and purchasing patterns. The storage capacity was quantified based on the dimensions of the metal storage racks and the size of the toothpaste cartons with detailed quantities per carton. This analysis revealed an increase from four shelves in the previous stock room, storing 1,584 cartons, to 12 shelves in the current room, accommodating 4,752 cartons. The demand forecasting approach, historically inconsistent, typically used a rolling three-month average plus a 20% buffer stock, with variations noted throughout the studied periods. Purchasing was generally aligned with the forecast data on a quarterly basis, though exceptions like the missed order in July 2022 were recorded. This comprehensive review sets the groundwork for identifying improvements in the company's inventory management strategies.

3.2. Problem Investigation

The problem investigation for the company's inventory management system has uncovered pressing issues. The capacity expansion to accommodate double the inventory did not resolve the over-capacity events, which persisted especially during several periods in 2022. Furthermore, assessment of the demand forecasting accuracy revealed considerable errors, with some forecasts deviating greatly from actual demand, pointing to the need for more accurate predictive methods. The examination of purchasing patterns also disclosed irregularities in order placements, leading to stock shortages [34] following unexpectedly high demand [35]. These insights emphasize the imperative for enhanced forecasting techniques and a more consistent purchasing schedule to stabilize inventory management.

3.3. Solution Proposal

To address the identified deficiencies in inventory management, this study proposes a novel operation management system derived from the integration of logistics and supply chain management principles. The proposal is grounded in the insights garnered from the comprehensive literature review, which highlighted the effectiveness of various forecasting and ordering techniques, and the subsequent problem investigation that revealed specific challenges within the company's inventory system.

3.3.1. Demand Forecast

The forecasting methodology is developed in response to the evident demand forecasting inaccuracies previously discussed. The section begins with a Pareto Analysis (ABC Analysis) to prioritize items based on their impact on inventory costs and demand characteristics [36]. This is followed by a selection of forecast methods that align with the demand patterns of Class A and B products. The steps for this methodology are underpinned by the systematic evaluation and refinement process, ensuring an iterative approach towards optimal forecast accuracy [37]. Calculations and selection of smoothing parameters for forecasting will be conducted using Excel.

3.3.2. Order Policy

Informed by the literature on 'Supply Chain Inventories—Make-to-Stock Environment' and the identified need for a more dynamic inventory management system, a 'Periodic Review with Safety Stock and Reorder Point' model is proposed. This hybrid strategy is designed to mitigate the risk of stockouts while catering to the fluctuating demand, a necessity highlighted by the high levels of forecast error and the bullwhip effect observed in the problem investigation phase. The model takes into consideration the company's existing quarterly ordering policy but introduces safety stocks and reorder points to ensure inventory levels are responsive to actual market conditions, rather than solely time-based reordering.

3.4. Result and Analysis

The implementation of this proposed solution is expected to reconcile the previously identified gaps between demand forecasts, order policies, and actual inventory requirements, moving towards an accurate forecast, resilient, and cost-efficient inventory system.

3.4.1. Demand Forecasting

The forecasting results for Class A and B items will be derived through the application of chosen statistical forecasting methods, with a focus on reducing the

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previously identified high Mean Absolute Percentage Error (MAPE). These results will be organized to concisely display forecast performance by SKU, accompanied by graphical representations of forecasted versus actual demand to visually assess the model's precision. The forecasting process depicted in the flowchart involves eight sequential steps as displayed in Fig. 11.

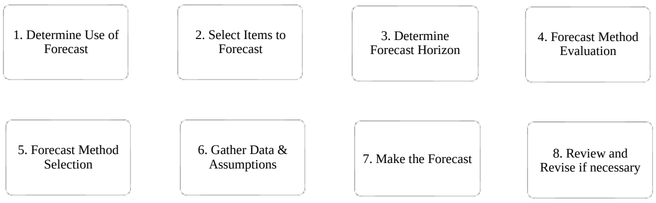

Fig. 11. Methodological Approach to Demand Forecasting.

In the selection of forecasting methodologies for this research, a variety of techniques ranging from traditional time-series models to advanced machine learning algorithms such as Artificial Neural Networks (ANN) [38] were considered. However, the decision to employ traditional forecasting methods, specifically Exponential Smoothing, and Holt-Winters's Additive and Multiplicative models, over ANN was driven by several key factors. Firstly, the scale of the dataset and the complexity inherent in ANN models did not match; traditional methods are known to perform well with smaller datasets and offer considerable accuracy for our research scope. Secondly, the interpretability and ease of implementation of traditional methods align better with the operational capabilities of a small trading firm, ensuring the findings are both accessible and actionable for the company. Lastly, given the practical constraints of expertise and computational resources, traditional forecasting methods presented a more feasible approach without compromising the reliability of the forecast outcomes.

3.4.2. Order Policy

The result of the order policy for Class A and B items will be calculated using the mentioned equations in section 2., the calculation steps are displayed in Fig. 12. These calculations will be based on statistical analysis, such as standard deviation and service level targets, to tailor the policy to the company's specific operational context. The calculated reorder points will determine when an order should be triggered, while the safety stock levels will account for uncertainty in demand and supply. The results will be presented in a structured format, with tables to display the reorder points and safety stock for each SKU within Class A and B categories.

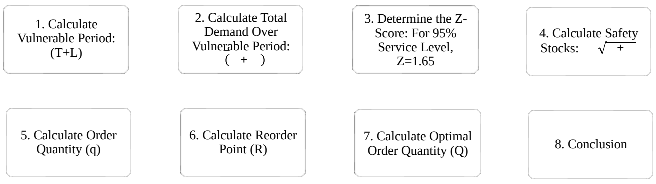

Fig. 12. Methodological Approach to Order Policy.

4. Results & Analysis

4.1. ABC Categorization

To identify the most critical products, the ABC analysis with a multiple criterion inventory categorization for the inventory control system was first applied [39]. Table 2. shows a calculation of the ABC categorization of 16 SKUs.

Table 2. ABC Categorization of 16 SKUs Using 2021 Data.

Item	Annual Demand	Unit Cost (THB)	Annual Spend (THB)	Annual Spend (%)	Cum. Annual Spend	Quantity (%)	Cum. % Item	C
WM 85 ML	4126	108.65	448290	20%	20%	20%	**20%**	**A**
SW 85ML	2434	108.65	264400	12%	32%	12%	**32%**	**B**
AM2 85 ML	2378	108.65	258370	11%	43%	11%	**43%**	**B**
CSM 85 ML	1619	108.65	175850	8%	51%	8%	**51%**	**B**
JM 85 ML	1176	108.65	127718	6%	56%	6%	56%	C
OBB 75 ML	1201	109.24	131197	6%	62%	6%	62%	C
AL 85 ML	976	108.65	105988	5%	67%	5%	67%	C
BF 75 ML	1125	108.65	122177	5%	72%	5%	72%	C
EGT 75ML	1031	108.65	112018	5%	77%	5%	77%	C
AM1 85 ML	810	108.65	87952	4%	81%	4%	81%	C
GM 85 ML	743	108.65	80727	4%	85%	4%	85%	C
SSR 75 ML	889	108.65	96590	4%	89%	4%	89%	C
BT 75ML	917	108.65	99632	4%	94%	4%	93%	C
CM 85 ML	690	108.65	74969	3%	97%	3%	97%	C
CMT 75ML	384	108.65	41722	2%	99%	2%	98%	C
TCK 3x25ML	219	158.05	34613	2%	100%	2%	100%	C

Class A should include WM 85ML, accounting for 20% of the items. Class B should include AM2 85ML, SW 85ML, and CSM 85ML covering the next 30% of the items. The rest should be Class C items. Class A and B items are prioritized and selected for further study.

4.2. Demand Classification

To evaluate demand forecastability, two coefficients are used, and the results are displayed in Table 3, [16]:

1. Average Demand Interval (ADI), or Mean Demand Interval (P) as cited by Boylan referencing Synetoes.
2. Squared Coefficient of Variation (CV^2).

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Table 3. Demand Classification of Class A and B Items.

WM 85ML					
STDEV	MEAN	CV	CV^2	P	Type of Demand
201.63	**340.04**	**0.59**	**0.35**	**1**	**Smooth**
SW 85ML					
STDEV	MEAN	CV	CV^2	P	Type of Demand
219.02	**277.85**	**0.79**	**0.62**	**1**	**Erratic**
AM2 85ML					
STDEV	MEAN	CV	CV^2	P	Type of Demand
71.07	**195.04**	**0.36**	**0.13**	**1**	**Smooth**
CSM 85ML					
STDEV	MEAN	CV	CV^2	P	Type of Demand
69.56	**152.56**	**0.46**	**0.21**	**1**	**Smooth**

In summary, based on the data supplied, WM, AM2, and CSM have smooth demand patterns, implying that they are generally easier to forecast and manage. SW's demand, on the other hand, is erratic, indicating greater uncertainty and the need for a more flexible, and perhaps more complex forecasting model to handle the unpredictability.

4.3. Demand Forecast

4.3.1. Use of Forecast and Forecast Horizon

Toothpaste is widely available on shop shelves, in a variety of retail venues and online platforms. Customers generally expect to get the toothpaste immediately when purchasing at the store, or as soon as possible when purchasing online [24]. Suppliers and distributors need to keep an inventory of finished goods on hand; suppliers and distributors are dependent on demand estimations. The use of forecasts for MTS products are:

1. **Inventory Management:** MTS items are manufactured in advance and stored to satisfy anticipated demand. Forecasting accuracy contributes to calculating ideal inventory levels [25]. This helps to balance the expenses of inventory keeping against the risks of possible shortages of goods.

2. **Supplier Coordination:** Forecasts are beneficial for working with suppliers [26]. The company should communicate anticipated demand to its suppliers, guaranteeing a seamless supply chain and avoiding interruptions caused by shortages or excess inventory [27].

3. **Promotional Planning:** Promotions and marketing activities could affect the demand. Retail promotions frequently cause demand variations, with sales soaring during the promotional period and then gradually reverting to regular levels thereafter [22]. Accurate projections could help in promotion planning by ensuring that enough inventory is available to fulfill increased demand during promotional times [28].

We argue that **an appropriate time horizon to forecast the selected products is a short-term, monthly forecast for the lead-time period**. The short-term, monthly forecast is quite common for consumer goods, including fast-moving consumer goods (FMCG) [23] e.g., toothpaste.

4.3.2. Forecast Method Evaluation

Exponential Smoothing is a time series forecasting approach that is especially useful and is mentioned as the best forecasting method most often utilized in enterprises for a variety of issues including inventory management and scheduling [29]. Exponential Smoothing is a common option in a variety of industries, including retail, manufacturing, financial services, energy, hospitality and tourism, transportation, and logistics, FMCG, healthcare, e-commerce, telecommunication, and agriculture [29].

Exponential Smoothing could be beneficial for establishing short-term projections in these sectors and for such types of goods [29]. Based on the individual properties of the data and the forecasting needs, the suitable variant of Exponential Smoothing (e.g., basic Exponential Smoothing, Holt's linear Exponential Smoothing, or Holt-Winters Exponential Smoothing) should be considered.

Holt-Winter's Multiplicative or Additive could be used to forecast monthly sales of a consumer product in the Fast-Moving Consumer Goods (FMCG) sector [30]. FMCG products often encounter shifting customer demand caused by variables such as seasonality, promotions, and changing consumer tastes [31]**.** This method could be appropriate for the case study products, especially WM 85ML and SW 85ML since sales tend to change in direct proportion to the quantity of advertising and marketing. Sales are often greater during the end of the year months owing to increased customer demand from the end of year sales.

4.3.3. Forecast Method Selection

Companies should select a prediction accuracy statistic that considers the perspectives of each business function as well as the overall performance of the organization [32]. Although statisticians believe that measurements with high statistical features should be used, practitioners prefer metrics that are simple to express and grasp [33]. Since the company prioritizes an overall percentage error, a MAPE is a criterion for selecting a forecast method. Additionally, graphical visualization will also be considered.

For the four products selected, we utilize the solver function in Excel to find the optimal parameter for the 3 models of each SKU. Then, actual demand from historical data, forecast from the Exponential Smoothing method, forecast from Holt-Winter's Multiplicative method, and forecast from Holt-Winter's Additive are plotted in a line graph for visual analysis. Historical data of actual demand during the year 2021-2022 were used in this assessment.

4.3.3.1. WM 85ML

Figure 13 illustrates a graph containing data on actual demand in a black line. The forecast of Exponential Smoothing using an alpha factor of 0 is displayed in yellow. A forecast of Holt-Winter's Multiplicative using an alpha of 0.04, beta of 0.94, and gamma of 0 is displayed in green. Lastly, a forecast of Holt-Winter's Additive using an alpha of 0.10, beta of 0.16, and gamma of 0.13 is displayed in blue.

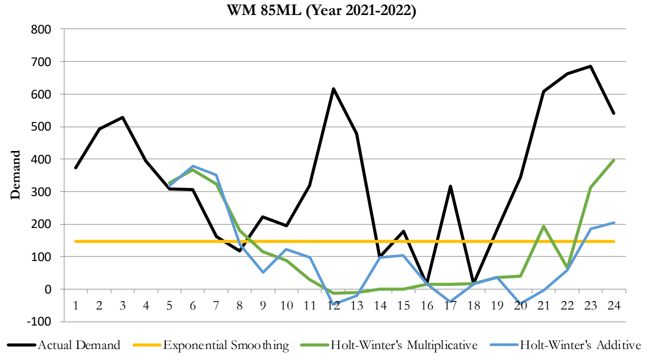

Fig. 13. WM 85ML, Actual Demand and Forecast of 3 Models

Table 4 below displays the mentioned forecasting models' ME, MAE, MSE, and MAPE values. Holt-Winter's Additive appears more fitting to the actual demand. The MAPE of the Additive method yields the lowest value of 61.51%. Although, from a graphical analysis, Holt-Winter's Multiplicative might be suitable, an overall MAPE of Additive yields better results. **The Holt-Winter's Additive method is selected for WM 85ML**. Additionally, the nature of WM 85ML is relatively stable. Although series data may be volatile or have abrupt changes, the amplitude of seasonal components is generally constant. From WM85ML being a mature product: seasonality due to promotions doesn't change much in magnitude over time. An Additive method could be more appropriate.

Table 4. WM 85ML, Forecasting Models Accuracy Measurement.

Method	ME	MAE	MSE	MAPE
Exponential Smoothing $\alpha = 0$	192	221.35	77319.96	121.86%
Holt-Winter's Multiplicative $\alpha = 0.04, \beta = 0.94, \gamma = 0$	194	224.26	85568.01	64.11%
Holt-Winter's Additive $\alpha = 0.10, \beta = 0.16, \gamma = 0.13$	218	246.74	111091.72	61.51%

4.3.3.2. SW 85ML

Figure 14 illustrates a graph containing data on actual demand in a black line. The forecast of Exponential Smoothing using an alpha factor of 0.9 is displayed in yellow. A forecast of Holt-Winter's Multiplicative using an alpha of 0.07, beta of 0.17, and gamma of 0 is displayed in green. Lastly, a forecast of Holt-Winter's Additive using an alpha of 0.1, beta of 0, and gamma of 0.39 is displayed in blue.

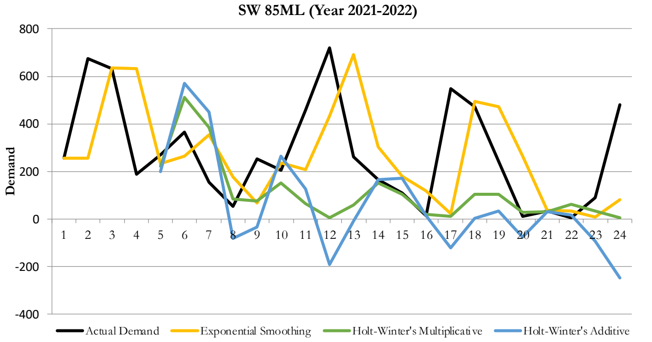

Fig. 14. SW 85ML, Actual Demand and Forecast of 3 Models.

Table 5 below displays the mentioned forecasting models' ME, MAE, MSE, and MAPE values. Given the seasonality of real demand (black line), Fig. 14., which seems to have a recurring pattern with distinct peaks and troughs, the optimal solution would capture this seasonality while reducing prediction inaccuracy.

The Holt-Winter's Additive catches seasonality however, its error measurements, particularly the MAPE, are higher. Holt-Winter's Multiplicative technique strikes an appealing mix by partly reflecting seasonality and having lower error metrics than the Additive method. Provided these findings, Holt-Winter's Multiplicative technique appears to be the best forecasting method for the data and demand characteristics. **The Holt-Winter's Multiplicative method is selected for SW 85ML**. In comparison to the other two approaches, it balances a lower MAPE, which suggests greater performance in terms of relative error. This implies that, while its mistakes may be substantial when they occur, it anticipates demand percentage changes more correctly than the other approaches on average.

Table 5. SW 85ML, Forecasting Models Accuracy Measurement.

Method	ME	MAE	MSE	MAPE
Exponential Smoothing $\alpha = 0.9$	9	189.68	60930.12	233.59%
Holt-Winter's Multiplicative $\alpha = 0.07, \beta = 0.17, \gamma = 0$	135	183.55	74633.03	110.03%
Holt-Winter's Additive $\alpha = 0.1, \beta = 0, \gamma = 0.39$	186	248.68	126660.83	135.70%

4.3.3.3. AM2 85ML

Figure 15 illustrates a graph containing data on actual demand in a black line. The forecast of Exponential Smoothing using an alpha factor of 0.01 is displayed in yellow. A forecast of Holt-Winter's Multiplicative using an alpha of 0.06, beta of 0.31, and gamma of 0.14 is displayed in green. Lastly, a forecast of Holt-Winter's Additive using an alpha of 0.05, a beta of 0.39, and a gamma of 0.37 is displayed in blue.

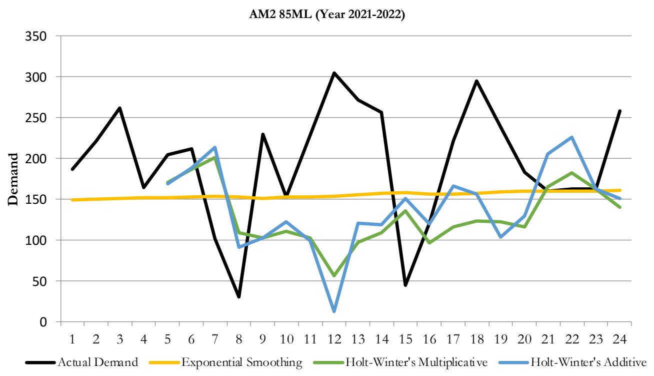

Fig. 15. AM2 85ML, Actual Demand and Forecast of 3 Models.

Based on the graphical analysis and statistical data supplied, in Table 6., **Exponential Smoothing appears to be the most appropriate** forecasting model owing to its lowest average errors, despite its simpler nature and probable underfitting displayed in the visualization. This could suggest that the seasonal fluctuations are not strong enough to warrant a more sophisticated model like Holt-Winters. Adding to the argument, AM2 exhibits the lowest CV^2 of 0.133**,** which is lower than that of WM 85ML and SW 85ML. Moreover, Exponential Smoothing could be the most appropriate solution for a Class B product if operational complexity is not required.

Table 6. AM2 85ML, Forecasting Models Accuracy Measurement.

Method	ME	MAE	MSE	MAPE
Exponential Smoothing α = 0.01	40	67.92	6685.14	53.27%
Holt-Winter's Multiplicative α = 0.06, β = 0.31, γ = 0.14	61.55	90.88	12336.11	59.58%
Holt-Winter's Additive α = 0.05, β = 0.39, γ = 0.37	51.60	90.26	12556.79	58.66%

4.3.3.4. CSM 85ML

Figure 16. illustrates a graph containing data on actual demand in a black line. The forecast of Exponential Smoothing using an alpha factor of 1 is displayed in yellow. A forecast of Holt-Winter's Multiplicative using an alpha of 0.05, a beta of 0.49, and a gamma of 0 is displayed in green. Lastly, a forecast of Holt-Winter's Additive using an alpha of 0.05, a beta of 0.5, and a gamma of 0.07 is displayed in blue.

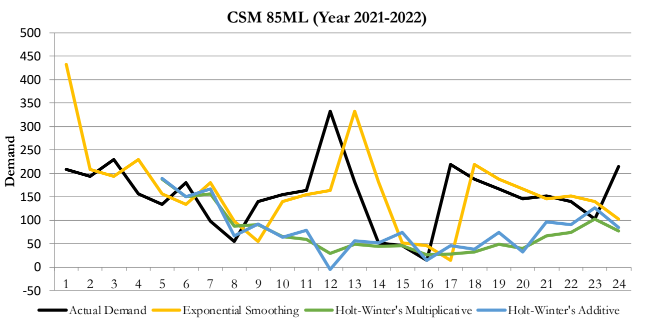

Fig. 16. CSM 85ML, Actual Demand and Forecast of 3 Models.

Based on the graphical visualization and statistical data of error metrics supplied, **Exponential Smoothing appears to be the most appropriate** forecasting model for CSM 85ML. Looking at the measurement metrics, Table 7., the Exponential Smoothing method with = 1 has the lowest Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE), indicating a more accurate fit to the data in terms of average error sizes and percentage of error relative to actual values. It also has a very low Mean Error (ME), indicating that the projections are not consistently skewed either way. Additionally, Exponential Smoothing's lesser complexity, as it requires fewer parameters to be established and maintained, matches the forecasting requirements of a Class B product. Despite having a slightly higher MAPE, the Exponential Smoothing approach is a superior choice in this situation due to its overall lower error metrics and simplicity.

Table 7. CSM 85ML, Forecasting Models Accuracy Measurement.

Method	ME	MAE	MSE	MAPE
Exponential Smoothing α = 1	0	59.17	6655.07	53.17%
Holt-Winter's Multiplicative α = 0.05, β = 0.49, γ = 0	70.86	86.63	12788.21	54.17%
Holt-Winter's Additive α = 0.05, β = 0.5, γ = 0.07	64.48	83.20	12637.52	48.68%

4.3.4. Assumption About Variables

The presented line graph, Fig. 17, depicts the actual demand pattern for the four previously stated items. This visual depiction can help to validate the demand classification. AM2 and CSM demand appear smooth. However, WM and SW appear to have some fluctuation and were further analysed.

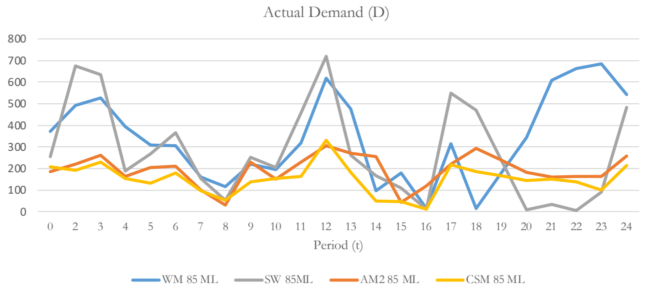

Fig. 17. Actual Demand, WM 85ML, SW 85ML, AM2 85ML, CSM 85ML, Year 2021-2022.

The study further examined the relationship between inventory levels, promotional strategies, and demand patterns for a specific toothpaste product i.e., WM 85ML and SW 85ML.

Three hypotheses were tested for WM85ML: Firstly, demand dips were inspected against inventory shortages, confirming that at least one significant drop in demand (period 8) was due to inventory shortage. Secondly, a year-over-year demand comparison suggested a cyclic, rather than seasonal, pattern, with no consistent demand peaks except around end-of-year festivities or promotions. Thirdly, it was observed that structured

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promotions led to demand spikes, yet during several periods (14, 16, and 18), promotions were absent, likely a consequence of insufficient stock levels. These findings highlight the intricate interaction between inventory management and promotion strategies in shaping consumer demand.

Three hypotheses were tested for SW 85ML: It was found that demand drops aligned with inventory shortages in certain periods, notably period 22, suggesting that insufficient stock levels likely influenced purchasing patterns. Year-over-year demand analysis indicated a pattern in demand changes, with similarities in rises and falls, except for the first quarter, pointing to a potential cyclical nature. Furthermore, promotional activities, specifically during periods 2-3, 12, and 17, appeared to significantly boost demand, underscoring the impact of promotional activities on sales volumes.

The analysis, while informed by two years of data, is indicative rather than conclusive, serving as a preliminary basis for developing forecasting models within the scope of this study. These insights have been instrumental in shaping a forecasting approach that is responsive to the factors affecting demand for this product.

4.3.5. Make the ForecastBottom of Form

In this research, a forecast has been developed for the period January 2023 to June 2023, which serves as the validation phase. This model utilizes the historical sales data from 2021 to 2022 as a foundation. Particular attention is given to the vulnerable period from January to May, where the forecast results are utilized in the development of order policy.

In the development of a forecasting model for WM 85ML toothpaste, a critical assumption was made to address the impact of stock shortages on-demand data. During period 15, an official stockout was announced, leading to a significant drop in demand. It was speculated that this drop did not accurately reflect customer purchasing behaviour, but rather the unavailability of the product. Consequently, the demand data for periods 14, 15, and 16 were substituted with the equivalent periods from the previous year. Using the Holt-Winters Additive method with optimized smoothing parameters ($\alpha = 0.10$, $\beta = 0.16$, $\gamma = 0.13$). The calculated forecast for WM 85ML resulted in an average demand of 401 units with a standard deviation of 40.03.

Table 8. Forecast of a Test Set of WM 85 ML.

Month	Jan	Feb	Mar	Apr	May	Jun
Period	1	2	3	4	5	6
Period (t)	25	26	27	28	29	30
Demand (D)	344	396	456	408	399	451
Level: L	259	273	286	300	314	307
Trend: b	13.74	13.73	13.73	13.73	13.73	10.60
Season: S	84.75	123.50	169.68	108.27	84.77	125.55
Forecast (F)	**344**	**396**	**456**	**408**	**399**	**451**
				Average Demand	401	
				Standard Deviation	40.03	

For SW 85ML, the Holt-Winters Multiplicative forecasting method was applied, employing smoothing parameters alpha at 0.07, beta at 0.17, and gamma at 0. Specifically, the demand for period 16, which was affected by stock shortages, was adjusted to reflect the demand from the corresponding period in the previous year, ensuring a more accurate representation of customer behaviour unaffected by inventory constraints. The same adjustment was made for periods 22, 14, 15, and 16, aligning them with periods 2, 3, and 4 of the previous year, respectively. The results, depicted in Table 9. yielded an average demand of 214 units and a standard deviation of 119.78 units for the identified vulnerable period.

Table 9. Forecast of a Test Set of SW 85 ML.

Month	Jan	Feb	Mar	Apr	May	Jun
Period	1	2	3	4	5	6
Period (t)	25	26	27	28	29	30
Demand (D)	125	347	341	107	151	416
Level: L	214	225	236	247	259	270
Trend: b	11.03	11.03	11.03	11.04	11.04	11.05
Season: S	0.58	1.54	1.44	0.43	0.58	1.54
Forecast (F)	**125**	**347**	**341**	**107**	**151**	**416**
				Average Demand	214	
				Standard Deviation	119.78	

The demand for AM2 toothpaste was forecasted using an Exponential Smoothing method with an alpha value of 0.01, indicating minimal adjustment from one forecast to the next. The result is displayed in Table 10. This produced a steady expected demand of 162 units for each month.

Table 10. Forecast of a Test Set of AM2 85 ML.

Month	Jan	Feb	Mar	Apr	May	Jun
Period (t)	**1**	**2**	**3**	**4**	**5**	**6**
Demand (D)	162	162	162	162	162	162
Forecast (F)	**162**	**162**	**162**	**162**	**162**	**162**
				Average Demand	162	
				Standard Deviation	0.00	

For the CSM toothpaste, an alpha of 1 was used, also suggesting a steady demand of 214 units each month. The result is displayed in Table 11.

Table 11. Forecast of a Test Set of CSM 85 ML.

Month	Jan	Feb	Mar	Apr	May	Jun
Period (t)	1	2	3	4	5	6
Demand (D)	214	214	214	214	214	214
Forecast (F)	**214**	**214**	**214**	**214**	**214**	**214**
				Average Demand	214	
				Standard Deviation	0.00	

4.4. Order Policy

To establish a hybrid order policy incorporating elements of both fixed-order quantity and fixed-time period models, several key equations are used. Data from the forecast is used to determine the order quantity for the upcoming review period, typically spanning three months, with a two-month lead time factored in to ensure product availability.

The fixed-time period model, which reviews inventory at specific intervals, uses Eq. (11) to determine the safety stock needed to cover the review period and lead time, accounting for demand variability. The quantity to order (q) at the time of review is calculated using Eq. (12), considering average demand, safety stock, and current inventory position. The result is displayed in Table 12.

The table is divided into four columns, each representing a different product: WM 85ML, SW 85ML, AM2 85ML, and CSM 85ML. The average monthly demand as calculated in the forecast section is 401 units, 214 units, 162 units, and 214 units, respectively. The review period is uniform for all products i.e., 3 months. The lead time is also assumed to be similar, 2 months, since all products' suppliers are single-sourced, and all products undergo the identical ordering process. Z-value is 1.65 from the established 95% service level.

Table 12. Order Quantity (q).

	WM 85ML	SW 85ML	AM2 85ML	CSM 85ML
Average Monthly Demand	401	214	162	214
Standard Deviation of Demand	40.03	119.78	0	0
Months Between Review Period	3	3	3	3
Lead Time	2	2	2	2
Z-Value	1.65	1.65	1.65	1.65
Inventory	1984	2062	597	1348
Period	2005	1070	810	1070
Safety Stock	148	442	0	0
Inventory	1984	2062	597	1348
Quantity (q)	**169**	**-550**	**213**	**-278**

The quantity (q) becomes 895 units for WM 85ML, -550 units for SW, 213 units for AM2, and -278 units for CSM. With the negative quantity (q), it could mean that the present inventory exceeds the projected stock level based on the demand forecast and safety stock calculations**.** In the case of SW and CSM, we proposed 2 possible actions the company could adopt:

1. **No replenishment**. No new stock should be ordered during the current review period since the existing inventory is adequate to fulfil the expected demand. However, this option could result in a bullwhip effect down the supply chain.
2. **Excess inventory**. The company could place a small order and have the excess inventory for sales and promotions, or other demand management methods that would increase the demand.

For the fixed-order quantity model, Eq. (8) defines the reorder point (R) based on average demand and lead time. For continuous daily monitoring, lead time has been converted from months to days. To accommodate for variability in demand, safety stock (SS), incorporating a z-value is factored into the reorder point in Eq. (10). The result is displayed in Table 13.

Table 13. Reorder Point (R).

	WM 85ML	SW 85ML	AM2 85ML	CSM 85ML
Average Daily Demand	13	7	5	7
Lead time in Days	60	60	60	60
Z-Value	1.65	1.65	1.65	1.65
Standard Deviation During Lead Time	56.61	169.39	0.00	0.00
Reorder Point (R) =	**895**	**708**	**324**	**428**

The total annual cost (TC) is determined by Eq. (6), accounting for annual demand, cost per unit, order size, setup cost, and holding cost. The optimal order quantity (Qopt) is calculated using Eq. (7).

Table 14. Optimal Order Quantity (Qotp).

	WM 85ML	SW 85ML	AM2 85ML	CSM 85ML
Annual Demand	4126	2434	2378	1619
Set Up Cost	8500	8500	8500	8500
Holding Cost	21.73	21.73	21.73	21.73
Optimal Order Quantity (Qopt) =	**1,797**	**1,380**	**1,364**	**1,125**

In summary, the order policy for the company is, (for example, WM 85ML), "Place an order of 169 units. Continue monitoring the inventory daily, if the inventory drops to 896 units, trigger a review to place another order". The company could place a small order or an optimal order quantity of 1,797 units.

5. Conclusion

This research has systematically addressed the challenge of optimizing inventory management and demand forecasting within a small trading company. Grounded in a comprehensive literature review and a robust research methodology, the study identified critical inefficiencies in the company's existing inventory and order systems and proposed strategic solutions to address these issues.

5.1. Research Question 1

"What is the suitable forecast method for the company.":

Class A Item
WM 85ML Holt-Winter's Additive
Class B Items
SW 85ML; Holt-Winter's Multiplicative
AM2 85ML; Exponential Smoothing
CSM 85ML; Exponential Smoothing

5.1.1. Percentage Improvement

Table 15 displays a comparison of forecasting errors between an existing forecasting method and the new proposed method. This is a comparison of the year 2021-2022 data.

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WM 85ML old forecast method yields a MAPE of 1706.74% while the new method yields a MAPE of 61.51% indicating that the forecast accuracy has improved by 96.40% from using the Holt-Winter's Additive method.

SW 85ML old forecast method yields a MAPE of 1654.29% while the new method yields a MAPE of 110.03% indicating that the forecast accuracy has improved by 93.35% from using the Holt-Winter's Multiplicative method.

AM2 85ML old forecast method yields a MAPE of 448.93% while the new method yields a MAPE of 53.27% indicating that the forecast accuracy has improved by 88.14% from using the Exponential Smoothing method.

CSM 85ML old forecast method yields a MAPE of 989.27% while the new method yields a MAPE of 53.17% indicating that the forecast accuracy has improved by 94.63% from using the Exponential Smoothing method.

Table 15. Comparison of Percentage Decrease of Forecasting Error, Year 2021 – 2022.

Product		**ME**	**MAE**	**MSE**	**MAPE**
WM 85ML	Old	-1088.08	1129.75	1947873.00	1706.74%
	New	217.70	246.74	111091.72	61.51%
		120.01%	78.16%	94.30%	**96.40%**
SW 85ML	Old	-687.40	726.06	700059.01	1654.29%
	New	134.75	183.55	74633.03	110.03%
		119.60%	74.72%	89.34%	**93.35%**
AM2 85ML	Old	-713.96	744.21	668348.29	448.93%
	New	39.74	67.92	6685.14	53.27%
		105.57%	90.87%	99.00%	**88.14%**
CSM 85ML	Old	-787.69	811.94	796817.55	989.27%
	New	0.22	59.17	6655.07	53.17%
		100.03%	92.71%	99.16%	**94.63%**

5.1.2. Validation with Actual Demand

By the time this research is concluded more actual demand data apart from the year 2021 to 2022 are available. The result of the forecast could be validated with actual demand data for periods 1 to 6 in the year 2023. The validation is conducted by comparing the forecast established by the proposed method in this research with an actual demand.

Table 16 displays the validation of forecast results with the actual demand of WM 85ML. Although, there are periods of under-forecast mixed with over-forecasted, the MAPE of 14% could be acceptable compared to 1706.74%.

Table 16. Forecast Validation with Actual Demand, WM 85ML, Period 1-6 Year 2023.

	Jan	Feb	Mar	Apr	May	Jun
Period	1	2	3	4	5	6
Demand (D)	359	364	668	417	361	608
Forecast (F)	344	396	456	408	399	451
Error	15.34	-32.23	211.88	8.54	-37.58	157.00
Absolute error	15.34	32.23	211.88	8.54	37.58	157.00
Squared error	235.36	1039.03	44893.68	72.95	1411.92	24649.00
Absolute percentage error	4.27%	8.86%	31.72%	2.05%	10.41%	25.82%

ME	53.83
MAE	77.10
MSE	12050.32
MAPE	14%

Table 17 displays the validation of forecast results with the actual demand of SW 85ML. The MAPE yields a result of 46%.

Table 17. Forecast Validation with Actual Demand, SW 85ML, Period 1-6 Year 2023.

	Jan	Feb	Mar	Apr	May	Jun
	1	2	3	4	5	6
Demand (D)	482	358	377	486	477	717
Forecast (F)	125	347	341	107	151	416
Error	356.87	10.59	35.79	379.37	326.09	301.47
Absolute error	356.87	10.59	35.79	379.37	326.09	301.47
Squared error	127354.41	112.08	1280.94	143923.93	106336.03	90883.38
Absolute percentage error	74.04%	2.96%	9.49%	78.06%	68.36%	42.05%

ME	235.03
MAE	235.03
MSE	78315.13
MAPE	46%

Table 18 displays the validation of forecast results with the actual demand of AM2 85ML. The MAPE yields a result of 26%.

Table 18. Forecast Validation with Actual Demand, AM2 85ML, Period 1-6 Year 2023.

	Jan	Feb	Mar	Apr	May	Jun
	1	2	3	4	5	6
Demand (D)	155	108	190	192	226	277
Forecast (F)	162	162	162	162	162	162
Error	-6.87	-53.87	28.13	30.13	64.12	115.12
Absolute error	6.87	53.87	28.13	30.13	64.12	115.12
Squared error	47.19	2902.12	791.13	907.53	4111.84	13253.09
Absolute percentage error	4.43%	49.88%	14.80%	15.69%	28.37%	41.56%

ME	29.46
MAE	49.71
MSE	3668.82
MAPE	26%

Table 19 displays the validation of forecast results with the actual demand of CSM 85ML. The MAPE yields a result of 27%.

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Table 19. Forecast Validation with Actual Demand, CSM 85ML, Period 1-6 Year 2023.

	Jan	Feb	Mar	Apr	May	Jun
	1	2	3	4	5	6
Demand (D)	192	118	196	256	157	226
Forecast (F)	214	214	214	214	214	214
Error	-22.00	-96.00	-18.00	42.00	-57.00	12.00
bsolute error	22.00	96.00	18.00	42.00	57.00	12.00
Squared error	484.00	9216.00	324.00	1764.00	3249.00	144.00
rcentage error	11.46%	81.36%	9.18%	16.41%	36.31%	5.31%

ME	-23.17
MAE	41.17
MSE	2530.17
MAPE	27%

To validate the research result, the 2019 forecasting and inventory benchmark study from E2open is useful. The report incorporates information from worldwide producers in a variety of industries and supplies MAPE benchmark. According to forecast accuracy depends on business context, Figure 5.1, at a tactical level it is stated that forecast accuracy should be at least 71%, meaning that forecasting error (MAPE) should not exceed 29%.

In summary, all items are up to standard, except for SW 85ML; with MAPE of 46% exceeding 29%. However, the result of SW 85ML could be justified since it was classified as erratic, it is more difficult to forecast and manage than the smooth demand product. Future studies, analyses, and adjustments could be conducted to further improve SW 85ML forecast accuracy.

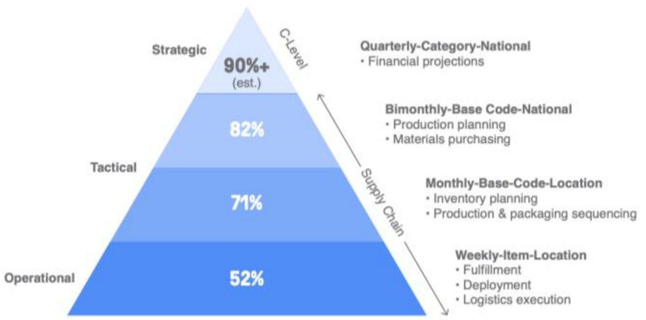

Fig. 18. Forecast Accuracy Depends on Business Context [40].

5.2. Research Question 2

"How to improve purchasing strategy for the company."

By established order policy: The order policy is "Periodic review with safety stock and Reorder Point". Every three months, review the inventory level then place an order according to the forecast plus safety stock to satisfy a 95% service level. Monitor the inventory level daily, if the inventory level drops below the reorder point, trigger a review to place an order. The company could place calculated quantity q, however, optimal order quantity should also be considered.

Validation with Inventory Cost: Table 20 displays the actual total inventory costs, calculated using Eq. (6), given that the actual ordering of the company in the year 2022 is 3 times, and the total units ordered are displayed in the table. The cost is in Thai Baht.

Compared with Table 21, the ideal total inventory costs, assuming an ideal scenario where the company placed an order with optimal order quantity.

In conclusion, the ideal inventory cost of WM 85ML, SW 85ML, AM2 85ML, and CSM 85ML are 29.88%, 32.04%, 29.41%, and 39.35% lower than the actual inventory cost, respectively.

Table 20. Actual Total Inventory Cost, Year 2022.

	WM 85ML	SW 85ML	AM2 85ML	CSM 85ML
Annual Demand	4126	2434	2378	1619
Cost Per Unit	108.65	108.65	108.65	108.65
Number of Orders	3	3	3	3
Total Units Ordered	20364	13188	11424	11868
Set Up Cost	8500	8500	8500	8500
Holding Cost Per Unit	21.73	21.73	21.73	21.73
Annual Purchase Cost	448290	264454	258370	175904
Annual Ordering Cost	25500	25500	25500	25500
Annual Holding Cost	221255	143288	124122	128946
Total Annual Inventory Cost	**695,045**	**433,242**	**407,991**	**330,350**

Table 21. Ideal Total Inventory Cost, Year 2022.

	WM 85ML	SW 85ML	AM2 85ML	CSM 85ML
Annual Demand	4126	2434	2378	1619
Cost Per Unit	108.65	108.65	108.65	108.65
Number of Orders	3	3	3	3
EOQ	1797	1380	1364	1125
Set Up Cost	8500	8500	8500	8500
Holding Cost Per Unit	21.73	21.73	21.73	21.73
Annual Purchase Cost	448290	264454	258370	175904
Annual Ordering Cost	19520	14993	14819	12228
Annual Holding Cost	19520	14993	14819	12228
I deal Total Annual Inventory Cost	**487,331**	**294,440**	**288,008**	**200,360**

5.3. Theoretical Implication

This research fills a gap in the current inventory management literature by concentrating on a niche luxury toothpaste brand, which is unique in a sector dominated by research on mass-market items.

This project challenges and expands existing forecasting models by offering time-series forecasting approaches customized to the unique demand nature of the product, which frequently do not account for the different patterns of expensive, specialized commodities.

The creation of a hybrid order policy encompasses both the fixed-order quantity and fixed-time period models, potentially adding to the theoretical framework of inventory management order policies in a small trading company context where promotional activities and single-source supply are dominant factors.

The paper presents a theoretical foundation for a comprehensive approach to inventory management by understanding the supply chain as an integrated system and applying lean methods to forecasting and purchasing. This system perspective is especially noteworthy in the context of small trade enterprises coping with the difficulties of managing inventory.

5.4. Practical Implication

The findings of the dissertation have practical implications for the case study company, providing them with a more accurate forecasting model that reduces the mean absolute percentage error from 2088% to a substantially lower amount, hence improving inventory management performance.

The implementation of a hybrid order strategy adapted to the company's particular circumstances might result in more efficient inventory levels, allowing for continued promotional operations without the threat of stock shortages or overstocking.

The company's supply chain may experience a reduction in the bullwhip effect by improving forecast accuracy and adopting a more effective order strategy, resulting in cost savings, more predictable supply chain operations, and a more resilient supply chain.

In response to the essential need for close coordination with our suppliers to portray the enhancements proposed in our forecasting and inventory management strategies, a comprehensive supplier engagement process has been initiated. We have agreed to establish a protocol for communicating our demand forecasts to our supplier on a yearly and quarterly basis. This regular update schedule ensures our supplier is well-informed of anticipated demand changes, allowing for better production planning and stock availability. Furthermore, the Forecast Accuracy Feedback Loop where the supplier can provide feedback on the accuracy of the forecasts received and its impact on their operations, and Joint Planning Sessions to discuss upcoming promotions, expected demand spikes, and any potential supply chain challenges are initiated as next steps.

5.5. Recommendation

Future research should try to gather and evaluate a larger set of historical data, ideally spanning many years, to capture a broader view of demand patterns and the consequences of sales promotions. The use of such software would allow for more accurate demand analysis and predictions through the application of advanced forecasting models that can handle complex data patterns and trends e.g., multi-linear regression, SARIMA-MLR, recurrent neural networks (RNN) [41].

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