

IMPROVEMENT OF INVENTORY MANAGEMENT SYSTEM: CHEMICAL RAW MATERIALS FOR HEALTHCARE AND PERSONAL CARE PRODUCTS MANUFACTURER

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Abstract

This research presents a case study examining the optimization of the inventory management system for a manufacturer of healthcare and personal care products within the fast-moving consumer goods (FMCG) industry. The study's objective is to enhance the inventory management process by employing the VED-FSN-SDE classification approach to prioritize and categorize items within an analytical framework. Following this classification, inventory management policies were established using the Economic Order Quantity (EOQ) model and the Silver-Meal heuristic method. The findings indicate that for the EFE category, where the variability coefficient (VC) was less than 0.2, the EOQ model was appropriate, resulting in a 27.42% reduction in annual inventory costs. For the DFD category, characterized by a VC greater than 0.2, the Silver-Meal heuristic method was applied, leading to a 35.99% reduction in inventory costs. These results demonstrate the effectiveness of the applied models in achieving significant cost savings and improved inventory efficiency. The practical implications of this study suggest that adopting tailored classification and control techniques can enable managers to optimize inventory levels, reduce costs, and enhance overall supply chain performance in the competitive healthcare and personal care products industry.

Keywords: Economic order quantity model; Inventory; Silver-meal method; VED-FSN-SDE Matrix analysis

Introduction

In the contemporary fast-moving consumer goods (FMCG) industry, logistics and supply chain management play pivotal roles (Mathu and Phetla, 2018). An effective system for inventory control and management coupled with well-defined policies for oversight of products and raw materials is critical to

ensure precise procurement and preparation processes. This enables companies to respond adeptly to the swiftly evolving demands of consumers while simultaneously enhancing organizational cost management efficiency (Mohamed, 2024).

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The company analyzed in this case study is engaged in the manufacturing and distribution of consumer health products, including hand sanitizers, throat lozenges, condoms, and lubricants. A significant challenge identified in inventory management concerns the procurement and storage of chemical raw materials essential for production processes, specifically pharmaceuticals, preservatives, colorants, and flavoring agents. These materials are often costly, subject to lengthy lead-times, and require substantial minimum order quantities. Despite this, there is a lack of explicit policies regulating inventory levels, which leads to a reliance on the experiential judgment of material planning for managing purchasing and inventory. This reliance has resulted in excessive stockpiling of some raw materials, inflating overall inventory costs, and increasing the risk of stockouts for others, along with the over-accumulation of certain items.

Poor inventory control can have serious implications for quality, cost, and compliance, especially in regulated industries, such as healthcare and personal care products. Inadequate inventory management may lead to the storage of expired or deteriorated materials, compromising product safety and efficacy, and risking regulatory penalties. Additionally, inaccurate inventory records can cause shortages or delays in production, leading to noncompliance with strict industry standards and potential legal repercussions. Excess inventory and obsolescence also increase holding costs and waste, further increasing operational expenses, and undermining product quality and safety.

For example, in the case study, the inventory value at the end of October 2021 was 134.5 million baht, but raw material usage in November 2021 was 41.7 million baht. The total inventory value of raw materials at the end of October was significantly higher than the total amount of raw materials required for use in November (approximately 92.8 million baht, or approximately 70%). These outcomes suggest that suboptimal inventory management practices may affect the overall efficiency and compliance.

This study addresses a significant gap in the existing literature by focusing on the systematic categorization and tailored management of chemical raw materials within the FMCG industry, particularly in regulated sectors such as healthcare and personal care products. Although previous studies investigated various inventory control techniques and cost-reduction strategies, few specifically examined the unique challenges associated with managing complex, costly, and regulation-sensitive chemical inventories. Moreover, there is a lack of comprehensive frameworks that integrate demand-based

categorization with appropriate control methods to optimize inventory levels, reduce costs, and ensure compliance with regulatory standards. This study aims to close this research gap by developing a targeted classification approach and evaluating suitable inventory control techniques for different categories of raw chemical materials.

This study addresses the following research questions: (1) How can raw chemical materials be systematically categorized to facilitate optimal inventory management? (2) Which inventory control techniques are most appropriate for the different categories of these materials?

To address these research questions, this study conducted a comprehensive analysis of chemical raw material inventory data from the manufacturing plant of the company. The analysis involved categorizing and evaluating chemical raw materials to enhance inventory management and developing a targeted management framework tailored to the specific characteristics of chemical raw materials. Furthermore, this study aims to identify the optimal inventory levels and implement strategies to maintain these levels efficiently. The focus was on a dataset comprising 213 raw chemical materials utilized in the production process over a 12-month period (January - December, 2021).

Therefore, the contributions of this study are significant. First, it allows for effective categorization of the chemical raw material inventory for enhanced inventory management. Second, this research supports the creation of efficient purchasing models and the formulation of policies for the improved management of chemical raw material inventories. Finally, it ensures that the inventory of raw materials is maintained at levels consistent with demand requirements. These findings provide valuable insights for decision-makers involved in inventory management. Developing tailored approaches provides a basis for informed decision making and policy formulation, ensuring that companies adopt best practices suited to their unique contexts.

Literature Review

Inventory is a type of current asset that a company or organization holds for sale or use in the production process. It can be categorized into various types and forms depending on the level of consideration, both at the business operation and manufacturing industry levels (Heizer and Render, 2004) as follows. Raw materials (RM): items, materials, or components used in the production process. Work In Process (WIP): Parts or materials currently involved in or awaiting further production

processes that have not yet completed all production stages. Maintenance, Repair, and Operating Supplies (MRO): Materials or parts used in operations, including those used in the production process but not as part of the final product, such as lubricants, repair parts, and adhesives. Finished Goods Products that are ready to be delivered to customers.

Lot sizing plays a crucial role in influencing the economic efficiency of the purchasing and production processes. Consequently, various methodologies have been investigated extensively. These approaches often consider the same cost factors, albeit in different ways, with each offering specific benefits and drawbacks (Battini *et al.*, 2014). Among these, the “Economic Order Quantity” (EOQ) model, introduced by Harris, along with a similar methodology developed by Andler, is typically categorized under “traditional” static methods. Through significant and well-regarded contributions, these static approaches have been adapted to dynamic lot-sizing techniques (Silver *et al.*, 2016). Considering time-varying demand patterns, Silver (1977) demonstrated that the Silver Meal heuristic, originally developed for discrete time-varying demand scenarios, can be adapted to approximate solutions for continuous time-varying demand patterns. Rather than identifying lot sizes that minimize the total ordering and inventory holding costs over the entire time horizon, Silver determined each lot size sequentially, one at a time, by locating the first local minimum of the total inventory cost per unit time. The literature indicates a prevailing preference for the Silver-Meal heuristic over other deterministic lot-sizing methods, such as Least Unit Cost and Part-Period Balancing, as demonstrated by Blackburn and Millen (1980) and Saydam and Evans (1990). Pujawan (2004), for instance, compared Silver-Meal and Least Unit Cost in a supply chain context characterized by stochastic demand variability from downstream channels. The results showed that Silver Meal tends to generate a sequence of orders with more consistent intervals but exhibits greater variability in order quantities. Conversely, the Least Unit Cost produces more stable order quantities, but results in more irregular order intervals. Additionally, Govindan (2015) reported a preference for Silver-Meal in two-echelon supply chain configurations comprising one vendor and multiple retailers by evaluating its performance under time-varying stochastic demand, including periods of zero demand.

Recent studies, including those by Deraz (2023), explored the potential of supervised machine learning algorithms to enhance inventory management in the FMCG sector. Specifically, this

study investigates various models, such as linear regression (LR), random forest (RF), boosted decision tree (BDT), and artificial neural networks (ANN), to develop accurate demand forecasting tools and estimate the Economic Order Quantity (EOQ). The primary focus of these models is to optimize inventory levels and support data-driven decision making within FMCG supply chains. However, it is noteworthy that the research predominantly concentrates on EOQ estimation alone, with limited consideration given to other inventory control aspects or broader supply chain optimization strategies.

The primary goal of inventory management is to determine the appropriate inventory levels. In practical applications, it is not feasible to manage all inventory items with an equal focus. The ABC classification system is the most used system for managing inventories. However, a notable limitation of the ABC system is its reliance on a single criterion for evaluation, which can oversimplify inventory prioritization and overlook other critical factors, such as criticality, shelf life, and regulatory importance (Chu *et al.*, 2008; Teunter *et al.*, 2010; Albayrak *et al.*, 2023). Consequently, this may lead to inefficient resource allocation, where items classified as low priority based solely on usage metrics require close supervision because of their importance in safety, quality, or compliance considerations.

An alternative approach proposed by Vaz *et al.* (2008) evaluated the annual drug expenditure at a hospital using ABC-VED analysis with the aim of identifying drug categories that necessitate enhanced supervisory attention. Inventory control techniques, including ABC analysis, VED analysis, and the combined ABC-VED matrix, were employed to assess hospitals' drug expenditures. The routine implementation of these inventory control methods in healthcare settings is advocated because they can significantly enhance patient care, optimize resource utilization, and prevent stockouts. Additionally, these techniques provide free capital for other developmental initiatives. Owing to their simplicity and usability, these methods are anticipated to gain popularity among healthcare managers, necessitating proactive promotion in the healthcare industry.

Nigah *et al.* (2010) applied ABC-VED analysis to 421 pharmaceutical items and identified distinct categories that necessitated stringent control. Their findings underscore the need for these techniques as standard practices to optimize resource utilization and mitigate stockout occurrences in hospital pharmacies. Pirankar *et al.* (2014) extended the utility of the ABC-VED Analysis in a tertiary care hospital scenario to

analyze drug usage. This dual-factor analysis effectively prioritized drugs, enhanced the management of pharmaceutical inventories by highlighting critical items, and improved management efficacy. Gizaw and Ebrahim (2021) further advanced inventory management efficiency using the ABC-VED-FNS matrix of 393 drug items, highlighting a nuanced categorization that supports strategic oversight and operational optimization, such as better storage management and reduced logistics costs. Teli *et al.* (2022) emphasized the application of ABC-VED Analysis in a hospital pharmacy in India, improving clinical service management by effectively classifying 334 drug items. Their research demonstrated significant enhancements in drug management efficiency, particularly for drugs associated with high-risk factors, such as Adverse Drug Events (ADE).

Abdul Rahim *et al.* (2018) employed the ABC inventory classification to enhance inventory management efficiency in the context of healthcare product manufacturing. This classification is based on the annual revenue generated by each product category. Suryaputri (2022) utilizes the ABC and XYZ classification methods to create an adequate inventory policy for raw medical materials based on their characteristics. However, neither study has presented substantial empirical findings that substantiate the effectiveness of this approach.

According to previous studies, there is a lack of diverse inventory control techniques that specifically address the unique challenges presented by chemical raw materials, such as their high costs, long lead times, and minimum order quantities. This study aims to explore techniques beyond traditional models (Chu *et al.*, 2008; Teunter *et al.*, 2010). Existing literature and practices often lack a tailored approach for categorizing raw chemical materials specific to the consumer health product sector. Although methodologies such as ABC and VED analyses are used in healthcare for pharmaceuticals, their application as chemical raw materials in FMCG remains unexplored (Vaz *et al.*, 2008 and Nigah *et al.*, 2010).

To effectively manage inventory in complex environments such as healthcare and chemical-based manufacturing organizations, classification techniques that align with the unique characteristics and risks associated with different inventory items must be adopted. While no single inventory classification technique can comprehensively address all operational requirements, each method possesses distinct advantages and is most effective when applied under appropriate contextual conditions. Table 1 presents a comparative overview of four widely adopted classification techniques-ABC, VED, FSN, and SDE-

emphasizing their primary strengths and the specific operational scenarios in which their application is most suitable.

Table 1. Comparative Overview of Inventory Classification Methods

Methods	Key Strength	Appropriate Application Context
ABC	Analyzes based on usage value	When minimizing total inventory cost is prioritized over item criticality
VED	Analyzes based on criticality	When managing regulated or high-importance items such as medical or chemical inputs
FSN	Analyzes based on movement frequency	When avoiding inventory obsolescence and managing slow- or non-moving items
SDE	Analyzes based on lead time	When lead time variability poses supply risks and advance procurement is essential

By addressing these gaps, research can provide frameworks that mitigate the risks of stockouts and overaccumulation. Effective inventory control ensures that materials are available when needed while avoiding unnecessary excess, which is critical for maintaining consistent production and satisfying consumer demand.

Research Methodology

To ensure that the research aligns with its objectives, the scope of the study is defined as follows. The study focuses on collecting and analyzing data related to 218 chemical raw material items within the case study. Data on five chemical raw material items stored on the Tank Farm were excluded. The analysis utilizes inventory quantity and valuation data of manufacturing from January 2021 to December 2021.

The case study company classified its raw materials into three categories for use in pharmaceutical manufacturing and product formation within the plant: (1) Active Pharmaceutical Ingredient (API), raw materials, or ingredient mixes intended for the production of pharmaceutical products. When used in manufacturing, these substances are the active pharmacological agents responsible for the therapeutic effects. (2) Critical Excipients: materials assessed as high risk and identified as critical owing to their potential impact on product quality or the manufacturing process. Examples include

preservatives and other excipients that are essential for maintaining product stability and efficacy. (3) Non-Active Ingredients / Excipients: materials that do not have therapeutic effects but serve as pharmaceutical adjuvants in formulations, such as coloring agents (Coloring agents) and flavoring agents (Flavoring agents).

The total number of chemical raw materials (Raw Materials: RM) was 218. All items were measured in kilograms (KG), with differing physical forms and packaging types, and were used across the manufacturing of Personal Care and Healthcare products. These raw materials are stored in the factory's internal warehouse, except for five items that are transferred to the Tank Farm, which houses and stores flammable chemicals in external steel tanks within the compound. Consequently, a comprehensive analysis focused on the remaining 213 chemical raw material items.

Data Collection

Data collection was conducted using two approaches: primary and secondary. The first type of data was obtained via semi-structured interviews with the planning manager of the case study factory. The interviews explored the processes involved in raw material procurement planning, including factors influencing ordering decisions, inventory management practices such as stock-level monitoring, purchase order management, item master data, Bill of Materials (BOM), supplier information, lead times, and relevant policies, including the Corporate Compliance Policy pertaining to chemical raw material management. Secondary data were sourced from the organization's records and included the following: inventory quantities of chemical raw materials; inventory valuation data; transactional data on the inflow and outflow of chemical raw materials used in the manufacturing process; material demand forecasts and actual requirements; and data related to item types, unit prices, procurement lead times, and associated operational costs such as labor, electricity, water, and storage expenses.

Data Categorization and Analysis

The collected data are analyzed across three dimensions and categorized into a matrix format using VED, FSN, and SDE analyses to improve inventory control efficiency. These dimensions are detailed below.

1. VED Analysis for Inventory Management:

Using VED Analysis, the inventory was categorized into three groups based on its criticality, according to the case study company's global policy for chemical materials. First, Vital (V) group: This

category includes critical items whose absence could severely impact operations, such as Active Pharmaceutical Ingredients (APIs). The second, Essential (E) group: Items in this group held moderate priority, including Critical Excipients. Finally, the desirable (D) group comprises general materials or items used in the processes, such as non-active ingredients and excipients.

2. FSN Analysis for Inventory Management:

FSN Analysis was used to group items based on usage frequency, which is typically measured in cycles per month. The researcher calculated the Days Inventory Outstanding (DIO) using the following criteria: The first is the fast-moving (F) group, which includes items in frequent demand, with a DIO ranging from 0 to 120 days. The second, the slow-moving (S) group, included items with moderate demand frequency per cycle, with a DIO between 121 and 243 days. Finally, Nonmoving (N) group, items with minimal demand were rarely used, with a DIO exceeding 243 days.

3. SDE Analysis for Inventory Management:

The SDE Analysis sorts items based on delivery lead times to assist in storage planning, with the following classification criteria: Scarce (S) raw materials: Materials with lead times of over 90 days. Difficult (D) raw materials have lead times between 31 and 90 d. Finally, Easily Available (E) raw materials: These materials have lead times between 0 and 30 days.

Three dimensions are employed to structure the inventory group in a detailed matrix format.

4. *Selection of Inventory Groups:* The inventory items were categorized based on volume of consumption and inventory value, with a focus on higher-priority groups. Specifically, the first-tier groups, Essential (E) and Desirable (D), were selected as sample groups for deriving new inventory management policies. This selection aims to target the items with the most significant impact on inventory costs and operational efficiency.

The Peterson-Silver coefficient of variation (Silver *et al.*, 2016) computed for the selected raw material groups to assess the suitability of demand patterns during the study period. This calculation serves as a measure to evaluate the degree of demand fluctuation, indicating the appropriateness of applying specific inventory control models.

$$VC = \left(\frac{Est.VarD}{\bar{d}^2} \right) \bar{d} - 1 \quad (1)$$

$$Est.VarD = \frac{1}{n \sum d_i^2} - \bar{d}^2 \quad (2)$$

$$\bar{d} = \frac{1}{n \sum d_i} \quad (3)$$

where d_i = demand over period i ,
 n = number of periods.

This measure normalizes the demand variance by the square of the mean demand and serves as a practical threshold for determining the appropriateness of inventory management strategies. Specifically, the Economic Order Quantity (EOQ) model is recommended when the variance coefficient (VC) is less than 0.2, whereas the Silver-Meal heuristic is more suitable when the VC is 0.2 or greater. This approach is particularly advantageous for inventory systems characterized by uncertain demand patterns.

Empirical studies have adopted similar methodologies. For instance, Routroy and Kodali (2005) employed the coefficient of variation to enhance EOQ models in environments with uncertain demand, validating the necessity of adaptive inventory policies in the face of higher demand variability. Similarly, Sharma and Agrawal (2012) conducted VC-based analyses to categorize items in a multi-item inventory context and subsequently proposed differentiated ordering strategies. Collectively, these studies underscore the efficacy of VC as a robust metric for guiding model selection in inventory management systems with varying demand patterns.

5. Economic Order Quantity (EOQ): For raw material groups exhibiting stable demand, the process involves calculating the ordering costs, holding costs, safety stock levels, and the reorder point (ROP). These calculations are employed to establish new inventory management strategies using the Economic Order Quantity (EOQ) method.

$$EOQ = \sqrt{\frac{2DC_o}{C_c}} \quad (4)$$

where D = annual demand,
 C_o = purchasing cost per time (baht)
 C_c = inventory cost per unit per year (baht).

$$ROP = \bar{d} * LT + Z * \sigma_d * \sqrt{LT} \quad (5)$$

where ROP = Reorder Point,
 $\bar{d}$ = Average demand,
 LT = Lead time
 σ_d = Standard deviation of demand
 Z = Z-score at 95% confidence level

6. Silver-Meal Heuristic: For raw material groups with variable demand patterns, order quantities were determined using the Silver-Meal Heuristic method. This technique calculates order quantities based on the projected demand in each period of a forward-looking timeframe (m) to identify the order quantity that minimizes costs. When the future demand for raw materials in each period is represented by $D_1, D_2, D_3, \dots, D_n$, $K(m)$ represents the average variable costs over the periods for which orders are placed in advance, and holding costs occur at the end of each period. The raw material demand in each period began to be used at the beginning of the period. The formula is as follows:

$$K(1) = A \quad (6)$$

$$K(2) = \frac{1}{2}(A + hD_2) \quad (7)$$

$$K(3) = \frac{1}{3}(A + hD_2 + 2hD_3) \quad (8)$$

$$K(m) = \frac{1}{m}(A + hD_2 + 2hD_3 + \dots + (m-1)hD_m) \quad (9)$$

where A = purchasing cost per time (baht),
 h = inventory cost per unit per year (baht).

The calculation is conditioned to stop when $K(m+1) > K(m)$, implying that the average cost of the current period exceeds that of the previous period. Ordering stops when the period at $K(m+1)$ incurs a higher cost than $K(m)$ at the first period, ensuring coverage of demand through m periods, with $Q1$ equaling $D_1 + D_2 + D_3 + \dots + D_m$. Calculations then restart at period $m+1$ and continue until the final ordering period for the raw materials (Silver *et al.*, 2016).

7. Total Cost Calculation: Upon acquiring information from the new inventory management methods, the researcher calculated the total cost of the new inventory management approaches, both the EOQ and Silver-Meal heuristic, and compared them with the total cost of the current inventory management practices of the case study company.

$$Total\ Cost\ (TC) = \frac{DC_o}{Q} + \frac{QC_c}{2} \quad (10)$$

where TC = total inventory management cost per year (baht).

The total inventory-related expenditure comprises procurement and inventory-holding costs. Procurement costs pertain to the expenses incurred during the ordering of raw chemical materials, which fluctuate proportionally with the number of purchase transactions. These costs are calculated based on data collected from January to December 2021 and include employee wages, office supplies, documentation, and communication expenses. Conversely, inventory holding costs encompass expenses that vary in direct proportion to both the volume and duration of raw material storage. The calculation of these costs is based on the average inventory value during the same period and comprises several components: capital, employee wages, electricity, equipment, and obsolescence costs. It is important to note that the storage space costs were not included in this calculation because of the company's policy of storing materials in-house and eliminating rental or leasing expenses. This cost-based approach aligns with classical inventory models, such as the Economic Order Quantity (EOQ) framework (Silver *et al.*, 2016), where the goal is to identify the policy that minimizes the sum of these costs over a planning horizon.

The findings are presented in the following two sections. The first section presents the results of the inventory classification and prioritization using VED, FSN, and SDE analyses. The second section focuses on determining appropriate inventory control levels using the EOQ and Silver-Meal heuristic techniques. This section also compares the total inventory costs before and after applying the EOQ and Silver-Meal heuristic techniques to evaluate whether they have successfully reduced inventory costs.

Results and Discussion

Prioritization and Structuring of Chemical Raw Material Inventory

To group the 213 chemical raw materials, VED, FSN, and SDE analyses were applied to prioritize their importance. Through VED Analysis, it was found that there were 12 items in the V (Vital) group, representing 6% of all raw materials; 36 items in the E (Essential) group, accounting for 17%; and 170 items in the D (Desirable) group, accounting for 77% of all raw materials.

In the FSN Analysis, the distribution was 81 items in the F (Fast-moving) group, representing 38% of all raw materials; 46 items in the S (Slow-moving) group, representing 22%; and 86 items in the N (Non-moving) group, comprising 40% of all raw materials.

The SDE analysis showed 47 items in the S (Scarce) group, representing 22%; 126 items in the D (Difficult) group, making up 59%; and 40 items in the E (Easily Available) group, comprising 19% of the total raw materials.

By analyzing and categorizing these materials in a matrix format across three dimensions, 27 groups of chemical raw materials used in the production process were identified, as illustrated in Table 2. The grouping process was facilitated by the VED, FSN, and SDE analyses. Based on this analysis, a systematic selection process was conducted to identify the key raw material groups, excluding Group V, which consisted of nine groups. This exclusion aligns with the company's inventory policy, which mandates that all API raw materials maintain a minimum inventory level equivalent to at least six months of supply.

The selection primarily targeted groups with the highest usage volumes and inventory values within Essential (E) and Desirable (D) categories. These groups were chosen to serve as the basis for determining the optimal order quantities and stock levels, thereby supporting the development of an improved inventory management strategy.

The analysis, conducted using Microsoft Excel, revealed that the EFE group accounted for the largest share of usage volume, representing 78.6%, and constituted 48.0% of the total inventory value of chemical raw materials. The EFE group included seven items out of 213 raw materials (approximately 3.3 %). The DFD group was identified as the second most significant group, accounting for 4.8% of the usage volume and 12.0% of the total inventory value. The DFD group comprised 32 items, constituting 15.0% of the total raw materials. These two groups, EFE and DFD, will be employed in subsequent analyses to formulate a new inventory management policy aimed at establishing appropriate stock levels and order quantities for these high-usage, high-value categories.

Table 2. Categorization of Raw Materials Using VED, FSN, and SDE Analysis Techniques

	F	S	N	
V	1	1	2	S
	3	2	3	D
	0	1	0	E
E	1	1	2	S
	11	3	5	D
	7	4	2	E
D	12	11	16	S
	31	18	49	D
	15	5	7	E

Upon calculating the coefficient of variation for each item within the EFE and DFD raw material groups, it was found that the EFE group had a

coefficient of variation of less than 0.2. This indicates a stable demand pattern, making it suitable for application to the Economic Order Quantity (EOQ) technique. In contrast, the coefficient of variation for each item in the DFD group was greater than 0.2, signifying a variable demand pattern. Therefore, the silver meal heuristic technique was applied to manage this variability.

Establishing Appropriate Inventory Control Levels

Applying the EOQ technique to the EFE raw material group revealed that the total inventory management cost for these chemical raw materials was initially 2,668,045 baht under the current management system. With the new inventory management approach using EOQ, the total cost decreased to 1,936,574 baht, demonstrating a reduction in total inventory costs by 731,471 baht or 27.42%. Table 2 compares the total costs of the current inventory management with the new EOQ-based approach for inventories, with a coefficient of variation of less than 0.2.

Table 3. Comparison of Total Inventory Management Costs between Current and the New Approach using EOQ for Inventories with a Coefficient of Variation Less Than 0.2

Item	Current Inventory Cost (baht)	New Inventory Cost (baht)	Cost Diff. (baht)	Cost Diff. (%)
A004	109,553	56,058	-53,495	-48.83
A005	40,689	44,704	4,016	9.87
A017	143,966	236,097	92,131	64.00
A027	628,779	503,596	-125,183	-19.91
A029	866,527	299,715	-566,812	-65.41
A088	326,025	274,762	-51,264	-15.72
A202	552,506	521,642	-30,864	-5.59
Total	2,668,045	1,936,574	-731,471	-27.42

According to Table 3, the primary cost reduction originated from lower inventory holding costs as the EOQ model optimized order quantities and minimized excess stock levels. While some items, such as A005 and A017, showed slight increases owing to changes in the ordering frequency or holding levels, the overall impact was positive. These findings confirm that differentiated inventory policies based on demand variability and item classification can lead to substantial cost reductions and improvements in operational efficiency.

Upon applying the Silver-Meal Heuristic to the DFD raw material group, characterized by a coefficient of variation greater than 0.2, the total cost prior to applying the Silver-Meal Heuristic was 1,300,568 baht. After applying the heuristic, the total cost is reduced to 832,546 baht. This

demonstrates a reduction in the total inventory costs of 468,022 baht (35.99 %). These findings are presented in Table 3, which compares the total costs of the current inventory management with the new approach using the Silver-Meal Heuristic for inventories, with a coefficient of variation greater than 0.2.

Table 4. Comparison of Total Inventory Management Costs between Current and the New Approach using Silver-Meal Heuristic for Inventories with a Coefficient of Variation Greater Than 0.2

Item	Current Inventory Cost (baht)	New Inventory Cost (baht)	Cost Diff. (baht)	Cost Diff. (%)
A008	35,835	50,730	14,896	41.57
A012	52,339	40,004	-12,336	-23.57
A013	24,388	13,323	-11,065	-45.37
A014	81,615	9,532	-72,082	-88.32
A024	30,471	10,212	-20,259	-66.49
A041	5,628	4,490	-1,138	-20.23
A050	23,811	16,614	-7,197	-30.23
A053	12,622	9,227	-3,395	-26.90
A054	94,112	10,125	-83,987	-89.24
A059	24,248	13,169	-11,079	-45.69
A060	22,871	25,159	2,288	10.01
A062	30,871	31,856	985	3.19
A072	75,418	40,431	-34,987	-46.39
A082	5,965	5,882	-84	-1.40
A084	6,711	3,999	-2,712	-40.41
A096	2,535	1,632	-902	-35.60
A110	66,832	61,088	-5,745	-8.60
A112	77,217	25,943	-51,274	-66.40
A115	3,425	2,276	-1,149	-33.53
A123	37,630	13,107	-24,523	-65.17
A128	4,491	2,842	-1,649	-36.72
A135	3,081	1,986	-1,094	-35.52
A137	37,843	20,173	-17,670	-46.69
A145	25,319	37,902	12,583	49.70
A149	32,389	39,209	6,820	21.06
A154	5,266	3,875	-1,391	-26.42
A159	21,623	26,572	4,949	22.89
A163	364,090	270,635	-93,455	-25.67
A164	20,469	13,534	-6,935	-33.88
A205	11,135	9,610	-1,525	-13.69
A207	18,565	7,082	-11,483	-61.85
A211	41,753	10,325	-31,427	-75.27
Total	1,300,568	832,546	-468,022	-35.99

Table 4 reveals that the primary drivers of cost reduction were decreased ordering frequency and optimized inventory levels, resulting in lower inventory-holding costs. Although a few items showed minor increases in cost owing to batch timing alignment or order sizing, most items experienced substantial savings. These results demonstrate the effectiveness of demand-sensitive inventory models for items with variable demand, particularly when conventional one-size-fits-all policies result in overstocking or understocking inefficiencies.

Focusing predominantly on high-priority groups (EFE and DFD) may have several implications for the management of other raw material groups. Primarily, this targeted approach could lead to the allocation of fewer resources and less attention toward lower-priority categories, potentially resulting in suboptimal inventory controls, such as insufficient safety stocks or less frequent replenishment oversight. Consequently, this may increase the risk of stockouts or excess inventory in these other groups, thereby affecting overall supply chain stability.

Additionally, emphasizing high-demand groups may cause imbalances in inventory levels across different categories, which could compromise responsiveness to unforeseen demand fluctuations and supply disruptions. This practice may also diminish the operational flexibility of the entire supply chain, especially if lead times, supplier dependencies, or regulatory requirements vary among groups. Furthermore, neglecting or inadequately managing lower-priority raw materials can result in long-term costs, including increased holding costs, obsolescence risks, and procurement inefficiencies. Therefore, while optimizing control over high usage, high-value groups can improve overall efficiency. It is essential to maintain appropriate oversight of other categories to ensure supply continuity and cost-effectiveness.

Conclusions

The application of the VED, FSN and SDE Analysis theories to prioritize and categorize chemical raw materials enables the identification of those critical to the production process that require special attention. This approach is particularly applicable to the FMCG pharmaceutical industry, in which certain products and raw materials are highly significant and require specialized management. This aligns with the research of Gizaw and Ebrahim (2021), who utilized matrix analysis through ABC-VED-FNS techniques to enhance the efficiency of inventory management in pharmaceutical warehouses. Their findings demonstrated that matrix analysis effectively distinguished drug item categories necessitating special oversight, improved storage management, reduced storage time and labor costs, and enabled better reorder point determination than current policies (Gizaw and Ebrahim, 2021).

By applying these theories and organizing the data into a matrix format, the inventory was divided into 27 groups. The EFE group had the highest usage, accounting for 78.6% of total raw chemical material consumption and 48.0% of total inventory

value. This group consisted of seven items, representing 3.3% of all chemical raw materials. The DFD group ranked second in terms of usage, with 4.8% consumption and 12.0% of the total inventory value, comprising 32 items or 15.0% of the total chemical raw materials. This selection aligns with the Pareto principle in which a small number of items typically account for the majority of the value. The EFE and DFD groups together represent over 60% of the total inventory value and usage, making them highly effective for cost-saving analysis and policy redesign. Focusing on these groups provides actionable insights highly relevant to management. The calculation of the coefficient of variation for each sample reveals that the EFE group has a coefficient of less than 0.2, indicating consistent demand patterns suitable for applying the EOQ technique. Previously, the total cost of this group's inventory was 2,668,045 baht. With the application of the EOQ approach, the total cost decreased to 1,936,574 baht, thus reducing inventory costs by 731,471 baht, or 27.42%.

In contrast, the DFD group exhibits a coefficient of variation greater than 0.2, indicating variable demand patterns. Therefore, a Silver-Meal Heuristic technique is employed. Initially, the total inventory cost for this group was 1,300,568 baht, which decreased to 832,546 baht after the application of the Silver-Meal Heuristic, achieving a cost reduction of 468,022 baht (35.99 %) as illustrated in Figure 1. These results demonstrate the efficacy of both techniques in significantly reducing total inventory costs for the respective groups, indicating their practical application potential.

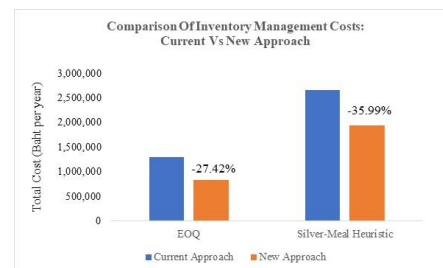


Figure 1. Inventory Cost Reduction Achieved Through EOQ and Silver-Meal Heuristic Methods

The primary aim of this study was not to conduct hypothesis testing in the traditional statistical sense, but rather to assess the feasibility and economic viability of differentiated inventory management policies based on item classification. This study seeks to demonstrate that employing a uniform ordering policy across all inventory items may not yield optimal results. Instead, by classifying inventory items using the VED-FSN-

SDE matrix and applying distinct order quantity models—namely, the Economic Order Quantity (EOQ) and Silver-Meal Heuristic—based on demand variability, this study aimed to compare the total inventory costs before and after implementing the revised policies.

Thus, this study was designed as a comparative feasibility analysis with a focus on quantifying the cost-efficiency gains resulting from alternative policy applications. The results clearly indicate substantial reductions in inventory costs, specifically, by 27.42% and 35.99%, respectively, when appropriate models are used according to item characteristics. These observed cost reductions serve as principal evidence supporting the feasibility and effectiveness of the proposed inventory policies rather than relying on statistical inference.

Furthermore, this approach is consistent with previous logistics studies that emphasize practical cost-based decision frameworks in supply chain optimization without resorting to statistical hypothesis testing (e.g., Battini *et al.*, 2014; Silver *et al.*, 2016). Sensitivity analysis and model validation were not conducted, because the intention was to provide a proof-of-concept highlighting the cost differences and managerial implications of applying differentiated policies.

Furthermore, these methods can be implemented in Excel to manage other raw materials effectively, providing a suitable policy framework that considers the overall costs of maintaining inventory levels at reasonable amounts. It is recommended that the case study company consider implementing new inventory management approaches to enhance its efficiency. In addition, expanding inventory management policies to other product and raw material groups is recommended. Introducing conditions aligned with the company's actual situation, such as uncertain lead times, shortage-related costs, or bulk order discounts, is also crucial for further improving inventory management efficiency.

Given the simplicity and adaptability of these methods, there is significant potential for their wider applicability across various industries characterized by high inventory turnover and complex raw material management, including the manufacturing, logistics, and retail sectors. By providing a practical policy framework that can be implemented in Excel, these approaches offer cost-effective and scalable solutions for organizations seeking to optimize inventory levels, manage costs effectively, and enhance supply chain efficiency.

Finally, this study conducts a comparative analysis to demonstrate the direct and measurable impact of inventory management policies on the costs associated with inventory management. The

findings suggest that the company's current operational practices present considerable opportunities to enhance performance. In particular, adopting inventory strategies tailored to the unique demand characteristics of each product category results in a significant reduction in overall operating costs. Although the proposed strategies have not yet been operationalized, the study prompted the company to undertake a critical reassessment of its current policy, which uniformly applies an identical inventory approach across all raw materials. This study underscores the fact that such a generalized strategy may be inadequate, particularly in environments with heterogeneous demand patterns and specific material attributes. Consequently, the company is considering transitioning toward a more flexible and efficient inventory management policy customized to the operational relevance and variability of each material group.

Future research should focus on several key areas to build on the findings of this study. First, differentiating and analyzing healthcare and personal care products separately can provide more targeted insights into their respective inventory management needs. Second, the integration of advanced data analytics, artificial intelligence, and machine learning techniques has the potential to enhance the demand forecasting accuracy and facilitate the automation of decision-making processes. Third, longitudinal studies are required to evaluate the long-term effectiveness and sustainability of the proposed inventory management strategies. Fourth, assessing the scalability and adaptability of these methods across various industries with high inventory turnover rates can help determine their broader applicability. Finally, examining the organizational and human factors that influence the successful implementation and acceptance of these strategies will contribute to a better understanding of and support for their practical adoption.

Limitations

This study has several limitations that may affect the interpretation and applicability of the findings. First, regarding the accuracy of the cost data, the costs, particularly the ordering and inventory holding costs, were primarily obtained through interviews and estimations. Consequently, some figures may deviate from the actual operational costs, potentially affecting the precision of the total-cost calculations.

Second, the practical application of the EOQ and Silver-Meal heuristic models may be limited to real business contexts. Although these models offer

theoretical advantages for inventory cost reduction, their implementation can be constrained by organizational factors, such as company structure, procurement policies, and supply chain configurations, which may hinder the full realization of their benefits.

Third, the analysis did not incorporate certain operational and environmental factors, such as fluctuations in material prices, supplier lead times, minimum order quantities, transportation constraints, and service-level requirements. These factors can significantly influence inventory management decisions and should be considered in future research to enhance the applicability and robustness of the proposed models.

Institutional Review Board Statement: The study was conducted in accordance with human research ethics and approved by the Ethics Committee of Burapha University (protocol code IRB4-183/2564; date of approval: July 13, 2021).

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