

Proposing a New Dynamic Safety Stock Adjustment System: Balancing Service Level Targets and Financial Constraints

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Abstract

This paper presents the design of a new system for dynamically adjusting safety stock levels based on real-time data. The proposed system addresses the challenge of balancing service level targets and financial constraints in inventory management. Service level targets, directly influencing safety stock levels, aim to ensure a high probability of meeting customer demand. However, financial constraints, such as budget limitations and cash flow considerations, impose restrictions on the amount of capital that can be allocated to inventory. To tackle this problem, in this research, the proposed system utilizes ABC classification to identify high-volatile items and prioritize them in the adjustment process. The goal is to minimize inventory costs while maintaining desired service levels, thus optimizing the allocation of capital and enhancing overall inventory management efficiency. The efficacy of the proposed model is demonstrated through a sample numerical data analysis, providing empirical validation of its effectiveness in real-world scenarios. We were able to create a model which can a) re-distribute the cycle service level value based on the required budget using linear programming and prioritizing high-volatile items, b) analyze various scenarios in regards to demand lead-time variations.

Keywords

Safety Stock Adjustment System, Service Level, ABC Classification, Inventory Management, Optimization

1. Introduction

In the ever-changing environment of global marketplaces, competition intensifies daily, compelling firms to enhance operational efficiency with available resources. In today's data-driven world, the ability to gather and understand vast amounts of information is essential for gaining a strategic advantage. Data is more than just a resource; it is a powerful tool for making well-informed decisions that set a firm apart from its competitors (Elahi and Franchetti, 2014). Leveraging this capacity for informed decision-making is critical across industries, fostering a fast-paced and proactive business climate. However, these decisions must be not only accurate but also timely, as delays can diminish a company's competitive edge (Haksever and Moussourakis, 2005; Mangotra *et al.*, 2009; Elahi and Wooten, 2019). Thus, the ability to make dynamic decisions is increasingly important. To address this need, this research paper focuses on offering an innovative inventory management approach via dynamic safety stock computation. Inventory management is a crucial component of supply chain management, encompassing the processes for ordering, storing, using, and selling a company's inventory (Franchetti *et al.*, 2017). Effective inventory management is vital for maintaining cash flow, ensuring customer satisfaction, and enhancing operational efficiency. The four main components of inventory management include: a) Order Management: Determines how much and when to order; b) Stock Control: Determines how much of each item should be in stock and when to replenish; c) Demand Forecasting: Predicts the quantity of each item expected from customer orders; and d) Warehouse Management: Manages the physical inventory, including storage and retrieval procedures. A major challenge associated with inventory

management is demand variability and the numerous external factors that can influence these fluctuations. Additionally, supply chain disruptions further complicate this already challenging task. Given these challenges, it is vital to use dynamic systems to effectively handle inventories in a constantly changing environment. The advancement of technology, particularly Artificial Intelligence (AI), is transforming inventory management. Major corporations are increasingly investing in AI to enhance their decision-making processes, which often require substantial computational resources. In this context, a technique that streamlines computations while using simpler methods yet produces high-quality results is essential. This research introduces a dynamic safety stock adjustment system that meets these requirements by merging real-time data analytics with optimized computational methodologies. This approach provides a robust solution to modern inventory management challenges, ensuring efficient and effective inventory control. Safety stock is a vital aspect of inventory management, as it safeguards against unexpected demand fluctuations and changes in lead time. By maintaining a safety stock, companies can avoid stockouts, ensuring that unexpected spikes in demand are met, buffering against extended lead times, and protecting against sudden price increases. The cycle service level is a key element of safety stock, determining the percentage of unforeseen events that the stock should cover. Higher cycle service levels offer greater protection but also come with higher costs.

1.1 Objectives

The primary objective of this research paper is to address inventory management by utilizing dynamic safety stock computations through an innovative approach. This proposed method employs the Pareto principle through ABC classification and linear programming. This dual approach facilitates dynamic safety stock adjustments within financial constraints, providing clear insights into optimal performance with given budgets while prioritizing high-performing Stock Keeping Units (SKUs). The research introduces a system designed to integrate real-time data analysis with strategic inventory management, ensuring that decision-making is both swift and economically sound. By adopting this new methodology, businesses can maintain and enhance their market competitiveness through smarter, more efficient inventory controls. In this research, the fill rate will be applied as a performance indicator for inventory management instead of solely relying on cycle service levels. While cycle service levels impose a penalty for any stockout during a supply cycle, affecting either a single SKU or multiple SKUs, the fill rate accounts for the number of SKUs that are short. This approach penalizes each unit that is short, providing a more nuanced and precise assessment of inventory performance. An example comparing two performance metrics—(a) the cost per stockout event and (b) the cost per item short—against the safety stock cost is illustrated in Figure 1. In this example, the demand has a normal distribution with mean of 62000 and standard deviation of 8000. Excess holding cost (c_e) is \$15 units per year. Replenishment lead time is 2 weeks. Cost per Stock Out Event (CSOE) or B_1 Cost is \$50,000 per event. Shortage cost (c_s) is \$45 per unit per year. Expected demand over lead time (μ_{DL}) is 2,385 units. Standard deviation of demand over lead time (σ_{DL}) is 1,569 units. Optimum Replenishment Order Quantity is 5,200 units per order.

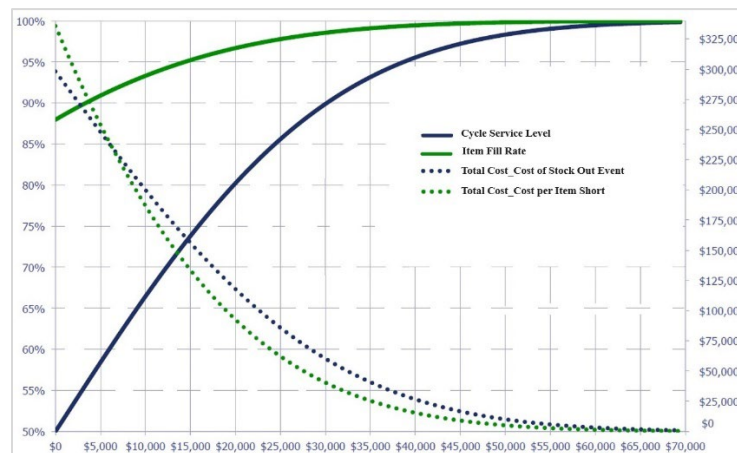


Figure1. Comparing two performance metrics—(a) the cost per stockout event and (b) the cost per item short—against the safety stock cost

2. Literature Review

Optimizing safety stock is a crucial aspect of supply chain management, prompting extensive research in this field. Benton (1999) presented significant research on safety stock and service levels in periodic review inventory systems.

In this study, Benton investigated the management of requirement uncertainty in Material Requirements Planning (MRP) systems within manufacturing firms, focusing on the complexities of safety stock requirements, lot sizing performance, and marginal safety stock needs under various service level policies. Benton (1999) combined simulation experiments and statistical analysis to examine safety stock requirements and lot sizing performance in MRP systems. The results empirically demonstrated that the marginal units of safety stock required for different service level policies follow a predictable pattern. The research also indicated that the economic advantages of well-known dynamic lot sizing procedures are diminished by the presence of requirements uncertainty.

Another important finding was the interaction between service level and lumpy requirements. High levels of the coefficient of variation and longer economic time between orders resulted in larger orders, reduced safety stock, and high service levels. Tratar (2009) addressed the forecasting problem within a demand-driven supply network to identify the probable range of expected demand, ensuring that supply can meet demand within the statistical range. The standard method for calculating safety stock relies on the targeted customer service level and cumulative forecast error from recent historical periods to determine the minimum amount of safety stock needed to cover sales until the next scheduled resupply. However, this method does not yield satisfactory results for highly seasonal products, as seasonality spans multiple months within a year. To address this issue, Tratar (2009) proposed a modification to the method. Instead of calculating the standard deviation across months within a given year, the standard deviation for a specific month across all available years was computed. This approach allows for the calculation of safety stock for each month independently, providing a better account for seasonality. The proposed revised method reduced the costs related to the safety stock approximately by 11.87% compared to the original method.

Shivsharan (2012) focused on optimizing safety stock inventory costs under target service level constraints. The main objective of this research was to determine safety stock values for all products in a multi-product inventory to achieve aggregate type 1 and type 2 service levels at the minimum inventory cost. For both models, a minimum threshold for individual type 1 and type 2 service levels for every product was maintained. Based on the literature studied on inventory cost optimization, two models for each type of service level were developed and solved using the Lagrangian relaxation technique. Since these models employed Lagrangian multipliers, they allowed for easy observation of changes in desired service level measures. Optimal service levels for a diverse array of products over various planning horizons were effectively delivered. Validation of results was conducted using discrete event simulation, employing both Poisson and normalized discrete demand. It was suggested that testing the robustness of the models' safety stock solutions for demands other than Poisson and Normal would also be useful. Becker *et al.* (2013) focused on a study related to safety-stock calculation and they showed that a lower level of stock in times with less demand and a higher service level in boom times are expected.

Mirzaee (2017) examined the problem of determining safety stock levels for the production of multiple items, each with random demand, across multiple facilities. The traditional methodology for calculating safety stock, which assumes that demand during lead time follows a normal distribution, was discussed, and an alternative method for improving service levels was proposed. A case study, based on data from a liquid consumer packaged goods company, was used to evaluate alternative techniques for setting target inventory levels. The first alternative approach studied, referred to as the service level adjustment method, involved increasing the Z-value associated with the normal distribution until the observed performance in the data set achieved the desired service level of 0.22% stock-outs. This required a Z-value of 4.3, which, according to the theoretical normal distribution, should generate 0.0009% stock-outs. A drawback to this approach was the extensive computational testing needed to evaluate the performance of alternative Z-values until one achieved the desired service level. Such an approach could be very difficult to implement in a situation with a large number of items and suppliers. Next, a hybrid approach utilizing the Gamma probability density function was examined. Various historical-based and forecast-based combinations were used to fit the Gamma distribution's shape and rate parameters. The Hybrid-2 approach, which utilized a forecast-based method for estimating both the Gamma distribution's shape and rate parameters, performed best in the test case example. It was shown that using the Gamma distribution with forecast-based parameters to determine inventory levels is effective for problems where demand during lead time has long-tail distributions, providing solutions that outperform the normal distribution approach.

Zowid *et al.* (2019) tackled the multi-criteria inventory ABC classification problem. They introduced and evaluated the Gaussian Mixture Model (GMM) as a solution to deal with this problem. In their numerical data analysis, a theoretical dataset consisting of 47 stock keeping units was applied. Unlike traditional single-criterion methods and some complex multi-criteria methods, GMM aims to provide a simpler and computationally efficient classification tool. Hardika *et*

al. (2023) conducted a systematic literature review on inventory management by focusing on the factors and perspectives influencing safety stock prediction. They found that safety stock increases the effectiveness of inventory management by minimizing product loss impact, reducing storage costs, and maintaining customer satisfaction. Their findings verified that another variable affecting safety stock is the lead time of the supply chain, which can be used as a key element in calculating safety stock. Literature reviews revealed a limited number of research papers addressing multiple SKUs. No research has discussed the possibility of redistributing the budget while prioritizing high-performing SKUs. Zowid *et al.* (2019) explored the Multi-criteria inventory ABC classification using the Gaussian Mixture Model, focusing on classifying SKUs with unsupervised learning methods. In this paper, a new approach is proposed to classify SKUs based solely on their annual dollar usage performance. This classification serves as the basis for redistributing the budget value among SKUs, allowing us to determine the optimal safety stock value for each item.

3. Methods

Inventory management decisions are intrinsically tied to a company's financial circumstances. These financial constraints can manifest in various forms, each posing unique challenges to maintaining optimal inventory levels. Budget limitations represent a common financial constraint that can significantly affect inventory management. Companies operate within finite capital, which must be allocated to inventory purchases. This budget is subject to influence from factors like the company's overall financial health, seasonal sales fluctuations, and unexpected expenses. Consequently, companies often face tough decisions regarding the volume and timing of inventory purchases. Cash flow considerations present another critical financial constraint. The timing of cash inflows and outflows is pivotal for operational stability. When a substantial portion of capital is tied up in inventory, it can diminish liquidity, impeding the ability to cover operational expenses or pursue growth opportunities. Striking a balance between inventory investment and cash flow is vital for sustainable business operations. The cost of capital also factors into inventory management decisions. Whether a company leverage borrowing or internal funds for inventory purchases, there are associated costs. This represents an opportunity cost, as capital used for inventory could potentially yield returns elsewhere. A high cost of capital may dissuade companies from maintaining excessive inventory levels, as financing becomes more expensive. Moreover, ongoing costs related to inventory holding, termed inventory carrying costs, must be considered. These costs include storage fees, insurance premiums, taxes, and risks such as obsolescence, damage, or theft. High carrying costs may incentivize companies to minimize inventory levels to mitigate expenses. In this context, maintaining appropriate safety stock levels is particularly crucial. Safety stock serves as a buffer against unexpected demand fluctuations or supply chain disruptions. Optimizing safety stock levels can help companies achieve desired service level goals, ensuring customer demand is met without stockouts. However, financial constraints often necessitate trade-offs between safety stock levels and other financial considerations. Prioritizing certain SKUs based on their value and demand volatility can enable effective allocation of limited inventory budgets. Financial constraints profoundly impact inventory management, influencing safety stock maintenance, order quantities, and the ability to adapt to demand fluctuations. Effectively managing these constraints, while strategically prioritizing safety stock for critical SKUs, is essential for optimizing inventory levels, minimizing costs, and ensuring overall business success.

ABC classification is a prevalent inventory management technique grounded in the Pareto principle, commonly known as the 80/20 rule. This principle posits that roughly 80% of effects stem from 20% of causes. In the context of inventory management, this translates to approximately 80% of a company's revenue or profit being generated by 20% of its inventory items. ABC classification utilizes this concept by categorizing inventory items into three groups of 'A' items: These are the most valuable items, typically representing a small percentage of the total inventory but accounting for a significant portion of the company's revenue or profit; 'B' items: These items hold moderate importance, representing a larger percentage of the inventory than A items but contributing less to overall revenue or profit; and 'C' items: These are the least valuable items, often comprising a large portion of the inventory but generating a relatively small portion of revenue or profit. The primary objective of ABC classification is to assist companies in prioritizing their inventory management efforts. By identifying and concentrating on the most valuable items (A items), companies can allocate resources more effectively, optimize inventory levels, and enhance overall profitability.

In this paper, a novel approach to ABC classification will be introduced that expands beyond traditional inventory item categorization. While upholding the core principle of differentiating items based on their value, we introduce an advanced resource allocation methodology employing linear programming to optimize budget distribution. This approach maintains the ABC classification system, categorizing items into three groups (A, B, and C) based on their

average annual dollar value. However, we enhance the utility of this classification by utilizing it as a foundation for a more strategic allocation of the total inventory budget. This methodology employs linear programming to reallocate the budget among different SKUs, prioritizing items classified as high-performing or profitable (typically A items). This ensures that a larger portion of the budget is directed towards items significantly contributing to the company's revenue or profit, while still maintaining appropriate stock levels for other categories. By integrating linear programming, our model dynamically adjusts the resource allocation based on the priority derived from the ABC classification. This approach facilitates a more refined and efficient distribution of the inventory budget, maximizing potential return on investment and mitigating risks associated with stockouts or overstocks. The proposed dynamic safety stock adjustment system aims to revolutionize inventory management by seamlessly integrating real-time data analysis with strategic decision-making. This system is specifically designed to address the inherent challenges of balancing service level targets with financial constraints—a common dilemma for many businesses. Traditional safety stock calculations often rely on historical data and static assumptions about demand and lead time variability. However, in today's volatile market conditions, these assumptions can quickly become outdated. Fluctuations in customer demand, supply chain disruptions, and economic shifts can all impact inventory levels.

A dynamic adjustment system is essential to adapt to these ever-changing conditions. By continuously monitoring real-time data, such as sales trends, supplier lead times, and inventory levels, the system can identify emerging patterns and adjust safety stock levels accordingly. This proactive approach ensures that inventory levels remain aligned with actual demand, minimizing the risk of stockouts while avoiding excessive inventory holding costs. While large corporations with sufficient resources may leverage advanced technologies like AI and complex optimization models for dynamic adjustments, these solutions often require substantial computational power and expertise. For most businesses, complete automation of this process may not be practical or cost-effective. Moreover, such systems can sometimes create a disconnect between top management and the real-time effects of their decisions, as the complexity of the algorithms obscures the underlying factors influencing inventory levels. Therefore, there remains a crucial need for a specialized expert who can interpret management's decisions, translate them into actionable inputs for the system, and make real-time adjustments as needed. This human-in-the-loop approach bridges the gap between automated calculations and strategic decision-making, ensuring that inventory adjustments are both timely and aligned with the company's overall goals.

The proposed system recognizes this need and is designed to empower these experts with a user-friendly interface and intuitive tools. It provides clear visualizations and actionable insights, enabling management to make informed decisions with a deep understanding of the real-time effects of their choices. Importantly, the system allows for easy experimentation and scenario analysis. Management can readily test different parameters and observe the resulting impacts on inventory levels, costs, and service levels. This interactive capability fosters a collaborative environment where both data-driven insights and human expertise contribute to optimal inventory management. In contrast to complex, resource-intensive solutions, our proposed system prioritizes simplicity and accessibility. It does not require extensive computational power or specialized technical knowledge, making it a practical and adaptable solution for businesses of all sizes. By democratizing access to sophisticated inventory management tools, the system empowers companies to optimize their inventory strategies and gain a competitive edge in the market.

4. Data Collection

Here, the design of the proposed dynamic safety stock adjustment system begins with a comprehensive analysis of past sales data. This data can be derived from the company's historical sales records, industry benchmarks, or forecasts for the upcoming year. In this research, this data has been collected for each SKU to understand their unique sales patterns and performance over time. To establish a baseline for the calculations, both the average and standard deviation of sales for each SKU over the relevant time period are computed. A key principle that underpins the proposed model is the Central Limit Theorem (CLT). This fundamental statistical concept states that the average of a sufficiently large number of independent observations will tend towards a normal distribution, regardless of the original distribution of the data. In this case, by averaging numerous sales observations for each SKU (this research aims for 1,000 or more datapoints where feasible), it can be reasonably assumed that the distribution of these average sales will approximately have a normal distribution.

This assumption of normality is essential for the proposed subsequent calculations in this research and allows to leverage statistical techniques that rely on the normal distribution for safety stock optimization. In addition to the sales data, the holding cost for each SKU has been taken into account, assuming a reasonable value of 15% of the unit cost per year. To account for lead time (the time between placing an order and receiving it) and ordering cost (the cost of

placing and processing an order), a random number generator using Python has been applied to simulate these variables as it is shown in Figure 2.

```
# Generating random numbers for Lead time and Ordering cost
import numpy as np
import pandas as pd

np.random.seed(2)
LD_T = np.random.randint(1, 6, size=283) # Simulating lead times between 1 and
5 days
Ord_c = np.random.randint(10, 20, size=283) * 10 # Simulating ordering costs
in multiples of 10
df = pd.DataFrame({'Lead Time': LD_T, 'Ordering Cost': Ord_c})
df.to_csv('random_numbers.csv', index=False)
```

Figure 2. Python codes for generating random number for lead time and ordering cost

5. Implementation of Scenarios, Results and Discussion

This data set has been utilized for testifying three various scenarios in order. Those scenarios help to dynamically calculate and adjust safety stock levels for each SKU.

Scenario#1: In this scenario, the prepared dataset is leveraged to develop a dynamic safety stock adjustment model. The dataset comprises essential information for each SKU, including average order quantity, standard deviation of demand, unit sale price, lead time, ordering cost, and holding cost. To gain a deeper understanding of the trade-offs between safety stock levels and potential stockout costs, a cost-exchange curve is generated (see Figure 3-actual plot). This curve visually depicts the relationship between the total value of safety stock held and the total value of items short across all SKUs. To construct this curve, three crucial metrics are calculated for each SKU including a) Economic Order Quantity (EOQ) which represents the optimal order quantity that minimizes the combined costs of ordering and holding inventory (Eq.1); b) Safety Stock (SS) which serves as a buffer against unforeseen fluctuations in demand or lead time (Eq.2); c) Value of Items Short (VIS): This metric quantifies the expected cost of stockouts (Eq.3).

$$Q^* = \sqrt{\frac{2 * c_t * D}{c_e}} \quad (1)$$

Where k is the safety factor determined by the desired service level (see table 1 as the reference), c_t is the fixed ordering cost (\$/order), and $c_e = c * h$ is the excess holding cost (\$ per unit per time) (c is the variable (purchase) cost of the item (\$/unit), h is the carrying or holding charge (\$/inventory \$/time) and D is the average demand (units/time).

$$SS = \sigma_{DL} * k * c \quad (2)$$

Where σ_{DL} is the standard deviation of demand during lead time.

$$VIS = \frac{D}{Q^*} * \sigma_{DL} * G(k) \quad (3)$$

Where $G(k)$ is the unit normal loss function, which corresponds to the service level.

Subsequently, the safety stock and value of items short for each SKU are determined, utilizing the formulas outlined in the previous section. A complete view of these metrics across the entire inventory is gained by aggregating the individual SKU values, obtaining the total safety stock value and total value of items short corresponding to each service level specified in the provided table. Parameter of k (safety factor) for Cycle Service Level (CSL) less than 0.50 will be 0. As it is shown in Figure 3-actual plot, the trade-off in inventory management is very critical and needs to be considered. This figure illustrates the inverse correlation between the financial investment in safety stock and the potential losses from stockouts, also referred to as the cost of items short. As the actual curve in figure 3 demonstrates, increasing the value of safety stock progressively reduces the value of items short. This highlights the primary purpose of safety stock – to act as a buffer against unforeseen demand surges or supply chain disruptions, thereby minimizing the risk of running out of stock and losing potential sales. However, this curve also reveals that

this relationship is not linear. The initial investment in safety stock yields the most significant reduction in stockout costs, but the marginal benefit diminishes as safety stock levels increase.

Table 1. Associated k and $G(k)$ values for each Cycle Service Level (CSL)

CSL	k	$G(k)$
0.99	2.33	0.2211
0.98	2.05	0.2057
0.97	1.88	0.1928
0.96	1.75	0.1816
0.95	1.64	0.1718
0.94	1.55	0.1632
0.93	1.48	0.1556
0.92	1.41	0.1489
0.91	1.34	0.1430
0.90	1.28	0.1379
0.89	1.23	0.1336
0.88	1.17	0.1299
0.87	1.13	0.1268
0.86	1.08	0.1244
0.85	1.04	0.1225
0.82	0.92	0.1203
0.81	0.88	0.1206
0.76	0.71	0.1294
0.73	0.61	0.1402
0.70	0.52	0.1549
0.65	0.39	0.1881
0.60	0.25	0.2319
0.55	0.13	0.2864
0.51	0.03	0.3380
0.50	0.00	0.3521

In other words, each additional unit of safety stock provides progressively smaller reductions in the cost of items short. Moreover, the curve enables managers to simulate the effects of altering their inventory budget. By adjusting the budget upwards or downwards, they can observe how the total safety stock value and the total value of items short change accordingly. This simulation capability allows for informed decision-making, as managers can assess the potential benefits and drawbacks of different budget allocations. They can identify the point on the curve that aligns best with their company's risk tolerance and financial goals, striking the optimal balance between inventory investment and stockout mitigation. Achieved results for this scenario is shown in Table 2.

Scenario#2: In this scenario, the plan is to initiate a developed model based on scenario #1. The annual dollar usage for each SKU is calculated by multiplying the average order quantity by the unit sale price. This metric serves as the primary criterion for ABC classification. Based on this annual dollar usage, each SKU is classified into one of three categories: A, B, or C. Specific thresholds are defined for each category, with A items representing the most valuable items, B items holding moderate value, and C items being the least valuable. This classification establishes a hierarchy for prioritizing safety stock allocation and budget distribution.

Service level targets are assigned using a predefined mapping that associates each ABC class with a desired service level (See Table 3). Based on the service level, we can define k and $G(k)$, where k is the safety factor and $G(k)$ is the unit normal loss function. These service levels represent the desired probability of not experiencing a stockout for each category of items. As an example, a 95% service level might be assigned to A items, an 85% service level to B items, and a 75% service level to C items. In this scenario, ABC classification is implemented based on the service

level preferences outlined in Table 3. Class A items were assigned a service level of 95%, Class B items received 85%, and Class C items were allocated 75%. To determine the optimal point where Total Cost Safety Stock (TCSS) and Total Value of Items Short (TVIS) intersect, these values were plotted against the cost-exchange curve (see Figure 3-ABC plot shown in green color). The ABC plot illustrates a convincing comparison between the actual cost-exchange curve and the green point obtained after implementing ABC classification. A key observation is that the ABC curve intersects the TVIS axis at a lower point than the actual curve. This signifies that the TVIS, representing the potential financial losses due to stockouts, is reduced under the ABC classification system.

This reduction is achieved by prioritizing safety stock for high-value “A” items, ensuring their availability even with a higher service level of 95%. Interestingly, the TCSS under the ABC classification remains relatively close to the point on the actual curve where the overall service level was 93%. This suggests that even with a differentiated service level approach prioritizing “A” items, the total investment in safety stock does not significantly increase compared to maintaining a uniform 93% service level for all items. This finding underscores the efficiency of the ABC classification system in optimizing inventory management. By strategically allocating resources to high-value items, companies can achieve a higher service level for these critical items without a substantial increase in overall safety stock costs.

This approach strikes a more effective balance between minimizing stockouts of high-impact items and controlling overall inventory expenses. Furthermore, the plot reveals that the ABC curve lies below the actual curve across a significant portion of the total value of items short range. This suggests that the ABC classification consistently outperforms the uniform service level approach in terms of reducing stockout costs, particularly for lower values of items short. Overall, the plot demonstrates the efficacy of the proposed dynamic safety stock adjustment system with ABC classification. It highlights the ability of the system to optimize inventory levels, reduce stockout risks, and minimize costs, all while aligning with the company's differentiated service level goals. This approach offers a practical and efficient solution for businesses seeking to enhance their inventory management practices within a constrained budget. While previous research has demonstrated the effectiveness of optimizing safety stock levels, practical implementation often presents a challenge. In real-world scenarios, companies cannot always rigidly adhere to the budget estimates generated by inventory systems. Market fluctuations, emerging industry insights, or shifts in strategic priorities may necessitate adjustments to the inventory budget.

Scenario #3: Managers often find it relatively straightforward to make decisions about new budget values in terms of dollars. However, translating these changes into the required safety stock levels for each SKU can be a complex task. While the cost-exchange curve can provide an overall estimate of the new total value of items short, granular information regarding individual SKUs remains elusive. To address this challenge, a novel approach utilizing linear programming is proposed here to redistribute the adjusted budget value to each SKU based on their classification priority (A, B, or C). This approach enables real-time generation of critical information during decision-making meetings, empowering managers to make more informed choices about inventory allocation. Linear programming offers a fast and computationally efficient method compared to other optimization models. The proposed linear programming approach here is designed to maximize the overall effectiveness of the safety stock allocation while respecting the constraints of the revised budget. Following objective function and constraints are considered in this scenario. This objective function aims to allocate resources in a way that prioritizes high-value items while maintaining adequate safety stock for all categories.

Objective Function: Maximize the sum of (safety factor multiplied by the preference weight according to classification (weight for class ‘A’=0.7; ‘B’=0.2; and ‘C’=0.1)).

S.t:

- Constraint #1: Class A item’s Safety factor (k) $\leq$ max limit of class ‘A’
- Constraint #2: Class A item’s Safety factor (k) $\geq$ min limit of class ‘A’
- Constraint #3: Class B item’s Safety factor (k) $\leq$ max limit of class ‘B’
- Constraint #4: Class B item’s Safety factor (k) $\geq$ min limit of class ‘B’
- Constraint #5: Class C item’s Safety factor (k) $\leq$ max limit of class ‘C’
- Constraint #6: Class C item’s Safety factor (k) $\geq$ min limit of class ‘C’
- Constraint #7: Total cost of safety stock $\leq$ New budget value

These constraints ensure that the safety factors for each class of items remain within acceptable ranges, reflecting their priority levels, and that the total cost of safety stock adheres to the revised budget. By solving this linear programming problem, optimal safety factor for each SKU is obtained, allowing us to recalculate the safety stock levels for all items

in the inventory. This enables a seamless and efficient adaptation to budget changes, ensuring that inventory management decisions remain aligned with the company's financial realities and strategic objectives. Here, a new value for TVSS with a budget limitation of \$1.2 million is obtained using the same objective function subject to the following constraints.

Table 2. Achieved results for scenario #1

CSL	Actual	
	Total Value of Items Short	Total Cost of Safety Stock
CSL=99%	\$5,115.90	\$2,298,349.75
CSL=98%	\$11,086.05	\$2,029,031.58
CSL=97%	\$17,540.04	\$1,858,157.83
CSL=96%	\$24,376.30	\$1,729,616.17
CSL=95%	\$31,542.34	\$1,625,057.44
CSL=94%	\$39,005.73	\$1,536,061.54
CSL=93%	\$46,744.50	\$1,458,029.55
CSL=92%	\$54,742.89	\$1,388,161.21
CSL=91%	\$62,989.20	\$1,324,618.74
CSL=90%	\$71,474.53	\$1,266,127.80
CSL=89%	\$80,192.06	\$1,211,766.58
CSL=88%	\$89,136.48	\$1,160,845.56
CSL=87%	\$98,303.74	\$1,112,834.76
CSL=86%	\$107,690.74	\$1,067,317.45
CSL=85%	\$117,295.16	\$1,023,959.68
CSL=82%	\$147,399.62	\$904,348.46
CSL=81%	\$157,862.94	\$867,330.61
CSL=76%	\$213,413.68	\$697,802.05
CSL=73%	\$249,383.20	\$605,437.65
CSL=70%	\$287,407.47	\$518,089.23
CSL=65%	\$355,592.65	\$380,683.05
CSL=60%	\$430,273.32	\$250,298.01
CSL=55%	\$512,180.57	\$124,148.98
CSL=51%	\$583,553.54	\$24,767.20
CSL=50%	\$602,287.71	-

Table 3. Service level and associated k and G(k) values for each class of item

Class	Service level	k	G(k)
A	0.95	1.64	0.17
B	0.85	1.04	0.20
C	0.75	0.67	0.23

Objective Function: Maximize the sum of (safety factor multiplied by the preference weight according to classification (weight for class 'A'=0.7; 'B'=0.2; and 'C'=0.1)).

S.t:

- Constraint #1: Class A item's Safety factor (k) $\leq$ max limit of class 'A' 99%
- Constraint #2: Class A item's Safety factor (k) $\leq$ max limit of class 'A' 99%
- Constraint #3: Class A item's Safety factor (k) $\geq$ min limit of class 'A' 92%
- Constraint #4: Class B item's Safety factor (k) $\leq$ max limit of class 'B' 85%
- Constraint #5: Class B item's Safety factor (k) $\geq$ min limit of class 'B' 77%
- Constraint #6: Class C item's Safety factor (k) $\leq$ max limit of class 'C' 75%
- Constraint #7: Class C item's Safety factor (k) $\geq$ min limit of class 'C' 67%
- Constraint #8: Total cost of safety stock $\leq$ New budget value \$1,200,000

Sensitivity analysis on the relationship between cycle service level and cost of safety stock when the demand of lead time changes (increases/decreases) by one week is shown in Figure 4. Figure 5 also demonstrate the sensitivity analysis on the relationship between cycle service level and total value of item short when the demand of lead time changes (increases/decreases) by one week.



Figure 3. Cost of safety stock vs cost of item short for all three scenarios



Figure 4. Sensitivity analysis on the relationship between cycle service level and cost of safety stock when the demand of lead time changes (increases/decreases) by one week

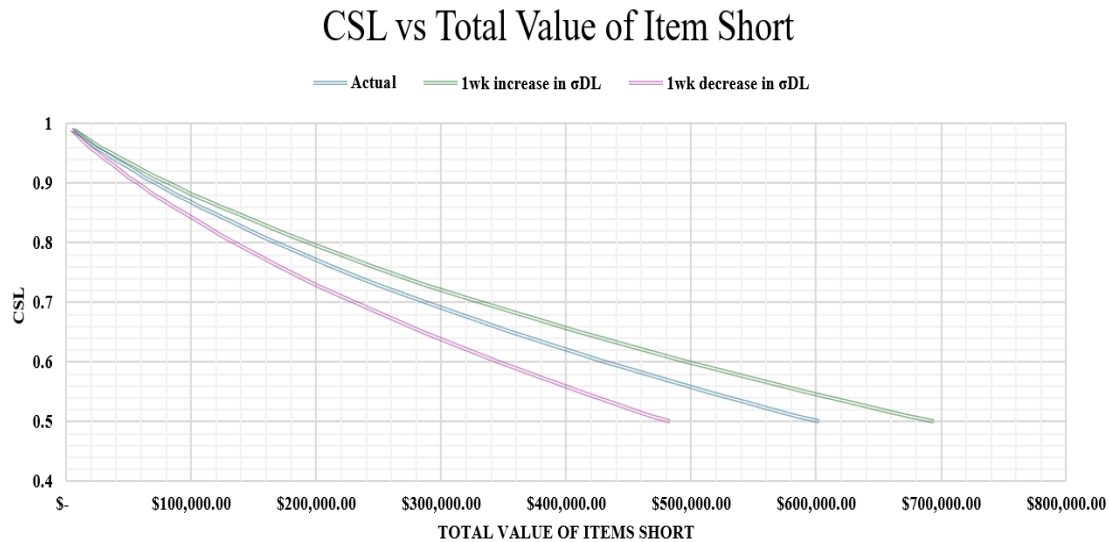


Figure 5. Sensitivity analysis on the relationship between cycle service level and total value of item short when the demand of lead time changes (increases/decreases) by one week

6. Conclusion

In this paper, three different scenarios were proposed to deal with the safety stock adjustment problem while considering a dynamic adjustment system with focus on balancing the service level targets and financial constraints while there are multiple items. Among all three proposed scenarios, scenario#3 was considered as the most beneficial approach. Scenario #3, utilizing ABC classification and linear programming, redistributes cycle service level values based on budget limitations while prioritizing SKUs according to their classification. By integrating ABC classification with linear programming, businesses are empowered to optimize inventory levels, prioritize high-value items, and adapt to budget fluctuations in real time. This approach ensures that resources are allocated efficiently, focusing on high-value items that contribute most to the company. The linear programming approach, known for its speed and computational efficiency, further enhances the practicality and adaptability of systems to real-world scenarios. A user-friendly interface has been developed to enable managers to experiment with different budget scenarios and observe their impact on inventory levels and service levels. This interactive capability fosters a collaborative environment where data-driven insights and human expertise converge to make informed decisions. This study has provided a practical tool that can be readily implemented by businesses without the need for specialized expert knowledge. The dynamic safety stock adjustment system, integrating ABC classification and linear programming, represents a significant step forward in balancing service level targets with financial constraints, ultimately leading to improved inventory performance and enhanced profitability.

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Biographies

Sachin Sivankutty joined San Jose State University (SJSU) as a Master's Student in Industrial and Systems Engineering Program in the Department of Industrial and Systems Engineering in 2022. He has over eight years of experience in Supply Chain Analytics. Prior to joining SJSU, he worked for IQVIA as a software engineer for more than one year. He was also planning engineer for a cable manufacturing company, National Cables Industry for more than 5 years in UAE. He earned his BS in Electrical and Electronics Engineering from Cochin University of Science and Technology in India. His research interests include Operations Research, Optimization, Mathematical Modeling and Linear/Non-Linear Programming, Lean Manufacturing and Enterprises, Supply Chain Planning, Operations and Productions Planning, and Data Analytics, Multi-Criteria Decision Making. He has done research projects using SQL, R studio, and Python. He is holder of Production and Inventory Management (CPIM) certificate and Lean Six Sigma Green Belt.

Dr. Behin Elahi is an Associate Professor in Industrial and Systems Engineering at San Jose State University (SJSU). Prior to joining SJSU, she was Associate Professor at Purdue University, Fort Wayne (2016-2023). She received her Ph.D. in Industrial Engineering from the University of Toledo in 2016 and holds a master's degree in the same field. She was a consultant and project manager of the Business Waste Reduction Assistance Program (BWRAP), a partnership between the Environmental Protection Agency (EPA), University of Toledo, and Lucas County in Ohio (2012-2016). Her research interests include application of robotics and virtual reality in manufacturing systems, human-robot interaction and collaboration, data mining, machine learning & deep learning, optimization of healthcare systems, operations research, decision making algorithms, supply chain optimization, lean manufacturing, water quality assessments, modeling and simulation of complex systems such as healthcare systems and automated manufacturing systems. Dr. Behin Elahi has published one book, three book chapters, and more than 35 research articles. She consistently strives to secure internal and external research funding, having successfully obtained nine grants from external funding agencies and three internal grants. As a Co-Principal Investigator, she has secured \$600,000.00 NSF grants for a research project in Human-Robot interaction and collaboration. She serves as the senator representing college of engineering. She devoted much effort to serving students and the professional society. Her research engaged with students resulted in SJSU Research, Scholarship, and Creative activities (RSCA) fellowship. She is currently the faculty advisor for 26 master's students from Industrial and Systems Engineering and Engineering Management programs at SJSU. She has established Human-Robot Interaction and Collaboration (HRIC) Research Lab at SJSU.