



A Study on Determining the Appropriate Target Inventory Levels for Consignment Machining Tools in a Glass Manufacturing Plant

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Abstract

Background and Aims: In glass manufacturing, effective inventory control of consignment machining tools is critical due to their high value and the operational risk of stockouts. However, in practice, such control is often overlooked, leading to high inventory-related costs. This study addresses a gap in the literature by focusing on the development of a simulation-based framework for determining optimal target inventory levels for consignment machining tools—a topic with limited prior research in the glass manufacturing context. The research specifically aims to (1) classify inventory items using established techniques and (2) identify cost-effective inventory control parameters that maintain desired service performance under consignment conditions.

Methodology: The study applied the Pareto-based ABC classification to prioritize inventory items by consumption value, reflecting their operational criticality. Two representative items from Category A—with contrasting demand profiles—were selected for further analysis. A simulation model was developed under a periodic review system to determine optimal target inventory levels and review intervals, incorporating key real-world constraints such as urgent shipment costs due to stock-out. ABC was chosen for its proven effectiveness in prioritizing inventory management efforts, while simulation was used to address the system's complexity and demand variability, which are typical in machining tool consumption patterns.

Results: Simulation findings revealed that no universal formula could determine optimal settings; instead, parameters must be tailored to individual items. Frequent inventory reviews reduced safety stock needs but increased transportation costs, while less frequent reviews required more inventory to sustain high service levels. The simulation demonstrated that appropriate tuning of these parameters could yield measurable benefits—for example, reducing total inventory costs by up to 50% compared to the plant's prior unmanaged system, while achieving over 95% service levels in critical tools.

Conclusion: Simulation is an essential tool for designing inventory policies in complex consignment contexts where demand variability and supplier ownership create unique challenges. The framework developed here is adaptable and can be applied to other manufacturing





environments that rely on high-value consumables. Future research should extend the model to broader product sets or explore dynamic control policies responsive to real-time conditions.

Keywords: Simulation; Target Inventory Level; Consignment Stock; Service Level; Pareto

Introduction

The glass manufacturing industry plays a significant role in many national economies, including Thailand, which has developed a strong base across packaging, architectural, and industrial-use glass production (The Department of Science Service, 2025). Amid increasing global competition and rising production costs, effective cost control, production planning, and inventory management have become essential to sustaining competitiveness. In particular, the management of machining tools—especially those used for fabricating and maintaining glass-melting molds—illustrates a classic inventory management challenge: balancing the high holding cost of specialized tools against the even higher cost of stockouts that can halt production. These tools are critical to ensuring continuous, high-quality output, and poor inventory control can lead to production delays and increased operational costs. This aligns with foundational inventory theories, which emphasize the trade-off between inventory carrying costs and service-level objectives.

This study focuses on a consignment inventory model in which machining tools—such as carbide end mills, reamers, and drills—are stored at the plant but remain under supplier ownership until use (Sarker, 2014). While this model supports improved cash flow and procurement flexibility, it also introduces challenges in inventory optimization. Consignment inventory falls under the broader umbrella of collaborative inventory strategies, such as Vendor Managed Inventory (VMI), which aim to enhance coordination between suppliers and manufacturers. Literature highlights several theoretical advantages of such models, including risk pooling, improved service levels, and mitigation of the bullwhip effect (Simchi-Levi et al., 2008). Overstocking leads to unnecessary storage and logistics costs, while understocking risks disrupting production. Effective management of consignment inventory is therefore not only operationally important but strategically necessary. Inefficiencies in stock control can lead to financial losses and misalignment with actual production needs.

According to internal data from the case study, frequent stock review led to excessive replenishment costs. Instead of aligning replenishment with actual consumption patterns, materials were restocked on a weekly basis, resulting in inefficient logistics operations and increased operational expenses. Additionally, replenishment quantities sometimes failed to reflect actual demand, resulting in urgent shipments. These issues represent deviations from fundamental inventory management objectives, particularly the aim of maintaining a target





service level while minimizing total relevant costs, including holding, shortage, and ordering costs. To address these issues, the study aims to identify appropriate inventory levels for consignment machining tools within a glass manufacturing plant. ABC analysis is used to classify tools by usage value, grounded in Pareto's principle, which suggests that a small number of items typically account for the majority of inventory value, allowing focused control over the most impactful tools. Simulation techniques are applied to model demand fluctuations and tool shortages during production, a method theoretically suited for capturing the stochastic nature of demand and lead times—limitations often inadequately handled by traditional deterministic models. The goal is to enhance inventory efficiency, minimize excess stock, and reduce related storage and transportation costs.

While various inventory strategies have been widely studied—such as ABC/XYZ analysis (Pandya & Thakkar, 2016), simulation under demand uncertainty (Jung et al., 2004), and vendor-managed inventory in various environments (Marques et al., 2010)—limited research exists on consignment models, especially in specialized sectors like glass manufacturing. Although these prior studies provide valuable frameworks for general inventory classification and coordination, they often assume consistent consumption patterns, shorter lead times, or frequent order cycles—conditions that do not align with the operational realities of high-value, critical-but-intermittently-used consignment machining tools. The distinct usage variability and high replacement costs of machining tools introduce complexities not fully addressed by traditional approaches. This gap highlights the need for a tailored approach that incorporates both the strategic nature of consignment inventory and the stochastic behavior of tool consumption in a high-mix, low-volume manufacturing environment.

This research seeks to bridge that gap by applying a simulation-based approach to investigate inventory strategies for consignment machining tools. This study contributes a refined simulation framework that captures the irregular demand patterns and high inventory-related costs associated with consignment inventory of specialized tools, offering a methodology applicable to other high-value, low-turnover inventory settings. The findings are expected to offer practical insights for both practitioners and researchers, contributing to improved operational efficiency, cost control, and customer service performance—key factors for maintaining competitiveness in the glass manufacturing sector. The current research also contributes to the theoretical discourse on inventory management by illuminating the cost trade-offs and service-level considerations unique to consignment arrangements in capital-intensive manufacturing environments.





Objectives

The objectives of this study are:

1. To classify consignment machining tools using the 80/20 Pareto principle, based on usage value and frequency, to improve inventory management efficiency.
2. To determine optimal target inventory levels for consignment tools that balance inventory-related costs with service level requirements, ensuring tool availability while minimizing overstock and stockout risks.

Literature Review

1. The 80/20 Principle (Coyle et al., 2016)

Inventory management is crucial for optimizing operations, particularly in controlling costs and enhancing efficiency. The 80/20 principle, or Pareto Principle, is widely used in inventory analysis to prioritize items based on their importance. Introduced by economist Vilfredo Pareto, it suggests that 20% of items account for 80% of the inventory's value. In inventory management, this means that a small percentage of high-value items represent the majority of the total value, deserving more focused attention.

To apply the principle, businesses often use ABC Analysis, categorizing inventory into three groups based on value:

- Category A: The top 20% of items, making up 80% of the value.
- Category B: Moderate value items, representing around 30% of the inventory.
- Category C: Low-value items, often accounting for 50% or more of the inventory.

Focusing on Category A items allows for better resource allocation, faster response to customer needs, and improved operational efficiency.

In the context of glass manufacturing, particularly for machining tools used in mold maintenance and fabrication, the 80/20 principle remains relevant. A small subset of specialized tools—such as high-performance reamers or carbide end mills—may represent a limited portion of the total tool types in use but have a disproportionately large impact on production continuity and cost if unavailable. When applied to consignment inventory, however, the valuation perspective in ABC analysis shifts: while ownership remains with the supplier, the operational risk and potential cost from stockouts are borne by the manufacturer. This necessitates adapting traditional ABC classifications to prioritize not just financial value, but also criticality to production. This distinctive ABC classification warrants further in-depth investigation in future studies.

2. Inventory Management (Water, 2003)

Inventory management involves the planning, control, and oversight of materials and goods to ensure operational efficiency while minimizing inventory costs. Its primary goal is to maintain





sufficient stock levels to meet demand without overstocking. Previous research (Olsson, 2019; Solari et al., 2024; Mesquita & Tomotani, 2022) has emphasized strategies for balancing inventory and ensuring smooth operations. However, when applied to consignment models—where inventory is owned by suppliers but stored at the manufacturer's site—the traditional principles of control and ownership must be adapted. In such cases, inventory policies require collaboration and clarity in responsibility between the supplier and buyer. The consignment arrangement is conceptually aligned with Vendor-Managed Inventory (VMI) and Supplier-Managed Inventory (SMI), which aim to enhance coordination while shifting some inventory management burdens to the supplier (Marques et al., 2010).

2.1 Inventory Control Policies

Effective inventory control policies are essential to align inventory levels with market demand. Companies that maintain excessive stock, especially of low-demand items, incur high holding costs, while insufficient stock of high-demand items leads to missed sales opportunities or shortage costs. Well-designed inventory control policies help mitigate these issues, ensuring businesses neither overstock nor run out of critical items. In consignment contexts, control policies are uniquely complex due to the split between ownership and operational responsibility. While the supplier may formally manage stock levels, the manufacturer bears the operational consequences of stockouts, such as production delays or equipment downtime. Therefore, clear control mechanisms and communication protocols are needed to manage these risks effectively.

2.2 Target Inventory Level

Setting an optimal target inventory level is fundamental to managing inventory effectively. This level is determined by considering factors such as customer demand, supply capabilities, and lead times. By accurately calculating the target inventory level, businesses can avoid overstocking, which leads to high holding costs, and understocking, which results in shortages. A variety of approaches exist for calculating target inventory, such as using average monthly sales figures or factoring in lead time for ordering goods. However, for consignment machining tools in the glass manufacturing context, some additional factors could be taken into account, for example, urgent shipment availability and reliability, tool life and usage rate, and losses due to tool unavailability. Moreover, the research in the future could consider some other relevant factors, such as historical tool consumption rates, preventive maintenance schedules, or production run forecasts.

2.3 Data Updates and Inventory Review

Maintaining accurate, up-to-date inventory data is crucial for effective decision-making. Inaccurate or outdated data can lead to significant errors in ordering, inventory management, and cost control. Technologies like ERP systems and automated inventory management tools facilitate





real-time tracking, ensuring the accuracy and timeliness of inventory data. These systems improve forecasting, reduce manual errors, and support precise ordering and inventory replenishment strategies.

In a consignment setup, the effectiveness of such systems hinges on data-sharing mechanisms between the manufacturer and the supplier. Real-time visibility and mutual access to inventory status, consumption rates, or even production plans are essential for timely replenishment. Key success factors are trust, information sharing, and collaboration. An intensive literature review on this issue can be found in Mandaviya (2017).

3. Customer Service

Customer service levels are key indicators of inventory system performance, reflecting metrics like on-time delivery, order fulfillment, and stock availability. Chopra (2020) highlights two common formulas:

- Service Level = Probability that demand \leq beginning inventory
- Service Level (or fill rate) = $1 - (\text{Unfulfilled items} / \text{Total order quantity})$

In the context of consignment-based machining tools used within a glass manufacturing facility, such tools are classified as MRO (Maintenance, Repair, and Operations) items. Although not directly involved in the production process, MRO items are vital to maintaining uninterrupted operations. Accordingly, evaluating the performance of MRO inventory requires consideration of various indicators, including inventory turnover rate, mean time to repair (MTTR), value of obsolete inventory, and stockout rate (Tractian, 2025). Furthermore, both service level and fill rate are applicable metrics within the MRO inventory context. While the service level is particularly useful for determining appropriate levels of safety stock, the fill rate serves as a measure of responsiveness—indicating how quickly maintenance needs can be fulfilled from existing inventory.

4. Simulation Techniques (Law, 2024)

Simulation techniques use mathematical models to replicate real-world processes, helping managers anticipate the outcomes of different decisions. These techniques allow businesses to test various scenarios without the need for costly and time-consuming real-world experiments. Simulation can be classified into two main categories:

- Static Simulation: Analyzes systems that remain unchanged over time, ideal for assessing current conditions or steady-state scenarios.
- Dynamic Simulation: Used to model systems that evolve, helping predict long-term effects of decisions and analyze processes that change.

Simulation plays a crucial role in optimizing inventory control systems by helping businesses forecast product demand and adjust stock levels accordingly. It allows managers to test different





stock planning scenarios and calculate appropriate inventory levels to avoid shortages or excess stock. Studies by Solari et al. (2024) and Mesquita & Tomotani (2022) have demonstrated how simulation techniques can enhance inventory management efficiency by predicting demand fluctuations and informing stock ordering strategies.

In the context of consignment machining tools in a glass manufacturing setting, simulation techniques provide a valuable framework for analyzing complex variables such as stochastic production demand and supplier lead time variability. These factors are particularly important for high-value, low-frequency-use tools where stockouts may cause significant production downtime. Simulation allows managers to test alternative inventory policies—such as varying reorder points or minimum stock thresholds—under different production conditions, supplier behaviors, and contractual terms of the consignment model. Moreover, it helps identify trade-offs between service levels and implicit holding costs (such as storage space, administrative effort, and coordination burden) borne by the manufacturer despite not owning the inventory.

Conceptual Framework

This study adopts an applied research and case study approach, focusing on a single glass manufacturing plant to determine optimal inventory levels for consignment machining tools. The case study methodology is well-suited for exploring complex, real-world operations phenomena in depth, particularly when boundaries between the phenomenon and context are not clearly evident (Yin, 2018). It allows for detailed examination of inventory practices under specific constraints, such as supplier agreements and urgent shipment with extra costs, offering insights that may contribute to theory refinement in operations management.

To address the research objective, the study integrates mathematical modeling and simulation techniques. A Mathematical model provides a structured and often simplified foundation for estimating initial target inventory levels. These models are grounded in classical inventory theory, offering deterministic insights based on factors like demand, holding cost, and lead time. However, real-world settings—especially in specialized industries like glass manufacturing—exhibit complexities such as demand variability which are difficult to capture fully through analytical models alone. Therefore, simulation is employed as a complementary method, allowing for the modeling of system dynamics, testing of “what-if” scenarios, and refinement of inventory policies under uncertainty (Law, 2024).

The primary conceptual framework for this research is illustrated in Figure 1, which outlines the flow of the research process. Key stages include:

1. Data collection from historical usage records and inventory logs,



2. Classification of tools using ABC analysis, grounded in Pareto's Principle, which asserts that a small number of items often account for the majority of value in a system (Coyle et al., 2016),
3. Purposive selection of two consignment tool samples from Group A, representing high-value, high-priority items,
4. Application of a mathematical model to obtain initial estimates of target inventory levels, and
5. Use of simulation modeling to refine and validate the optimal consignment inventory levels based on performance metrics such as service level (fill rate) and holding cost impact.

The study deliberately limits its scope to the determination of optimal inventory levels for consignment tools and does not address interrelationships between multiple inventory drivers or broader supply chain concerns. This focused approach allows for a deep and tractable investigation into a core operational problem: maintaining high service levels for critical tools while minimizing inventory-related costs under a consignment agreement. The exclusion of wider system interactions is acknowledged as a deliberate scoping decision, with implications for future research.

By focusing on consignment inventory, this research contributes to the theoretical understanding of risk-sharing and collaboration between manufacturers and suppliers, as consignment arrangements shift working capital burdens while requiring high levels of coordination and data transparency. The outcomes are expected to provide practical recommendations for businesses aiming to optimize inventory strategies under similar high-value, supplier-owned inventory settings, while also advancing scholarly discourse on inventory control in hybrid ownership models.

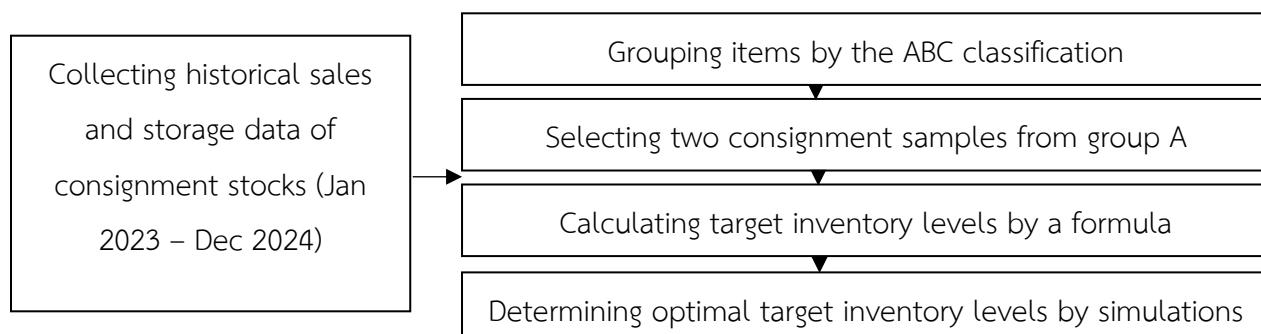


Figure 1 Research Framework

Methodology

1. Research Design

This study adopts an applied research design using a single case study approach, aiming to solve a practical operational problem within a real-world context. The focus is on a glass





manufacturing plant that utilizes consignment-based machining tools, making it an appropriate and information-rich case for detailed investigation.

The case study method is selected for its strength in exploring contemporary phenomena in depth, particularly when the researcher has limited control over events and when the boundaries between the phenomenon and context are complex or blurred (Yin, 2018). This plant was chosen due to its well-documented production processes, availability of historical tool consumption and inventory data, and the presence of an active consignment agreement with a tool supplier—factors that support rigorous empirical analysis.

By focusing on a single, context-specific case, the study aligns with the purpose of applied research: to develop practical, contextually relevant solutions that can inform decision-making within the organization while contributing insights that may be transferable to similar industrial settings.

2. Consignment Samples

The research is conducted within the context of a single case study involving a glass manufacturing plant. The consignment inventory—comprising over 500 machining tool items—is first categorized using the ABC principle, which ranks items by their consumption value to prioritize management focus. Based on this classification, Group A consists of high-value items that contribute disproportionately to total usage costs and are therefore critical to operational continuity.

From Group A, two representative products are purposively selected for in-depth analysis. The selection is based on their contrasting usage behavior, aiming to capture a broad range of consumption patterns within the high-value group. Specifically:

- One product exhibits high and stable usage frequency, with low demand variability.
- The other shows intermittent usage with high variability, often linked to specialized or irregular production tasks.

These two products are selected to represent the extremes of usage behavior in Group A, allowing the study to explore how different demand patterns influence inventory strategy under consignment arrangements. By analyzing both stable and variable items, the research seeks to develop insights into how inventory policies might be tailored across usage profiles.

While the findings are centered on these two extremes, they may provide indicative guidance for other Group A items with more moderate usage characteristics, although such generalization is treated with caution. This focused sampling strategy enables a manageable scope while ensuring relevance to the plant's most critical tooling needs.





3. A mathematical model

To estimate the initial target inventory levels (T) for consignment machining tools, this study applies a modified version of a periodic review inventory model, which is well-suited for environments where inventory is reviewed and replenished at regular intervals. The adapted formula for this particular context is as follows:

$$T = (D)(W_{R+L}) + k(\sigma_{R+L})$$

Where:

- D = Average daily demand on days when withdrawals occur (units)
- W_{R+L} = Expected number of withdrawal days within the review period plus lead time (days)
- R = Review period (days)
- L = Supplier lead time (days)
- k = A positive integer safety factor
- σ_D = Standard deviation of the daily demand series observed over multiple $R+L$ periods
- σ_{R+L} = Standard deviation of D during period $R+L$ ($\sigma_{R+L} = \sigma_D \{W_{R+L}\}^{1/2}$)

This model is modified from the (R, S) periodic review system (Silver et al., 2016), where orders are placed every R days, and stock is replenished up to the level S , calculated based on expected demand during the protection period (review period plus supplier lead time) and a safety stock term.

Clarification of Components:

- The term $(D)(W_{R+L})$ estimates expected total demand during the protection period, but it is calculated only over the days where actual withdrawals occur—this approach reflects the non-continuous, event-driven nature of tooling demand, which is common in machining operations.
 - W_{R+L} is not equal to $R+L$; rather, it reflects how many of those $R+L$ days are active usage days (i.e., tool withdrawals occur). This better accounts for sporadic usage patterns typical of some machining tools.
 - The standard deviation term σ_{R+L} is defined as the standard deviation of demand over period $R+L$, derived from historical consumption data. This is consistent with conventional safety stock theory, which uses variability in cumulative demand during lead time to buffer against uncertainty (Chopra, 2020).





This formulation provides a pragmatic balance between analytical rigor and practical applicability for real-world consignment environments, where usage may be intermittent and visibility into actual consumption is more granular than with finished goods.

4. Simulation experiments

This study uses simulation experiments to determine optimal inventory policies for consignment machining tools by systematically varying two key input parameters from the inventory model:

- Review Period (R): This is the interval at which inventory levels are reviewed and replenished. It forms part of the protection period R+L.
- Safety Factor (k): A multiplier applied to the standard deviation of demand over the protection period to account for demand variability and service level targets.

These parameters influence the target inventory level (T), calculated using the formula:

$$T = (D)(W_{R+L}) + k(\sigma_{R+L})$$

Simulation is performed under two distinct demand pattern scenarios:

- Stationary Demand: Represents consistent tool usage over time.
- Lumpy Demand: Captures intermittent, irregular withdrawal patterns.

For each scenario, the simulation model evaluates total inventory costs, which include:

- Holding Costs: Based on the interest of carrying inventory.
- Normal Ordering Costs: Costs incurred when replenishment is done during regular review.
- Urgent Ordering Costs: Expedited costs for emergency orders due to stockouts.

The objective of the simulation is to identify combinations of R and k that minimize total inventory costs while maintaining acceptable customer service levels (fill rate).

Service performance is measured by:

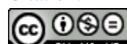
$$\text{Service Level} = 1 - (\text{Number of unfilled orders} / \text{Total number of orders})$$

In this context, the "customer" refers to the engineering department of the glass plant, and an "unfilled order" corresponds to instances where a machining tool is requested but not available. This internal service level metric provides a practical measure of inventory effectiveness in supporting uninterrupted working.

5. Data Collection and Analysis

This study uses secondary data sourced from a glass manufacturing plant operating under a consignment agreement. The dataset spans January 2023 to December 2024 and includes:

- Daily withdrawal records for all consignment items





- Inventory holding costs
- Normal and urgent ordering costs

To conduct the simulation analysis, two representative Group A consignment products were purposively selected:

- A1 (Stationary demand): High-frequency usage item with relatively stable demand
- A2 (Lumpy demand): Intermittently used item with irregular withdrawal patterns

These selections enable the model to capture a broad spectrum of demand behaviors found in the case study context.

Simulation experiments were implemented in Microsoft Excel under the following assumptions:

1. Historical withdrawal behavior is used as the basis for simulating future demand.
2. Demand modeling:
 - A1 follows a normal distribution, with parameters (mean and standard deviation) estimated from historical daily usage data.
 - A2 follows a compound stochastic process, where demand occurs 1–3 times per week. The inter-arrival pattern is generated using a discrete uniform distribution ($U[1,3]$ times per week), and the demand quantity per event follows a normal distribution with item-specific parameters.
3. Cost structure (holding, ordering, and urgent ordering costs) is derived and simplified from actual company data.
4. Lead time is assumed to be zero for simulation purposes. The lead time is assumed to be zero days, based on the plant's operational practice. Stock reviews are conducted on Friday evenings, the final working day of the week. Replenishment shipments arrive on Monday mornings, before working resumption. As Saturday and Sunday are non-operational days for the department, no withdrawals occur during this period. Therefore, the effective lead time experienced by the system is negligible, justifying the zero lead time assumption.
5. Initial inventory levels are set to match the target inventory levels calculated from the mathematical model, ensuring the system begins in a theoretically balanced state.
6. The safety factor (k) takes on values from 0 to positive integer numbers.
7. Review periods (R) are varied across five intervals: 5, 10, 20, 30, and 40 days.
8. System performance is assessed using:
 - Total inventory cost (holding + normal ordering + urgent ordering)
 - Service level = $1 - (\text{Number of unfilled orders} / \text{Total number of orders})$





If inventory is insufficient to meet demand, urgent replenishments are assumed to arrive instantly but incur a cost three times higher than standard replenishment, reflecting expedited administrative and logistics expenses.

This comprehensive methodology provides a robust foundation for analyzing the cost-efficiency and service performance of consignment inventory policies. The combination of historical data and controlled simulation scenarios offers practical insights into optimizing stock levels for critical items under dynamic demand conditions.

Results

1. ABC grouping

To establish effective inventory control priorities, the study first categorized all 505 consignment items using the ABC classification method, with the total sales value over two years (2023–2024) serving as the basis for classification. This approach is grounded in Pareto's Principle, which posits that a small proportion of items typically accounts for a disproportionately large share of the total value.

The classification results are summarized in Table 1. Items in Group A—comprising only 68 SKUs (13.5% of all items)—contributed approximately 78.94% of the total sales value. These items are typically characterized by higher unit prices and are issued in relatively large quantities, underscoring their strategic importance in inventory management.

In contrast, Group B and Group C items contributed 15.79% and 5.27% of the total value, respectively. Group C, which includes the largest number of items (317 SKUs), tends to consist of low-unit-price products. Despite their high issuance volume, these items collectively account for a small fraction of the overall sales value.

This classification provides a basis for differentiated inventory control strategies. In particular, Group A items warrant close monitoring and more sophisticated inventory policies, such as the simulation-based optimization conducted in this study.

Table 1 Results from the ABC classification.

Group	Items	Worth (Million Baht)	Percentage
A	68	23.0	78.94
B	120	4.5	15.79
C	317	1.5	5.27
Total	505	29.0	100.00





2. Simulation example (Stationary Demand Case)

To illustrate the mechanics of the simulation model, a scenario representing stationary demand (Product A1) was selected. In this case, demand occurs daily and follows a normal distribution with a mean of 10 units and a standard deviation of 2 units ($\sigma_D = 2$). The review period is set to 5 days, and the lead time is assumed to be zero, based on the department's operational routine, where stock reviews are conducted on Friday evenings, and replenishments arrive on Monday mornings, with Saturday and Sunday being non-operational days.

The key parameters used in this simulation are as follows:

- Product unit price: 300 Baht
- Normal ordering cost: 100 Baht per shipment
- Urgent ordering cost: 300 Baht per shipment
- Annual interest rate (for holding cost): 6%
- Review period (R): 5 days (Current practice)
- Lead time: 0 days
- Safety factor (k): 1 (baseline case)
- Standard deviation of demand during R+L (σ_{R+L}): $\sigma_{R+L} = 2 \times (5)^{1/2} \approx 4.47$ ($W_{R+L} = 5$)

The target inventory level (T) is calculated using the modified formula:

$$T = (D)(W_{R+L}) + (k)(\sigma_{R+L}) = (10 \times 5) + (1 \times 4.47) \approx 50 + 4.47 = 54.47 \rightarrow 54 \text{ (rounded)}$$

A simulation was run for 3,650 days to evaluate system performance under these parameters. Table 2 presents a portion of the simulation results for the first few cycles, highlighting beginning inventory, demand, ending inventory, orders placed, and associated costs.

Table 2 Partial Simulation Results for A1 (Stationary Demand, k = 1).

Day	Beginning Inventory	Demand	Ending Inventory	Order QTY	Shortage (Y or N)	Normal Order (฿)	Urgent Order (฿)	Product Cost (฿)	Interest (฿)
1	54.00	12	42.00	-	N	-	-	12,600.00	2.07
2	42.00	11	31.00	-	N	-	-	9,300.00	1.53
...
5	10.00	7	3.00	51.00	N	100.00	-	900.00	0.15
...
3650	16.00	10	6.00	48.00	N	100.00	-	1,800.00	0.30

Note: Only selected days shown for brevity. Full results available upon request.





The interest cost is calculated daily based on the ending inventory value using the formula:

$$\text{Daily Holding Cost} = \text{Ending Inventory} \times \text{Product Price} \times (\text{Annual Interest Rate}/365)$$

The summary of results from this simulation run is presented below:

• Target inventory level (T):	54 units
• Total cost:	114,821.92 Baht
◦Normal ordering cost:	73,000 Baht
◦Urgent ordering cost:	37,500 Baht
◦Holding cost (interest):	4,321.92 Baht
• Service level:	96.58%

These results demonstrate that the majority of inventory cost arises from ordering activities, particularly urgent shipments, which accounted for more than 30% of the total. This underscores the importance of adjusting the safety factor (k) to reduce urgent orders and improve cost-efficiency.

To examine this effect, the simulation was repeated under the same conditions while varying the value of k from 1 to 5. The results are summarized in Table 3.

Table 3 Simulation Results of A1 (Stationary Demand) under Different Safety Factors (k).

k	Total Cost (฿)	Normal Orders (฿)	Urgent Orders (฿)	Interest (฿)	Service Level
1	114,821.92	73,000.00	37,500.00	4,321.92	0.97
2	83,304.76	73,000.00	5,100.00	5,204.76	0.99
3	78,923.38	73,000.00	0.00	5,923.38	1.00
4	79,823.38	73,000.00	0.00	6,823.38	1.00
5	80,543.38	73,000.00	0.00	7,543.38	1.00

The optimal value of k = 3 yielded the lowest total cost (78,923.38 Baht), while also achieving a 100% service level and eliminating the need for urgent shipments entirely. Increasing k beyond 3 led to marginal increases in holding costs without further service improvement. Thus, k = 3 is considered the most cost-effective safety factor for this stationary demand scenario.

This simulation highlights the trade-off between ordering frequency, urgency of replenishment, and inventory holding costs, and provides actionable insights for optimizing inventory policies under stationary demand conditions.





3. Optimal target inventory level, T

This section investigates the optimal target inventory level (T) by systematically varying two key parameters: the safety factor (k) and the review period (R). The simulations were conducted under two demand scenarios—stationary and lumpy—to evaluate how these parameters influence total inventory cost and service levels.

3.1 General Case and Baseline Observations

Initially, simulations were run under a general baseline scenario based on the settings in Table 2, where the review period R was fixed at 5 days (current practice of the case study). The safety factor k was varied incrementally. As shown in Table 3, the total inventory cost reached its minimum value of 78,923.38 baht when k was set to 3. Values of k lower than 3 resulted in service levels dropping below 99%, which led to higher urgent shipment costs due to increased stockouts. Conversely, higher values of k elevated holding costs without providing additional cost savings.

This trade-off reflects the classical inventory control principle: while increasing k improves the service level by increasing safety stock, it also inflates holding costs. The cost minimum at k = 3 represents a balance between the penalty costs from stockouts and the burden of excess inventory.

3.2 Optimal Settings under Stationary vs. Lumpy Demand

To explore more realistic and varied scenarios, the simulation was extended to evaluate multiple combinations of k and R. Figure 2 illustrates the optimal k values for each review period. For stationary demand, the minimum total inventory cost of 39,071.35 baht was achieved at k = 2 and L = 20 days, with a service level of 99.95%. This suggests that under stable demand conditions, a moderately long review period with a modest safety factor is most cost-effective, representing a 50.5% saving, compared to the best of current practice (78,923.38 → 39,071.35).

In contrast, for lumpy demand, the optimal configuration occurred at k = 7 and R = 30 days, with a total inventory cost of 30,183.41 baht and a service level of 99.81% (also representing more than 50% saving, compared to the current practice of 5-day review). The results reflect the more irregular and unpredictable nature of lumpy demand, which necessitates greater safety stock and less frequent reviews to avoid costly stockouts. These findings suggest that systems facing sporadic, high-quantity demand patterns benefit from larger buffers and extended replenishment intervals.

While the author notes that increasing k generally enhances service levels and reduces stockout risk, it also raises holding costs. These observations are consistent with established inventory management theory (e.g., Silver et al., 2016), particularly for periodic review systems. The policy in this case closely aligns with an (R, S) structure, where R corresponds to the review period and T to the order-up-to level.



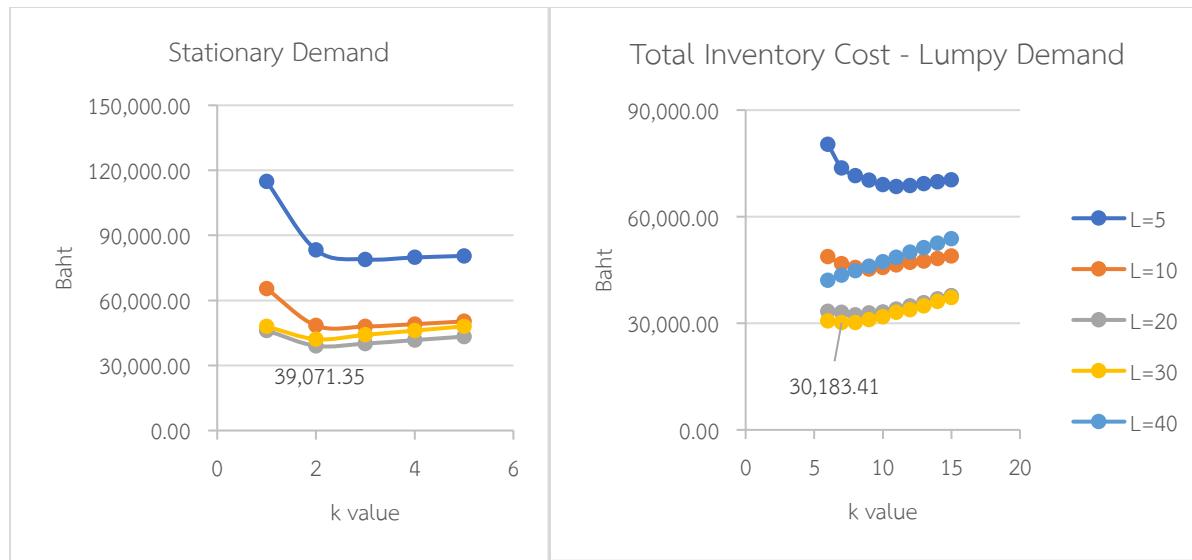


Figure 2 The k value at the optimal points for each number of L.

3.3 Impact of Demand Variability on Optimal k

The study further extended these optimal configurations by simulating changes in demand variability (standard deviation) to assess the sensitivity of the optimal k values under uncertainty. As depicted in Figure 3:

- For stationary demand, the optimal k remained constant at 2, even as demand variability increased. However, the total inventory cost rose steadily with higher variability, confirming the added cost burden of managing uncertainty.
- For lumpy demand, the optimal k exhibited a counterintuitive pattern: it decreased as demand variability increased. One possible explanation is that, in highly variable lumpy environments, holding large safety stock becomes inefficient due to the infrequency of orders. Instead, the system favors a lower safety factor and potentially relies more on responsiveness or flexible replenishment.

This result is particularly notable because it challenges the conventional expectation that higher variability should necessitate higher safety factors. Further investigation is warranted to assess whether this trend is context-specific or generalizable, particularly in systems with consignment stock or delayed replenishment signals.

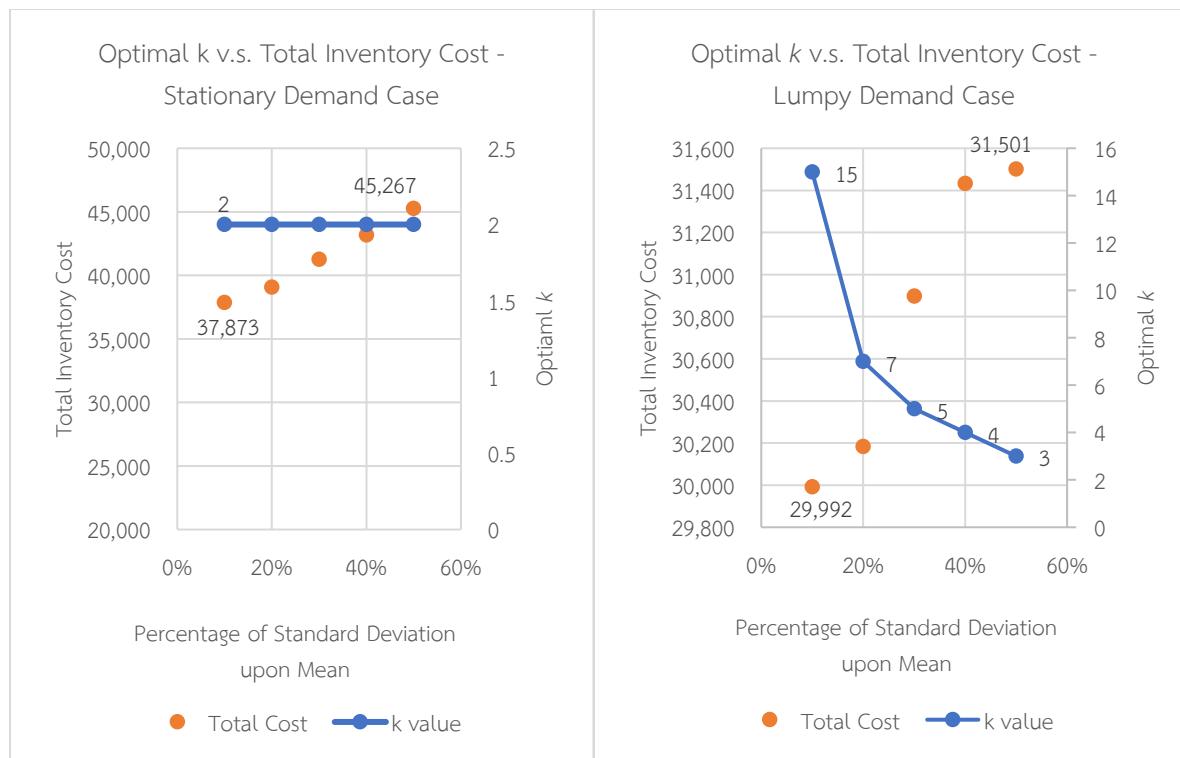


Figure 3 The k value at all optimal points and the related total inventory costs.

3.4 Summary of Key Observations

The simulation results confirm that:

- There is no one-size-fits-all value of k or R ; optimal settings depend on the demand profile.
- For stationary demand, a moderate safety factor with a mid-length review period minimizes cost.
 - For lumpy demand, higher k and longer review periods yield better performance.
 - Increased variability always raises total inventory costs, but its effect on the optimal safety factor differs between demand types.

While this section ends with the statement that the identified optimal values of R and k offer a practical solution for the case study, such judgments are better discussed in the concluding sections. Here, the focus remains on presenting the empirical relationships revealed by simulation.

Discussion

This study underscores the strategic value of ABC classification based on Pareto's 80/20 principle as an effective inventory management approach. By categorizing items according to their relative importance, organizations can allocate managerial and operational resources more



efficiently—applying rigorous controls for high-priority Group A items, while employing simpler methods for Groups B and C. This approach is particularly beneficial in managing consignment machining tools within the operational context of a glass manufacturing plant. Besides, categorizing items based on some other critical criteria beyond sales value might be applicable, for example, tool criticality and maintenance schedules. Because they can have an impact on production continuity. Such considerations ensure that managerial attention focuses on items whose availability most directly affects operational performance, consistent with the theoretical advantages of ABC analysis in prioritizing limited resources (Salazar et al., 2022).

Regarding the determination of optimal consignment stock levels, the results confirm that no universal inventory policy fits all circumstances. Effective strategies must be tailored to specific variables, including demand patterns, variability, product cost, desired service level, delivery expenses, and financial costs like interest rates. Simulation proved instrumental by enabling decision-makers to evaluate multiple scenarios, balancing inventory holding costs against service level objectives. This study's approach, which relies on a target inventory level policy within a periodic review system framework, complements the continuous review (Q, r) policy based on the Economic Order Quantity (EOQ) model employed by Salazar et al. (2022). Both studies converge on key insights: quantitative modeling and simulation are powerful tools for identifying cost-service trade-offs and optimizing inventory parameters despite differing control mechanisms.

The consignment inventory model itself adds a unique dimension to optimal stock level determination. Since ownership and associated risks are shared between the supplier and the glass manufacturer, this arrangement may influence acceptable inventory levels, potentially allowing for higher stock quantities without imposing full capital costs on the manufacturer. This dynamic can shift the traditional trade-off balance, warranting further investigation in future research.

The study also highlights the inherent trade-off between achieving near-perfect service levels and controlling inventory costs. The simulations reveal that attaining a 100% service level requires substantially higher inventory investment, increasing capital and holding costs. Conversely, accepting a minimal risk of stockouts leads to significantly lower costs but introduces potential operational risks. This cost-service trade-off echoes foundational inventory management theory, which balances stockout penalty costs against holding costs. In the context of a continuous glass production environment, stockouts of critical machining tools may cause costly line stoppages, amplifying the consequences beyond mere replacement costs. Therefore, decisions on service level targets must consider the operational impact of stockouts alongside financial costs.





Moreover, the consignment agreement may modify how these costs and risks are perceived and distributed between supplier and manufacturer. For instance, suppliers may absorb some stockout risks or provide more flexible replenishment terms, which could alter optimal inventory policies and economic outcomes. Future research could explore integrated models that incorporate qualitative stockout costs, service level penalties, or innovative consignment contracts to better capture these complexities.

In summary, this study confirms that tailored inventory policies, supported by simulation-based analysis and informed by ABC classification, can effectively manage consignment machining tool stocks in glass manufacturing. It also underscores the critical importance of balancing service levels and cost-efficiency within the operational and contractual context.

Recommendation

1. Recommendations for Applying the Research Findings

This study applied simulation techniques to analyze inventory control for consignment products in a specific case. To adopt similar practices, companies should consider the following:

1. Product-Specific Simulation

This approach aligns with the principle of differentiated inventory control, which tailors inventory policies based on individual item characteristics such as demand patterns, criticality, and usage frequency. Such differentiation is supported by inventory classification theories like ABC analysis. For example, machining tools in a single plant can vary widely in how often they are used and replaced, making a uniform inventory policy suboptimal. Each product should be simulated separately, considering its specific demand behavior and operational context, to determine appropriate inventory levels.

2. Key Influencing Factors

Several elements must be factored into simulations:

- Withdrawal Behavior: Patterns of use and demand variability.

This factor relates closely to demand forecasting theories, which are crucial for determining appropriate safety stock levels to buffer against variability.

- Service Level Policy: If a perfect service level isn't required, stock levels—and thus holding costs—can be reduced.

This reflects the fundamental inventory trade-off between holding costs and stockout costs. Different service level targets affect reorder points or target inventory levels (S) in periodic review systems, influencing the balance of inventory investment and service performance.

- Cost Structure: Include unit cost, shipping cost, frequency, interest rates, and tolerance for delayed deliveries.





These components are central in many inventory models, such as the Economic Order Quantity (EOQ) framework and its variants. Interest rates, as part of holding costs, directly affect the optimal inventory quantity by influencing capital cost considerations, even in consignment arrangements where ownership differs.

2. Suggestions for Future Research

This research focused on a periodic target inventory level approach. Future studies should explore alternative control models that may offer improved cost efficiency and flexibility, such as continuous review or adaptive policies with adjustable parameters. These approaches may optimize delivery planning and reduce total system costs without compromising service performance.

Continuous review policies—such as (s, Q) or (s, S) systems—are often more responsive to demand fluctuations compared to periodic review systems. This responsiveness can lead to lower average inventory levels for equivalent service levels, particularly for items with high demand uncertainty or criticality, which is typical for machining tools in manufacturing contexts.

Adaptive inventory policies dynamically adjust parameters such as reorder points and order quantities based on evolving demand patterns or cost structures. This feature is especially relevant for machining tools, where demand may shift due to changes in production schedules, product mix, or tool wear characteristics—a dynamic commonly highlighted in manufacturing inventory research.

Future research could also investigate hybrid inventory control models that integrate predictive maintenance data with inventory decisions, offering potential efficiency gains for high-value consumables like machining tools.

Moreover, exploring game-theoretic models to analyze and optimize interactions between the glass manufacturing plant (consignee) and the tool supplier (consignor) may provide insights into collaborative consignment inventory management. Such supply chain coordination frameworks could help achieve mutually beneficial inventory levels and cost-sharing arrangements, a topic increasingly discussed in consignment and supply chain literature.

References

Chopra, S. (2020). *Supply chain management: Strategy, planning, and operation* (7th ed.). Pearson.

Coyle, J., Langley, C., Novack, R., & Gibson, B. (2016). *Supply chain management: A logistics perspective* (10th ed.). Cengage Learning.



Jung, J. Y., Blau, G., Pekny, J. F., Reklaitis, G. V., & Eversdyk, D. (2004). A simulation-based optimization approach to supply chain management under demand uncertainty. *Computers & Chemical Engineering*, 28(10), 2087–2106.

Law, A. M. (2024). *Simulation modeling and analysis* (6th ed.). McGraw-Hill.

Mandaviya, M. (2017). Trust in supply chain integration: A review. *International Research Journal of Management Science & Technology*, 8(12), 371–384.

Marques, G., Thierry, C., Lamothe, J., & Gourc, D. (2010). A review of vendor managed inventory (VMI): From concept to processes. *Production Planning & Control*, 21(6), 547–561.

Mesquita, M. A., & Tomotani, J. V. (2022). Simulation-optimization of inventory control of multiple products on a single machine with sequence-dependent setup times. *Computers & Industrial Engineering*, 174, 108793. <https://doi.org/10.1016/j.cie.2022.108793>

Olsson, F. (2019). Simple modeling techniques for base-stock inventory systems with state-dependent demand rates. *Mathematical Methods of Operations Research*, 90(1), 61–76.

Pandya, B., & Thakkar, H. (2016). A review on inventory management control techniques: ABC-XYZ analysis. *Journal on Emerging Trends in Modelling and Manufacturing*, 2(3), 82–86.

Salazar, J., Salinas, E., Flores, A., Alvarez, J., & Hasachoo, N. (2022). Improving the level of service through an inventory management model for a spare parts marketing company. In *Proceedings of the 8th International Conference on Human Interaction and Emerging Technologies (IHET 2022)* (pp. 742–750). Université Côte d'Azur.

Sarker, B. R. (2014). Consignment stocking policy models for supply chain systems: A critical review and comparative perspectives. *International Journal of Production Economics*, 155, 52–67.

Silver, E. A., Pyke, D. F., & Thomas, D. J. (2016). *Inventory and production management in supply chains* (5th ed.). CRC Press.

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2008). *Designing and managing the supply chain: Concepts, strategies, and case studies* (3rd ed.). McGraw-Hill/Irwin.

Solari, F., Lysova, N., & Montanari, R. (2024). Perishable product inventory management in the case of discount policies and price-sensitive demand: Discrete time simulation and sensitivity analysis. *Procedia Computer Science*, 232, 1233–1241.

The Department of Science Service. (2025, May 2). *Interesting articles*. <http://otop.dss.go.th/index.php/en/knowledge/interesting-articles/138-2017-06-30-03-27-50>

Tractian. (2025). What is MRO? A guide to maintenance, repair, and operations. <https://tractian.com/blog/what-is-mro-guide-to-maintenance-repair-and-operations>

Waters, D. (2003). *Inventory control and management* (2nd ed.). John Wiley & Sons.



Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). SAGE Publications.

