Multi-level Safety Stock Synchronization and Inventory Optimization within a Multinational Consumer Goods Company

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ABSTRACT

Companies often determine safety stock requirements for each stage of their supply chain network using a siloed approach that overlooks the interdependencies between stages. This fragmented approach results in excess inventory and elevated holding costs. To address this problem, the Guaranteed Service Model (GSM) was selected—following a comprehensive literature review—for its ability to optimize safety stock allocation across an integrated, multi-stage network while minimizing inventory holding costs. The model's performance was evaluated across nine scenarios with varying holding rates and cost structures, and its robustness was validated through an analysis accounting for demand variability. The results demonstrate safety stock holding cost reductions between 20% and 38%, driven by the mitigation of the bullwhip effect, the pooling effect across products and locations, and the optimal safety stock allocation. The model offers potential for broader industry application and can be adapted and scaled to different products and network configurations. This research provides a solid foundation for transitioning from a single-echelon to a more efficient, integrated multi-echelon inventory management, enabling cost savings that can be reinvested in strategic initiatives to enhance overall supply chain performance.

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1. INTRODUCTION

In supply chain management, safety stock is a well-known term that refers to inventory that is held to protect against forecast errors and demand or supply variability. The purpose of this type of stock, also known as buffer stock or reserve stock, is to provide better customer service by reducing the frequency of stockouts (King & Bigler, 2021). Important consequences of incorrectly defining the safety stock level are product obsolescence and excess inventory, which results in a significant increase in the holding cost, or lost sales due to low safety stock that is unable to fulfill customer demands.

1.1 Motivation

The project sponsor (which will be referred to as "the company" throughout this paper) is a multinational consumer goods firm operating across five business units: Baby, Feminine and Family Care; Beauty; Health Care; Grooming; and Fabric and Home Care. One of the company's top priorities for 2025 is to optimize its inventory management and, more specifically, its safety stock management. Its supply chain is set up as a multi-echelon system which is formed by sourcing, manufacturing, and distribution processes. Currently, the company calculates its inventory level at each echelon independently; however, this approach has proved to be suboptimal and cost-ineffective, as it fails to consider the interdependencies among the various echelons within the supply chain (Eruguz et al., 2015). There is therefore room for improvement.

The company aims for high service level, efficient production setup, and competitive Cost of Goods Sold (COGS). However, its non-productive inventory accounts for about 25% of its total inventory value. For the company, non-productive inventory refers to excess inventory that cannot be sold due to network changes, new-product launch preparation, or demand changes. For this reason, the motivation for this project was to develop an approach for optimizing inventory levels and costs through the correct allocation of safety stock across the company's multi-echelon system.

The project focused on the European market for one of the company's flagship grooming brands. The product under study—**a pack of six razors**—was selected by the company due to its high sales volume and complex operational structure. Specifically, its multi-echelon supply chain offered a suitable basis for in-depth analysis. Further details regarding the supply chain structure are presented in Section 1.2.

1.2 Problem Statement

At present, the company holds safety stock at each material stage involved in razor production: raw materials, work-in-progress goods, and finished goods. Safety stock levels at each stage are determined using distinct approaches, with decisions made in isolation rather than through a coordinated, end-to-end supply chain approach. This fragmented approach frequently results in excess inventory, particularly stock that would not effectively contribute to improved service levels. Consequently, the company holds elevated levels of non-productive inventory, leading to increased holding costs stemming from storage requirements, capital immobilization, and the risk of obsolescence.

In addition, the product under investigation presented its own operational challenges. While the company possesses adequate long-term production capacity to fulfill overall demand, short-term capacity frequently falls short of meeting real-time requirements. To address the existing backlog and establish sufficient safety stock for future needs, the production facility must operate on a continuous basis.

Given this problem setting, we intended to address the following high-level research questions (RQs):

RQ1. For the product in scope, which approach should the company adopt to effectively determine safety stock levels across its multi-echelon supply chain—ensuring target service levels are met while minimizing costs?

RQ2. To ensure scalability, how can the proposed approach be adapted and applied to other products of the company?

RQ1 is addressed in Chapters 2 and 3, which examine relevant approaches from the existing literature and detail the implementation of the selected methodology. RQ2 is subsequently explored in Chapter 4 through a robustness analysis against demand uncertainty, aimed at evaluating the adaptability and scalability of the chosen approach within the context of this project.

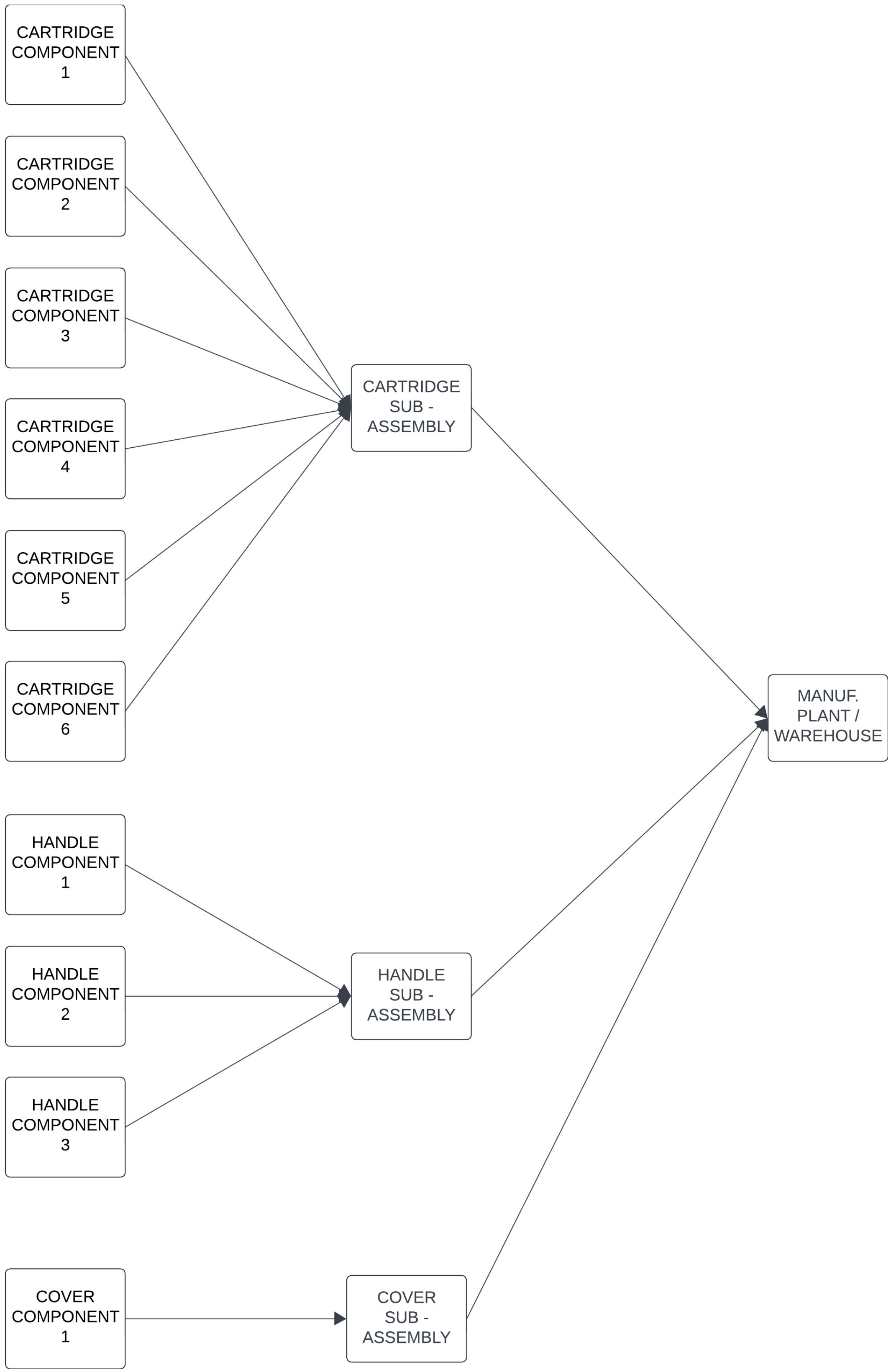
A clear understanding of the product's supply chain structure is essential for determining optimal safety stock levels across the various echelons of the network.

On the one hand, for the upstream segment of the supply chain, three hierarchical levels were considered, as illustrated in Figure 1. The first level includes the individual components required for sub-assembly production. The second level involves the sub-assemblies themselves—cartridge, handle, and cover. The third level represents the manufacturing plant and warehouse, where the final assembly occurs and finished goods are stored.

The company emphasized the importance of determining optimal safety stock quantities at the component and sub-assembly levels, rather than specifying physical stocking locations. As a result, components and sub-assemblies were modeled as virtual nodes within the supply network. To streamline the analysis and focus on high-impact areas, further upstream components were excluded based on two criteria: their relatively low contribution to overall product value and the limited availability of reliable data necessary for robust modeling.

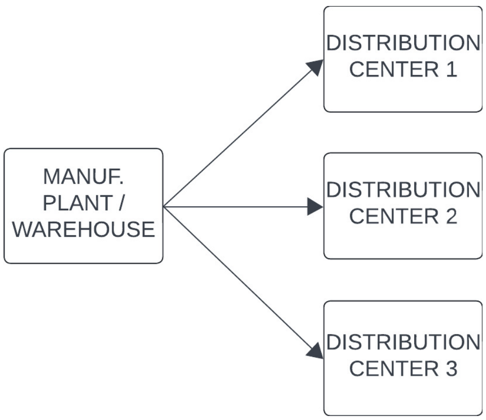
Furthermore, it was essential to account for the composition of the finished product. As an illustrative example, a razor consists of three primary sub-assemblies: one cartridge, one handle, and one cover. The cartridge itself requires several components, such as three blades and two clips, among others. As such, the Bill of Materials (BOM) serves as a key input to determine the component ratios necessary for assembly. These ratios are critical when optimizing the allocation of safety stock across the supply network.

Figure 1. *Illustration of upstream segment of the supply network for the product in scope*



On the other hand, regarding the downstream segment of the supply network, this study focused on three distribution centers, as depicted in Figure 2. These nodes were selected based on their strategic importance as primary distribution points for the product in scope. Despite this specific focus, the proposed approach was designed with sufficient flexibility to accommodate alternative finished goods flows by adjusting the connectivity between nodes, thereby allowing for broader applicability across different supply network configurations.

Figure 2. *Illustration of downstream segment of the supply network for the product in scope*



1.3 Scope: Project Goals and Expected Outcomes

The main objective of this project is to support the company in improving its inventory management practices, with a specific focus on safety stock optimization. To accomplish this, it was necessary to leverage an approach to determine optimal safety stock levels across the supply chain for the product in scope while reducing inventory-related costs and guaranteeing a target service level.

In this context, the principal deliverable to the company is a decision-support approach that provides supply chain managers with optimal safety stock levels for each echelon of the supply chain. This will enhance resource efficiency and release cash flows, which can be redirected toward other strategic business initiatives.

The remainder of this project is structured as follows. In Chapter 2, we conduct a comprehensive literature review of potential approaches that can be applied to address the problem at hand. Next, in Chapter 3, we outline the chosen methodology, along with the explanation of the data processing approach. Then, in Chapter 4, we present the results obtained from testing the proposed approach under multiple scenarios, including an analysis to assess its robustness and adaptability against demand uncertainty. Finally, in Chapter 5, we summarize the project's key points, provide recommendations, and suggest directions for future research.

2. STATE OF THE PRACTICE

To address the previously defined problem and objective of this project, a comprehensive literature review was conducted with two aims: first, to identify established methodologies employed to solve comparable inventory optimization problems; and second, to evaluate the applicability of these methodologies to the company's specific context and determine the most appropriate one.

The literature review served as the theoretical foundation which, when integrated with both quantitative (e.g., BOM, lead times, demand parameters) and qualitative (e.g., interviews with key stakeholders) inputs gathered from the company, enabled the development of a tailored solution to address the inventory management challenge under investigation.

2.1 Single vs. Multi-Echelon Inventory Optimization

In a multi-echelon system, each of the stages included within it represents a potential location for holding safety stock. There are two approaches for determining the amount of stock to allocate at each stage: the **single-echelon inventory optimization (SEIO)** approach, and the **multi-echelon inventory optimization (MEIO)** approach.

On the one hand, the **SEIO** approach considers each stage as an isolated entity and seeks to minimize costs independently at each stage. In other words, it ignores the interdependencies between suppliers and customers (Achkar et al., 2024). As noted by Eruguz et al. (2015) and Chu et al. (2015), this approach results in poor customer service levels and non-cost-optimal solutions. This is the approach currently employed by the company.

On the other hand, the **MEIO** approach considers all the stages simultaneously to get optimal inventory levels and their allocations across the network. According to Gartner (2016, as cited in Achkar et al., 2024), this approach has enabled companies to reduce their inventories by up to 30% and improve item availability by up to 5%. Also, Aberdeen Group (2012) mentions that deploying a MEIO approach enables companies to improve their service level by 3.1% and reduce their cash-to-cash cycle by 15%. However, Achkar et al. (2024) indicate that MEIO is a challenging task due to the non-linear objective function and decision variables impacting more than one stage.

In the literature, there are several methodologies that fall under the MEIO approach. Chu et al. (2015) propose a simulation-based model to optimize multi-echelon systems where the (r, Q) inventory policy is used for each node. The primary outcomes measured are the inventory cost and the service level quantified by fill rates, and the solutions are validated using statistical tests to find a local optimal solution. Aahron et al. (2009) propose the use of the Globalized Robust Counterpart (GRC) method to decrease costs and control the bullwhip effect in serial supply chains. An important limitation of this method is that it relies on deterministic inputs and does not account for any type of uncertainties. Geevers et al. (2024) propose the use of a Proximal Policy Optimization (PPO) algorithm, a deep reinforcement learning approach, to minimize holding and backorder costs in three different multi-echelon inventory systems: serial, distribution and general.

2.2 Stochastic vs. Guaranteed Service Models

In addition to the emerging and less-established methodologies outlined above, we found that there are two main methodologies commonly applied to MEIO: the **Stochastic Service Model (SSM)** and the **Guaranteed Service Model (GSM)**. These two methodologies differ primarily in how they address service times and demand variations. Since their creation, more than 50 years ago in both cases, a vast amount of research has been carried out and multiple extensions have been developed to tackle some of their original limitations, as demonstrated by the work of Graves and Willems (2008), Humair et al. (2013), Sitompul et al. (2008), and Grahl et al. (2014), among others.

The **SSM** assumes that each stage deals with demand uncertainty by using inventory only. When there is unsatisfied demand, it will be backlogged and, therefore, stochastic delays will ultimately affect the replenishment time for the downstream stages (Li and Wu, 2018). Thus, the replenishment time is a key component for determining the inventory to keep at each stage to meet the targeted service level (Eruguz et al., 2015). The SSM also assumes that the system behaves the same under all demand conditions. In other words, each stage operates under a consistent policy regardless of whether inventory is available or a stock-out occurs (Graves and Willems, 2003). In addition, according to Diks et al. (1996), Axsäter (2003), and Simchi-Levi and Zhao (2012), the SSM approach is more appropriate for serial, assembly, and distribution network structures.

In contrast, the **GSM** assumes that each stage can use measures, such as overtime production or subcontracting, to fulfill demand that exceeds prespecified demand bounds, so that it can always satisfy the deterministic service time commitment. GSM's aim is determining the best service times that minimize costs and inventory levels while meeting the service requirements for the customers. A critical point is that the GSM assumes that outside measures are always available to address demand or supply uncertainties, but it does not address which measures to use or how to use them (Graves and Willems, 2003). Research on the GSM approach has attracted increased interest in recent years, mainly due to its computational efficiency for optimizing a multi-echelon system (Eruguz et al., 2015).

The company emphasized the critical importance of maintaining its targeted service level to avoid potential sales losses, reputational damage, and erosion of market share, as consumers may shift their preference toward competitors' products. Consequently, it is essential to adopt an approach that ensures the required service level while optimizing costs and inventory levels. Based on insights from the literature and considering the complexity of the company's multi-echelon supply chain, the GSM was selected as the most suitable methodology. Although alternative multi-echelon inventory models provide valuable frameworks, they often require extensive computational resources or lack the ability to incorporate service time constraints. In contrast, the GSM offers a practical approach that addresses these two limitations, making it well-suited for determining optimal safety stock allocation across the company's multi-echelon network.

3. METHODOLOGY

This chapter provides an extensive overview of the Guaranteed Service Model, detailing its mathematical formulation, underlying assumptions, input requirements, and data processing approach. The model was implemented in Python, with the code designed for flexibility and scalability in alignment with the company's needs. It generates the outputs outlined in Section 3.4.

3.1 GSM Mathematical Formulation

The GSM is a mixed-integer programming model that is used to define inventory allocation while minimizing the overall safety stock costs, given that each upstream echelon must supply the downstream echelons while meeting a targeted service time (Moncayo–Martínez and E. Mastrocinque, 2024 & Eruguz et al., 2015). This model considers the supply chain as a network where different stages are represented as nodes (*N*) and flows from upstream to downstream nodes are denoted as arcs (*A*). In this model, inventory can potentially be held at any of the nodes.

The GSM formulation is based on several assumptions. First, the stage time T_i at each node $i \in N$ is known and constant. It represents the time to process, convert, and transport the components that will be used in the next downstream node(s). Second, it is assumed that the production lead-time is independent from the order size, and that capacity is unlimited. Third, all nodes are assumed to use the same review period (r_i) and the same base-stock replenishment policy. Fourth, demand parameters—mean and standard deviation—are assumed to only occur at the furthest downstream nodes of the supply chain. Finally, mean demand is assumed to be an independent and identically distributed (i.i.d.) variable.

Based on these assumptions, the GSM can be formulated as follows:

$$min \sum_{i \in N} \alpha C_i z \sigma \sqrt{\tau_i} \tag{1}$$

Where:

$$\tau_i = SI_i + T_i + r_i - S_i \tag{2}$$

Subject to:

$$SI_i + T_i + r_i - S_i \geq 0, \qquad \forall\, i \in N, \qquad (3)$$

$$SI_i \geq S_k, \qquad \forall\, (k,i) \in A, \qquad (4)$$

$$S_i \leq E_i, \qquad \forall\, i\!: \nexists j \in N \,|\, (i,j) \in A, \qquad (5)$$

$$S_i \geq L_i, \qquad \forall\, i \in N \qquad (6)$$

$$S_i, SI_i \geq 0, \qquad \forall\, i \in N \qquad (7)$$

The GSM objective function, as defined in Equation **(1)**, aims to minimize the total safety stock cost across all supply chain nodes. Here, α represents the holding cost rate per unit of inventory per time period, which is defined by the company. C_i denotes the cumulative cost of the final product up to node *i*.

The company's target service level is represented by *z*. It represents the probability of not hitting a stock-out during lead time, therefore higher service levels (e.g., 95%, 99%) reduce the risk of stock-outs but increase safety stock level and cost. This probability is then converted into a z-score using the standard normal distribution.

The standard deviation of the demand, denoted by σ, quantifies the variability or uncertainty in demand over a given period. Higher variability necessitates a higher amount of safety stock to maintain the desired service level and buffer against potential stock-outs.

The net replenishment time (τ_i) is the effective lead time available to node *i* for inventory replenishment and production activities, accounting for both upstream constraints and downstream service requirements. Equation (2) explains how it is calculated. The square root of τ_i is taken because the model incorporates the standard deviation of demand rather than the variance (σ^2). Since the variance of independent variables accumulates linearly over time, the corresponding standard deviation grows with the square root.

Ultimately, the objective function can be interpreted as the product of two components: unit cost and quantity. The first component—unit cost—is derived from the multiplication of α and C_i, which corresponds to the holding cost at node *i*. This cost includes several elements, such as storage, service, risk, and opportunity costs. The second component—quantity—results from the multiplication of z, σ, and $\sqrt{\tau_i}$ and represents the safety stock level required at node i. The objective function then aggregates these safety-stock costs across all nodes in the supply chain, with the goal of minimizing the total safety stock cost.

Equation **(2)** defines how τ_i is calculated. The incoming service time (SI_i), which is the longest service time quoted to a node by its upstream supplier(s), is added to the stage time (T_i) and review period (r_i). From this total, the outgoing service time (S_i), which is the service time a node quotes to its downstream-adjacent customer(s), is subtracted. The incoming and outgoing service times are the variables that the GSM seeks to optimize, as they drive the amount of time each stage has to cover with safety stock.

In addition, five constraints are considered. Constraint **(3)** ensures that the net replenishment time is greater than zero and forces the outgoing service time at a node to not exceed the largest service time quoted to the node (SI_i) plus its stage time and review period. Constraint **(4)** ensures that the incoming service time for a node must be at least the same as the largest service time of its previous nodes, because a node cannot start its process without receiving all the inputs. Constraint **(5)** enforces that the outgoing service time for the furthest downstream nodes does not exceed the maximum allowable lead time (E_i) that the company must guarantee to the final customer(s). As emphasized by Graves and Willems (2024), without this constraint the furthest downstream nodes could quote extremely long service times, thereby eliminating the need for upstream nodes to hold safety stock. Constraint **(6)** ensures that the outgoing service time for the furthest downstream nodes is greater than or equal to the minimum transportation lead time (Li), which represents the shortest feasible time required to deliver the product to the final customer(s). This constraint guarantees that service time commitments remain realistic and physically achievable, accounting for the inherent limitations of transportation and logistics operations. Constraint **(6)** is not applied to other nodes because the company stores its in-scope raw materials and sub-assemblies at the same manufacturing facility. Constraint **(7)** restricts all service times to be positive.

A summary of the notation used in the GSM formulation is presented in

Table ***1***.

Table 1. *GSM notation summary*

Notation	Definition	Used in
i	Upstream node	Across all the formulation
j	Downstream node	Across all the formulation
N	Nodes	Constraints (3), (5), (6) and (7)
A	Arcs	Constraints (4) and (5)
Ti	Stage time for node i	Constraints (2) and (3)
$\boldsymbol{SI_i}$	Incoming service time for node i	Constraints (2), (3), (4), (7) and (8)
$\boldsymbol{r_i}$	Review time for node i	Constraints (2) and (3)
$\boldsymbol{S_i}$	Outgoing service time for node i	Constraints (2), (3), (5), (6), (7) and (8)
$\boldsymbol{\tau_i}$	Net replenishment time for node i	Constraint (2)
$\boldsymbol{S_k}$	Longest service time of previous nodes	Constraint (4)
$\boldsymbol{E_i}, \forall\, \boldsymbol{i}: \nexists \boldsymbol{j}$	Maximum outgoing time (for the furthest downstream nodes of the supply chain)	Constraint (5)
$\boldsymbol{L_i}$	Minimum outgoing time (for the furthest downstream nodes of the supply chain)	Constraint (6)

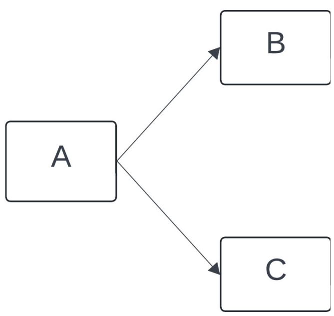
Following the detailed overview of the GSM, the next step involved its practical implementation within the scope of the project. This required the collection and preparation of relevant input data in accordance with the model's specifications. Sections 3.2 through 3.4 outline the key inputs and associated assumptions, describe the data processing approach used to transform raw data into a structured format, and present the resulting model outputs.

3.2 Model Inputs

The GSM relies on several input parameters. First, the mean demand and standard deviation of demand were collected for the furthest downstream nodes only. In accordance with multi-echelon inventory optimization theory, demand is assumed to propagate upstream, meaning it is not independently defined at each node. Therefore, demand parameters are specified only for nodes that directly supply end-customer demand, while demand at upstream stages is derived from these values (Graves and Willems, 2024).

To illustrate how the model propagates demand parameters from downstream to upstream nodes, consider the simple three-node network shown in Figure 3. In this configuration, Node A supplies Nodes B and C, which represent customer-facing nodes. Suppose the mean demand for Nodes B and C is 15 and 22 units, respectively, and the standard deviations are 7 and 9 units. The mean demand at the upstream supplier node (Node A) is the sum of the downstream demands, resulting in 37 units. The standard deviation at Node A is calculated as the square root of the sum of the squares of the downstream standard deviations, yielding ($\sqrt{7^2 + 9^2}$ = 11.40.

Figure 3. *Illustration of a simple network design*



It is important to note that both the mean and standard deviation of demand were assumed to be constant and known over the planning horizon, reflecting the company's current practices.

Another input that was requested from the company was the node cost, which represents the processing cost incurred at each node and contributes to the cumulative cost of the final good. Due to confidentiality reasons, the company chose not to disclose actual cost data. Therefore, realistic but hypothetical cost values were used in the model. Similarly, fictional holding rates were applied. While these values do not reflect the company's true cost structure, they preserve the integrity of the analysis and demonstrate the functionality and applicability of the model.

Stage time was another input requested from the company. Consistent with the company's operational assumptions, stage times were considered constant and known, with no variability. The review period was also obtained as part of the input data. It was assumed to be uniform across all nodes in the supply network. The minimum and maximum outgoing service times for the furthest downstream nodes were also requested from the company.

Finally, two important assumptions are worth highlighting in this context: (1) the company considers both production and distribution capacities to be more than sufficient for the product under consideration; consequently, capacity constraints were excluded from the model formulation. (2) The target service level was fixed at 98.5%, corresponding to a z-value of 2.17, and was assumed to be known and constant throughout the analysis.

3.3 Data Preprocessing

To facilitate the efficient processing of the input parameters described in the previous section and their integration into the model implementation, two standardized data templates were developed. They were designed to support large-scale data entry while ensuring compatibility with the developed code, which can seamlessly read and interpret them. A key advantage of this approach lies in its reusability: The templates can be used for other products without requiring code modifications. A brief overview of the two templates is provided below:

- <u>Inputs Template</u>: Captures the inputs for each of the nodes to be included in the optimization code. All inputs must correspond to the same time horizon, e.g., combining annual with weekly frequencies will yield an error. See APPENDICES A.
- <u>Network Template</u>: Consists of a matrix in which each node is represented both as a row and a column to capture the connectivity between all pairs of nodes. In essence, it defines the arcs of the network, where a value of 0 indicates no connection, and a value of 1 signifies a connection between nodes. This template is flexible enough to be easily adapted to different product flows, making it scalable. See APPENDICES B.

3.4 Model Outputs

The GSM was implemented in Python considering the research questions outlined in Section 1.2, along with the input parameters and assumptions detailed in Sections 3.1 and 3.2. The implementation aimed to generate actionable outputs that directly support the project's objective of optimizing safety stock levels across the supply network.

Table 2 outlines an illustration of the outputs generated by the model. Along with the Optimized Total Safety Stock Cost for the entire network, the model provides node-level insights, including the optimized safety stock level and safety stock cost. Collectively, these outputs provide a comprehensive view of network performance and serve as a benchmark for evaluating and comparing the company's current inventory management practices.

Table 2. *Outputs generated by the model*

Total Safety Stock Cost: 763.44

Node ID	Safety Stock Level	Safety Stock Cost
CART_COMP_1	5,793	12.75
CART_COMP_2	139,027	12.75
CART_COMP_3	139,027	12.75
CART_COMP_4	278,055	12.75
CART_COMP_5	417,082	12.75
CART_COMP_6	1,306	24.28
HAND_COMP_1	620	29.22
HAND_COMP_2	13	29.57
HAND_COMP_3	34	31.24
COV_COMP_1	1,642	20.66
CARTRIDGE_ASSEM	0	0.00
HANDLE_ASSEM	0	0.00
COVER_ASSEM	0	0.00
PLANT_WH	0	0.00
DC_1	15,567	146.13
DC_2	34,827	326.93
DC_3	9,763	91.65

4. RESULTS AND DISCUSSION

This chapter presents the results of applying the GSM within the company's operational context. Section 4.1 outlines the outcomes of implementing the GSM across multiple scenarios over a representative sample time period. Section 4.2 provides an analysis to evaluate the model's robustness against demand variability. Finally, Section 4.3 discusses the limitations of the GSM.

4.1 Scenario-Based GSM Analysis for a Sample Week

This section analyzes the performance of the proposed GSM for a randomly selected week, chosen to be statistically representative of any other week within the analysis period, across nine distinct scenarios with varying holding rates and FP cost structures applied to the network's nodes. As illustrated in Figure 1 and Figure 2 in Section 1.2, the company's supply chain consists of a four-tier network with raw materials (RM), sub-assembly (SA), manufacturing (MF), and distribution center (DC) nodes. The GSM's results are then compared to the ones generated under a single-echelon base stock policy, enabling us to analyze the impact of cost variations on inventory allocation decisions. A detailed overview of each scenario is presented in Table 3.

Table 3. *Summary of assumptions for scenarios*

Scenario #	Weekly Holding Rate	FP Cost Structures		
		RM	SA & MF	DC
1	Flat: 0.18% for all nodes	30 %	50%	20%
2	Flat: 0.18% for all nodes	50 %	20 %	30 %
3	Flat: 0.18% for all nodes	20 %	30 %	50 %
4	Increasing: 0.09% for RM, SA and MF 0.18% for DC	30 %	50%	20%
5	Increasing: 0.09% for RM, SA and MF 0.18% for DC	50 %	20 %	30 %
6	Increasing: 0.09% for RM, SA and MF 0.18% for DC	20 %	30 %	50 %
7	Decreasing: 0.18% for RM, SA and MF 0.09% for DC	30 %	50%	20%
8	Decreasing: 0.18% for RM, SA and MF 0.09% for DC	50 %	20 %	30 %
9	Decreasing: 0.18% for RM, SA and MF 0.09% for DC	20 %	30 %	50 %

The values for the GSM parameters (average demand, demand standard deviation, stage time, review period, maximum outgoing time, minimum outgoing time and composition) corresponding to the selected sample week were provided by the company and are detailed in APPENDICES C. Note that, due to confidentiality constraints, the holding rates and cost parameters used in the analysis were realistic but hypothetical. These two parameters are the drivers of variation across the scenarios.

Regarding the stage time, we can observe that the RM nodes have an average stage time of 15.3 days, reflecting the extended lead times typically associated with the activities performed in the upstream part of the supply chain. In contrast, the SA and MF nodes operate with a stage time of 1 day, which reflects the efficiency of the company's manufacturing processes. The DC nodes, meanwhile, have an average stage time of 4.7 days, reflecting the time required for warehousing and transportation activities necessary to distribute the final product.

In addition, a consistent review period of seven days was considered for all nodes. Similarly, consistent minimum and maximum outgoing times were considered but, in this case, only for the DC nodes, as requested by the company. Finally, the material composition from the BOM was incorporated to convert FP demand into the corresponding RM demand.

We decided to categorize the scenarios into four groups, as the scenarios within each group yield identical safety stock allocation across the supply network regardless of variations in holding rates and cost structures. Note that, to ensure an accurate comparison between the base stock policy and the GSM outcomes, inventory quantities should be evaluated at equivalent supply chain stages—for example, comparing raw material to raw material and finished product to finished product. Table 4 presents the groups and the scenarios they contain.

Table 4. *Groups of scenarios*

Group #	Scenarios
1	1, 3, 4, 6
2	2, 5
3	7, 9
4	8

Group 1: Despite the scenarios within this group being characterized by different cost structures, this difference does not affect the GSM outcome, i.e., all these four scenarios yield the same safety stock allocations. As shown in Table 5, the GSM allocates safety stock at all nodes, except at the SA nodes. In addition, when comparing the results in safety stock inventory units between the base stock policy and the GSM, Table 5 indicates a 58% increase at the MF node and a 25% reduction at the DC nodes. This behavior is driven by the lower cost at the MF node compared to the DC nodes. However, due to the minimum and maximum outgoing time constraints at the DC nodes, the GSM still requires the allocation of safety stock at these nodes to ensure that customer demand is met within this timeframe. In terms of safety stock holding cost savings, Scenarios 1, 3, 4, and 6 achieved reductions of 20%, 22%, 22%, and 23%, respectively, compared to the base stock policy.

Table 5. *Group 1 Results*

Node ID	Node Type	Baseline	GSM
		SS (Units)	SS (Units)
CART_COMP_1	RM	3,749	5,794
CART_COMP_2	RM	162,802	139,033
CART_COMP_3	RM	162,802	139,033
CART_COMP_4	RM	325,604	278,067
CART_COMP_5	RM	488,405	417,100
CART_COMP_6	RM	2,052	1,306
HAND_COMP_1	RM	592	620
HAND_COMP_2	RM	12	13
HAND_COMP_3	RM	35	34
COV_COMP_1	RM	1,568	1,642
CARTRIDGE_ASSEM	SA	162,802	-
HANDLE_ASSEM	SA	171,370	-
COVER_ASSEM	SA	132,812	-
PLANT_WH	MF	124,243	196,623
DC_1	DC	11,715	8,578
DC_2	DC	26,204	19,195
DC_3	DC	5,978	5,273

Group 2: For the scenarios in this group, rather than holding safety stock at the SA nodes—which would increase the lead time to supply the DC nodes from one to two days—the GSM strategically allocates safety stock at the MF node. Extending the lead time would either compromise service levels or require higher safety stock levels, resulting in increased holding costs. As shown in Table 6, the GSM allocates 94% more safety stock units at the MF node compared to the base stock policy. This increase allows more FP to be supplied from the MF node, effectively extending the replenishment window for RM nodes. Table 6 also shows that the GSM allocates no safety stock at RM nodes with a stage time of one day, while only minimal safety stock is allocated at RM nodes with longer stage times to account for their longer replenishment windows. This behavior is further supported by the fact that in the scenarios within this group, the RM nodes account for 50% of the FP cost, while the SA and MF nodes together account for 20%, keeping a consistent cost ratio between these nodes. In terms of safety stock holding cost savings, Scenarios 2 and 5 achieved both a reduction of 24% compared to the base stock policy.

Table 6. *Group 2 Results*

Node ID	Node Type	Baseline	GSM
		SS (Units)	SS (Units)
CART_COMP_1	RM	3,749	-
CART_COMP_2	RM	162,802	-
CART_COMP_3	RM	162,802	-
CART_COMP_4	RM	325,604	-
CART_COMP_5	RM	488,405	-
CART_COMP_6	RM	2,052	1,111
HAND_COMP_1	RM	592	557
HAND_COMP_2	RM	12	12
HAND_COMP_3	RM	35	31
COV_COMP_1	RM	1,568	1,292
CARTRIDGE_ASSEM	SA	162,802	-
HANDLE_ASSEM	SA	171,370	-
COVER_ASSEM	SA	132,812	-
PLANT_WH	MF	124,243	240,813
DC_1	DC	11,715	8,578
DC_2	DC	26,204	19,195
DC_3	DC	5,978	5,273

Group 3: The scenarios in this group feature a decreasing holding cost rate, with the holding rate at the DC nodes set at 0.09%, which is 50% lower than the 0.18% rate applied at the other nodes. Consequently, as shown in Table 7, the GSM allocates 37% more safety stock units at the DC nodes, as this is a more cost-effective option compared to allocating inventory at the upstream SA and MF nodes, where no safety stock is allocated. Additionally, the GSM's preference for allocating more safety sock at the DC nodes is further supported by the lower volume of inventory to be stored there, as one unit of FP stored at the DC nodes corresponds to six sub-assemblies stored at the SA and MF nodes. In terms of safety stock holding cost savings, Scenarios 7 and 9 achieved reductions of 38% and 26%, respectively, compared to the base stock policy.

Table 7. *Group 3 Results*

Node ID	Node Type	Baseline	GSM
		SS (Units)	SS (Units)
CART_COMP_1	RM	3,749	5,794
CART_COMP_2	RM	162,802	139,033
CART_COMP_3	RM	162,802	139,033
CART_COMP_4	RM	325,604	278,067
CART_COMP_5	RM	488,405	417,100
CART_COMP_6	RM	2,052	1,306
HAND_COMP_1	RM	592	620
HAND_COMP_2	RM	12	13
HAND_COMP_3	RM	35	34
COV_COMP_1	RM	1,568	1,642
CARTRIDGE_ASSEM	SA	162,802	-
HANDLE_ASSEM	SA	171,370	-
COVER_ASSEM	SA	132,812	-
PLANT_WH	MF	124,243	-
DC_1	DC	11,715	15,549
DC_2	DC	26,204	34,794
DC_3	DC	5,978	9,559

Group 4: For the scenario within this group, since RM nodes represent 50% of the FP cost and have a holding rate of 0.18%, the GSM allocates no safety stock at the RM nodes with a stage time of 1 day, and only the minimum necessary safety stock at the RM nodes with longer stage time. Consequently, the safety stock level reduction at the RM nodes leads to a longer replenishment time. To offset the reduction in safety stock levels at the RM nodes, the GSM increases the allocation of safety stock at the DC nodes by 58% compared to base stock policy, as shown in Table 8. The GSM favors allocating safety stock at the DC nodes rather that at the MF node, given that the holding rate at the DC nodes is 50% lower than the one at the MF node. In terms of safety stock holding cost savings, Scenario 8 achieved a 36% reduction relative to the base stock policy.

Table 8. *Group 4 Results*

Node ID	Node Type	Baseline	GSM
		SS (Units)	SS (Units)
CART_COMP_1	RM	3,749	-
CART_COMP_2	RM	162,802	-
CART_COMP_3	RM	162,802	-
CART_COMP_4	RM	325,604	-
CART_COMP_5	RM	488,405	-
CART_COMP_6	RM	2,052	1,111
HAND_COMP_1	RM	592	557
HAND_COMP_2	RM	12	12
HAND_COMP_3	RM	35	31
COV_COMP_1	RM	1,568	1,292
CARTRIDGE_ASSEM	SA	162,802	-
HANDLE_ASSEM	SA	171,370	-
COVER_ASSEM	SA	132,812	-
PLANT_WH	MF	124,243	-
DC_1	DC	11,715	18,052
DC_2	DC	26,204	40,394
DC_3	DC	5,978	11,097

The results demonstrate that the GSM could achieve safety stock holding cost reductions ranging from 20% to 38%, depending on the scenario analyzed. These improvements were mainly driven by three factors. First, the model uses the demand parameters (mean and standard deviation) of the furthest downstream stages to calculate the same parameters for upstream stages, effectively mitigating the bullwhip effect. Second, the pooling effect—resulting from the aggregation of products distributed to multiple locations—reduces demand variability, thereby decreasing the amount of safety stock required to buffer against uncertainty. Third, by considering the entire network, the GSM simultaneously determines the optimal safety stock quantity and placement, ensuring service levels are maintained at minimal cost.

4.2 Robustness Analysis Against Demand Variability

To assess the robustness of the GSM results against demand variability, a multi-period analysis was conducted by running the GSM for each of the nine scenarios over the demand realizations spanning a consecutive 30-week period. The results, presented in Table 9, demonstrate consistent safety stock holding cost savings across all scenarios and weeks, thereby reinforcing the findings from the sample week analysis discussed in Section 4.1.

Furthermore, the variation in savings by scenario, relative to the average, remains within a narrow range of 1% to 2%, indicating a high degree of stability, robustness and applicability in the outcomes of the model. These findings provide strong evidence that the GSM can be confidently deployed to support inventory decisions and reduce working capital while maintaining service levels and operational resilience.

Table 9. *Weekly Safety Stock Holding Cost Savings by Scenario*

Week	S1	S2	S3	S4	S5	S6	S7	S8	S9
W1	-21%	-22%	-21%	-21%	-23%	-23%	-38%	-37%	-27%
W2	-20%	-22%	-21%	-21%	-23%	-23%	-37%	-35%	-26%
W3	-21%	-25%	-22%	-22%	-24%	-23%	-36%	-34%	-24%
W4	-19%	-22%	-21%	-21%	-23%	-23%	-37%	-35%	-25%
W5	-18%	-20%	-19%	-20%	-22%	-22%	-35%	-34%	-24%
W6	-18%	-20%	-19%	-20%	-22%	-22%	-35%	-34%	-24%
W7	-18%	-20%	-19%	-19%	-21%	-22%	-35%	-33%	-24%
W8	-19%	-23%	-21%	-21%	-23%	-22%	-35%	-33%	-23%
W9	-18%	-20%	-19%	-19%	-21%	-22%	-35%	-33%	-24%

W10	-18%	-20%	-19%	-19%	-21%	-22%	-35%	-33%	-24%
W11	-18%	-20%	-19%	-19%	-21%	-22%	-35%	-33%	-24%
W12	-19%	-21%	-20%	-20%	-22%	-23%	-36%	-35%	-25%
W13	-21%	-25%	-22%	-22%	-24%	-23%	-36%	-34%	-23%
W14	-20%	-22%	-21%	-21%	-23%	-23%	-37%	-36%	-26%
W15	-19%	-22%	-21%	-21%	-23%	-23%	-37%	-35%	-25%
W16	-20%	-22%	-21%	-21%	-23%	-23%	-37%	-36%	-26%
W17	-21%	-25%	-23%	-22%	-24%	-23%	-37%	-35%	-25%
W18	-21%	-23%	-21%	-21%	-23%	-23%	-38%	-37%	-27%
W19	-21%	-23%	-21%	-21%	-23%	-23%	-38%	-36%	-27%
W20	-19%	-22%	-20%	-21%	-23%	-23%	-37%	-35%	-25%
W21	-20%	-24%	-21%	-21%	-23%	-22%	-35%	-32%	-22%
W22	-18%	-19%	-18%	-19%	-21%	-22%	-35%	-33%	-23%
W23	-18%	-19%	-18%	-19%	-21%	-22%	-35%	-33%	-23%
W24	-18%	-20%	-19%	-20%	-22%	-22%	-35%	-34%	-24%
W25	-20%	-23%	-21%	-21%	-23%	-23%	-37%	-36%	-26%
W26	-21%	-25%	-23%	-22%	-24%	-23%	-37%	-35%	-25%
W27	-21%	-23%	-21%	-21%	-23%	-23%	-38%	-36%	-27%
W28	-21%	-23%	-21%	-21%	-23%	-23%	-38%	-37%	-27%
W29	-19%	-21%	-20%	-20%	-22%	-22%	-36%	-34%	-25%
W30	-21%	-25%	-22%	-22%	-24%	-23%	-36%	-34%	-24%
Average	**-20%**	**-22%**	**-21%**	**-21%**	**-23%**	**-23%**	**-36%**	**-35%**	**-25%**

4.3 GSM Limitations

Despite the promising results presented in this report, the proposed GSM has several limitations. The GSM assumes that the lead time of each stage is constant and known, which neglects the potential volatility of lead time that the upstream supply chain may have. In addition, this model does not consider the opportunity of shared components across different products, which could further reduce the safety stock level. Moreover, the model does not reflect any purchasing requirement that the company needs to fulfill with its upstream suppliers, such as Minimum Order Quantity (MOQ). The GSM also assumes the demand is stationary, which may not hold in industries characterized by seasonal or rapidly evolving demand patterns. Furthermore, the model does not incorporate capacity constraints, which can be critical for safety stock decisions and service levels. Lastly, the model does not account for critical human and system factors, such as coordination between planning teams managing different inventories or system integration across the end-to-end supply chain.

5. CONCLUSION

This chapter presents a concise summary of the project, outlines recommendations derived from the model's results, and proposes potential avenues for future research.

5.1 Project Summary

Currently, the company calculates safety stock requirements for each stage of its supply chain network using a siloed approach that overlooks the interdependencies between stages. This often leads to excess inventory and, consequently, higher operational costs. To address this problem, the objective of this project was to develop a model that evaluates the supply chain as an integrated system—considering all stages simultaneously—and determines optimal safety stock allocation at each stage. The model also needed to be flexible enough to be adapted to different products and network configurations.

Following a comprehensive literature review, the Guaranteed Service Model (GSM) was selected for its ability to minimize total inventory costs while guaranteeing a desired service level. The GSM optimizes service times across the network, enabling efficient safety stock allocation. To validate the model’s applicability and robustness, nine scenarios were created, each incorporating different assumptions.

Our results shows that the GSM can achieve safety stock holding cost reductions ranging from 20% to 38%, depending on the scenario analyzed. These cost savings are mainly driven by three factors: (1) mitigation of the bullwhip effect, (2) the pooling effect resulting from aggregating products distributed across multiple locations, and (3) the GSM’s ability to simultaneously optimize both the quantity and placement of safety stock. These results were validated through a robustness analysis accounting for demand variability.

Despite its advantages, the GSM has several limitations that need to be addressed through future extensions to the original model. For example, it assumes constant lead times, overlooks the use of shared components across products, and ignores upstream purchasing constraints such as Minimum Order Quantities (MOQs). Additionally, it presumes stationary demand, omits capacity constraints, and fails to consider human and organizational-level factors.

5.2 Recommendations

Based on the outcomes of this project, we recommend that the company initiate a pilot implementation of the GSM. This pilot should focus on a specific product line or segment of the supply chain to allow for the calibration of parameters and validation of assumptions in a controlled environment. Such an approach will facilitate the evaluation of the model's performance in the company's environment, including its impact on inventory levels, service metrics, and cost savings. Following a successful pilot, the model can be gradually scaled and adapted across other product lines and network configurations. To ensure a smooth transition, change management strategies and staff training programs should be employed to facilitate organizational adoption and model sustainability over time.

5.3 Future Research Suggestions

Future research should focus on extending the GSM to account for the dynamic nature of supply chains, including non-stationary and seasonal demand, lead time variability, capacity constraints, and hybrid inventory policies. These enhancements would improve the model's performance in more real-world conditions, enabling the sponsor company to make more resilient and cost-effective decisions. Additionally, designing coordinated supply contracts to manage risk and ensure consistent productivity across partners could strengthen collaboration and stability across the network, offering strategic advantages beyond the current model's capabilities.

The GSM offers a solid foundation for transitioning from a traditional single echelon to an integrated multi-echelon inventory management approach. The findings of this project are not only relevant to the company in question but also hold broader applicability across various industries. By enabling more efficient inventory management, the GSM has the potential to provide significant savings which can then be reinvested into other strategic objectives, thereby enhancing overall supply chain performance. As such, the GSM serves as a valuable approach for organizations seeking to adopt more advanced, data-driven inventory optimization practices.

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APPENDICES

Appendix A: Inputs Template

Node ID	Type	Avg_demand	Std_Dev_Demand	Service_Level	Hold_Cost_Rate	Stage_Time	Review_Period	Cost	Ei	Li	Comp
CART_COMP_1	RM										
CART_COMP_2	RM										
CART_COMP_3	RM										
CART_COMP_4	RM										
CART_COMP_5	RM										
CART_COMP_6	RM										
HAND_COMP_1	RM										
HAND_COMP_2	RM										
HAND_COMP_3	RM										
COV_COMP_1	RM										
CARTRIDGE_ASSEM	SA										
HANDLE_ASSEM	SA										
COVER_ASSEM	SA										
PLANT_WH	MF										
DC_1	DC										
DC_2	DC										
DC_3	DC										

Appendix B: Network Template[1]

Node ID	CART_COMP_1	CART_COMP_2	CART_COMP_3	CART_COMP_4	CART_COMP_5	CART_COMP_6	HAND_COMP_1	HAND_COMP_2	HAND_COMP_3	COV_COMP_1	CARTRIDGE_ASSEM	HANDLE_ASSEM	COVER_ASSEM	PLANT_WH	DC_1	DC_2	DC_3
CART_COMP_1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
CART_COMP_2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
CART_COMP_3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
CART_COMP_4	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
CART_COMP_5	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
CART_COMP_6	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
HAND_COMP_1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
HAND_COMP_2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
HAND_COMP_3	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
COV_COMP_1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
CARTRIDGE_ASSEM	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
HANDLE_ASSEM	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
COVER_ASSEM	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
PLANT_WH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
DC_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DC_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DC_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

[1] The template is populated with sample data for reference.

Appendix C: Parameter Values for Sample Week[2]

Node ID	Type	Avg_demand	Std_Dev_Demand	Service_Level	Hold_Cost_Rate	Stage_Time	Review_Period	Cost	Ei	Li	Comp
CART_COMP_1	RM				0.18%	1	7	1.20			0.0417
CART_COMP_2	RM				0.18%	1	7	0.05			1.0000
CART_COMP_3	RM				0.18%	1	7	0.05			1.0000
CART_COMP_4	RM				0.18%	1	7	0.03			2.0000
CART_COMP_5	RM				0.18%	1	7	0.02			3.0000
CART_COMP_6	RM				0.18%	22	7	10.14			0.0049
HAND_COMP_1	RM				0.18%	35	7	25.71			0.0019
HAND_COMP_2	RM				0.18%	36	7	1,259.76			0.0000
HAND_COMP_3	RM				0.18%	41	7	496.62			0.0001
COV_COMP_1	RM				0.18%	14	7	6.86			0.0073
CARTRIDGE_ASSEM	SA				0.18%	1	7	0.17			1.0000
HANDLE_ASSEM	SA				0.18%	1	7	0.17			1.0000
COVER_ASSEM	SA				0.18%	1	7	0.17			1.0000
PLANT_WH	MF				0.18%	1	7	0.33			6.0000
DC_1	DC	6,480	3,952.80	98.5%	0.18%	6.06	7	2.00	6.06	6.06	1.0000
DC_2	DC	21,060	8,845.20	98.5%	0.18%	6.05	7	2.00	6.05	6.05	1.0000
DC_3	DC	3,240	2,430.00	98.5%	0.18%	2.00	7	2.00	2.00	2.00	1.0000

[2] Holding Cost Rates and Costs are hypothetical parameters that vary across the different scenarios.