Inventory Rebalancing through Lateral Transshipments

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Abstract

Disruption in supply and demand causes imbalances in inventory positions across an enterprise's supply chain network. In the medical device industry, having the right product at the right location in the right quantity is of critical importance. Therefore, companies thrive to maintain an optimal inventory position across their distribution network. Boston Scientific, a global leader in the medical device industry, has been facing an inventory imbalance post-Covid across its distribution network. To optimize the inventory position across the company's distribution network, this study has explored lateral transshipment, a practice of repositioning inventory between same echelon distribution centers. We have primarily used Mixed Integer Linear Programming (MILP) to find the optimal transshipment solution at each SKU and distribution center level. Existing inventory classifications systems, and newly developed heuristics to select high priority SKUs for optimization. Simulation studies were conducted to generate stochastic demand, and analyze how the optimized inventory model compares to the current model. Our research shows that lateral transshipment reduces 10% to 25% of total inventory cost while maintaining a superior inventory position compared to the current inventory model under varying demand.

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Himanshu Halbe

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Jinwoo Je

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1. Introduction

1.1 Company Background

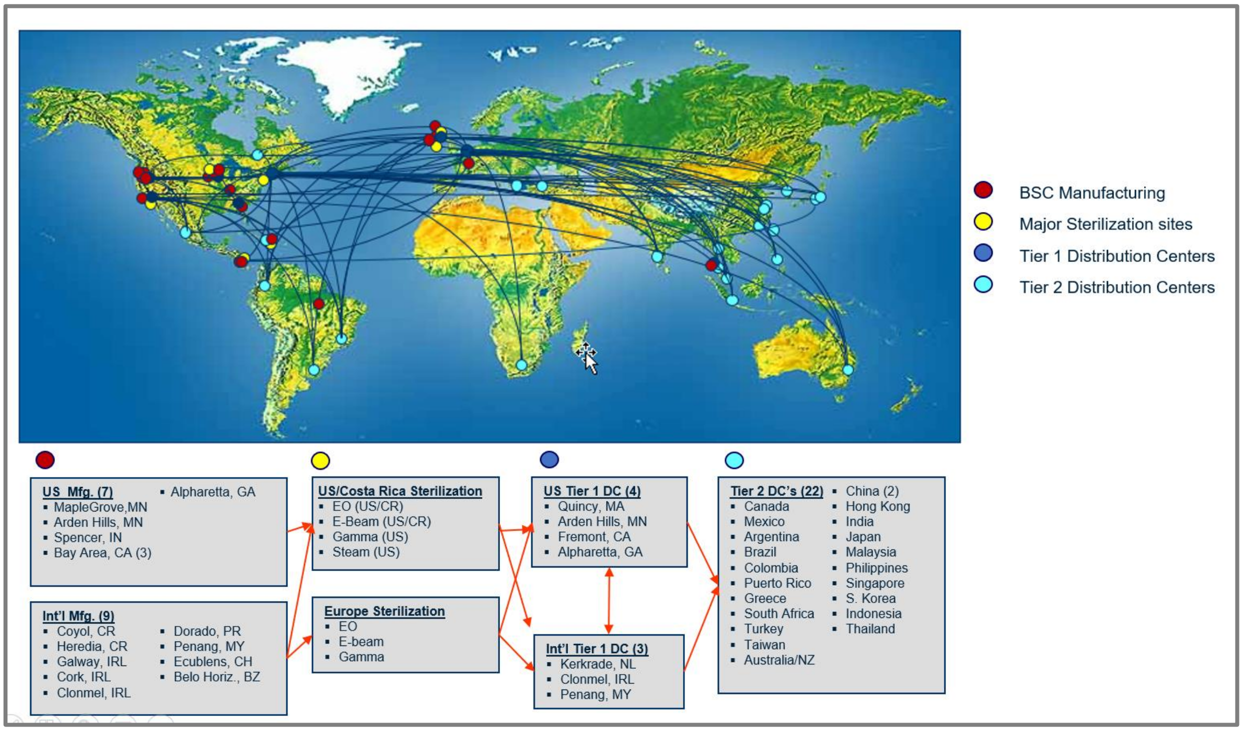
Boston Scientific (BSC) is a leader in the global medical device industry. BSC operates in over 120 countries, generating $10B in revenue annually and serving over 35,000 hospitals worldwide with over 30M patients treated each year.

The sponsor company is an industry leader in minimally invasive devices for diagnosing and treating gastrointestinal, pulmonary, heart, vascular, neurological, urological, urogynecological, and gynecological conditions. BSC also helps transform lives with minimally invasive therapies for arterial disease, venous disease, and cancer. BSC develops techniques that treat irregular heart rhythms, and heart failure and help protect against sudden cardiac arrest. As quality control is of utmost importance, BSC has strong manufacturing capabilities and is vertically integrated.

To support its global operation, the company orchestrates a global supply chain consisting of 11 global manufacturing sites, seven sterilization facilities, and a worldwide distribution network composed of seven Tier 1 distribution centers (DC) and 22 Tier 2 DCs (see Figure 1). All manufacturing plants and Tier 1 and Tier 2 DCs are owned and staffed by BSC, and the sterilization sites are owned and contract sites. These nodes are interconnected through 140 air, road, ocean, and rail transportation lanes. BSC's supply chain is capable of shipping over 33 million units a year globally. The company works with global third-party logistics (3PL) companies for its distribution requirements.

Figure 1

Boston Scientific Supply Chain Network



1.2 Problem Statement and Research Objective

BSC has $728M of finished goods inventory within its global distribution network. BSC faces the challenge with the excess and deficit of inventory levels globally in distribution centers, leading to additional scrap and backorder processing costs.

This project aims to provide a potential cost saving solution through inventory rebalancing. In this study, inventory rebalancing is defined as adjusting the inventory level through transshipment from one DC to another DC within the same tier. By investigating the inventory and service level along with demand patterns of each DC within the distribution network, we examine opportunities for inventory relocation, and thus, potential solutions for inventory balancing within the distribution network. An understanding of the costs associated with the transshipment of products across the distribution network and the costs for backorders, scrap and expedited orders is required for deriving the solution.

Data for this project is acquired mainly from BSC's Enterprise Resource Planning (ERP) system. BSC implements SAP for business execution and adopted Rapid Response for planning. A unique characteristic of the system is that it implements a Control Tower module where metrics data across all functions is centrally collected, which is efficient for gathering KPI data across the enterprise for this project. Most of the data required for this project, such as inventory level, forecasts, safety stock, lead time, shipping schedule and performance data is collected through the ERP system. Other data, such as transshipment costs for routes that currently do not exist, were acquired separately through web-based UPS CTC (Calculate Time and Cost) tool.

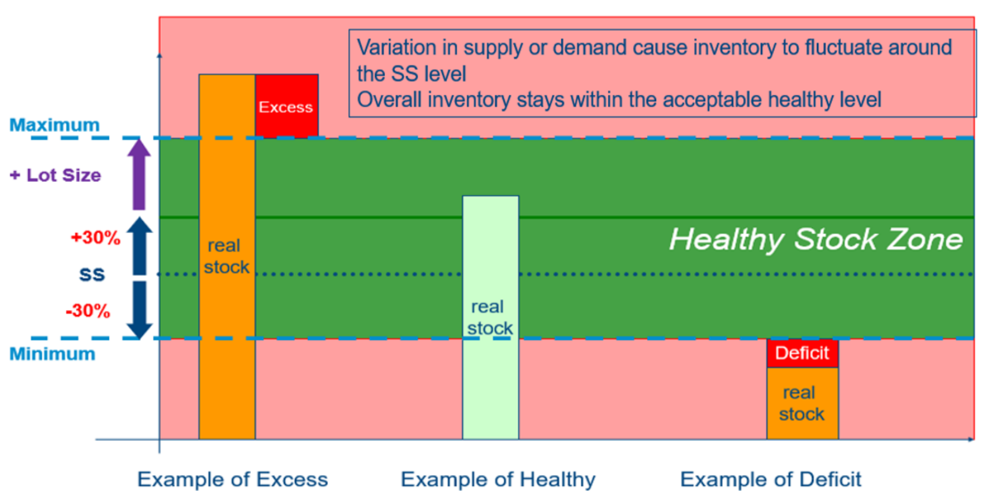
This project investigates the optimal inventory levels through Mixed Integer Linear Optimization (MILP) optimization by evaluating the current inventory levels, forecasts, safety stock, backorders, lead time, and transshipment costs as inputs. Constraints will be modeled to factor in cost, lead time, business processes, and movement limitations. Based on the model, the project will propose optimal inventory balance across the global distribution network including its' impact on cost savings and inventory position. A Monte-Carlo simulation study is performed to measure the performance of the rebalanced inventory model under stochastic demand. The project also aims to provide guidelines for implementing a periodic review policy to assess inventory discrepancies and arrange transshipment to balance inventory within the network.

1.3 Current Practice and Motivation

BSC uses a "Healthy stock model" to determine whether an inventory for an SKU is within an acceptable range or is either in excess or deficit (see Figure 2). The healthy stock zone is defined as safety stock (SS) +30%+ Lot size for an upper limit and SS-30% for a lower limit. The demand/supply variability along with service level is incorporated into the network safety stock calculation. The upper and lower limits of the healthy stock zone account for demand variability for new products, and emerging markets. The thresholds can be adjusted based on the strategic decisions of supply chain leaders at BSC. Any product with an inventory level above this threshold is considered to be in excess, and below this level is considered to be in deficit.

Figure 2

Boston Scientific Healthy Stock Model



A deeper investigation into the increased backorders and scrap cost reveals that this inventory discrepancy profile varies by individual nodes; within the network 36% of overall inventory is in excess, while 9% is in deficit. There is potential for addressing this imbalance internally by relocation of stocks. However, currently there is no process that allows for transshipment of this inventory back and forth between the distribution tiers. The flow of products is currently unidirectional, flowing from the manufacturing plant to Tier 1 DC to Tier 2 DC. There is no reverse flow from Tier 2 to Tier 1 nor flow among DCs within Tier 2. This is mainly because of the low volume and frequency of shipping demand for these routes when the network was designed. Therefore, excess inventory is held until shelf-life expiration, resulting in scrapping, and deficit inventory results in backorders and lost sales.

Furthermore, the impact of the Covid-19 pandemic throughout recent years required BSC to ramp down its production of inventory and adhere to various demand profile scenarios. When government regulations eased up BSC had to quickly ramp up production. This also resulted in inventory imbalance at various nodes, especially the Tier 1 DCs.

1.4 Relevance

Many companies are facing stock imbalances within their supply chain distribution network as markets face higher uncertainty, demand volatility becomes higher, and product life cycle become shorter. From the supply side, lengthening supply chains are increasing the difficulty of matching supply and demand to coordinate optimal inventory levels at the local level. This is especially true for the healthcare industry, as it is going through vast transformation pivoting towards personalized healthcare. Demand variability as well as supply chain complexity is expected to intensify as a result. This study on balancing of inventory within the supply chain distribution network provides insight for supply chains facing similar problems, not limited to medical devices or healthcare industry. Demand changes geographically and with time. By being able to rebalance inventory companies can be proactive against global and regional volatility. This will support overall product availability and inventory costs improvement.

2. Literature Review

This capstone project is intended to further explore the inventory optimization policies applied by Medical devices companies, specifically Boston Scientific (BSC). Even with the most robust inventory optimization policies, intangible factors that cause high supply/demand variability leads to an excess/deficit of inventory in local nodes. As quoted by George E.P. Box, “All models are wrong, some models are useful”, an understanding of the inventory optimization policy currently used by the company is required. Therefore, we present a review of multi-echelon inventory optimization (MEIO) policies to provide a better understanding of the general context, followed by a discussion on MEIO policies adopted by BSC. Next, we review previous studies on the topic of lateral transshipment for inventory balancing to obtain how inventory movement within the same echelon is approached and modeled in academia. This chapter will be concluded with a summary of key insights and their relevance to our research.

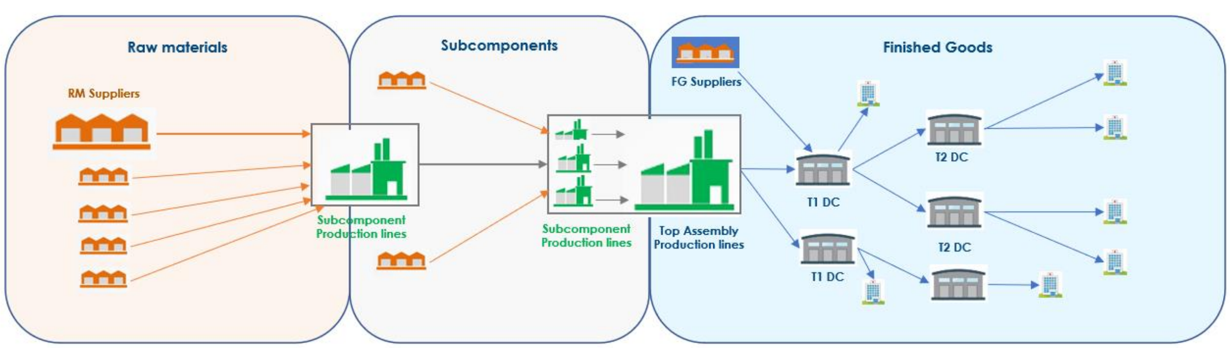
2.1 Multi Echelon Inventory Optimization policies

Multi-Echelon Inventory Optimization (MEIO) is an approach to determining optimal inventory levels across an end-to-end supply chain network in order to maximize the service level and minimize inventory costs (Grob, 2019; Vandeput, 2020). MEIO has been widely studied using mathematical approximations. A supply chain network with multiple tiers, viz. Suppliers, Manufacturing plants, Central DCs, Local DCs and Customer warehouses (consignment inventory), can be characterized as an example of a multi-echelon network. An example of such a supply chain network is depicted in Figure 3. In this network, raw materials suppliers source to internal manufacturing plants that produce subcomponents. These subcomponents, along with externally sourced subcomponents, are transferred into production lines that build finished products/goods. These finished goods, along with externally sourced finished products, are then stored in multiple tiers of distribution centers before finally reaching customers globally. MEIO intends to reduce the bullwhip effect by pooling demand and lead time. Demand pooling supports smoothing demand variability as we move upstream, and demand gets more stable as we move up from the lowest tier to the manufacturing plant. Conversely, lead time pooling smoothens the supply variability downstream, and lead times increase as we move down from the manufacturing plant to the lowest tier (Vandeput, 2020).

In a global supply chain, MEIO intends to optimize inventory at each distribution holistically. This is essentially called network pooling (in other words, demand and lead time pooling), where service levels and supply/demand variability are analyzed to determine correct inventory levels at each DC. The goal of MEIO is to continually monitor, evaluate and update forecasts and safety stock to provide the most optimal signal back to Manufacturing plants in terms of net requirement and, in turn, get an optimal inventory level policy for each DC (Grob, 2019; Vandeput, 2020).

Figure 3

Multi-echelon models in a global end-to-end supply chain

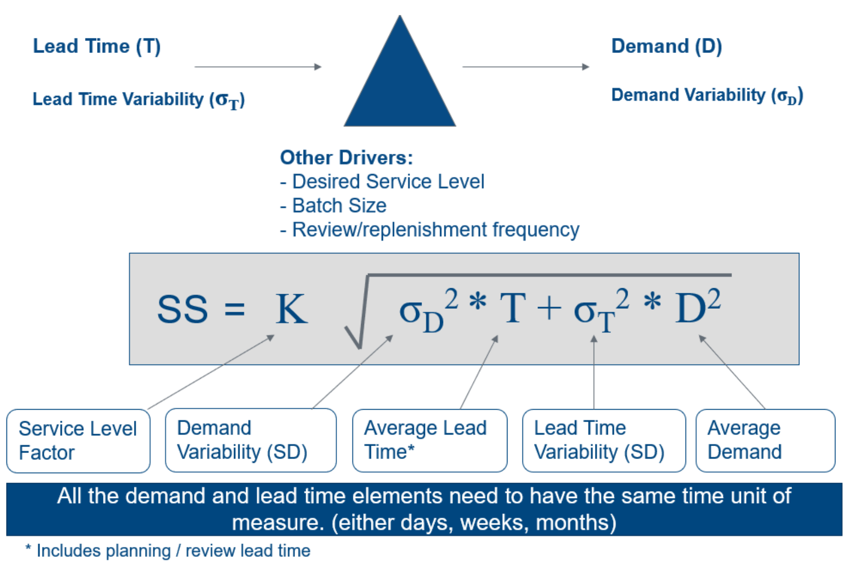


2.2 MEIO at Boston Scientific

BSC is a vertically integrated company with a network of 20 manufacturing plants and 30 DCs across 60+ countries and over 16,000 finished goods to support more than 35,000 hospitals. To support these 30 DCs, BSC has adopted an MEIO model (see Figure 4) that uses service level, demand/supply variability, average lead times, and average demand at each DC (Boston Scientific, 2015). According to Figure 4, Safety Stock (SS) is a buffer against demand and supply variability. The inputs that go into the SS calculation are average demand, demand variability, average lead time, lead time variability. Other drivers for the calculation can be batch sizes and replenishment strategies (weekly, monthly, and quarterly).

Figure 4

MEIO model adopted by BSC (Boston Scientific, 2015)



In the BSC's model, demand is used as a primary input to calculate statistical safety stock. The historical demand captures shipments from a DC to customers across a 6-month horizon. The average and corresponding standard deviation are captured across the same interval. Lead times are represented by transit times between DCs within the network and drive SS recommendations for subcomponents at manufacturing plants and finished goods at DCs to optimize safety stock inventory levels to buffer for potential fluctuations in future supply. These inputs generate a "Time-phased safety stock recommendation" across 24 months in the future, which is the final output of this MEIO model.

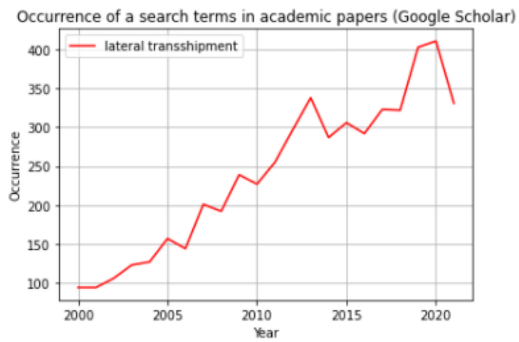
2.3 Lateral Transshipment for Inventory Balancing

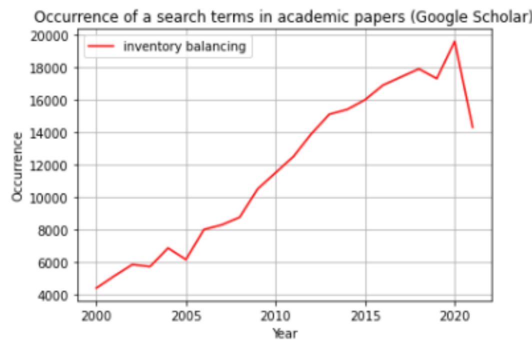
The inventory system of BSC is a hierarchical structure, meaning goods flow from the higher echelon to lower echelon. Under this inventory system, inventory levels at distribution centers and warehouses are adjusted through replenishment and scrapping, with limited cases for returns mainly driven by quality reasons. This capstone project focuses on a more flexible method that could be implemented along with the BSC's MEIO policy, specifically lateral transshipment.

"Lateral transshipment is defined as the redistribution of stock from retailers with stock on hand to retailers that cannot meet customer demands or to retailers that expect significant losses due to high risk (Y. H. Lee et al., 2007, p. 1)." Lateral transshipment and inventory balancing is an area of the growing interest of study in the literature (Figure 5). Academic literature publications the topics on lateral transshipment as well as inventory balancing have quadrupled over the past two decades.

Figure 5

Academic Literature Keyword Search Results



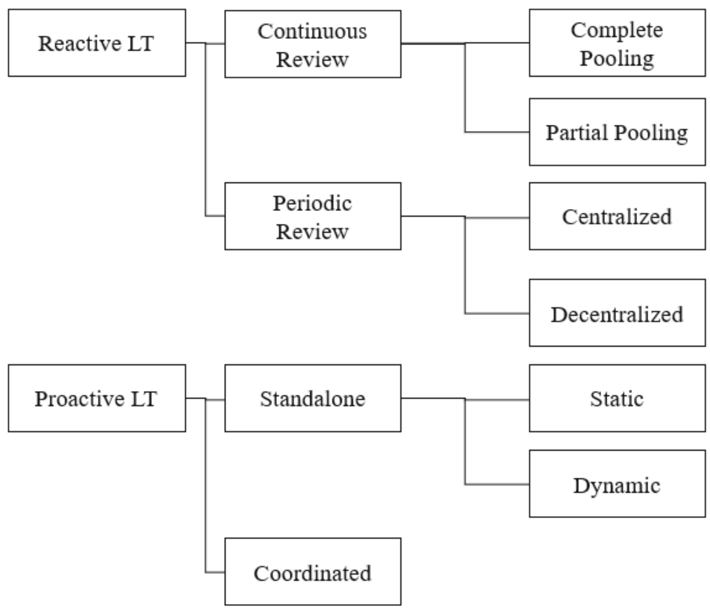


Keyword: Lateral Transshipment Keyword: Inventory Balancing

In a comprehensive literature review on this subject matter, Paterson et al. (2011) categorize lateral transshipment into two main types, viz. proactive transshipment and reactive transshipment and provide a framework of classification of lateral transshipment models based on their key characteristics (Figure 6). Focusing on this, the cases where transshipments take place prior to demand realization are referred to as proactive transshipment, whereas transshipments executed to respond to stockout are defined as reactive transshipment. Proactive and reactive models are also commonly referred to as preventive transshipment and emergency transshipment in the literature, respectively. Literature review on these topics will be provided in the following two subsections, followed by the conclusion of the literature review.

Figure 6

Lateral Transshipment Model Classification (adopted from Paterson et al. (2011))



2.4 Reactive Lateral Transshipment

For reactive lateral transshipment, the decision on transshipment quantity is proceeded after demand realization. Therefore, reactive transshipment can be practiced under both periodic review and continuous review policy environment.

The earliest study on the reactive model under periodic review was carried out by Krishnan and Rao (1965) and was further developed by Robinson (1990) and Nonås and Jörnsten (2007). Robinson (1990) developed an optimization solution for multiple identical nodes or two non-identical nodes under a single echelon model. Nonås and Jörnsten (2007) derived an alternate greedy transshipment policy to optimize under single echelon with three nodes. Tagaras (1989) and Hu et al. (2005) expanded to incorporate multiple locations under zero replenishment lead time and transshipment lead time assumptions. All the above-mentioned studies are carried out under the assumption of centralized systems, where transshipment decision is made centrally to optimize network-wide cost.

Decentralized systems, on the other hand, consist of another strand of research and have been studied through the game theory approach (Anupindi et al. (2001); Rudi et al. (2001); Slikker et al. (2005); Liao et al. (2020)). In the decentralized systems, each node makes decisions on inventory level to optimize its' objective function independent from the supply chain wide optimization. Studies of lateral transshipment with 2 or more different entities within same echelon, such as different distribution companies or competing retailers sourcing from the same supplier fit in this category. This capstone focuses on BSC's Tier 1 and Tier 2 DCs, which are owned and managed by BSC; therefore, it can be considered as a centralized system.

Reactive transshipment under continuous review refers to systems where a stockout event triggers the transshipment procedure. A key feature in the transshipment model can be identified as the concept of complete pooling and partial pooling. Complete pooling allows for sharing of all on-hand inventory for transshipment to other nodes while partial pooling holds back certain portion of the stock to cover future demand (Patriarca et al., 2016).

Complete pooling is widely used in spare parts supply chains due to high stock out and holding cost along with high requirements for service and parts availability for customer's business continuity. Sherbrooke (1968) developed a spare parts framework model METRIC, where items are repaired at the central facility and replenished to individual locations. Lee (1987) and Axsäter (1990) studied models under stochastic demand modeling and order decision heuristics to minimize cost under service level constraints. Further research has been done with alternations in assumptions, echelon structures and application of different heuristics by Kukreja et al. (2001) and

Wong et al. (2005). Partial pooling studies are more complex due to the additional decision of how much inventory to keep for future demand. (Axsäter, 2003) proposed a system state-based approach to decide on the quantity to transship and retain. Our study could be considered partial pooling since the outbound transshipment stock will be constrained by safety stock rules enforced on the node.

2.5 Proactive Lateral Transshipment

Most studies of proactive lateral transshipment are under periodic review policy (Paterson et al., 2011). Under the periodic replenishment system, the inventory assessment schedule is embedded in the corporate calendar. Conducting additional analysis for lateral redistribution within this pre-existing schedule instead of setting up new process and schedule is efficient and natural for businesses. Proactive transshipment can be divided into two types based on their relationship with the replenishment cycle: standalone and coordinated.

Standalone redistribution ignores the replenishment ordering process and considers decision-making on proactive transshipment as an independent problem. Depending on the timing of transshipment, it could either be a static point of time such as the beginning of the ordering cycle (Allen, 1958, 1962), mid-ordering cycle, or dynamic transshipment based on demand and inventory level (Agrawal et al., 2004). According to Agrawal et al., (2004), dynamic decision-making divides the order period into *N*-sub periods to determine time optimal sub period to execute the transshipment transaction. Their results demonstrated its' superior performance to other policies with static ordering rules. However, implementing such a process in practice would be challenging due to its complexity and additional effort required for operating such sub-period calculation and varying time order process. In the study, the authors presented a greedy heuristic and showed that the model performs close to optimal.

Banerjee et al. (2003) introduced transshipment inventory equalization (TIE) heuristics which redistributes inventory levels so that all second echelon nodes have the same inventory levels in terms of days of supply. The study showed that TIE performs better than reactive transshipment in terms of cost (Burton & Banerjee, 2005). Lee et al. (2007) proposes a new lateral transshipment policy called service level adjustment (SLA). This heuristic uses estimated probability of stockout during the order cycle by stock points and sets upper, lower and target to decide on lateral transshipment decision so that nodes with highest surplus transship to nodes with highest deficit. The authors showed that SLA outperforms other pre-mentioned heuristics.

Coordinated redistribution considers lateral transshipment decision in alignment with order replenishment system, and therefore increases the complexity of the lateral transshipment problem. Gross (1963) introduces a heuristic that minimizes average shortage, inventory, and transportation cost. Further studies have been conducted by expanding the problem with multiple nodes and introducing lead time (Diks and de Kok 1996). This capstone project considers BSC's the existing ordering policy as a constant and therefore has characteristics of a standalone problem.

2.6 Literature Review Conclusion

By reviewing methodologies of the current inventory management system at BSC and the literature on inventory balancing through lateral transshipment, we have discovered key insights that could transition over to the capstone study. First, the added option of lateral transshipment to the hierarchical inventory model improves cost and service level by providing additional opportunities to match demand and balance between order replenishment cycles. Second, the transshipment policy is effective in cases where lateral transportation cost is low in comparison to holding cost and shortage costs. Third, lateral transshipment performs when order replenishment lead time, or distance from echelon 1 node to echelon 2 nodes, is significantly higher than lead time through redistribution among echelon 2 nodes. Forth, the benefits of transshipment increase with the number of nodes within the same echelon due to the inventory pooling effect. Finally, ease of implementation must be considered in the practical environment. No matter how optimal an algorithm may be, it should rely on easy and straightforward steps that blend well with pre-existing business processes in order for it to work effectively in a professional environment.

Although there are concepts and thought processes that this project could benchmark from previous studies, directly applicable models or methodology is limited due to the characteristics of this project. Our project differs in terms of network size and the number of SKUs involved. Previous studies have modeled lateral transshipment problem as a mathematical model with a small size network consisting of one or two echelon, with one one distribution center and two retailers, with single commodity, identical demand profile among nodes and neglectable transshipment cost and lead time. The distribution network this project considers is comprised of two to three echelons with over 50 nodes, 16,000 SKUs, varying demand profiles among geographically dispersed nodes with a realistic transportation cost and lead time.

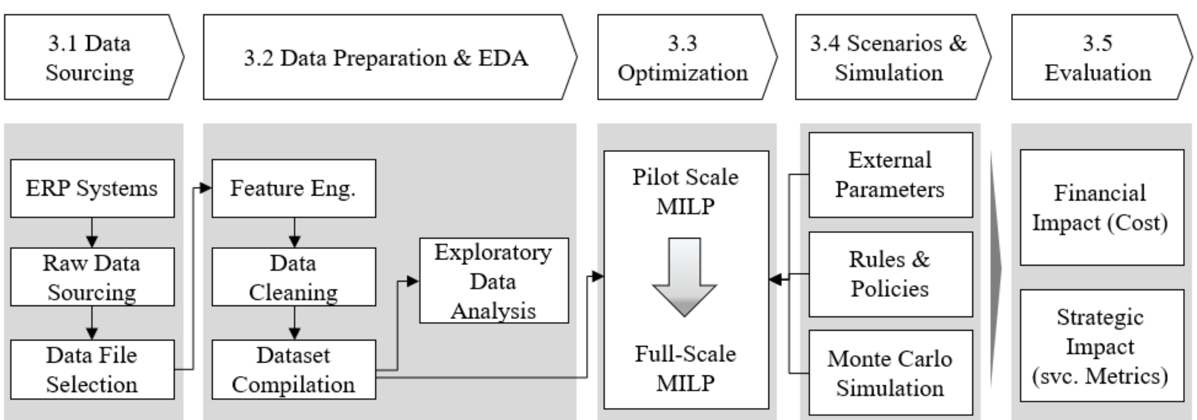
Our study contributes to the field of inventory balancing studies by providing application-oriented study in a larger network size, considerations for multiple products, and incorporation of realistic assumptions particularly regarding transshipment cost and lead time. Our approach would be a mixture of proactive and reactive transshipment, where we will use SS and healthy stock model to determine excess and deficit and use optimization and heuristics to find optimal or near-optimal efficient solutions. The detailed methodology will be covered in the following chapter.

3. Methodology

The main objective of this capstone project is to seek for potential cost and service improvements through rebalancing stock among multiple-tier distribution center nodes. Tier 1 – Tier 2 balancing is not in the scope of this project as it is a replenishment strategy. In this section, the methodology is covered in detail so that the same process and results could be reproduced by the sponsoring company with future datasets. First, we discuss the data sourcing and selection process, and explain the basic IT system of the company. Next, we prepare the dataset through feature engineering, data cleansing, and random sampling methods. Once the dataset is prepared, the optimization model and preliminary findings is presented in detail, covering key components such as input data, assumptions, objective functions, and constraints. Post-hoc analysis using different scenarios to examine how the model performs under different circumstances and stochasticity is addressed, followed by the evaluation of the model in terms of cost and service performance metrics. The topic and order of this chapter are summarized in Figure 7.

Figure 7

An overview of the Methodology Chapter



3.1 Data Sourcing

As briefly covered in Section 1.2, BSC currently implements two ERP systems: SAP/R3 for management and execution and Rapid Response for planning and analysis. The datasets used for this project were extracted from the Rapid Response system. Table 1 displays the five anonymized datasets that have been provided to the project team by the company. For the remainder of this paper, the abbreviations of each dataset's name listed in Table 1 is used to reference the datasets. For instance, the 'Periodic ending inventory details' file is referred to as 'PEI'. All datasets were provided as the default export format, which is xlsx type.

Table 1

Company-provided raw data dictionary

Abbreviation	**Dataset**	**Description**
TPS	Time Phased Safety Stock	Safety stock for each product-dc time phased over the next 12 months
SRC	Sourcing General	Source for each product-dc, manufacturing/purchasing costs, lead times for each node
INV	Sept 2021 Inventory	Inventory status for each product-dc
PEI	Period ending inventory details	Healthy stock model
GIV	GSC Inventory Visual Variability	Safety stock, supply/demand variability, future/historical demand, service level, LT, and Std Dev LT as of Oct 2021

The key data required for this capstone include the following attributes: product, distribution node, current inventory level, and the three target inventory level thresholds set by (Chapter 1.3) BSC's healthy stock model (Safety Stock, Minimum Stock, Maximum Stock). Based on exploratory data analysis, the PEI dataset included most of these attributes and therefore was selected as the main dataset for the project. GIV and INV were used to supplement the PEI dataset.

Critical information that was not included in the company-provided datasets are the distance matrix and transportation cost since there were no established routes between multiple tier-nodes. Our project requires distance information and transportation cost for approximately 1,600 transportation lanes. The distance information was acquired using a two-step approach. First, we acquired address and geocode information using Google maps and then fed the location data into Llamasoft's Supply Chain Guru X to calculate the distance matrix, which considers the circuity factor. For the transportation cost, external data will be sourced. We considered options such as i) acquiring aggregate level transportation cost modeling data from research papers, ii) getting input from BSC's transportation team, or iii) using cost estimation tools provided by major parcel delivery service companies such as UPS. We opted for acquiring the transportation cost from UPS CTC (Calculate Time and Cost) tool, mainly due to accessibility.

3.2 Data Preparation

The data acquired and selected from Section 3.1 needs to be cleaned and converted so that it is an appropriate format to feed into the optimization model. The data preparation has been conducted in three steps: feature engineering, data cleaning and formatting, and dataset compiling.

3.2.1 Feature Engineering

Among the 46 columns within the PEI dataset, 18 key columns were selected (Table 3). In the PEI dataset, each row consists of a unique product (encoded as 'Part' in the PEI table) – distribution node (encoded as 'Site' in PEI table) pairing; therefore, the 'Part'- 'Site' combo serves as a composite key for the dataset. The current inventory level is the starting point of this project and therefore included in the key columns. The inventory target levels generated by

BSC's MEIO and Healthy stock model are critical data since they determine whether the current inventory level on hand is within the healthy zone ($0.7*SS < IP < 1.3*SS + \text{Lot Size}$) or in excess or deficit. Columns that are used in the calculation of the healthy stock zone such as safety stock level, lot size, and stock limit min/max are all considered key columns. For all the inventory data columns both the quantity and value columns are included in the key columns to analyze both in unit terms and in USD Cost/Value terms in modeling and analysis. We will refer to the PEI dataset with only the key columns as PEI_kc to distinguish it from the original PEI dataset. Key columns for the 'distribution nodes' dataset and the 'routes' dataset have been selected and filtered out in a similar fashion based on the importance (see Table 2).

Table 2

Dataset Key Columns

PEI table Key Columns

	Part	Site	Projected Balance Quantity	Projected Balance Value	Lot Size Quantity	Lot Size Value	SS Quantity	SS Value	Stock Limit Min Quantity	Stock Limit Min Value	Stock Limit Max Quantity	Stock Limit Max Value	Healthy Quantity	Healthy Value	Deficit Quantity	Deficit Value	Excess Quantity	Excess Value
0	938	D950	16.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	15.00	0.11
1	56559	D275	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	56559	D315	2.00	700.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.00	700.00
3	56559	D335	16.00	5,600.00	3.00	1,050.00	0.00	0.00	0.00	0.00	3.00	1,050.00	3.00	1,050.00	0.00	0.00	13.00	4,550.00
4	56559	D525	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Nodes table Key Columns

	Plant	Description	Latitude	Longitude
0	D525	Kerkrade	50.885439	6.039818
1	D275	Quincy	42.293845	-71.033891
2	D625	Japan Kawasaki	38.259357	140.114665
3	D950	Australia	-33.927256	151.186807
4	D375	Canada	43.651612	-79.609058

Distance table Key Columns

ID	Source	Destination	Travel Time	Distance
1	D215	D215	0.00	0.00
2	D275	D215	2.61	3,445.80
3	D315	D215	4.63	6,115.04
4	D325	D215	5.97	7,884.30
5	D335	D215	4.83	6,369.68

3.2.2 Data cleaning

The columns of PEI_kc require data cleaning and datatype adjustment. All rows of the key column's raw data have been confirmed to be null-value free. However, some columns like Part were categorized as float values which were converted to object datatype. By utilizing simple Python functions for data cleaning, we have enforced datatype integrity of the columns. Table 3 displays the post-processed columns with the formatted datatype.

Table 3

Datatype Summary

PEI Dataset

```
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Part                        86573 non-null  object
 1   Site                        86573 non-null  object
 2   Projected Balance Quantity  86573 non-null  int32
 3   Projected Balance Value     86573 non-null  float64
 4   Lot Size Quantity           86573 non-null  int32
 5   Lot Size Value              86573 non-null  float64
 6   SS Quantity                 86573 non-null  int32
 7   SS Value                    86573 non-null  float64
 8   Stock Limit Min Quantity    86573 non-null  int32
 9   Stock Limit Min Value       86573 non-null  float64
 10  Stock Limit Max Quantity    86573 non-null  int32
 11  Stock Limit Max Value       86573 non-null  float64
 12  Healthy Quantity            86573 non-null  int32
 13  Healthy Value               86573 non-null  float64
 14  Deficit Quantity            86573 non-null  int32
 15  Deficit Value               86573 non-null  float64
 16  Excess Quantity             86573 non-null  int32
 17  Excess Value                86573 non-null  float64
```

Nodes Dataset

```
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Source       1444 non-null   object 
 1   Destination  1444 non-null   object 
 2   Travel Time  1444 non-null   float64
 3   Distance     1444 non-null   float64
```

Distance Dataset

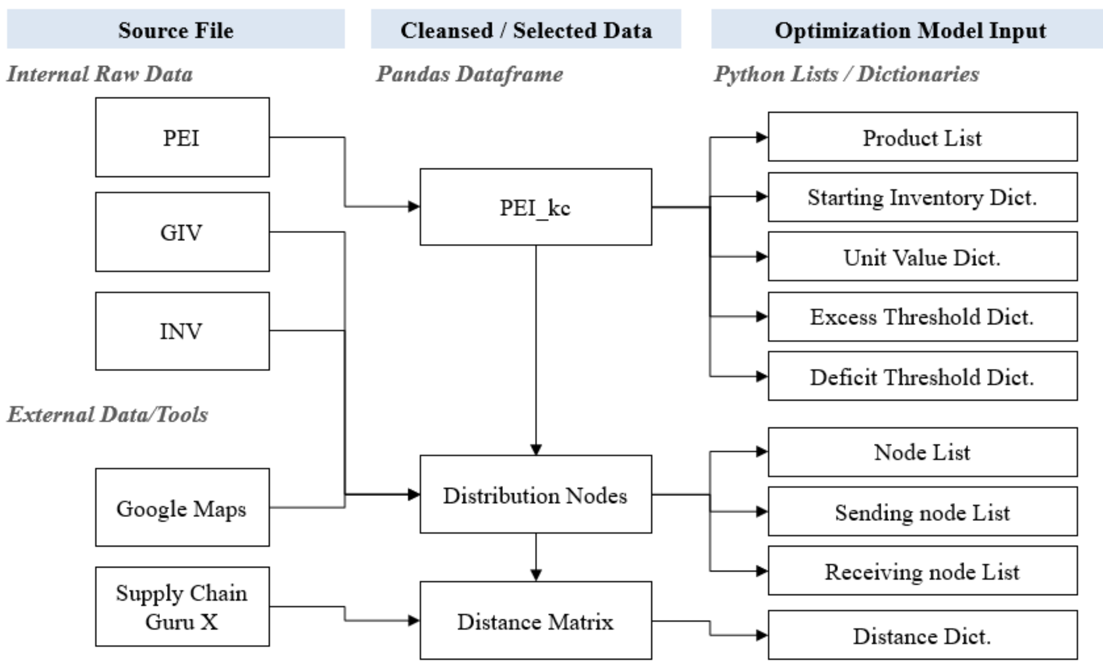
```
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Plant        38 non-null     object 
 1   Description  38 non-null     object 
 2   Address      38 non-null     object 
 3   Latitude     38 non-null     float64
 4   Longitude    38 non-null     float64
```

3.2.3 Dataset Compilation

As a final step of data preparation, the pre-refined datasets were restructured into sub-datasets for easier indexing and model loading. Python lists for distribution nodes (ERP 'Plant' code) and products (ERP 'Parts' code) were created for enumeration and looping. Python dictionaries for the current, pre-rebalanced, and inventory were created using distribution node – product tuple as key and the inventory quantity as value. The transportation routes dictionary was generated with sending node – receiving node as key and the distance as value. The final dataset prepared for loading to the optimization model is depicted in Figure 8.

Figure 8

Dataset Preparation for Optimization Model

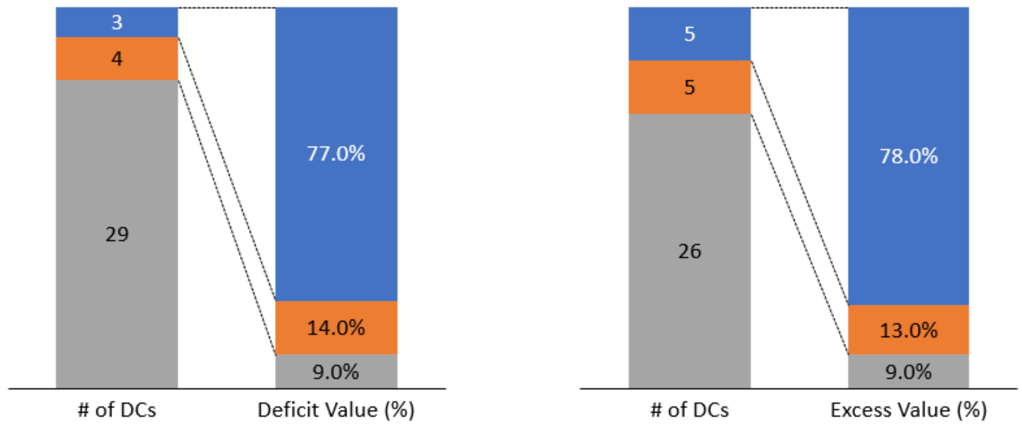


3.2.3 Exploratory Data Analysis

Based on the cleaned data, exploratory data analysis was conducted to understand the current inventory status of BSC at a high level prior to optimization modeling. The PEI dataset includes inventory information for each end-product SKUs stored in every manufacturing and distribution facility. The dataset includes approximately 24,000 unique end-product SKUs and 38 Distribution nodes. Based on these two dimensions, the PEI dataset has approximately 87,000 unique 'Product' – 'Node' pairs, which are represented as rows. Among these pairs, 39% are currently in excess, or beyond the maximum stocking level defined by the healthy stock model and 13% percent of pairs are in deficit. As seen in Figure 9, seven DCs contribute to 91% of the total deficit inventory whereas ten DCs contribute to 91% of the total excess inventory.

Figure 9

Excess and Deficit DC summary

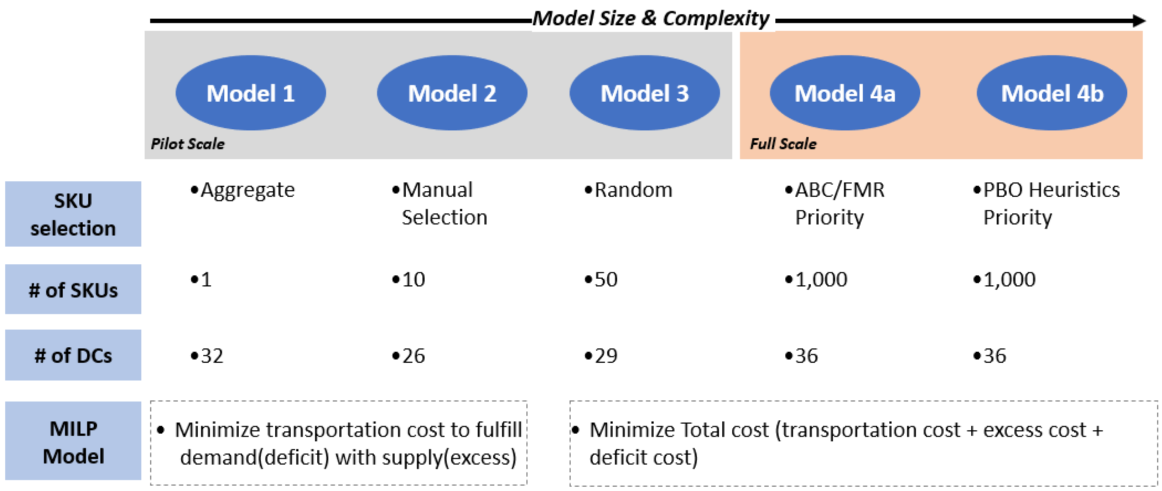


3.3 Model Building and Solving

This project primarily implements Mixed Integer-Linear Programming (MILP) network optimization model. To reduce trial-and-error and accelerate the analysis process, we have started with a small problem size, and scaled it to a larger size (see Figure 10). Initial models have smaller selection of SKUs and a simpler objective function (Model 1 to 3), whereas the final model (Model 4) incorporates larger selection of SKUs with complex objective functions. A single product minimum transportation cost model is first introduced, followed by a 10-SKU multi-product expanded version of the model. Next, a fifty-SKU multi-product model with transportation, excess, and deficit costs included in the objective function is covered.

Figure 10

Model Scaling Approach



The optimization models are formulated and then solved using both Python with PuLP/Gurobi optimizer and Llamasoft's Supply Chain Guru X to leverage the strength of both tools, and for applicability for either tool when implemented by BSC. The mathematical notations used in this chapter are summarized below.

Sets

N: set of DC nodes, $N = \{i = 1, .., n\}$
S: set of shipping nodes, S = {s = 1, .., n}
R: set of receiving nodes, R = {r = 1, .., n}
P: set of Products, $P = \{p = 1, .., p\}$

Variables

x_{ir} : aggregated quantity of product at node i
x_{sr} : aggregated quantity of product from node s to node r
x_{srp}: quantity of product p to transship from node s to node r
y_{sr}: binary variable for whether transshipment occurs from node s to node r
IE_{ip}: inventory level after transshipment execution for product p at node i

Parameters

IS_i : starting aggregated inventory level at node i
IS_{ip}: starting inventory level of product p at node i
VC_{sr}: variable transportation cost/unit from node s to node r
FC_{sr}: per shipment fixed tsp cost/unit from node s to node r
SC_p: shortage cost for product p - remanufacturing cost in the current model
EC_p: excess cost for product p - scrap cost in the current model
SS_{ip}: MEIO Safety Stock Threshold of product p at node i
ES_{ip}: MEIO Excess Stock Threshold of product p at node i
DS_{ip}: MEIO Deficit Stock Threshold of product p at node i
DRC_{ip}: Demand over replenishment and delivery lead time for SKU p at DC i
DLT_{ip}: Delivery lead time for SKU p at DC i
RCT_{ip}: Replenishment cycle time for SKU p at DC i
μ_{ip}: Daily mean demand for SKU p at DC i CV: Coefficient of variation for daily demand (moderate: 0.66, high: 1.3)

3.3.1 Model 1

3.3.1.1 Overview

The first model is the transportation cost minimization model. In this model, we use a single-product approach where the aggregate inventory across all SKUs is considered as the single product. A two-dimensional decision variable x_{sr} is used with indices set for shipping nodes and receiving nodes. The objective function is the minimum total transportation cost, and it is bound by the constraint to fulfill demand, which is set as the deficit quantity of each node (see Equation (1)). S_s is the maximum capacity at each node which is equivalent to the excess quantity for each node, meaning, all excess quantities can be shipped to other nodes for rebalancing. Since the products in this model are at the aggregate level, a constraint to prohibit transshipment to itself was applied (see Equation (2)).

Objective Function

$$Min \sum_{s\in N}\sum_{r\in N} VC_{sr}x_{sr} \quad (1)$$

Constraints

$\sum_{r\in N} x_{ir} \leq IS_i$ $\quad \forall i, r\in N \quad$ (2)

$x_{sr} \geq 0$ & integer $\quad \forall s, r\in N \quad$ (3)

3.3.2 Model 2

The second model is an expansion of the first model to incorporate multi-products. Among the total products, 10 SKUs which the team was aware of regarding the imbalance among distribution network were handpicked. A 3-dimensional decision variable x_{srp} is used with indices for shipping, receiving node, and the product SKU. The same min-transportation cost objective function is set to run the optimization (see equation (4)).

Objective Function

$$Min \sum_{s\in N}\sum_{r\in N}\sum_{p\in P} VC_{sr}x_{srp} \quad (4)$$

Constraints

$\sum_{r\in N} x_{irp} \leq IS_{ip}$ $\quad \forall i, r\in N \quad$ (5)

$x_{srp} \geq 0$ & $integer$ $\quad \forall s, r\in N \quad$ (6)

3.3.3 Model 3

3.3.3. Overview

To test with the same conditions of the full-scale problem in a relatively smaller problem, we have built a MILP model with 50 randomly sampled SKUs and their relevant distribution nodes.

Objective Function

$$\text{Min} \sum_{s\in N}\sum_{r\in N}\sum_{p\in P} VC_{sr}x_{srp} + \sum_{i\in N}\sum_{p\in P}\text{MAX}\big(IE_{ip} - ES_{ip}, 0\big)EC_p + \sum_{p\in P}\text{MAX}\ (DS_{ip}\ IE_{ip}, 0)SC_p \qquad (7)$$

Constraints

$$\sum_{r\in N} x_{irp} \le IS_{ip} \qquad \forall i, r \in N, p \in P \qquad (8)$$

$$IE_{ip} = IS_{ip} + \sum_{s\in N} x_{sip} - \sum_{r\in N} x_{irp} \qquad \forall i, s, r \in N, p \in P \qquad (9)$$

$$x_{srp} \geq 0\ \&\ integer \qquad \forall s, r \in N, p \in P \qquad (10)$$

A key distinction of this model besides the size is the objective function and the constraints (see equation (7)). The previous models covered in 3.3.1 and 3.3.2 consider the deficit quantity of inventory as the demand, and therefore introduce demand fulfillment requirement constraints so that all deficit quantities across all distribution nodes are met. The objective function therefore only considers the transportation cost. However, the model in this chapter considers inventory levels that are outside of the 'healthy stock zone' as cost factors. Quantities below of the lower threshold assume shortage (deficit) cost, while quantities above the upper threshold assume excess (scrapping) cost and are modeled in the objective function. There are no 'need to meet' hard-wired demand requirements in this model. In the previous models (Model 1 and 2), the deficit quantities were forced to be fulfilled through supply-demand constraint. However, in this model, transshipment decision is determined intrinsically by the objective function based on the cost profile, or the tradeoff relationship of the transportation cost and the excess and deficit cost. One issue that occurred during implementing the MILP model was that the 'max' function within the objective function was nonlinear. Auxiliary variables and constraints were introduced to set-up the maxima logic suitable for the MILP model.

3.3.4 Model 4

As the final optimization model, 1,000 SKUs from the dataset have been loaded to the model to be solved. The objective function and constraints are equal to that of model 3.3.3 (see equation (7)), but the number of decision variables and constraints are much larger. MILP is NP-Hard; therefore, the increase of decision variables and constraints will cause the complexity and solution time to increase exponentially. Since not all SKUs are selected for this phase of the analysis, two methods for selecting impactful SKUs were implemented.

3.3.4.1 Model 4a

The first SKU selection method is based on BSC's pre-existing inventory classification. BSC categorizes all SKUs according to a ABC/FMR classification scheme. ABC refers to the SKU's priority in terms of revenue size (A-Highest revenue, B-Medium revenue, C-Lowest revenue). FMR considers the velocity of the SKU (F-Fast moving, M- Medium moving, R- Slow moving). This classification is based on SKU at each node level, meaning the same SKUs can have different classification depending on the node they are in. Only the ABC classification was considered in the analysis, and to reduce the dimensionality, the highest ABC ranking across all nodes was selected to represent the SKUs' priority. The top 1,000 SKUs for the optimization model were selected to be loaded into the optimization model.

3.3.4.2 Model 4b

To increase the potential savings through lateral transshipment, Potential Balance Opportunity (PBO) heuristic was developed. PBO calculates minimum value between the total excess and total deficit for a SKU across all nodes (see equation (11)). The metric shows the level of inventory imbalance in monetary value, which is the maximum potential saving that can be achieved through inventory rebalancing. The top 1,000 SKUs based on the PBO ranking have been selected as the sample for the optimization.

$$PBO_p = \min\left(\sum_{i \in N} max(IS_i - ES_i, 0), \sum_{i \in N} \max\left(DS_i - IS_i, 0\right)\right) \qquad (11)$$

3.4. Scenario analysis & simulation

After modeling and solving the optimization, a scenario-based sensitivity analysis has been conducted. To compare the performance of the original and rebalanced inventory model, stochastic demand was generated using Monte-Carlo simulation. Demand over replenishment cycle time and delivery lead time was generated to isolate the impact of inventory replenishment and solely assess the performance of the rebalancing. Additional data required for the simulation were the daily demand data, delivery lead time data, and the replenishment cycle time data. Daily demand and coefficient of variance (CV) data were collected from the ERP system and used as input for demand generation. Based on historical order data, BSC has an average CV value of 0.66, and this figure was used as the ‘moderate’ demand scenario. A higher CV value of 1.3 was used for the ‘high’ demand scenario. Delivery lead time data was pulled from the ERP system as well. The demand was assumed to follow Gaussian distribution with a lower bound of 0, so that all negative demand values were capped at 0 (see equation (12)). The simulation was 1,000 iterations for each SKU-node level, and the results were aggregated as the mean value. The results of the simulation will be discussed in detail in Chapter 4 – Results & Analysis.

$$DRC_{ip} = \sum_{d=1}^{RCT_{ip}+DLT_{ip}} max(\,N(\mu_{ip}, CV \times \mu_{ip}), 0) \tag{12}$$

3.5 Evaluation

Based on the optimization and simulation results, the performance of pre/post-balancing has been analyzed in both cost and strategic metrics. Detailed costs analysis has been conducted to understand how each system performs in terms of transportation cost, and excess and deficit inventory cost. Service and operation metrics such as inventory level within healthy stock zone, risk of stockout and scrapping have been reviewed and KPIs for the inventory model, such as stock-out events, units short, monetary values short, excess inventory, and deficit inventory were calculated to analyze the models' performance under stochastic demand.

4. Results & Analysis

The results for the Pilot-scale (Model 1,2 and 3) and full-scale (Model 4a and 4b) optimization models will be discussed in this chapter. Monte Carlo simulation studies for Model 4a and 4b have been conducted for sensitivity analysis.

4.1 Model 1 Optimization Results

Model 3.3.1 considers excess (1.10m) and deficit (380k) quantities at 32 nodes as a sample dataset. A base MILP function as stated in equation (1) was solved using the Python optimizer PuLP (python linear programming modeler). The initial model uses 0.03 USD per unit per km as a variable cost (V_{sr}) for transshipment between nodes. Thus, the optimizer minimizes the transportation costs based on the shortest path possible between the nodes. After satisfying the deficit, the model is still left with ~700k units in excess which is a potential scrap of ~$19M. The optimal transportation cost is ~$17M. These initial costs are just for reference to assess the base model behavior. Real costs have been compared with future models as they are refined.

4.2 Model 2 Optimization Results

This model was initiated and solved in Llamasoft's supply chain guru software. The variable cost (V_{sr}) is set at 0.03 USD per unit per km, the same value applied for model 3.3.1. Figure 11 shows the flows between 26 nodes that have excess capacity, and 15 nodes that have a deficit. Some sites with excess capacity are never activated, as the model considers the closest node first to minimize transportation costs. The biggest receiving node is in the Netherlands which receives products from many sites worldwide. Otherwise, all the other transshipments are very region-specific which is expected due to the shortest path optimization.

Figure 11

Inventory Flow for Optimization

4.3 Model 3 Optimization Results

In the current problem setting with 50 SKUs and 29 DCs, the business-as-usual case where no rebalancing occurs results in a \$646K total cost with \$424K of excess cost and \$222K of deficit cost. The optimal solution through rebalancing improved the total cost by 8.4%, resulting in a total cost of \$582K. This saving is achieved by executing 65 transshipments which can be easily found by examining the number of non-zero x_{srp} values in the optimal solution set. The excess and deficit level improves after the rebalancing as well. Prior to balancing there is a total of 9,582 units of stock are in deficit and 5,367 units in excess across the 29 DCs. This figure is improved to 9,157 of deficit and 4,982 of deficit, respectively, balancing the overall inventory level to conform to BSC's healthy stock zone.

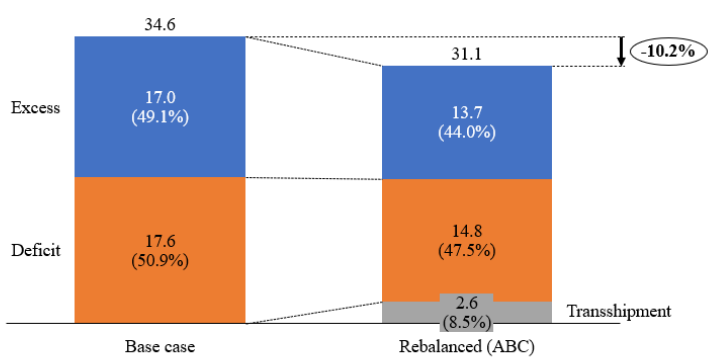
4.4 Model 4a Results

4.4.1 Optimization Results

The top 1,000 SKUs were selected using the ABC classification resulting in a total of 9,566 SKU-node combinations (rows). Among these SKU-node pairs, 37.4% of them were in inventory excess position, while 14.6% were in inventory deficit position. In the base case, where the inventory is managed as-is, the total cost is $34.6M with cost distributed equally among excess and deficit cost. Running the optimization model resulted in 1,666 lateral transshipments incurring $2.6M of shipping cost. The total cost was reduced by 10.2% to $31.1M, with $3.3M reduction in excess cost and $2.8M savings in deficit cost (see Figure 12).

Figure 12

Base case vs. rebalanced (ABC) cost comparison

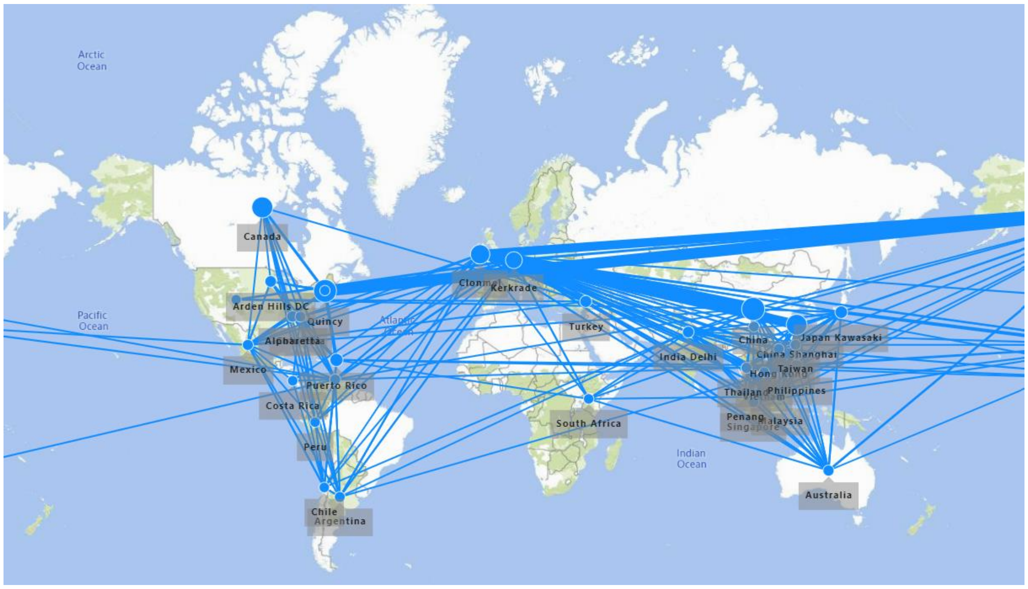


The executed transshipments are visualized in Figure 13. As expected, the concentration of transshipments is between Europe and Asia (48% of total volume) and between

North America and Latin America (20% of total volume). The third-largest transshipment occurs between Europe to North America (7% of total volume). There is no transshipment from Asia to North America; this is primarily due to transportation costs and to Europe being closer to North America to fulfill its demand

Figure 13

Transshipment flow (ABC)

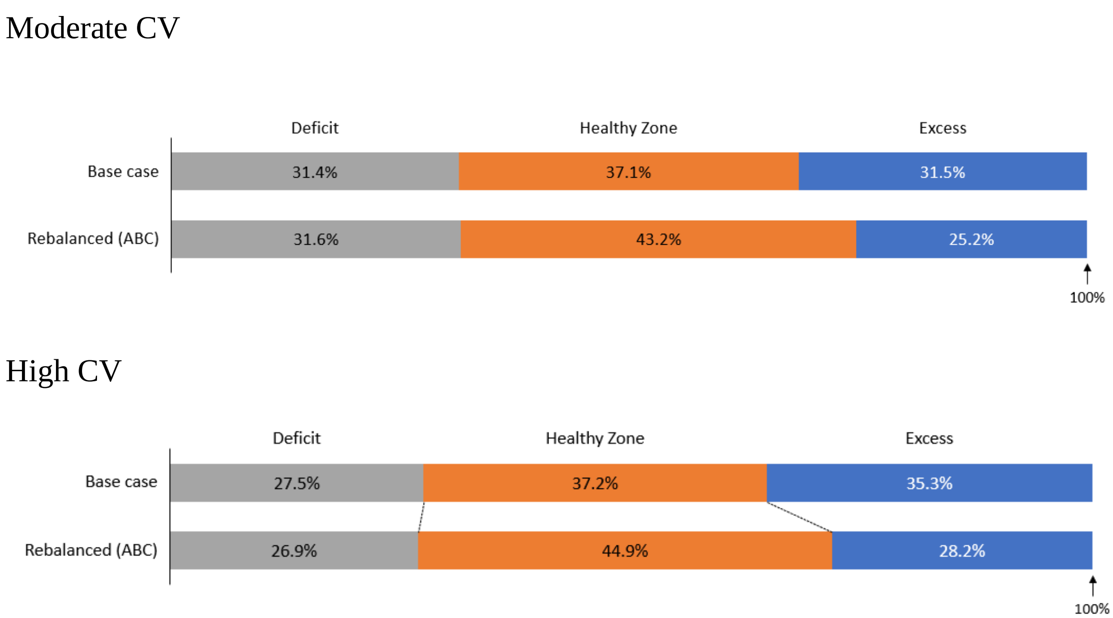


4.4.2 Simulation Results

Stochastic demand was generated using moderate and high CV scenarios to see how the inventory model performs under variability. Figure 14 shows the results after the demand was generated. In the moderate CV case, the rebalanced state has 43.2% of the SKU-DC pairs in the healthy stock zone, while the base case state has 37.1%. The number of excess SKU-DC pairs is improved from 31.5% in base case to 25.2% in the rebalances state. The deficit SKU-DC pairs slightly deteriorate from 31.4% to 31.6%.

Figure 14

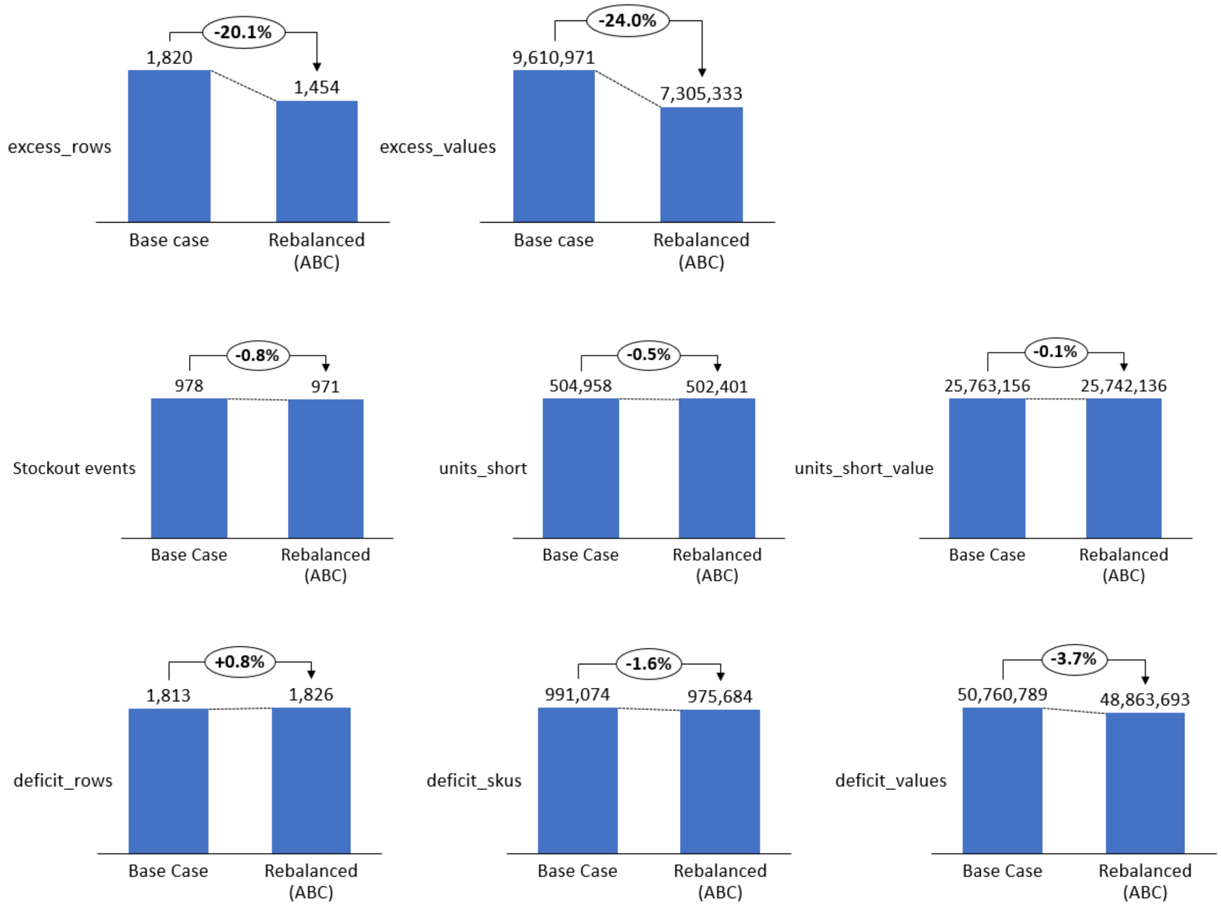
Simulation results (ABC)



For the high CV case the improvements are more significant. The rebalanced state has 44.9% of the SKU-DC pair in the healthy stock zone, higher than the base case which has 37.2%. The number of deficit and excess SKU-DC pairs increased significantly as well. Key inventory and cost KPI are displayed in Figure 15. Rebalancing has the highest impact is in reducing the impact of excess inventory.

Figure 15

Simulation results details



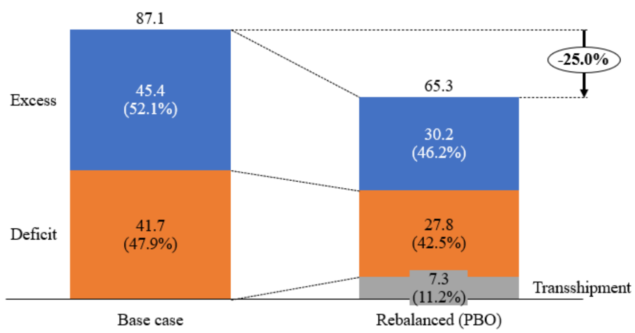
4.4 Model 4b Results

4.4.1 Optimization Results

The 1,000 SKUs selected based on PBO heuristics yielded 11,674 SKU-node pair combinations (rows). Among these pairs, 39.6% were in inventory excess position, while 19.4% of them were in inventory deficit position. A total of 3,681 lateral transshipments were executed through the optimization model incurring $7.3M in transportation cost. The model reduced the total cost by 25% from $87M to $65M (see Figure 16).

Figure 16

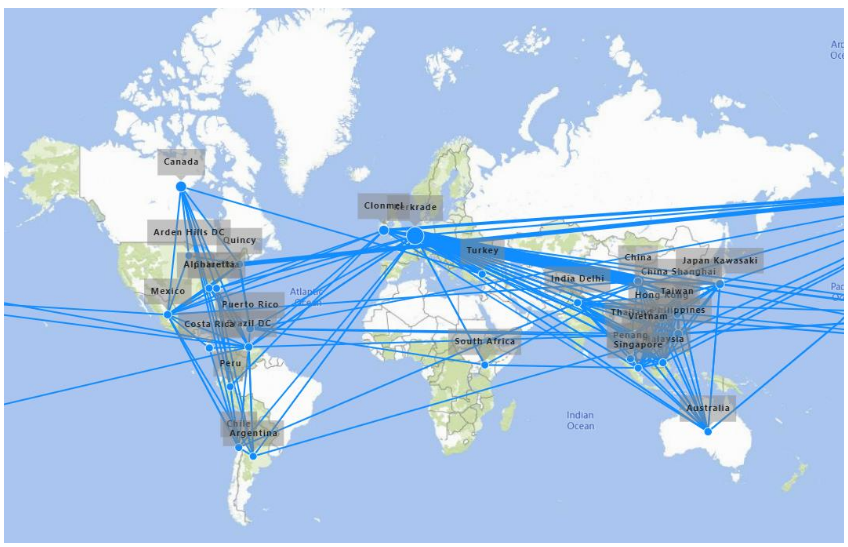
Base case vs rebalanced (PBO) cost comparison



The executed transshipments are visualized in Figure 17. The transshipment flow for PBO is very similar to ABC. Europe – Asia and North America – Latin America represent 36% and 32% of total transshipment volume respectively. Europe – North America represent 11% of the total transshipment volume.

Figure 17

Transshipment flow (PBO)



4.4.2 Simulation results

After applying the stochastically generated demand to each inventory model, the SKU-DC pairs within the healthy zone were 44.8% for the moderate CV and 47.7% for the high CV scenario rebalanced case. These figures were higher than those of the baseline case, which were 34.7% and 34.8%, respectively. Excess inventory SKU-DC pairs were improved as well, with 10%p lower share. The deficit SKU-DC pair slightly increased (0.5%) for the rebalanced case in the moderate CV scenario but decreased (1.3%) in the high CV scenario. Key inventory and cost KPIs are displayed in Figure 19 and depict that the highest impact is in reducing the excess inventory.

Figure 18

Simulation results (PBO)

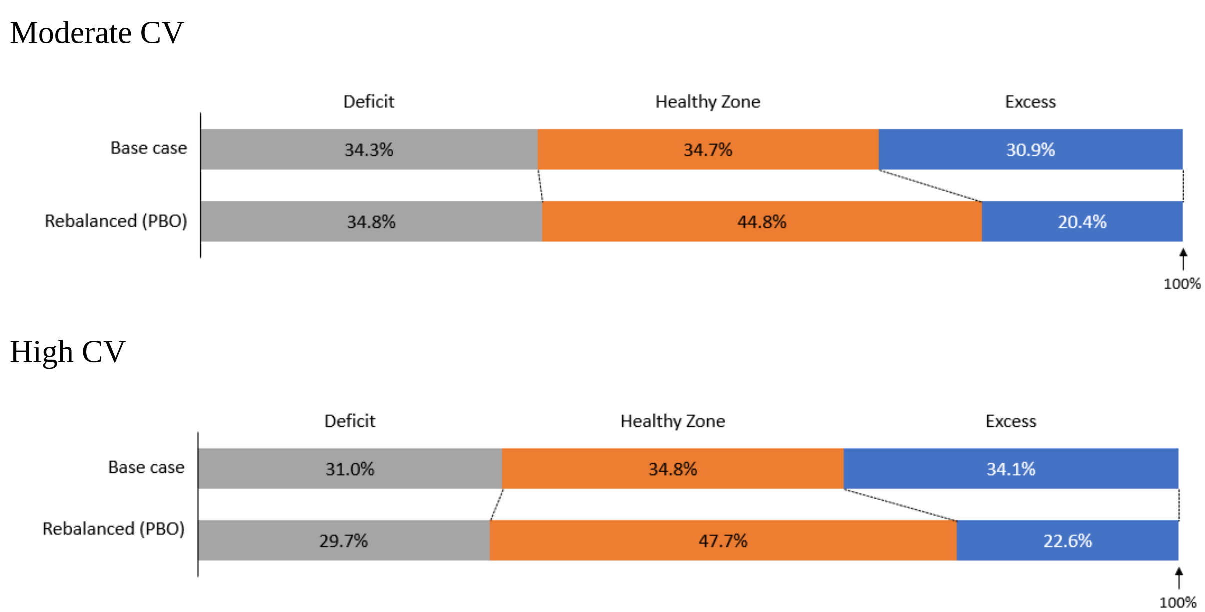
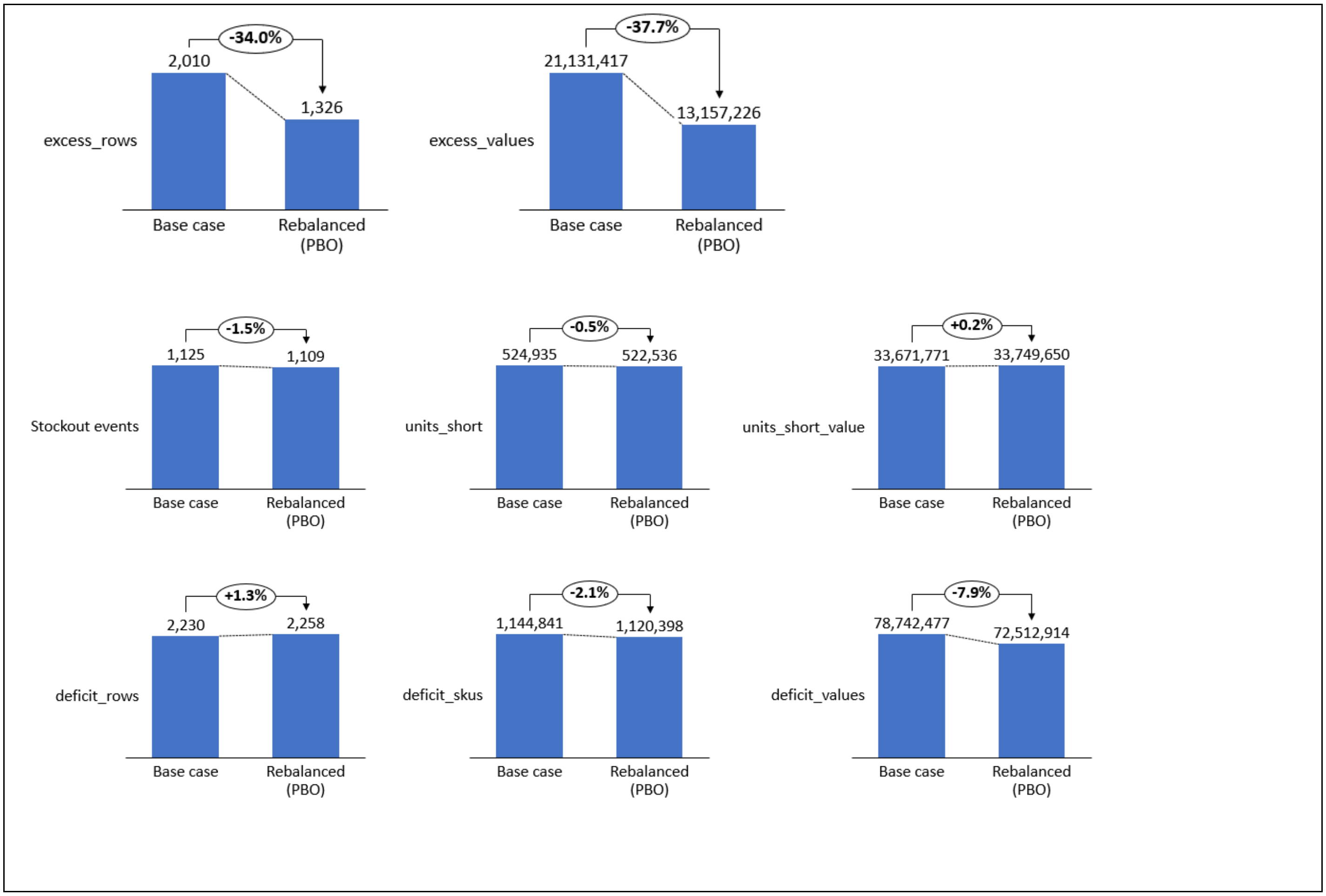


Figure 19

Simulation results details



5. Discussion

The capstone results show that lateral transshipment has the potential of saving 10% to 25% of total inventory costs. The study covers the full process of optimizing inventory level through lateral transshipment, from data sourcing, selecting the high impact SKUs, to calculating the optimal transshipment volume across the distribution network. At its core, the model balances the cost of holding excess inventory and the cost of being in deficit, while considering the transportation cost to execute direct shipment between same tier DCs.

There are several managerial insights we would like to address. First, when applying inventory rebalancing in practice, a stepwise approach is recommended. Starting with a pilot project by selecting SKUs based on pre-existing classification method and gradually scaling the size and incorporating sophisticated SKU selection methods will allow for easier adoption. BSC can start a pilot project using the ABC/FMR classification to select potential SKUs for the optimization model as discussed in section 3.3.4.1. If the pilot results are promising, the company can expand to the PBO heuristics introduced in Section 3.3.4.2. The PBO heuristic require additional steps and data processing to select SKUs but has higher potential for cost savings. Second, integrating inventory rebalancing into BSC's periodic inventory review process is suggested. The selection of SKU and calculation of optimal transshipment requires company-wide resource allocation, and therefore difficult to implement on a continuous basis. Since inventory levels are assessed during the periodic inventory review, it is an opportune time to review and execute stock repositioning initiatives, with minimal additional planning and resource input. Third, the integration of the lateral transshipment models with existing supply chain ERP systems is required for a streamlined adoption by users. Practitioners operate on a daily basis interacting with the ERP system to operate and manage supply chain activities.

Establishing a custom view to monitor the imbalance level and being able to execute transshipment within the system is advised. Finally, it is recommended to get accurate information on optimized transportation costs from logistics partners. The model for this project used direct parcel shipment from DC to DC. The cost can be improved by volume consolidation and optimal routing by collaborating BSC's logistics service providers.

There are limitations to this study due to data accessibility and assumptions for optimization. First, handling cost within the distribution center was not accounted for in the optimization model. The objective function includes only the transportation cost, excess cost, and deficit cost. In practice, transshipment requires additional handling activities within the warehouse, such as pick/pack/shipping activities in sending nodes and receive/sort/put-away activities in receiving nodes. Second, the transportation costs are modeled as variable costs in this study. In reality, there would be associated fixed costs for new shipping lane set up activities, such as vendor selection, training, account management, etc., which should be considered in the cost function. Finally, global regulations on medical devices may restrict transshipments on certain lanes. Different countries have different regulatory agencies regarding healthcare products that enforce prior approval or authorization procedures. The study on global regulations in medical devices was beyond the scope of this research, and therefore was not included as constraints in this study. It is advised that these limitations must be considered and accounted for when implementing inventory rebalancing in practice.

6. Conclusion

The objective of this study was to provide cost saving solutions through inventory rebalancing. To do so, the project team has collected and prepared the data, developed heuristics for SKU selection, built and ran a MILP optimization model with varying scale of model size in terms of number of DCs and SKUs included as decision variables. The optimized inventory model's performance was tested upon stochastic demand using Monte-Carlo simulation.

Based on the MILP optimization results, inventory rebalancing can reduce the total cost up to 25%. Lateral transshipments enable significant savings in excess cost and shortage cost by redistributing inventory to the right location. The rebalanced inventory model demonstrated superior performance under stochastic demand as well. Simulation results show that more SKUs were within the Healthy Stock zone for the rebalanced model (47.7%) compared to the base case (34.8%) post-demand generation in high variability scenario.

This capstone project supports Boston Scientific with their objective of further improving inventory levels across the distribution network. For the field of lateral transshipment, this project provides a large-scale, application-oriented study which can be scaled to other industries where imbalances across the distribution network impact the bottom-line and service level..

There are two areas of further studies in the field of lateral transshipments that are recommended. The first is the interaction between replenishment process and lateral transshipment process. In a typical distribution network, the replenishment process only accounts for the downstream demand when calculating the optimal inventory level. When lateral transshipment policies are adopted company-wide, the inventory movement could result in significant volume. Further understanding is required to understand the dynamics between intra-company orders for transshipment and inventory model for replenishment cycles. The second is application of lateral transshipment in fast-paced, low margin industries. The medical devices industry is characterized by high margins, relatively stable demand, and high importance on service levels. Studying the effectiveness of lateral transshipment in industries such as e-commerce or consumer packaged goods (CPG), with different cost structures, distribution networks, and service level requirements could provide different business insights.

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