# BIDDING ENABLED INVENTORY REDISTRIBUTION IN A RETAIL NETWORK

by

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Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT ARLINGTON

May 2021

Acknowledgements

First and foremost, all praises and thanks to the Almighty Allah for helping me to finish my research work. I also want to thank the people of my country, Bangladesh. Because of their tax money, I was able to graduate with B.Sc. in Engineering. This degree later persuaded me to do my Ph.D.

I want to thank and convey my gratitude to my Ph.D. Supervisor Dr. Brian L. Huff. His intelligent vision, continuous guidance, and support helped me incessantly advance and complete my research work. I want to thank my committee members, Dr. Jamie Rogers and Dr. Yuan Zhou. Dr. Jamie Roger's class lectures and class project helped me understand logistics and distribution system design better. My heartiest gratitude to Dr. Yuan Zhou for providing the opportunity to learn about Agent-based simulation. Her offered course on agent-based simulation helped me study the use of Anylogic Software to develop simulation models. My research model has been set based on hybrid simulation in Anylogic Software.

I want to offer my gratitude to Mr. Quamrul Hasan, Head of Supply Chain of a retail company in Bangladesh, for providing the data related to my research work. My sincerest thanks to my teacher Shahadat Hossain for sowing the seed of interest in Science and Mathematics at my early age of high school study.

I wish to thank all the staff members of the Industrial, manufacturing, and System engineering department of UTA for their cooperation. I want to thank the advisor of the Ph.D. student of our department, Dr. Victoria Chen, for being understanding and helpful throughout my years in UTA.

Finally, I want to thank my parents for their prayers, encouragement, belief, and support to complete my research work. I want to thank my husband for his continued support throughout the

good and bad times. My gratitude to my husband for taking care of our two-year-old son while I was busy with my research works.

April 23, 2021

Abstract


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The University of Texas at Arlington, 2021

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This research aspires to develop a systematic approach to minimize the demand and supply gap of products and product expiration in a feasible way. Inventory replenishment policy, uncertain customer demand, and forecast inaccuracy are some of the reasons that create imbalanced stocks in the outlets. Lateral transshipment or redistribution, donation, and promotion have been discussed in the existing literature separately as ways to balance and utilize inventory. Redistribution needs to account for extra transportation costs due to stock transfer. Existing literature on redistribution fails to address products' physical attributes, valuation of products as a function of time, and constraint on receiving products' life. An integrated process for identifying the most suitable products for redistribution and donation is also absent in the literature. While considering redistribution, it is helpful for the retailer to know which products can provide the best benefit from redistribution. Identification of products based on their redistribution benefit cannot be found in current works.

This work presents a process for categorizing products according to their predicted profitability as a result of redistribution. A decision support tool has also been introduced to identify the products which can be donated and redistributed. A redistribution model of a stochastic two-echelon, multi-period, multi-product, multi-outlet retail network has been developed based on a bidding strategy to address the imbalance of stock levels. This model incorporates the use of the product's weight, volume, allowable life constraints and dynamically considers product value as a

function of time. Donation option has been included with redistribution in our mode to balance inventory and reduce waste.

A hybrid agent-based and discrete-event simulation model was constructed to represent this complex system. Actual data from an existing retail chain has been used to represent the demand of 155 SKUs over a ten-store retail chain. A “periodic review-order up to level” inventory control system was utilized.

Results indicate that redistribution has impacted the total retail system’s performance significantly for Net Cash Inflow, customer satisfaction (Fill Rate), and cash inflow over cost ratio. On the other hand, slow-moving items get the most benefit from disposal through donation.

Table of Contents

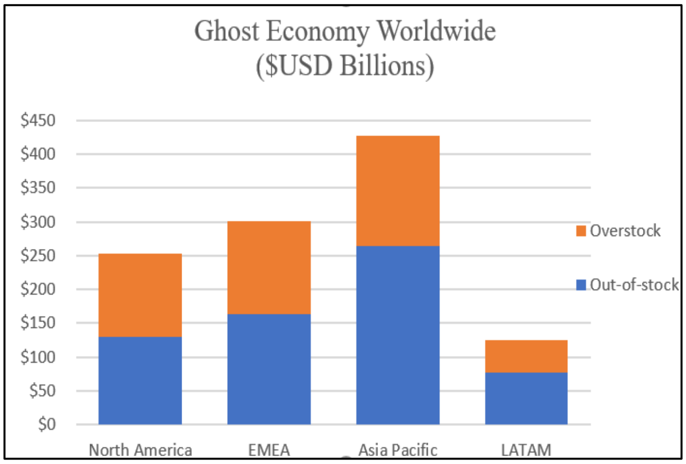
List of Tables

List of Figures

# Chapter 1 Introduction

## 1.1 Background

Retailing has a significant impact on a country's economy. The Retail industry contributes to a nation's GDP (gross domestic product) and creates many employment opportunities. In 2019, the contribution of the retail sector to U.S. GDP was 5.5% [97]. A retail business's success lies in proper inventory management for both the online and physical retail industries. After the impact of COVID-19, purchasing products from physical stores has reduced while online purchasing has increased. This purchasing trend does not mean that it is not required to have physical outlets or balance inventory throughout a retail chain's physical outlets. Based on global research and advisory firm report for the retail and hospitality industries, IHL, nearly 90% of all retail sales in 2021 will be from local stores [50]. Most of the local stores or outlets will work as a digital order fulfillment center. In this new age, retail outlets will not be the end shipping points. Customer's online orders will be delivered from these outlets [70]. The imbalance between supply and demand impacts retail businesses by increasing costs. Some costs like holding costs, ordering costs, and maintenance costs are visible to the retailers, but some other costs are not seen and addressed as ghost economies [14]. In the 14.5 trillion global retail economies, lost revenue opportunities were $1.75 trillion in out-of-stock, overstock, and sales returns [51]. Out Of that $ 1.7 trillion in 2015, overstock carried $417 billion, which was 30 percent more than 2012, and out of stock contributed $ 634.1 billion, 39% higher than 2012. In 2018, worldwide retail sales increased to approximately $24 trillion [98], where the cost of out-of-stock was $987 billion.




*Source: IHL Group/ Dynamic Action (2015)

**Figure 1-1** Region-wise worldwide overstock and out-of-stock costs [51]

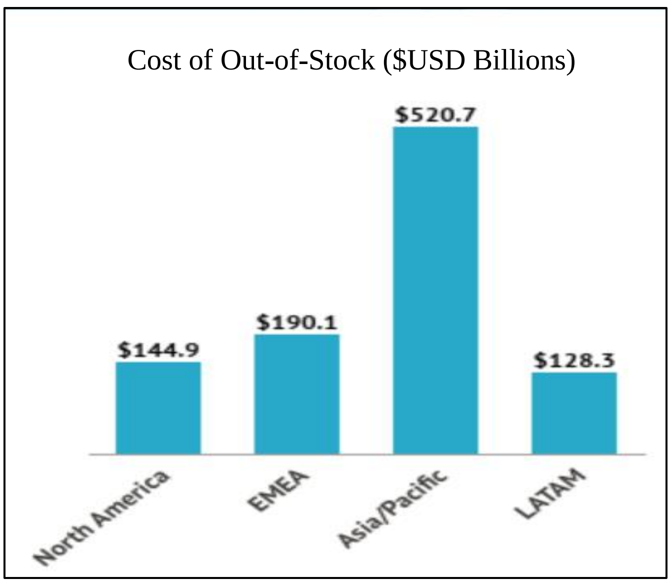
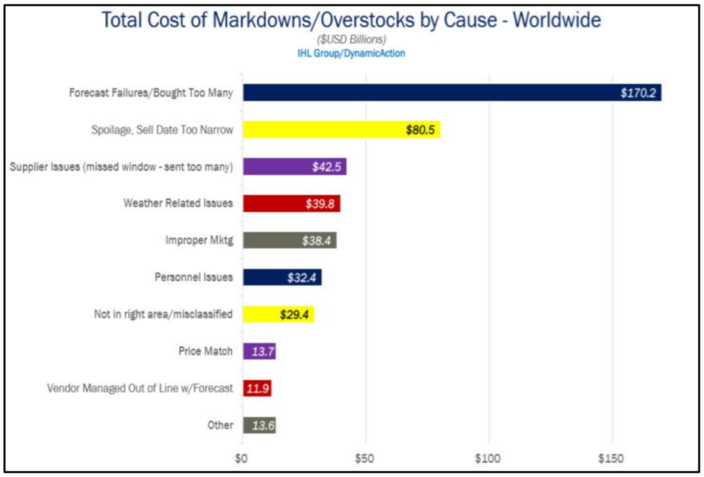



**Figure 1-2** Region-wise worldwide out-of-stock costs (2018)

Forecasting error, and other operational uncertainties, made it difficult to maintain optimum stock levels in a supply chain network. Forecasting error leads to overstock and understock conditions. Both overstock and understock events result in higher costs or lost revenues. Figure 1-3 represents the causes of overstocks with respective expenses. Though most of the reasons are uncertain, companies can fix specific problems like improper marketing strategies. Accepting other uncertainties, proper utilization of overstock items can help a company minimize losses to a certain extent. It is a severe concern for a company to decide how they can get rid of these products.




*Source: IHL Group/ Dynamic Action

**Figure 1-3** Overstocks by cause, worldwide (2015)

Root causes of out-of-stock conditions have been studied by researchers [29][74]. Poor data synchronization, perpetual inventory failure, distorted forecasting, excessive backroom inventory, faulty shelf space allocation, low planogram compliance, and poor stocking practice contribute to out-of-stock in outlets [45]. It was found from the study that about 47% of out-of-stock events occur because of distorted forecasting, where inadequate shelf replenishment accounts for 25% of out-of-stock events [45]. Out-of-stock conditions lead to customer dissatisfaction and the risk of losing future customers. To avoid out-of-stock situations, sometimes retailers pay money for replenishing out-of-stock items when they have cash stuck for carrying huge overstock for the same products at a different location.

Another area of concern for retail outlets is expired products. US retail food outlets generate eight million tons of waste every year, accounting for $18 billion of lost value. Profits from food sales are half of the value of wasted foods [87]. The undesirable behavior of customers when handling products can contribute to product waste. Some of the other reasons for the product or food waste in retail are inefficient personnel and less time gap between product delivery date and product expiry date [105][26].

This research will focus on strategies that enable the balancing of inventories throughout a company's network of outlets, thereby decreasing the number of expired products and minimizing the number of out-of-stock events.

## 1.2 Problem Statement

Attempts to minimize the impact of out-of-stock, overstock, and expired products have been an active academic research area [29][74] [26][4][2][103][59][28]. The supply chain is a complex network. Better integration of different supply chain components and correct information flow is required for its better performance. The identification of factors that can influence or have an impact on the network is essential. Because it is difficult to correctly identify the cause of stock imbalance (overstock, out-of-stock, near expiry products), companies that are dealing with the imbalanced stocks face loss. To treat the overstock items, retails sometimes offer discounts [28].

Lateral product transshipment, or redistribution, has also been used by industry and studied by the researchers to handle overstock and out-of-stock situations [64][84][19][7][83]. Redistribution balances the stock and reduces the cost of buying additional products. Without redistribution, retailers need to purchase out-of-stock items when the same items are overstock at other outlets. The practice of considering a product's life while doing redistribution has not been well studied by academics and is not well-practiced by industry.

Most of the models developed for decreasing stock imbalance consider only outlets' data related to sales and stocks [64][84][19][7][83]. But the error of data synchronization is an indisputable fact. Thus, most of the time, sales data and stock data do not represent an outlet's actual scenario [40]. A specific increase in customers' demands is not possible to address in the sales forecast if the product was out-of-stock most of the time in the forecasting period. As there are no sales for these products though customers want them, the system cannot have potential sales data, and as a result, the actual demands are not accounted for. To avoid this error, feedback from a sales representative from the sales floor is a must requirement. This feedback can be both descriptive and quantitative. Feedbacks from the sales floor regarding demands have not been considered sufficiently in literature for redistribution. Knowing the actual need for a product directly from the sales floor is essential to forecasting and redistribution activities.

The value of a product is not constant throughout its life. With time, products lose their quality. The decrease in the product's value with time can best be seen in perishable products. For overstock products, retail outlets sometimes do inventory liquidation. For this, they need to mark down the price. In an article published in inboundlogistics.com, it has been mentioned that retailers can sell their products on the secondary market for 15 to 50 percent of their original value [52]. A schematic representation has been illustrated in Figure 1.3 based on the article's suggested liquidation rate. A retail chain having several outlets has a different sales history of the same product throughout the outlets. Products with imbalanced stocks throughout the outlets create an opportunity to reduce inventory liquidation by adapting lateral transshipment or redistribution.

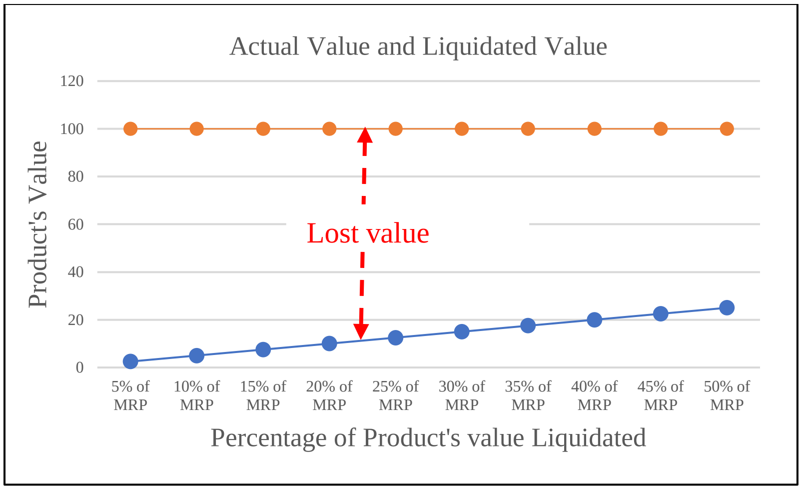



**Figure 1-4** A schematic representation of actual value and liquidated value of a produc

Rudi et al. (2001) [91], Liao et al. (2020) [72] have considered product salvage value as an essential factor while considering redistribution. They only mentioned that the summation of salvage value and transshipment cost should be lower than the stock receiving point's revenue. But they didn't describe any systematic approach to calculate salvage value based on a product's shelf life. On the other hand, consideration of the remaining life threshold for the products receiving by any outlets is very limited in the research field [34][58].

Donating products to charitable organization, help retailers to get a tax deduction [73][43][35][65][63]. While considering lateral transshipment, retailers can also assess the donation option. To my best of knowledge, no work has been done considering both options based on product life, product value based on the life, and feedback from outlets altogether.

While doing lateral transshipment/redistribution, it will help retailers dealing with thousands of products to know which products will bring more profit among all the redistributable products. We didn't find any existing research work discussing categorizing redistributable products based on their retail contribution.

The need for identifying products for redistribution, donation, and disposal considering product attributes, life-based value, actual sales for balancing inventory, and reduce expiration justifies the development of a simulation-based decision support tool for retailers. Complexities in the system of the supply chain need the use of simulation. An agent-based simulation can address the interactions among the model's components and react to the behavior of other features described as agents. Products movements in the distribution center can be well addressed in discrete event simulation. These motivated me to build my model using a hybrid simulation model (a combination of agent-based simulation (ABS) and discrete-event simulation (DES)) for this research.

## 1.3 Purpose of the Study

The study aims to build a decision support tool for retailers for balancing inventories and decrease product expiration. This tool will identify the redistributable, donatable, and disposable products. After identifying redistributable products, this tool will conduct a bidding-based redistribution process and calculate the redistribution impact on the total retail system's performance. This tool will also measure the impact of donation and disposal of products on the retail design as a whole. To achieve this overall purpose, we had to accomplish a series of sub-objectives:

1) Identify and represent-different components of a retail chain and their interactions in an agent-based simulation for redistribution.
2) Identify-the factors that influence the decision to redistribute products.
3) Understand existing bidding mechanisms and propose a bidding framework compatible with the redistribution of consumer products.
4) Identify the relationship between a product's perceived value and its remaining shelf life.
5) The identification of decision options for retailers while considering product redistribution under different situations.
6) The verification of the model

## 1.4 Research Approach

This section presents the major activities performed to achieve the overall research purpose.

1) Identify and represent-different components of a retail chain and their interactions in a hybrid simulation for redistribution.

The retail network comprises different components like suppliers, distribution centers(DCs), outlets, and vehicles. DC and outlets deal with different categories of products with other characteristics. Various parts of the retail network and additional attributes of products have been studied for this research work. While considering redistribution of products, it is required to view the stock situations in different outlets in a multi-outlet retail chain. Our primary concern here is to explore using a bidding mechanism for modeling redistribution of the products. Depending on the stock situation, any outlet can act as a buyer or seller both in this model. To see how products are delivered from the distribution center (DC) to retail outlets, outlets, and DC, Geographic information system (GIS) map can visually understand the product movement. Interaction of different components of the supply chain (i.e., supplier, DC, outlets, orders, vehicles), processes of works under various components, a large number of retail outlets, the impact of the number of products and their conditions, bidding mechanism, make it challenging to use in the equation-based model. For addressing these factors, we have used hybrid simulation modeling (HYSM) for my research.

2) Identify-the factors that influence the decision to redistribute products.

The factors needed to be considered for product redistribution are related to the outlets' stock levels, transportation costs, and products' characteristics. The main factor for deciding redistribution is the stock situation of the products. Overstocked outlets have triggered the need for product redistribution, and stock needed outlets asked the bid. In this way, the overstocked outlets are getting rid of products that have low demand to the customers of those outlets and can use the occupied spaces for demanded products by the customers.

While considering redistribution, distance is also an essential factor as it costs to move products from one destination to another. As the stock points are at different locations, while bidding, participants responsible for providing shipping cost, need to check whether it is feasible for them to bid for getting products. As different types of products have different characteristics, it is required to know those characteristics to handle those products properly. Here, products' shelf life has been considered an essential factor that varies depending on the products.

Customer arrival variation means the demand variation of products. Variation in demand is one of the most important factors for modeling this system. Sometimes these demands cannot be satisfied from on-hand stocks. High variation leads to overstock or out-of-stock situations. Product replenishment frequency can influence the decision of redistribution. Non-frequent replenishment of products to the outlets can bring a risk of imbalanced stocks resulting in redistribution.

3) Understand existing bidding mechanisms and propose a bidding framework compatible with the redistribution of consumer products.

By doing a literature review, the existing bidding mechanism can be understood. Bidding has been used in different areas (i.e., construction, energy, retail). The use of bidding in lateral shipment or redistribution of products has been studied from the existing literature. The factors considered for building the bidding mechanism has been identified and analyzed. Based on our research, a different bidding mechanism has been developed, and how this is different from existing research works has been described.

4) Identify the relationship between a product’s perceived value and its remaining shelf life.

The quality of a product deteriorates with time. When it passes its entire life, it becomes non-saleable. A literature review was conducted to identify the link between a product's value with its shelf life. Based on the literature review and retail company’s policy, an algorithm has been developed to calculate the dynamic price of a product as a function of time.

5) The identification of decision options for retailers while considering product redistribution under different situations.

Under different circumstances, retailers will decide whether to redistribute products or not. The decision is taken based on products' stock, sales, remaining shelf-life, and transportation price. If not possible to redistribute, the donation option has also been considered. Different types of experiments have been performed in a later chapter to show in which situation or for which class of products, redistribution, and donation perform better.

6) Verifying the model

After building the model, it is required to check whether the built model works the way it was thought to work before building. This can be done by checking the outputs and match with desired results. Statechart, vehicle movement on GIS map, time plot chart, dataset output have been used for verifications.

## 1.5 Dissertation Overview

Existing research works on the causes of imbalanced inventory, redistribution/ lateral transshipment, bidding mechanism, bidding for redistribution, and donation for treating overstock products are discussed in chapter 2. Chapter 3 discusses our research methodology, algorithm development for bidding-based redistribution, donation, and transportation cost calculation for redistribution. Input data analysis, model development, and implementation have been discussed in chapter 4. In chapter 5, we have discussed the steps taken for our model verification. Experimentation on our model for different situations has been illustrated in chapter 6. Summary of our research work, essential findings, limitations of this work, and future work scopes have been discussed in chapter 7.

# Chapter 2 Literature Review

## 2.1 Introduction

The Retail industry's objectives are stocking products that the buyer wants, selling products profitably by using pricing policies and promotions, and not overstocking products by over-purchasing [39]. Management faces several problems for obtaining desired customer service level while managing inventory. These problems include budget limitations, vendors' lead times, and other restrictions [95]. Forecast accuracy and inventory replenishment frequency have a reasonable correlation with the stock-out events [80]. Overstock events can happen for forecast inaccuracy. Inventory redistribution can play a role in cost savings, correcting mismatch between inventories and uncertain demands, and overall supply chain performance [56][90]. Sometimes, overstock causes retailers to return those products to suppliers, which might be the key cost driver that eats into the retailer's or supplier's profit, responsible for return transportation cost. Product return from the customers to retail outlets can also result in overstock [115]. Customers' buying patterns can be influenced by different factors [28], which can cause an improper number of stocks in the outlets. Our research focused on feasibly balancing stocks over the outlets in a retail network and utilizing the products by donating that cannot be redistributed among the retail networks. While doing a literature review for our research, first, we tried to understand the cause of improper stock (i.e., overstock, out of stock, expired products). After that, we continued to study research works on redistribution models, bidding models, and the use of bidding in redistribution. In this chapter, we have discussed the literature review followed by the research gaps.

## 2.2 The Reasons for Imbalanced Inventory

Demand planning for cost-effective, timely, and efficient operations are vital for any supply chain business. According to supply chain insight [86]

"Demand planning is the most misunderstood and most frustrating of any supply chain planning application."

The process of predicting the future demand of a product is called forecasting. A paramount concern for retail organization is demand forecast, as purchase planning, workforce planning, strategic planning depends on demand forecast. Forecast inaccuracy can result in an imbalanced stock situation, leading to a company's financial and reputational loss. When there is more product variety, forecast bias is more. This situation sometimes can result in over or under forecast [116]. Forecast accuracy has a significant impact on a company's operational performance, like – cost [32]. Sometimes, historical data is not all for doing the forecast. Doing a forecast with statistical forecast and judgmental adjustment can reduce inventory holdings and increase forecast accuracy [102]. Automatic calculation of response factor can be tuned to forecast for adjustment [10]. Researchers have developed forecasting models [27][49][5] for improving forecast accuracy that can lower the risk of having overstock or stock out situations in retail stores.

Although works have been done for forecast accuracy improvements, still demands and other factors like out of stock of products at suppliers' end and other environmental issues are uncertain. These can impact sales as well as outlets' stocks. Forecasting methods have an impact on bullwhip effects. Zhang et al., in their work, analyzed that bullwhip effect measures can be different for different forecasting methods [127]. The Bullwhip effect is a cause of excessive inventory. In their paper, Lee et al. identified that demand forecasting updates, order batching, price fluctuation, rationing, and shortage gaming are the main reasons for the bullwhip effect. They suggested avoiding multiple forecast updates, breaking order batches, stabilizing prices, and eliminating gaming in shortage situations, can counteract the bullwhip effect [66]. In their words, the choice of the companies is clear:

“Let bullwhip effect paralyze you or find a way to conquer it.”

The bullwhip effect increases the wastage of products as it increases the system's inventory level [21]. Though the bullwhip effect is detrimental to all inventory items, perishable items are more easily affected. Wang et al. developed a system dynamic model where they showed that the bullwhip effect can be reduced by adjusting the order cycle and delivery delay time [117]. When a risk-pooling effect and the supply chain are simple, the bullwhip effect is overestimated [99].

Misplaced items, seasonal, damaged out-of-date items, internal and external theft contribute to system inventory information inaccuracy. Fleisch et al. developed a simulation model which was based on a three-echelon supply chain system. They found that if physical inventory and the inventory information systems are aligned together at the end of each period, it can reduce inventory inaccuracy [40]. The occurrence of overstock and out-of-stock situations can be reduced if the actual inventory level can be known.

## 2.3 Redistribution

Redistribution or lateral transshipment (LT) is the transaction of products from the overstock locations to the shortage stock or out-of-stock locations of the same echelon, out of the regular replenishment schedules. To minimize the risk of overstock and understock, increase customers satisfaction level, have efficient supply chain operations, retailers in different regions have adopted stock redistribution or lateral transshipment [91][36][94][69]. Less transshipment cost than holding and back-ordering cost, less lead time for transshipment than regular replenishment lead time, having stock more than the future demand are some of the situations where it is suitable to embrace redistribution [64]. Researchers have developed different redistribution models. Their work can be categorized based on the number of items, number of locations, number of echelons, identical locations (identical costs), and unsatisfied demand (lost sales or backorders) [84].

According to Min Chen (2008), redistribution of products or lateral transshipment can be divided into three categories, emergency lateral transshipment (ELT), preventive lateral transshipment (PLT), and service level adjustments (SLA) [19].

Table 2-1 Types of Lateral Transshipment

| Types of Lateral Transshipment / Redistribution | Characteristics |
|---|---|
| Emergency Lateral Transshipment (ELT) | It is required when a customer cannot be satisfied with on-hand stock. Stock is redistributed to meet that customer's demand. |
| Preventative Lateral Transshipment (PLT) | Based on product availability policy, stocks are redistributed to the retailer with an ample amount. Based on the stock equalization policy, products are redistributed so that all stores have the same days' stock levels. |
| Service level Adjustments (SLA) | Combination of emergency and preventative lateral transshipment |

By using mathematical models for his study, Min Chen (2008) found out that these three redistribution policies can contribute to a specific inventory system to maximize customer satisfaction and reduce management cost. However, some of his study's limitations were not to consider different costs at different stores and lost sales. Feng et al. studied ELT and PLT with two retailers in a single selling season to investigate replenishment and transshipment policies [38].

From their work, they found that for ELT solution, it satisfies partial backorder where PLT converges to newsvendor problem when transshipment cost increase. As in ELT, demand is realized after the selling season; transshipment cost is high for satisfying backorders by the customers at high transportation mode. Under the ELT system, the transferred quantity is equal to the backorder quantity. There is a penalty cost for lost demand and back-ordering cost equal to or less than the penalty cost. Based on the previous period's inventory level and related cost parameters of lateral transshipment, the transfer quantity is measured for the PLT system. Unsatisfied demand from the previous period is considered wholly lost. Furthermore, unsatisfied demand during transfer lead time is considered as completely backordered. From Topan et al.'s research work, there is sometimes a slight increase in cost for integrated PLT and ELT [107].

Before implying the lateral transshipment policies, it is required to have some decision rules based on which lateral transshipment (LT) will occur.  Decision rules for triggering redistribution have been studied by researchers [64][7][83]. Henry Lau et al. [64] developed five steps for implementing LT. These are to determine whether to transship emergency stock from other lateral transshipment points (LT point, outlets for our case) or to backorder from suppliers (based on the cost of transshipment to backorder (BO)), size of transshipment, favorite wholesaler (LT point), preferred supplier, and extra quantity for preventive LT. The decision will start from the first step of evaluating the costs of LT and BO. If BO oct is lower than LT, then the supplier with the lowest cost will be chosen. If not, then the total amount required for LT will be calculated, and then the warehouse(LT point) with stocks and lowest cost will be chosen. If it is impossible to meet the demand from that warehouse(LT point) thoroughly, then another warehouse(LT point)  with the lowest cost and available amount will be chosen. In this way, LT will take place. Some studies use mathematical formulation that may not be comprehensible for the store managers or complex practical situations. On the other hand, random choice, choice based on the maximum amount of stocks on hand and smallest numbers of the pipeline or outstanding orders can be chosen to make a stock point to be eligible for LT [4]. Including transshipment amount and whether all the demands should be met from the same echelon or not and time for shipment are essential factors while implementing LT. Time for redistribution can be at the beginning of a period [4] or a specific period. This time can also be obtained by dynamically observing the demand [2] using dynamic programming. Non-identical transportation times had been considered in Tagaras' and Valchos' work, who also addressed the importance of variability and type of assumed demands [103]. Redistribution time can be fixed or flexible. In Kieseullar's and Minner's work, they found that in highly uncertain demand and low-profit margin situations, flexible transshipment time or decision-making flexibility is beneficial [59].

In the supply chain network, based on stock control and cost-sharing, a supply chain system can be centralized or decentralized. In a centralized system, the decision of LT is taken centrally. At the beginning of each period, this decision will be taken based on retailers' anticipated stochastic demands [4]. The centralized system has fewer expected costs than the decentralized system because of its high holding cost and penalty cost [18]. For calculating expected costs, each store is considered separately in a decentralized system, while in the centralized system, the net cost of total reinforcements is calculated. Sometimes retailers need to pull products from the warehouse instead of other retailers for having excess stocks to improve their customer service level [119]. Our study has considered redistribution will take place decentrally with and without the centralized system's control. Two different LT models: supervised and unsupervised models have been developed.

While considering redistribution among retailers, continuous inventory review, periodic inventory review both have been studied [13][82][78][77][120][12][44]. For periodic inventory review with order up to level policy has been considered in some literature [82][78][12][11]. As the cost is the critical factor for redistribution, it is necessary to consider different retail stores' costs. In some research work, transshipment or redistribution time and costs are neglected [54]. While minimizing back-ordering cost, in some works, non-identical transportation cost had been considered [11]. As extra transportation cost is required for redistribution, researchers studied vehicle routing problems to minimize transportation cost. Using variable neighborhood search, Turan et al. [109] developed a model for perishable products, which will select the retail store pool for inventory rebalancing and the sequence of visiting the retail stores. From his study, a positive impact of transshipment was found when the demand is very uncertain. We have developed in our model a transportation cost calculation mechanism based on the shipping cost calculation process used by USPS. This calculation process has practical use and added a standard to our entire LT model.

Dehghani and Abbasi [34] used threshold life for perishable products to be a lateral transshipment candidate. In an environment of demand with Poisson distribution, they designed their model with transportation, holding, purchasing, and back-ordering cost. They compared three cases: no lateral transshipment, unidirectional, and Mutual/Bidirectional lateral transshipment. From their study, bidirectional transshipment provides the lowest cost. We have considered the threshold life for all types of products.

Transfer prices have a crucial role in deciding the amounts of products going to be transferred between retailers. When the decision is made centrally, this price does not influence the coordination of product transfer. However, for a decentralized system where retailers make their orders, transfer price influence the order quantity. High transfer price results in average high-order quantities and high order quantity, resulting in the price of the first and quantity first models based on Villa and Katok’s work [114]. They observed how retailers' behavior deviates at different product profitability ratios (three different levels: low, medium, and high) while negotiating price and order quantity for transfer. While setting the transfer price, they ignored product profitability ratios. Though redistribution of products helps retailers balance their inventories, they sometimes prefer to do it once every season [104]. In our model, we have considered transportation cost as the transfer price. This cost depends on the product's physical attributes and distance traveled for transfer which are more practical to calculate transfer or transportation cost.

Inventory transshipment or redistribution can help to manage inventory of disaster relief in the humanitarian situation. In their study, Pedro et al. [89] compared the situation of having inventory transshipment and not having transshipment in a two warehouses system dynamic model using Vensim software. Their result shows that transshipment can reduce the cost and increase the service level to the disaster-affected victims. In some cases, though the transshipment cost may be high, it can offset the extra purchasing cost for the needy warehouse to support the victims. This scenario is the same as regular products' redistribution.

The number of unique products under consideration of lateral transshipment or redistribution can be more than one. In a multiproduct and three stages (supplier, distribution centers, and customers) supply chain, Zhi and Keskin [128] tried to find an efficient network design where the main goal was to minimize total fixed facility and transportation cost. In their model, they considered direct shipment and lateral transshipment. Paterson et al. [85] worked on a transshipment approach wherein a continuous inventory review policy, location with shortage product was supplied with more than required to meet the emergency shortage and future risk of becoming stock out. They established an algorithm that will optimally give the transshipment amount and transfer location inventory. Store manager's feedback can be taken for calculating redistributed or lateral transshipments amount [58].

Olsson [81] in his work with continuous review policy and demand with Poisson distribution, studied unidirectional transshipment. In unidirectional transshipment, not all the locations can send and receive products. In his work, it was assumed that for lateral transshipment, all the shipments coincide. Because of discrimination among customers, lateral transshipment or product redistribution may not happen in many retail stores for low priority customers. Adopting lateral transshipment can benefit the retailers who used to ignore low priority customer demand by following both reactive and proactive lateral transshipment policy [55].

Table 2-2 Some literature on Lateral Transshipment/Redistribution

| Researcher | Year | Number of Echelons | Lateral Transshipment /Redistribution Locations | Number of Items | SKU's physical attributes | SKU's life | SKU's life based Dynamic value for Lateral Transshipment | Sales floor's feedback | Remaining life constraint before Lateral Transshipment | Emergency Lateral Transshipment (ELT)/Preventative Lateral Transshipment (PLT) | Transportation cost Calculating based on |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Min Chen [19] | 2008 | 2 | N | 1 | No | No | No | Not considered | No | ELT, PLT | Per unit shipped |
| Sven Axsäter [7] | 2003 | 1 | N | 1 | No | No | No | Not considered | No | PLT | Per unit shipped |
| Olsson [83] | 2009 | 1 | 2 | 1 | No | No | No | Not considered | No | ELT | Per unit shipped |
| Henry Lau et al [64] | 2016 | 2 | 5 | 1 | No | No | No | Not considered | No | ELT, PLT | Per unit shipped |
| Tagaras et al [103] | 2002 | 2 | 2 | 1 | No | No | No | Not considered | No | PLT | Per unit shipped |
| Villa et al [114] | 2018 | 2 | 2 | 1 | No | No | No | Not considered | No | ELT | Per unit shipped |
| Rudi et al [91] | 2001 | 2 | 2 | 1 | No | No | No | Not considered | No | ELT | Per unit shipped |
| Feng et al [38] | 2018 | 2 | 2 | 1 | No | No | No | Not considered | No | ELT, PLT | Per unit shipped |
| Zhi et al [128] | 2019 | 3 | N | M | No | No | No | Not considered | No | PLT | Per unit shipped |
| Paterson et al [85] | 2012 | 2 | 2 | 1 | No | No | No | Not considered | No | ELT, PLT | Total Units Shipped |
| Dehghani et al [34] | 2018 | 2 | 2 | 1 | No | Yes | No | Not considered | Yes | PLT | Total Units Shipped |

Table 2-2 Continued.

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Lee | 2007 | 2 | N | 1 | No | No | No | Not considered | No | ELT, PLT | Per unit shipped |
| Burton et al [13] | 2005 | 2 | N | 1 | No | No | No | Not considered | No | ELT, PLT | Per unit shipped |
| Olsson[82] | 2015 | 1 | 2 | 1 | No | No | No | Not considered | No | ELT | Per unit shipped |
| Nakandala et al [77] | 2017 | 3 | N | 1 | No | No | No | Not considered | No | ELT | Per unit shipped |
| Nakandala et al[78] | 2017 | 2 | N | 1 | No | No | No | Not considered | No | ELT, PLT | Per unit shipped |
| Wei et al [119] | 2018 | 2 | 2 | 1 | No | No | No | Not considered | No | PLT | Per unit shipped |
| Bouma et al [12] | 2016 | 1 | 2 | 1 | No | No | No | Not considered | No | PLT | Per unit shipped |
| Archibald et al [44] | 2015 | 1 | N | 1 | No | No | No | Not considered | No | ELT, PLT | Distance and time |
| Agarwal et al [2] | 2004 | 2 | N | 1 | No | No | No | Not considered | No | PLT | Total Units Shipped |
| Kiesmüller et al [59] | 2009 | 1 | 2 | 1 | No | No | No | Not considered | No | PLT | N/A |
| Chang et al [18] | 1991 | 2 | N | 1 | No | No | No | Not considered | No | PLT | Function of demand |
| Wee et al [119] | 2005 | 1 | 2 | 1 | No | No | No | Not considered | No | ELT | Per unit shipped |

Table 2-2 Continued

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Jonsson | 1987 | 2 | N | 1 | No | No | No | Not considered | No | PLT | Per unit shipped |
| Turan Et al [109] | 2017 | 2 | N | M | No | No | No | Not considered | No | PLT | Total Units Shipped |
| Tagaras [104] | 1989 | 2 | 1 | 2 | No | No | No | Not considered | No | PLT | Per unit shipped |
| Reyes et al [89] | 2013 | 2 | 2 | 1 | No | No | No | Not considered | No | PLT | Per unit shipped |
| Kelly [58] | 2013 | 2 | N | M | No | Yes | No | Considered | yes | PLT | Route/Zone, total units shipped, lead time |
| Avci et al [6] | 2016 | 2 | N | M | No | No | No | Not considered | No | PLT | Total Units Shipped |
| Li et al [71] | 2008 | 2 | N | 1 | No | No | No | Not considered | No | PLT | Total Units Shipped |
| Yu et al [125] | 2019 | 1 | 2 | 1 | No | No | No | Not considered | No | PLT, ELT | Per unit shipped |
| Topan [107] | 2020 | 2 | N | M | No | No | No | Not considered | No | PLT, ELT | Per unit shipped |
| Liao [72] | 2020 | 1 | 2 | 1 | No | No | No | Not considered | No | ELT | Per unit shipped |
| Ours | 2021 | 2 | N | M | Yes | Yes | Yes | Considered | Yes | PLT | The route, total unit, SKU attributes |

** N represents multiple lateral transshipment locations, and M represents multiple items. SKU is stock keeping unit. The same product with different attributes like height/color/ weight will have different SKU numbers.

## 2.4 Bidding

Bidding is an offer of the price for getting certain products at specific amounts. The practice of bidding exists in the supply chain for better network performance [15][79][111][67]. Bidders can bid on a single item as well as a bundle of items in combinatorial auctions [31]. McAfee and McMillan [75] define an auction as follows:

"An auction is a market institution with an explicit set of rules determining resource allocation and prices based on bids from the market participants."

"Bidding is an offer (often competitive) to set a price by an individual or business for a product or service *or* a demand that something be done" [122].

Bidding can be used to determine the value of a product. The auction rules determine policies like: the minimum bid amount, starting time, ending time, and bid increments. There are different formats of auctions [113][76][60][48]. This difference is based on a single item or multiple items for bid, single seller-buyer, or multiple seller-buyer. Auctions can be single-sided or double-sided. Bidding with the single seller with multiple buyers and vice versa is called single-sided, where multiple buyers and multiple sellers are double-sided. Klemperer [60] classified four different types of single-sided auction.

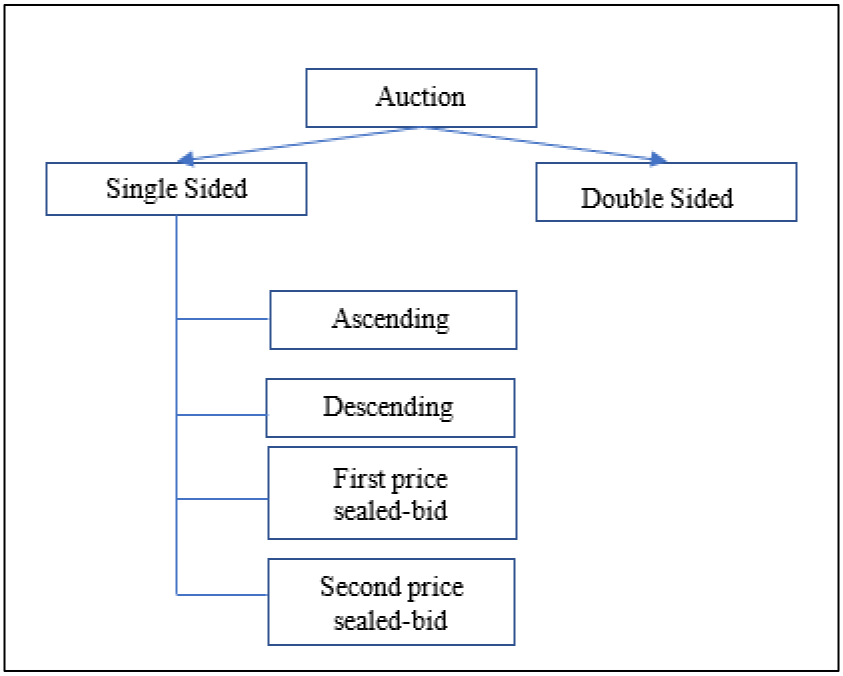



**Figure 2-1** Different Types of Auctions

Ascending Auction: In this type of auction, the bids are announced publicly. Bidders bids in an ascending way mean the current bid must be higher than the previous bid. English auction is this kind of auction and a standard one. Here there is a single seller and multiple buyers. When the auction is terminated, the highest bidder wins and pays the amount of his last bid.

Descending Auctions: Dutch auction is this kind of auction. Here the auctioneer announces the price and lowers the price till a bidder wants to buy it.

First price sealed-bid: Bidders submit their single sealed bid in this auction. No bidder can know the bid price of his competitors. The one with the highest bid price wins the bid and pays his bid price.

Second price sealed-bid: All bidders submit their bid price in a sealed form like the first price sealed bid. But the highest bidder wins and pays the second-highest bid price.

In a Double-sided auction, multiple buyers and sellers submit their bids. Buyers offer to buy, and sellers offer to sell products or services. Bids are called ‘orders’ in the double-sided auction.

All the bids are collected in an order book at different sections for buyers and sellers. Price determination depends on the rule of auction. Then the best possible order match is searched [113]. According to Wikipedia, the buyer submits their bids, and sellers simultaneously submit their asking price to the auctioneer. The auctioneer chooses a price. Sellers who submitted price equal to or less than that price and buyer with bid price more or equal to that price, buy the product at that price. There is always competition among bidders to get the product if it is within their buying limit [48]. Whether the first starting price has an impact on the final price was studied by the researcher [30]and found there is a positive correlation.

In our model, the bidding strategy is a combination of double-sided and second-priced sealed-bid.

To understand how the bidders will behave under different competition, how it will affect bidding outcomes, Adeli et al. [1] designed and developed software agents that replicated human bidding behavior. From their work, they found that different bidders are affected differently under different bidding competitions. Social factors and financial factors can influence the behavior of bidding participants. It was found from the study that social factors are more important than financial factors [62].

Different bidding models in the supply chain used a different method to build it [42]. The use of genetic algorithms [42], reinforcement learning [100], Fuzzy Analytical Hierarchy Process (FAHP) [33], and Multiple agent systems (MAS) [17] for developing the bidding process can be found in existing research work related to the bidding process. Our bidding model acts as a multiple agent system.

There are bidding strategies in online auctions with different ending rules and value assumptions. Dang et al. used bidding strategies to support decision-making. He developed a combined framework of the Fuzzy Analytical Hierarchy Process (FAHP) and regression-based simulation for the bidding process in his work. First, the FAHP method integrates the AHP with fuzzy set theory to determine the weights of factors that influence a project's cost. Second, the integration of the cumulative distribution functions generated by the Monte Carlo simulation with a regression model, yields bid amounts. These bid amounts correspond to various confidence levels. They proposed that the systematic bid assessment model and the cost-probability curve can be used as strategic tools for quantifying project risks and calculating bids [33]. MAS(Multiple agent systems) is the future trend on system-wide modeling in supply chain studies. In this system, agents are the internal parties of the supply chain or different industries. One agent can announce the job to others that are calling for bids. Each agent has its capacity. The agents bid when bids are asked. The primary agent accumulates the bid and does a multiple criteria analysis, and ranks the bids. The highest bidder is offered the job [17].

Bidding model creation without knowing the item's actual value follows a version of the law of large numbers [123]. Van et al. worked on adaptive bidding that is single-sided auctions under uncertainty. They used an agent-based approach for this work. It was assumed that that the seller is one, but the bidder is multiple as it is a single-sided system. Two bidding systems were considered: ascending bidding or ascending auction (AA) and sealed bidding (SB). In AA, the bidder can bid more than onetime where in SB, they can bid once. That work treated bidders as agents. Two types of agents were considered: static and dynamic. Static is a certain bidder, know the value of the bid.

On the other hand, dynamic (certain/uncertain) do not know first, after getting information with a cost; know the value of the bid. AMASE (agent-based market simulation environment) software was used to see the action of the bidders at different states (situations). The payoff for the agents playing was calculated (2 agents environment/5 agent environment/with or without information acquisition). The payoff of the auctioneer was also calculated. From the simulation result, it was found that payoff is greater in SB compared to AA for agents (certain players). For an uncertain agent with a certain agent, the resulting pattern was the same as before, but the pay-off value is less now. It is because of lack of information, uncertain player bids worse.

In AA, if the bid was lower than the actual highest bid but greater than the second-highest bid, it was named as the new $2^{nd}$ highest bid. The winner paid $2^{nd}$ high price. Valuation of a bid in a range(a,b) for certain bidders was different with a different distribution. In their work, Van et al assumed that uncertain agents can get information at a certain price like c. Bidding action sets for certain and uncertain bidders were established. The highest and second-highest bids were updated in each period. Stationary agents were classified as early stationery (HE), late stationery (HL), price signaling agent (HP), and random agent (HR). They were static about their valuation and did not change it. But Dynamic agents (DA) could change their valuation. DA could be certain or uncertain. The highest bidder status was established as $H \in \{-4,-3,-2,-1,0,1,2,3,4,10\}$. 0 represented that the agent didn't place any bid and negative means bid was lower than the highest bid. For each bidding action of the agents, the respective highest bidder status was formulated. Here, reinforcement learning algorithms were used to implement a decision approach for agents by mapping received rewards of state-action pairs into future probabilities of choosing a certain action. Then payoff matrix was calculated for each type of combination. From that, the bidder could know whether they should bid in an uncertain state, what could be their payoffs what auctioneer would get [112]. Early bidding and snipping are the most famous strategies in internet bidding literature. A calibration method for a functional agent-based model and applying this method to the context of online auction simulation, are of high interest in MASE [46]. Botond, Pfeiffer and Monostori built an agent-based bidding system in a discrete event simulation environment [55]. Each agent used their rules for bidding. These rules are related to the cost factors associated with the task for which they are bidding.

Research work related to bidding-based product transfer can be found in a short range [6][71]. Avci, Gonca, and Selim [6] used bidding for premium orders when one plant's inventory location falls under safety stock and the time of regular product delivery from distribution center or supplier, is not near. Location with surplus stock offer quantity to the stock shortage outlet. After that required plant calculates the cost for alternative supplier plants, the supplier plant is selected based on the minimum cost. While calculating the cost, they considered holding cost, purchasing cost, and premium freight cost. The simulation was done in Matlab. Li et al. [71] also used a bidding mechanism for redistribution or lateral transshipment. Based on their study, there is only a one-time bargaining process where all participants bid after checking their stocks. Retailers with low cost consisting of holding, ordering, and transportation cost, win the bid and can transfer the products. They used the relationship among the supplier and buyer retailers as an important factor that influenced the costs. The model was done in any logic simulation software. The bid price is an important part of bidding-based redistribution. This can be calculated as a percentage of profit margin for products under redistribution [92]. In our work, we have calculated the bid price based on the eBay bidding process.

## 2.5 Donation and Valuation of Products

While transshipment can be used between retail stores to rebalance inventories among the stores by reducing the need for products to be supplied by warehouses [83], retailers' surplus products can be donated to a charitable organization to feed low-income people [3]. Retailers with overstock products can get tax benefits by donating those products [73][43]. As retailers are holding inventory, they need to evaluate their inventory correctly. The practiced inventory valuation method is done using specific identification methods, first-in, first-out (FIFO), last-in, last-out (LIFO), and weighted average (WA) methods. To save income tax, the company uses LIFO [47]. Products' shelf life has an impact on their value and as well as on inventory evaluation. According to the Business Dictionary, shelf life is described as,

"Periods during which product remains effective and free from deterioration as well as saleable."

Use of radio frequency identification technology (RFID) and time-temperature indicator (TTI) has been used by retailers to track the product, temperature, humidity, and period during which the product has been exposed to the supply chain [61][68][57][129]. The price of products dynamically changes based on the quality of the products [118]. Change of price of products with time should be considered for all types of products. Though some products' quality does not deteriorate with time, because of the impact of seasonality and change of fashion trends, the value of some products may change or become obsolete. Different types of pricing strategies have been studied by researchers [8][108][110][25][20][124][106]. It is widely practiced in retails to give a discount to a product [8][108][110] as it is close to expiry or overstock. Chung et al. [25] have carried a survey about the pricing strategy of perishable products. This survey revealed that most retailers give a 20-50% discount (two-period pricing) during the last few days of a product's shelf-life.

On the other hand, some retailers do not discount suppliers' requests (single-period pricing). Their research showed that a multi-period pricing policy is more profitable for perishable products than a single or two-period pricing strategy. The joint strategy of inventory control and pricing is profitable for perishable products [20]. Selling near expiry perishable products to a salvage value [124][106]. reduces disposal cost and contributes to profit increase. Liao et al. [72] and Yu et al. [125] mentioned the use of salvage value as a constraint for lateral transshipment in their work. They have considered that the difference of redistributed product's revenue and transfer price will not be less than the salvage value. The main difference between our and Liao et al.'s [72] study is salvage value selection. He did not mention any systematic way for this process. Our model calculated seller outlets' price (worked as salvage value) as a price discount for buyer outlets in the network. This price will be calculated based on the remaining shelf life of products. We have considered that a product's value/price will decrease as salvage value after passing a certain period of life based on the retail enterprise's policy. We have developed an algorithm for determining the salvage value (reserve price for our bidding-based redistribution model). Detail of developing the algorithm has been discussed in chapter 3.

From the above discussions, we can see that the lateral transshipment or redistribution model can be made based on different strategies, factors, using different methods and tools. Supply chain management integrates planning, coordination, and control of all processes and activities for superior customer satisfaction at less cost while satisfying the need of all stakeholders. Because of complexity, it is impossible to construct an analytical model to evaluate a supply chain network. Simulation pragmatically deals with the supply chain by considering several dependent factors [101]. We have conducted our research based on a hybrid simulation model to address the complexities and interactions of different supply chain components. We also found from research studies that donation can help retailers to utilize their overstock products. In table 2-2, we have summarized some of the research works on redistribution and compared them with our model. We have identified some research gaps that are very important for a practical redistribution model. In the next part of this chapter, we have discussed those research gaps where our study can contribute.

## 2.6 Research Gap

### *2.6.1 Consideration of products' physical attributes for lateral redistribution*

For any product movement, it is necessary to know the products' physical attributes, like weight and dimension. In the existing research on redistribution, we did not find the use of a product's weight and dimension for calculating transportation cost. Most of the works considered a fixed transportation cost/unit. Some have calculated prices based on the total unit transferred and the distance traveled. Our study considered products' weight, dimension, the total unit transferred, and distance traveled to calculate transportation cost for redistribution.

### *2.6.2 Consideration of Shelf life*

To the best of knowledge, very few of the literature considered the products' life while considering lateral transshipment, and all of them were for perishable products. However, other consumable products like commodities (ex. Flour) also expire with time. In our study, we have considered shelf lives for all types of products.

### *2.6.3 Consideration of life threshold constraint to qualify for redistribution.*

When products are redistributed from one outlet to another, receiving outlet should check the quality and life remaining of the products. If they do not check these after receiving the products, they might not be able to sell because of those products' short remaining lives. Very few works on redistribution have considered this life threshold constraint to qualify for redistribution. We have considered this constraint in our work.

### *2.6.4 Consideration of donation option along with the redistribution*

We have considered donation options and lateral transshipment/redistribution, and the use of a decision tool to generate the options at the product level automatically. To the best of our knowledge, these combined options have not been studied before. All of the works on utilizing overstock or near expiry products studied the use of redistribution or donation separately.

### *2.6.5 Consideration of life-based dynamic value of products*

In our work, we have considered that the seller outlets can sell their overstock products to another outlet, at least at the overstock products' life-based dynamic value. Some researchers considered that the seller outlet’s selling price is not related to the product's life in the existing literature. Some researchers have used a constraint that the selling price should be greater than the summation of transportation cost and salvage value while considering redistribution. Though the salvage has been considered, the process of acquiring it was not discussed in any study for redistribution. They only mentioned or assumed a value as salvage value. Retails dealing with thousands of products should have a detailed systematic and automatic process for calculating the seller outlet’s selling price. In our study, we have developed an algorithm that will check all the products in the system, their stocks, and remaining shelf-life; and calculate the seller’s minimum selling price at the time of selling. To the best of our knowledge, no works have been done on using the life-based dynamic value of the products for setting the minimum selling price (reserve price) of the seller outlet for redistribution.

### *2.6.6 Strategy to identify most beneficial products for redistribution.*

Our literature review didn’t find any work discussing segregating products to identify which products will get more benefits and which will get less if required for redistribution. In this study, we have developed a strategy to segregate products based on their demand variability over a retail chain's outlets. This technique will help the retail company to choose the most benefitted products from redistribution. When the redistribution-related facility is limited, then this strategy will be helpful.

Based on the above discussion, we can say that for a retail chain comprising multiple stores with multiple products of different shelf lives and different lots, decision tools for identifying redistributable and donatable products have not been studied in existing research works. Moreover, the development of life-based dynamic value for redistribution is also new in the redistribution-related research field. Other researchers calculated transportation cost for redistribution as per unit items transferred/total unit transferred/route and total unit transferred. Our model developed an algorithm to calculate transportation cost based on product weight, dimension, route, and total units transferred. We believe our transportation cost calculation process is more practical than the existing research for calculating transportation costs. Overall, our entire model addressed several things that were not or rarely present in redistribution-related research works as far as we know. We can say that the total system developed is unique in this research area. In the next chapter, we will discuss our research methodology and algorithm development for our model.

# Chapter 3 Methodology

## 3.1 Introduction

In the retail business, sales are impacted by many factors, including product availability, quality, and customer satisfaction [126][16]. It is required to understand better products' shelf life, stock levels, and sales while considering lateral transshipment or redistribution. For decreasing loss of overstock and old products, the donation of excess items can be a good solution [88], too, in addition to redistribution. We have developed our model with both options of redistribution and donation. An enterprise can choose any of the two or both. In this chapter, we have discussed the research design followed for this study. The discussion on the method of developing the entire model has been divided into five parts:

1. Inventory policy used and Algorithm for the base model.
2. Shipping cost model used.
3. The essential features for Bidding Process used for redistribution.
4. The Evaluation and architect of the Redistribution Models.
5. The algorithm used for the donation process.

In our model, the main product flow to the outlets is conducted by the enterprise. Products are transferred from the DC like a centralized system. Products or items are addressed as stock-keeping units (SKU) in inventory management. This is distinct for all the items depending on their attributes (i.e., weight, dimension, color, shape). For transferring SKUs to the outlets, it is required to monitor the inventory and decide the replenishment amount. We have introduced the redistribution option and donation option in the retail system for this study. To check the impact of these two systems on the total retail network's performance, we need to have a base model to compare with. Shipping cost is a crucial part of redistribution. The shipping cost model used for our study has been described in this chapter. Our redistribution model has been developed based on the bidding strategy. We have used a bidding strategy for our study, followed by eBay's online auction system, in a modified way. Architect of different redistribution models has also been addressed following by the donation process.

## 3.2 Research Design

As our research industry is retail, we have tried to develop our research design to become more useful for retailers working with thousands of SKUs. Before starting our research, we had to identify the data source and collect the data. Our collected data accounts for around eight thousand SKUs, ten outlets, and one distribution center (DC). Considering the complexity of the model, simulation time, and urgency for making the research work more beneficial for retails, we have developed our research design in multiple steps.

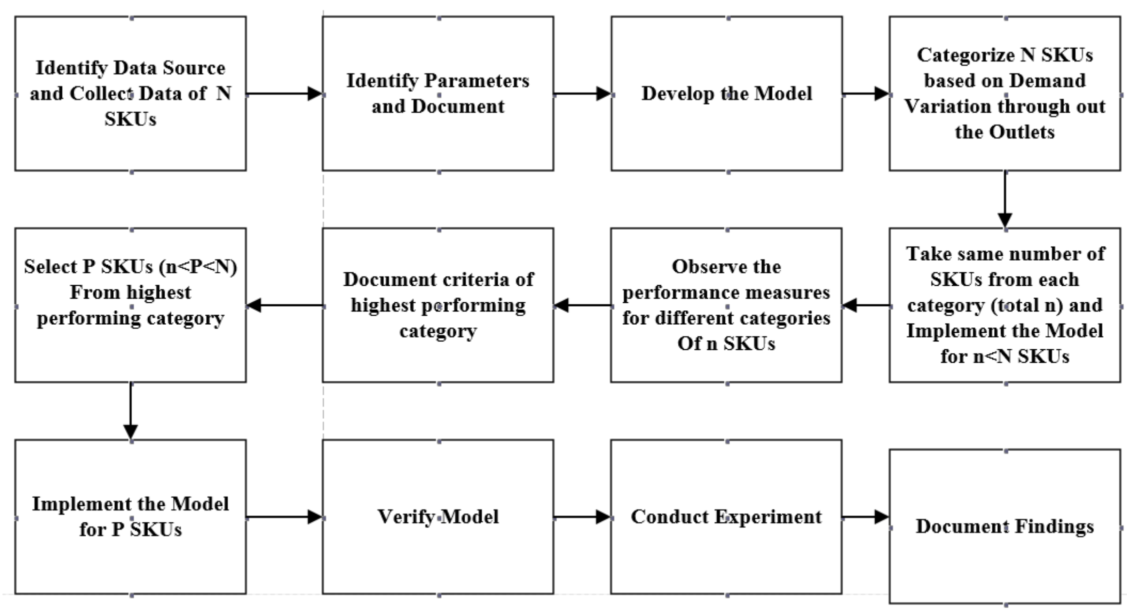



**Figure 3-1** Research Design

After collecting the data of a large number of SKUs (N) we analyzed the data to see how the sales vary over the outlets and the number of customers of different outlets. Based on the data, and identified parameters, we developed our model. We found out from data that the same SKU's demand varies throughout the retail network outlets. To check whether the demand variability impacts output (effect of redistribution) or not, we categorized our total SKUs based on their demand variability over all the outlets, first. Categorization based on only demand variation will not provide a correct picture as demand variation (standard deviation of demand) for an SKU can be big as a number. However, concerning its mean value, it might be low. Opposite observation can be seen for the SKUs, which has low standard deviation of demand than the rest of the SKUs. So, we have categorized the SKUs based on the ratio of their standard deviation of demand over average demand for all the retail network outlets.

Table 3-1SKU Category based on demand variability.

| SKU Category Based on Demand Variability | Description |
|---|---|
| High Demand Variability | (Standard Deviation/Average)>0.8 |
| Medium Demand Variability | 0.8>=(Standard Deviation/Average)>0.4 |
| Low Demand Variability | (Standard Deviation/Average)<=0.4 |

We collected the same number of SKUs from each category. After that, we implemented our model for SKU groups from each category with the same life, in total n SKUs where n is less than the total number of SKUs in the database. Our developed model is complex, and it is time-consuming to run for a large number of SKUs. For this reason, we ran our model for n number of SKUs. The category-wise performance was observed. More SKUs (P SKUs>n SKUs) were collected from N SKUs from the highest performing category after identifying the highest performing category. We have implemented the model again for the P number of SKUs. The reason for doing this is, we wanted to run the model and conduct experiments for the SKUs, which have a high possibility to get benefit from redistribution. We also know that for experimentation, large data size is better than small data size.

The summary process flow of our entire model with both redistribution and donation options is illustrated in Figure 3-2. The process starts with identifying inventory levels for each ~~SKUs~~ separately. For each SKU, seller, and buyer outlets are identified. Based on the feasibility of redistribution, SKUs are redistributed.

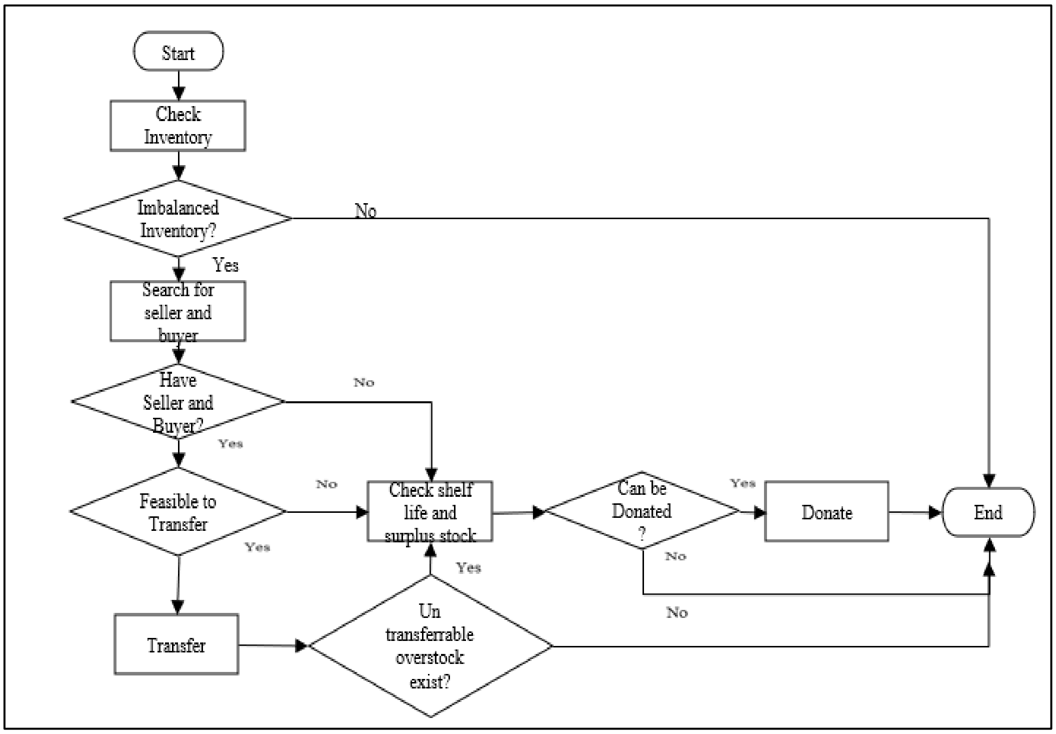



**Figure 3-2** Summary Process Flow of Our Full Model

SKUs that cannot be redistributed despite having overstock (based on sales and based on shelf life and sales) are considered for donation. This process flow continues for all the SKUs in the system of a retail chain. The detailed process respective to different redistribution models and the donation method have been discussed in this chapter's later sections.

### 3.3 Inventory Policy Used and Algorithm for the Base Model

A periodic inventory review policy with orders up to level (T, S) and a two-stage supply chain (Distribution Center and Retailer) has been considered as the centralized inventory system for this study. Here, T represents the inventory review period, and S represents the required inventory level for each order.

This research investigates four different redistribution models. We have used the same inventory system for the centralized product distribution to the outlet for all the models. Our base model is a supply chain distribution model with no option for redistribution or donation.

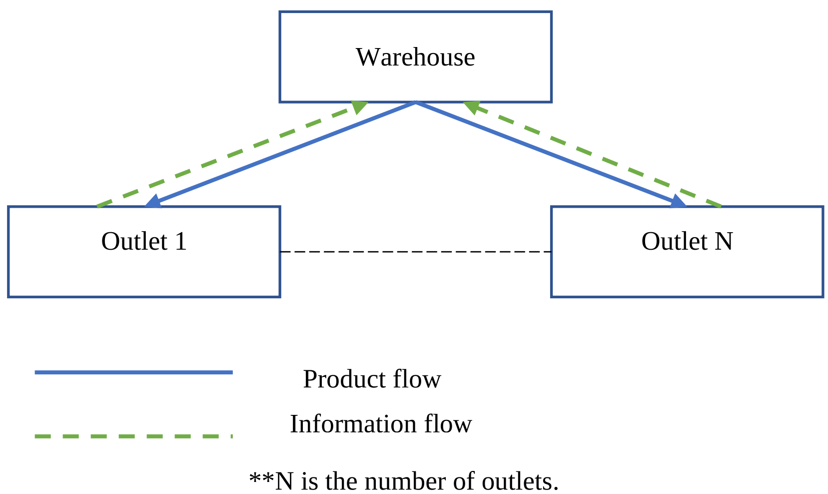



**Figure 3-3** Supply Chain Network

#### *3.3.1 Base Model*

It is necessary to have a distribution network for a supply chain [22]. We are considering the base case for our model as a supply chain network with no redistribution and no donation options available. Products are delivered to the stores based on a periodic inventory policy [93][53][41]. In this policy after a fixed period (T), inventory is reviewed. An order is placed with the order quantity set to a quantity that will bring stock levels back to a predefined inventory level (S). All the orders are processed by the DC and send to the stores/outlets. Outlets get products only from a single source-the DC.

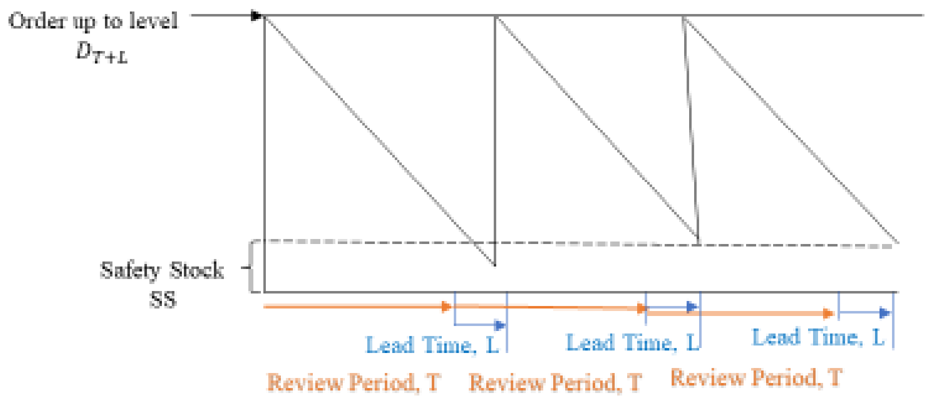



**Figure 3-4** Periodic Inventory review

We have considered here that the forecast will be modified every month. After observing the actual sales for a month, next month's forecast will be adjusted based on the exponential smoothing forecasting method. In our base model, inventory up to level is calculated based on the forecasted demand. The number of days stock is decided by the enterprise to be considered as stock up to level days. Based on the monthly forecasted demand, stock up to level is calculated for decided stock up to level days. At every inventory review period, the required product amount is calculated to take the existing stock level to the desired level(stock up to level). In this case, if the value of the inventory review period is less than the stock up to level days, then the difference between stock up to level days and the inventory review period is considered as safety stock days. Demand for safety stock days are calculated based on the monthly forecast and addressed as safety stock. To develop the algorithm for our base model, we have used some parameters. The parameters and steps of the algorithm have been described below.

**Nomenclature for the Base Model:**

| | | |
|---|---|---|
| $q$ | = | SKU index |
| $n$ | = | Outlet index |
| $t$ | = | Time index |

Notation

| | | |
|---|---|---|
| $T$ | = | Inventory review interval (Days) |
| $L$ | = | Lead time for replenishment from Distribution Center to outlets. |
| $Q$ | = | Number of SKUs |
| $N$ | = | Number of Outlets |
| $D\ _q$ | = | Monthly demand of SKU q |
| $D_{q,n,T+L}$ | = | Demand of SKU q at store n during T+L |
| $S_{q,n}$ | = | Order up to the level for SKU q at store n |
| $I_{q,n}$ | = | Current inventory of SKU q at store n |
| $SS_{q,n}$ | = | Safety stock of SKU q at store n |
| $A_{q,n}$ | = | Monthly actual Sales of SKU q at store n |
| $O_{q,n}$ | = | Order amount of SKU q at store n |
| $s_{q,n}$ | = | Daily sales amount of SKU q at store n |
| $\propto$ | = | Smoothing Constant |
| $F_{q,n}$ | = | Updated Forecast of SKU q at store n |

Formula Used

Mean demand during T+L, $D_{T+L}$ = $(T + L) * D$

Safety Stock, SS = $(D * r)/30$ [here r is the number of days to have safety stock, r>0]

Order up to level is, S = $D_{T+L} + SS$

Order amount = $S - I$

Updated Forecast, F = $D + (A - D) * \alpha$

**Algorithm:**

1. Check stocks of all the Q SKUs in all the stores.
2. Check the forecasted demand of all the SKUs for all the outlets.
3. For all the SKUs at all the stores, orders are generated if the inventory level meets the criteria:

   $$I_{n,q} < D_{q,n,T+L} + SS_{n,q}$$

   The amount of order $O_{qn}$ is calculated as $D_{qn,T+L} + SS_{nq} - I_{nq}$
4. After receiving the order, inventory is updated as $I_{nq} + O_{qn} - \sum_{t=T}^{T+L} s_{qn}$
5. The monthly forecast is updated as $F_{qn} = D_{qn} + (A_{qn} - D_{qn}) * \propto$. $F_{qn}$ is used as $D_{qn}$ for next order cycle.

## 3.4 Shipping Cost Model

Shipping cost is an integral part of the redistribution process. This cost is the extra cost that the retailers have to bear. The feasibility of the redistribution process mainly depends on this shipping cost. Most of the scholars have used transportation cost as per unit product basis [64] [19][7][83]. The use of different kinds of delivery services like USPS and FedEx are common for delivering products. Some retailers use rented vehicles for this work [46].

Delivery service companies calculate the shipping cost based on the distance of travel, weight, and volume of the product. On the other hand, usually for rented vehicles, the renter needs to pay fuel cost and the fixed cost of driving for a fixed amount of time.  The proposed model will use a method similar to that used by the United States Postal Service (USPS) for determining transportation costs. Like the USPS, we have categorized our outlets in different zones. We have considered the Priority mail 2 days delivery cost chart [52] of the USPS. Our model can also calculate cost based on retail ground shipping. In this chart, prices have been listed for nine different zones [96] for weight ranges from less than one pound to seventy pounds (Figure 3-5). For priority 2-day mail, delivery is available only for SKUs weighing less than 70 pounds in this chart. Our model assumes that it can be possible to transfer products weighing more than 70 pounds. Instead of using the actual shipping cost from the chart respective to the weight of the products, we have used average price increase for a one pound increase to calculate the shipping cost. The average price increase for a one-pound increase in product weight can be calculated from the chart (Figure 3-5).

## Priority Mail

### Retail—Letters, Large Envelopes & Parcels

| | |
|---|---|
| Flat Rate Envelopes (12-1/2" x 9-1/2" or smaller): | $7.95 |
| Legal Flat Rate Envelope: | $8.25 |
| Padded Flat Rate Envelope: | $8.55 |
| Small Flat Rate Box: | $8.45 |
| Medium Flat Rate Box: | $15.50 |
| Large Flat Rate Box: | $21.90 |
| APO/FPO/DPO Large Flat Rate Box: | $20.40 |

| Weight Not Over (lbs.) | Zone[1] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Local, 1 & 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 1 | $7.70 | $8.10 | $8.25 | $8.50 | $8.80 | $9.10 | $9.90 | $16.85 |
| 2 | 8.55 | 8.85 | 10.10 | 11.10 | 11.95 | 13.90 | 15.20 | 26.75 |
| 3 | 9.05 | 9.90 | 11.10 | 12.80 | 13.50 | 17.20 | 20.40 | 35.80 |
| 4 | 9.55 | 10.75 | 11.75 | 14.20 | 17.60 | 21.20 | 23.60 | 41.45 |
| 5 | 10.60 | 11.50 | 12.50 | 14.65 | 20.00 | 24.30 | 27.20 | 47.95 |
| 6 | 11.40 | 12.00 | 13.30 | 16.30 | 22.90 | 27.15 | 30.65 | 54.15 |
| 7 | 12.40 | 13.60 | 16.00 | 19.70 | 25.40 | 30.35 | 34.45 | 60.85 |
| 8 | 12.80 | 15.05 | 17.75 | 23.45 | 28.80 | 33.75 | 38.55 | 68.10 |
| 9 | 13.30 | 16.25 | 19.70 | 26.75 | 31.30 | 36.40 | 42.90 | 75.80 |
| 10 | 14.15 | 17.45 | 21.20 | 29.00 | 33.90 | 40.00 | 46.75 | 82.60 |
| 11 | 15.55 | 19.20 | 23.40 | 31.10 | 38.10 | 46.30 | 53.75 | 91.40 |
| 12 | 16.90 | 20.60 | 25.15 | 34.50 | 41.45 | 50.10 | 57.15 | 98.10 |
| 13 | 17.90 | 21.75 | 26.55 | 36.45 | 44.50 | 52.10 | 59.80 | 101.60 |
| 14 | 19.00 | 23.20 | 28.25 | 38.80 | 46.95 | 55.00 | 62.90 | 106.70 |
| 15 | 19.70 | 24.50 | 29.85 | 41.05 | 49.00 | 56.30 | 64.50 | 109.75 |
| 16 | 20.35 | 25.85 | 31.50 | 43.35 | 51.70 | 59.35 | 68.10 | 115.75 |
| 17 | 21.30 | 27.20 | 33.15 | 45.55 | 54.35 | 62.50 | 71.65 | 121.90 |
| 18 | 21.65 | 28.15 | 34.50 | 47.80 | 57.20 | 65.55 | 75.35 | 128.10 |
| 19 | 22.30 | 28.85 | 35.25 | 49.15 | 58.30 | 67.00 | 76.90 | 134.15 |
| 20 | 23.20 | 29.20 | 35.85 | 49.80 | 59.75 | 69.35 | 80.50 | 140.35 |
| 21 | 24.00 | 29.55 | 36.35 | 50.70 | 60.75 | 70.50 | 82.35 | 144.70 |
| 22 | 24.55 | 30.25 | 37.25 | 51.90 | 62.10 | 72.20 | 84.30 | 148.30 |
| 23 | 25.15 | 30.85 | 37.85 | 52.75 | 63.25 | 73.65 | 85.80 | 150.85 |
| 24 | 25.70 | 31.50 | 38.75 | 53.90 | 64.55 | 75.50 | 87.90 | 154.60 |
| 25 | 26.00 | 32.00 | 40.30 | 56.35 | 65.35 | 77.35 | 89.35 | 157.15 |
| 26 | 27.00 | 32.60 | 41.80 | 57.50 | 67.00 | 79.25 | 92.20 | 162.15 |
| 27 | 27.85 | 33.10 | 43.05 | 58.65 | 68.00 | 81.15 | 95.65 | 168.20 |
| 28 | 28.70 | 33.50 | 44.35 | 60.10 | 68.80 | 83.00 | 99.25 | 174.55 |
| 29 | 29.55 | 33.90 | 45.45 | 61.00 | 70.00 | 84.85 | 101.95 | 179.25 |
| 30 | 30.45 | 34.35 | 46.55 | 61.80 | 71.95 | 86.85 | 104.15 | 183.20 |
| 31 | 31.35 | 34.70 | 47.35 | 62.65 | 73.05 | 88.70 | 106.20 | 188.35 |
| 32 | 31.70 | 35.50 | 48.10 | 63.35 | 73.95 | 90.60 | 108.40 | 192.20 |
| 33 | 32.25 | 36.40 | 49.30 | 64.15 | 75.40 | 92.45 | 110.40 | 195.85 |
| 34 | 32.50 | 37.40 | 50.55 | 65.55 | 77.15 | 94.40 | 112.50 | 199.45 |
| 35 | 32.85 | 38.30 | 51.15 | 66.95 | 79.20 | 96.25 | 114.35 | 202.80 |
| 36 | 33.20 | 39.40 | 51.90 | 68.35 | 81.30 | 97.55 | 116.40 | 206.30 |
| 37 | 33.50 | 40.05 | 52.65 | 69.60 | 83.40 | 98.80 | 118.25 | 209.70 |
| 38 | 33.90 | 41.10 | 53.30 | 70.95 | 85.70 | 100.00 | 120.15 | 213.10 |
| 39 | 34.25 | 42.05 | 54.00 | 72.45 | 87.75 | 102.60 | 121.95 | 216.30 |
| 40 | 34.65 | 42.90 | 54.70 | 74.05 | 89.15 | 104.90 | 123.70 | 219.30 |

| Weight Not Over (lbs.) | Zone[1] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Local, 1 & 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 41 | $34.95 | $43.75 | $55.35 | $74.70 | $90.60 | $107.15 | $125.50 | $224.20 |
| 42 | 35.20 | 44.50 | 55.90 | 76.30 | 92.20 | 108.50 | 127.15 | 227.35 |
| 43 | 35.70 | 45.25 | 56.40 | 78.05 | 94.45 | 109.95 | 128.75 | 230.15 |
| 44 | 35.90 | 46.00 | 57.15 | 79.60 | 95.95 | 111.20 | 130.30 | 232.95 |
| 45 | 36.15 | 46.50 | 57.50 | 81.45 | 97.00 | 112.45 | 131.95 | 235.85 |
| 46 | 36.40 | 46.80 | 58.15 | 82.90 | 98.05 | 113.65 | 133.50 | 238.70 |
| 47 | 36.75 | 47.25 | 58.70 | 84.80 | 99.15 | 114.90 | 135.00 | 241.25 |
| 48 | 37.10 | 47.65 | 59.25 | 86.45 | 100.45 | 116.00 | 136.45 | 243.90 |
| 49 | 37.30 | 47.95 | 59.70 | 88.05 | 101.75 | 117.25 | 137.85 | 246.35 |
| 50 | 37.45 | 48.25 | 60.15 | 89.75 | 103.10 | 118.75 | 139.20 | 248.90 |
| 51 | 37.60 | 48.75 | 60.70 | 91.30 | 104.55 | 120.50 | 140.50 | 253.15 |
| 52 | 38.10 | 49.05 | 61.10 | 92.00 | 105.65 | 122.25 | 142.15 | 256.30 |
| 53 | 38.75 | 49.35 | 61.45 | 92.75 | 106.55 | 124.20 | 144.05 | 259.60 |
| 54 | 39.20 | 49.55 | 61.90 | 93.50 | 107.30 | 126.10 | 146.05 | 263.20 |
| 55 | 39.90 | 49.90 | 62.25 | 94.20 | 108.10 | 128.05 | 148.00 | 266.70 |
| 56 | 40.45 | 50.25 | 62.60 | 94.80 | 108.90 | 129.85 | 149.40 | 269.20 |
| 57 | 41.05 | 50.40 | 62.95 | 95.35 | 109.65 | 131.85 | 150.50 | 271.15 |
| 58 | 41.70 | 50.65 | 63.40 | 96.00 | 110.30 | 133.65 | 151.65 | 273.15 |
| 59 | 42.35 | 50.85 | 63.70 | 96.60 | 110.95 | 134.45 | 152.85 | 275.35 |
| 60 | 42.90 | 51.05 | 64.30 | 97.05 | 111.50 | 135.20 | 153.80 | 277.15 |
| 61 | 43.55 | 51.35 | 65.45 | 97.55 | 112.15 | 136.00 | 155.90 | 281.00 |
| 62 | 44.00 | 51.45 | 66.25 | 98.10 | 112.70 | 136.65 | 158.45 | 285.40 |
| 63 | 44.85 | 51.70 | 67.40 | 98.50 | 113.30 | 137.25 | 160.95 | 290.05 |
| 64 | 45.30 | 53.30 | 68.35 | 98.95 | 113.75 | 137.95 | 163.35 | 294.40 |
| 65 | 45.90 | 53.45 | 69.25 | 99.35 | 114.20 | 138.55 | 166.00 | 299.10 |
| 66 | 46.50 | 53.65 | 70.40 | 99.80 | 114.70 | 139.05 | 168.30 | 303.35 |
| 67 | 47.25 | 53.75 | 71.60 | 100.10 | 115.00 | 139.60 | 170.55 | 307.30 |
| 68 | 47.80 | 53.85 | 72.45 | 100.35 | 116.50 | 140.15 | 172.40 | 310.65 |
| 69 | 48.40 | 53.90 | 73.35 | 100.65 | 117.90 | 140.50 | 174.25 | 313.90 |
| 70 | 49.00 | 54.10 | 74.55 | 101.00 | 119.40 | 141.00 | 176.15 | 317.25 |

1. Parcels that exceed one cubic foot (1,728 cubic inches) are charged based on the actual weight or the dimensional weight, whichever is greater (as calculated in DMM 123.1.3).

**Figure 3-5** USPS shipping cost chart for priority mail

To illustrate the way for calculating the average price increase for a one-pound increase, we are using figure 3-6.

| | Zones | | |
|---|---|---|---|
| Weight (lb) | 1&2 | 3 | 4 |
| 1 | X11 | X21 | X31 |
| 2 | X12 | | |
| 3 | X13 | | |
| 4 | X14 | | |

**Figure 3-6** Schematic representation of Chart

Average cost/pound=$((X_{12} - X_{11}) + (X_{13} - X_{12}) + (X_{14} - X_{13}))/3$

For average cost/pound calculation, we used only zone one's costs. To reduce the complexity of this shipping cost model, we are using only four zones.

To calculate shipping costs, the respective zones for the buyer and seller are determined. The weight and volume of the SKU item are then checked. These four parameters can then be used to determine the shipping cost. USPS provides a flat rate option for products having a volume of less than one cubic foot. This study uses flat-rate cost for only a small box (figure 3-5). If the volume is more than one cubic foot, the cost is calculated based on the actual weight or dimensional weight of the SKU, whichever is big. In USPS, dimensional weight is calculated by following the formula listed below:

Dimensional Weight = (L x W x H) ÷ Divisor

L = Length in inches

W = Width in inches

H = Height in inches

Divisor for Daily Rates = 139

Divisor for Retail Rates = 166

In this study, we are only using actual weight. In our model, we have considered that weight can be greater than 70 pounds. In USPS, the transfer zone is calculated based on the difference of the zones from where the product is transferred and the zone to where the product is transferred. For calculating shipping cost for our model. For example, if the zone of the "Sending From" location is 5 and the zone of the "Sending To" location is 1, then the transfer zone will be 4. When calculating shipping cost, zone 4's prices are considered. We have used the same way to calculate the transfer zone. We have addressed transfer zone as transfer zone delta when transfer zone's value is more than one. As mentioned before, we are not going to consider the actual price. We will use the average cost/pound increase to calculate shipping cost. The reason for this is, we are considering that it is possible to transfer products weighing more than 70 pounds where the price charts (figure 3-5) only include the price for up to 70 pounds.

The algorithm developed for calculating shipping cost has been illustrated in Figures 3-7. To develop the algorithm for shipping cost, we have considered some parameters. These are listed below:

Parameters for Shipping cost calculation:

| | | |
|---|---|---|
| V | = | The volume of an SKU |
| W | = | Weight of an SKU |
| $Z_i$ | = | Zone of Buyer Outlet |
| $Z_j$ | = | Zone of Seller Outlet |
| $W_{p1}$ | = | Cost for transferring one pound product for transfer zone one. |

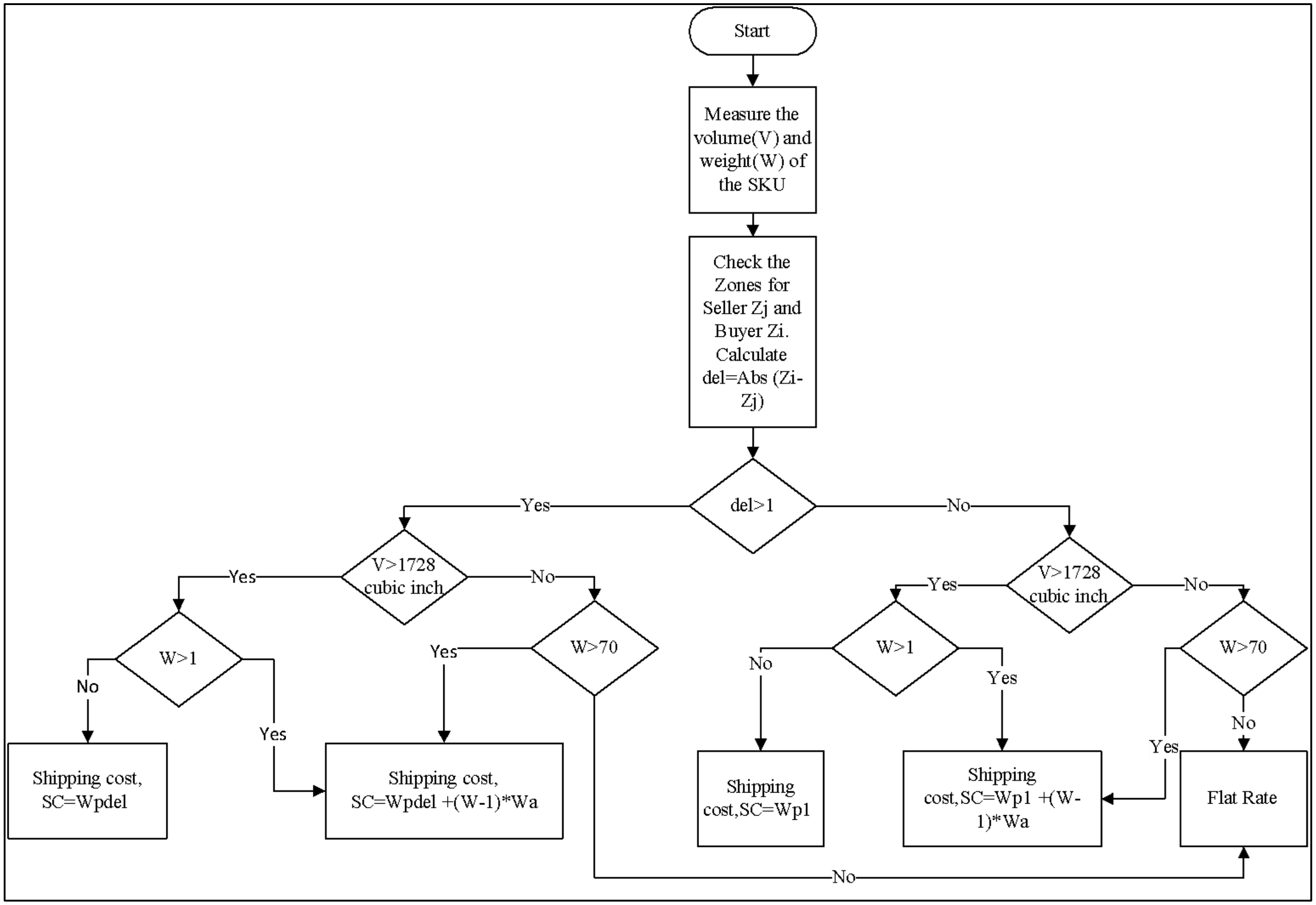



**Figure 3-7** Flow chart for representing the Algorithm for calculating shipping cost

## 3.5 The Essential Features for Bidding Process Used for Redistribution.

Our bidding model has been developed based on some features or essential factors. These are described below:

### *3.5.1 Bidding decision*

When sellers and buyers participate in the bidding, some factors influence their decision to bid [124-127]. Depending on the area of bidding, these factors may vary. External (job-related), environmental and internal (organizational) factors can influence the bidding decision. We have considered that the stock levels will be the decision criteria for bidding. For this research, outlets in an understock state will become buyers, and outlets in an overstock condition will attempt to become sellers. The decision to be a buyer or sell is determined on an SKU-by-SKU basis.

### *3.5.2 Seller's Reserve Price*

Our bidding strategy follows eBay's bidding strategy. Sellers in the eBay auction platform has a reserve price. This reserve price is the price under which a seller will not sell the product. In our redistribution model, we have also considered the seller's reserve price for conducting the bidding process. The calculation process for setting this reserve price has been discussed later in this chapter.

### *3.5.3 Buyer's maximum willingness to Pay.*

This is the highest price a buyer can pay or willing to pay for a product. The final transaction price can be less or equal to the buyer's maximum price he is willing to pay. Our model considered that the retail market price, a buyer can pay at maximum for a product.

## 3.6 Evaluation of the Redistribution System and Redistribution Architecture

We have used a hybrid simulation model (agent-based and discrete) for developing a bidding mechanism for our redistribution system.  In our model, the model's main elements are the items to be sold, the seller who wants to sell the product, the transaction rules, and the bidders who want to buy the product. Based on the bidding process, our redistribution models have been classified into two primary classes: Unsupervised and Supervised Redistribution models. These two classes have further been classified as price-based and imbalance amount-based redistribution models. The later classification determines whether the bidding process will start based on the seller-buyer price combination or stock imbalance amount combination. Details of these models have been portrayed in the following discussion.

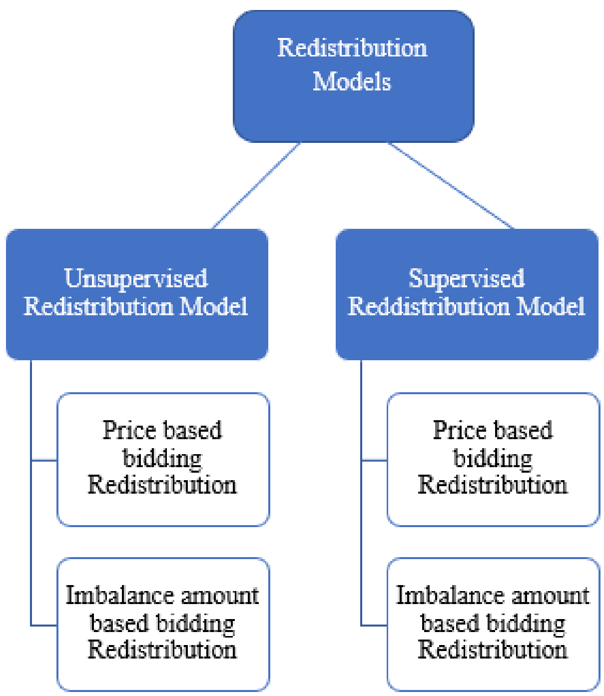



**Figure 3-8** Types of Redistribution Models

Every day, the stock levels are checked for each SKU at each outlet level in our model. Based on the stock levels, buyer outlets and seller outlets are selected. For the redistribution models, outlets receive products from other outlets, including from the DC. Stock up to level-periodic inventory review policy is maintained for centralized product distribution ( products distributed from the DC). Every two days, products are transferred by redistribution. To develop the algorithm for our redistribution model, we have used some parameters. Though the supervised models' parameters are more than the unsupervised models, the same parameters used for both types of models are listed below. Other extra parameters will be discussed later for supervised redistribution models.

**Nomenclature of the Redistribution Model**

**Indices**

| | | |
|---|---|---|
| $q$ | = | SKU index |
| $n$ | = | Outlet index |
| $t$ | = | Time index |
| $i$ | = | Buyer outlet's index |
| $j$ | = | Seller outlet's index |

**Notation of Parameters**

| | | |
|---|---|---|
| T | = | Inventory review interval in days |
| $Q$ | = | Total number of SKUs |
| $N$ | = | Number of outlets [ outlets = $i, j \in N$] |
| $f_q$ | = | Shelf life of SKU q |
| $l_{q,t}$ | = | Age of SKU q at time t |
| $D_{q,i}$ | = | Monthly forecasted demand of SKU q at store i |

| | | |
|---|---|---|
| $D_{q,j}$ | = | Monthly forecasted demand of SKU q at store j |
| $I_{q,i,t}$ | = | Inventory of SKU q at the store $i$ at time t |
| $I_{q,j,t}$ | = | Inventory of SKU q at the store j at time t |
| $d$ | = | Time remaining for getting products from DC |
| $d_1$ | = | Days of stock considered as Overstock |
| $U$ | = | Recent number of days considered for addressing actual sales trend while calculating needed stock for bidding. |
| $V$ | = | Total sales of an SKU in U days. |
| $J$ | = | Number of days considered for calculating needed stock for bidding, based on recent average daily sales (V/U) |
| $W_{q,ji,t}$ | = | Stock transfer quantity available of SKU q from store j to store $i$ at period t |
| $X_{q,ji,t}$ | = | Final stock receiving amount of SKU q from store j to $i$ at period t |
| $X_{q,ij,t}$ | = | Final stock transfer amount of SKU q at store $i$ from store j at period t |
| $s'_{q,i,t}$ | = | Total sales of SKU q at the store $i$ at period t |
| $s'_{q,j,t}$ | = | Total sales of SKU q at the store j at period t |
| $B_{q,i,t}$ | = | Bid amount (needed stock) of SKU q by store $i$ at period t |
| $C_{q,j}$ | = | Market Retail Price (MRP) or selling price of SKU q at store j |
| $Y_{q,i}$ | = | Market Retail Price (MRP) or selling price of SKU q at the store $i$ |
| $P_{q,j,t}$ | = | Reserve price of SKU q at store j at time t. |
| $T_{q,ij,t}$ | = | Transportation cost of SKU q from store $i$ to j at period t |
| $B_{q,p}$ | = | The final transaction price of SKU q |
| $Z$ | = | Minimum remaining shelf life of an SKU accepted by the buyer |

**Overstock deciding criteria**

$I_{q,j} > \left(D_{q,j} * d_1\right)/30$

Overstock = $I_{q,j} - \left(D_{q,j} * d_1\right)/30$

**Understock deciding criteria**

$I_{q,i} < \left(D_{q,i} * d\right)/30$

Needed stock, $B_{q,i}$ = $\left(D_{q,i} * d\right)/30 - I_{q,i} + \left(V_q/U\right) * J$

**Criteria to check the feasibility for bidding**

**Cost-Based Criteria:**

$B_{q,i,t} * P_{q,j,t} \leq ((Y_{q,i}) * B_{q,i,t} - T_{q,j,i}) \quad if\ B_{q,i,t} \leq W_{q,ji,t}$

$W_{q,ji,t} * P_{qj,t} \leq ((Y_{qi}) * X_{q,ji,t} - T_{qji}) \quad if\ B_{q,i,t} > W_{q,ji,t}$

**Shelf-life Based Criteria:**

$f_q - l_{q,t} \geq Z_q$

**Final transfer amount constraint**

$X_{q,ji,t} \leq B_{q,i,t}$

<u>**Inventory Update**</u>

$$I_{q,i,t+1} = I_{qi,t} + \sum_{j \neq i}^{j=N} X_{q,ji,t} - s'_{q,i,t}$$

$$I_{q,j,t+1} = I_{q,j,t} - \sum_{i \neq j}^{N} X_{q,ij,t} - s'_{q,j,t}$$

**<u>The price offered by Seller:</u>**

The price offered by the seller depends on a function based on the product's shelf life. We have provided a brief description below:

**<u>SKU’s life-based dynamic Value</u>**

Instead of giving promotions or selling overstock products to third parties, our objective is to sell the products at their MRP. To achieve this, we are proposing a shelf-life-based value function for overstock items. This function has been developed based on Chung et al.’ s work on a two-period pricing strategy for customer discounts [24]. They considered that the sales price would be the same until a certain period of a lifetime (threshold). After that period, the price will decrease. A discount rate was fixed when the life of the product reaches this threshold point. After that, the discount rate was calculated based on the aggregated discounts, total shelf life, and remaining shelf life.

We have used this strategy for the retail network outlets Instead of using this discounting method for end customers. However, in our case, we have considered that there will not be any fixed discount rate after reaching the threshold life. The discount rate will be calculated based on the SKU’s entire shelf life and remaining shelf life. Chung et al. considered this strategy only for perishable products. We are considering using life-based values for all SKUs. Because different types of products lose value at different rates, we have set different life thresholds for different products, after which their value will decrease. Depending on where the product stands on its life span, value is measured. The seller store asks this price from the buyer store for product transfer.

Table 3-2 Threshold age for different shelf lives for calculating seller outlet's reserve price.

| Shelf Life | First Percentage of Life till when Reserved price =full MRP |
|---|---|
| 45 Days | 0.33 |
| 60 Days | 0.33 |
| 120 Days | 0.60 |
| 180 Days | 0.60 |
| 365 Days | 0.80 |
| 730 Days | 0.80 |
| 1095 Days | 0.80 |

This value has been referred to as the reserve price for the sellers. If a product's life passes a certain percentage of its full life (threshold), its reserve price will decrease linearly over time. This percentage will be decided based on the Enterprise policy.

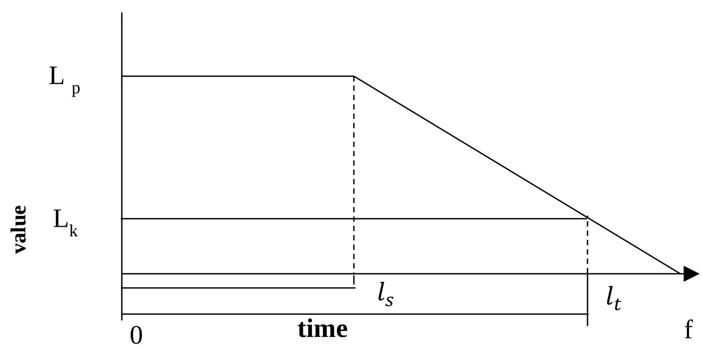



Figure 3-9 Product's Value curve

The reserve price has been calculated based on our developed value function:

$$L_k = \left\{ \begin{matrix} Lp \;\; if\ the\ life\ of\ an\ SKU\ is\ within\ l_s \\ or \\ (f - l_t) * L_p \big/ (f - l_s) \end{matrix} \right\}$$

Here,

$L_k$ = Price value (reserve price) of an SKU of life $l_t$

| | | |
|---|---|---|
| f | = | Shelf life of the product |
| $l_t$ | = | Age of product at time t |
| $l_s$ | = | Age of product after which it's no longer salable at full price |
| $L_p$ | = | Market Retail Price (MRP) of an SKU |

Here,

$$P_{q,j,t} = L_k$$

*3.6.1 Unsupervised Redistribution Model*

In this model, stores are allowed to participate in bids. Within the process, the stock transaction amount is not controlled by the enterprise. Based on the forecast and variation of customer demand, stores generate SKUs' data with surplus stock and low stock first. Built on the company's strategy, they choose between price-based and Imbalance amount-based redistribution models. In the price-based bidding model, buyers are listed for participating in the bidding process in descending order of their maximum willing price. Sellers are listed in ascending order of their reserve price. On the other hand, for the imbalanced-based bidding redistribution model, both buyer and seller stores are listed in descending order of their imbalance amount. These listings are done before starting the bidding. All the algorithms for different models have been developed in the Anylogic software by using Java language. In this paper, we have used swim lane process map to represent the algorithm in a simple way with some detail explanations. The process of price-based and Imbalance amount-based unsupervised bidding redistribution process of our model has been demonstrated in the following part.

**Price based Unsupervised Bidding Redistribution Model-Process**

Bidding will start simultaneously for all stores when the regular shopping hours will be closed. The algorithm has been presented by using swim lane process map (Figure 3-10). The detail steps have been discussed after the swim lane process map. Different colors for connectors have been used to separate the immediate step from other steps and continuity of the same logic in the swim lane process map. Dash lines have been used to meet the same purpose.

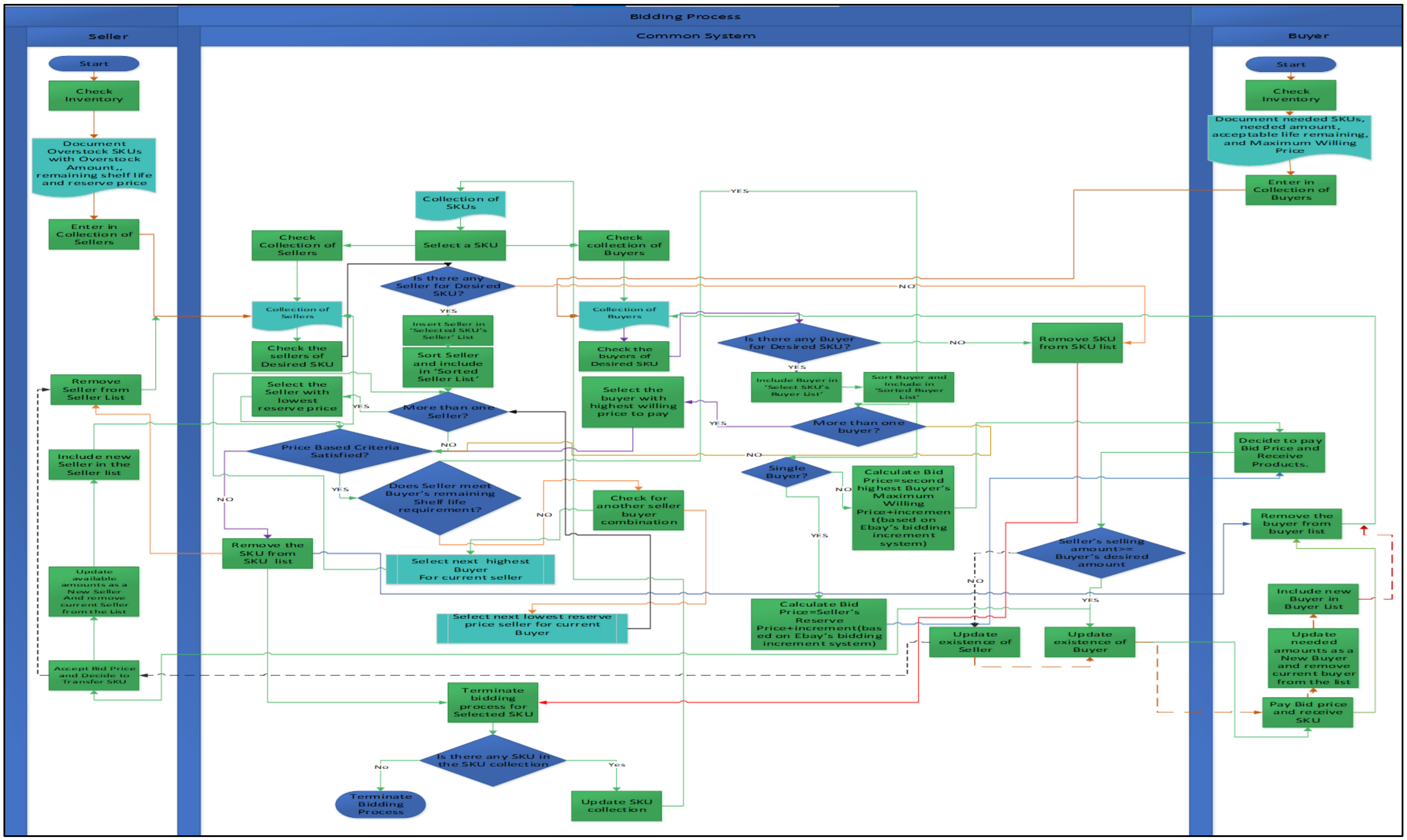



**Figure 3-10** Swim lane process map of Price-based unsupervised bidding redistribution model

Detail Steps for price -based unsupervised bidding redistribution are:

1. All the Q number SKUs list is created (figure 3-11)

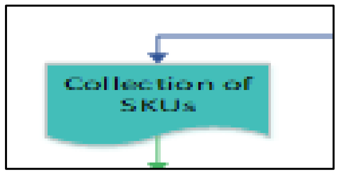



**Figure 3-11** SKU collection step in Swim lane process map

2. Outlets with overstocks and outlets with low stocks are checked.

3. For each outlet, every SKU's stock is checked. If any SKU's inventory meets the criteria

   $I_{q,i} < (D_{q,i} * d)/30$ [Here, $i$=1, 2, 3, .., $n_1$]

then the store is listed in the Buyer store's list. Buyers needed amount is calculated as Amount needed=

$(D_{q,i} * d)/30 - I_{q,i} + (V_q/U) * J$. The maximum willing price is set as the MRP for the stock needed SKU for that buyer's store (figure 3-12)

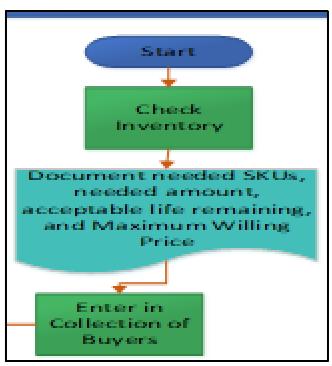



**Figure 3-12** Step of Creating buyer outlets' list as a collection in Swim lane process map

4. Outlets are also checked for overstock SKUs. If any outlet's any SKU's stock meets the criteria

$I_{q,j} > (D_{q,j} * d_1)/30$ [ Here j=1,2,3,..,n$_2$]

then the store is listed in the Seller store's list (figure 3-13)

The Reserve price of the overstock product is set based on shelf life and time remaining of the SKU number q in that store.

Reserve price= $P_{q,j,t}$

amount overstock= $I_{q,j} - (D_{q,j} * d_1)/30$

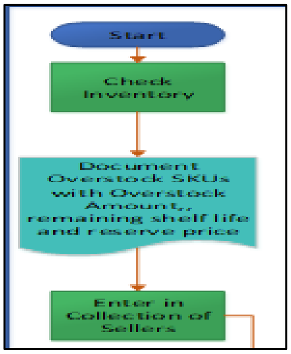



**Figure 3-13** Step of Creating seller outlets' list as a collection in Swim lane process map.

5. From the list of all the SKUs, the first SKU in the list is taken (figure 3-14)

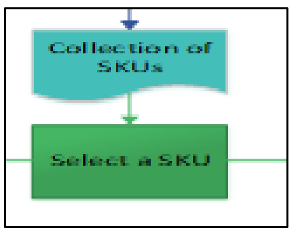



**Figure 3-14** SKU selection step in Swim lane process map

6. From the Buyer's list, the first buyer is taken and checked whether this buyer is a buyer of the first SKU taken from the SKUs list or not (figure 3-15) If the selected buyer is the first SKUs buyer, then it is listed in another list called 'Selected SKUs Buyer'. This process continues for all the buyers on the buyer's list for the selected SKU.


**Figure 3-15** Step of checking buyer of selected SKU in Swim Lane process map

7. If there is no buyer for the selected SKU, SKU is removed from the SKU collection list (figure 3-16)

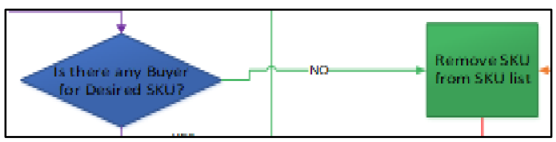



**Figure 3-16** Step of removing SKU without any Buyer in Swim lane process map.

8. From the Seller's list, the first seller is taken and checked whether this seller is a seller of the first SKU taken from the SKUs list or not (figure 3-17). If the selected seller is the first SKUs seller, then he is listed in another list called 'Selected SKUs Seller'. This process continues for all the sellers on the seller's list for the first selected SKU.

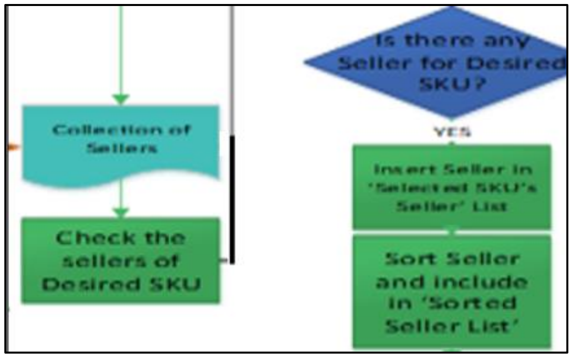



**Figure 3-17** Step of checking Seller of selected SKU in Swim Lane process map

9. If there is no Seller for the selected SKU, SKU is removed from the SKU collection list (figure 3-18). Red framed ones in the below figure represent this step.

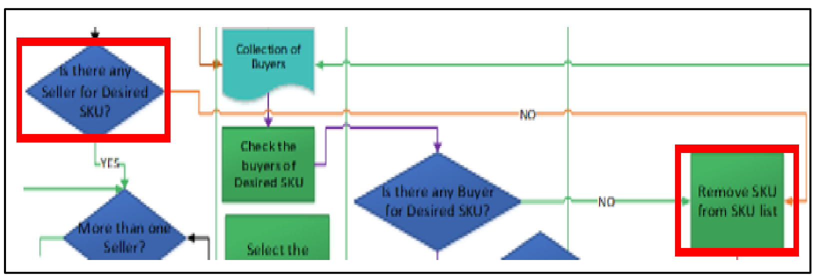



**Figure 3-18** Step of removing SKU without any Seller in Swim lane process map.

10. 'Selected SKUs Buyer' list is rearranged by sorting the buyers with their maximum willing price in descending order. Sorted buyers are listed in a new list 'Sorted Buyer List'.
11. 'Selected SKUs Seller' list is rearranged by sorting the sellers with their reserve price in ascending order. Sorted sellers are listed in a new list 'Sorted Seller List'.
12. From the 'Sorted Buyer List', the first buyer store i where i is equal to 1, is taken. Needed stocks are checked for the first buyer selected from the 'Sorted Buyer List'. The first buyer is the buyer with the highest maximum willing price to pay in the sorted list (figure 3-19). Red framed ones in the below figure represent this step.

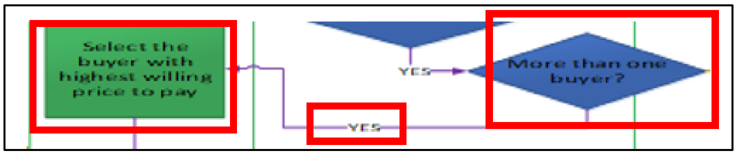



**Figure 3-19** Step of checking the highest buyer in Swim lane process map.

13. For the first buyer from the 'Sorted Buyer List', from the 'Sorted Seller List', the first seller store j where j is equal to 1, is taken (figure 3-20). Overstock is checked for the first seller selected from the 'Sorted Seller List'. The first seller is the seller with the lowest reserve price in the sorted list. Red framed ones in the below figure represent this step.

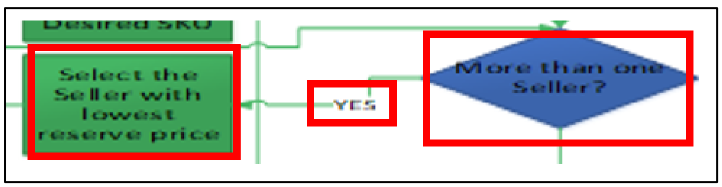



**Figure 3-20** Step of checking the lowest seller in Swim lane process map.

14. Transportation cost, $T_{q,ji}$ is calculated for the transferrable stock from the seller j to the buyer i for SKU q where q is 1 (first selected SKU).
15. The feasibility of biding is checked on two criteria for the first SKU (q=1)

First criterion (Price based):

$$B_{q,i,t} * P_{q,j,t} \leq ((Y_{q,i}) * B_{q,i,t} - T_{q,j,i}) \quad if\ B_{q,i,t} \leq W_{q,ji,t}$$

$$W_{q,ji,t} * P_{qj,t} \leq ((Y_{qi}) * X_{q,ji,t} - T_{qji}) \quad if\ B_{q,i,t} > W_{q,ji,t}$$

Second criterion (Shelf life based):

$$f_q - l_{q,t} \geq Z_q$$

16. If the first criterion is not feasible, the first buyer and first seller are removed from the respected lists (figure 3-21). The first SKU is removed from the SKU list.

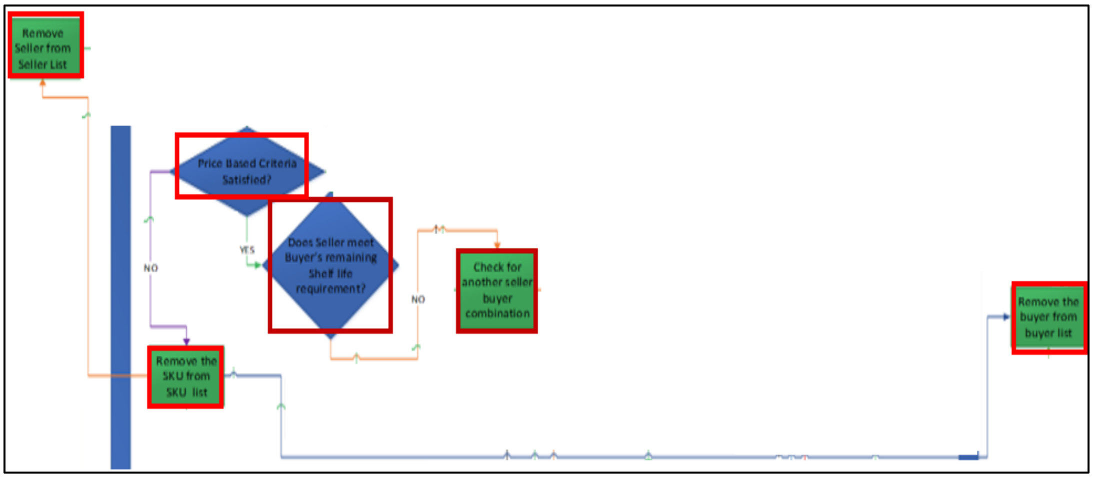



**Figure 3-21** Steps of feasibility checks-in Swim lane process map

17. If the second criterion is not feasible, then the second next lowest reserve price seller is selected from sorted seller list and steps 13-17 are repeated for the second seller (figure 3-21). This continues for all the sellers of the first SKU for the current buyer till the feasibility is achieved. The value of 'j' will change based on the seller rank in the sorted seller list.

18. If feasible to bid, the first buyer will offer a bid price. This price will be equal to the next highest feasible buyer's price plus an increment (figure 3-22). For our model, we are using the bid increments used by eBay.

The bid price as the final transaction price for the first buyer by the system:

$B_{p,1}$=$Y_{i-1}$ + Bid increment.

Bid price $^{n}$th outlet:

$B_{p,n}$=$Y_{n-1}$+Bid increment.

If there is only one buyer, then the final transaction price or bid price will be calculated by adding the bid increment to the seller's reserve price (figure 3-22).

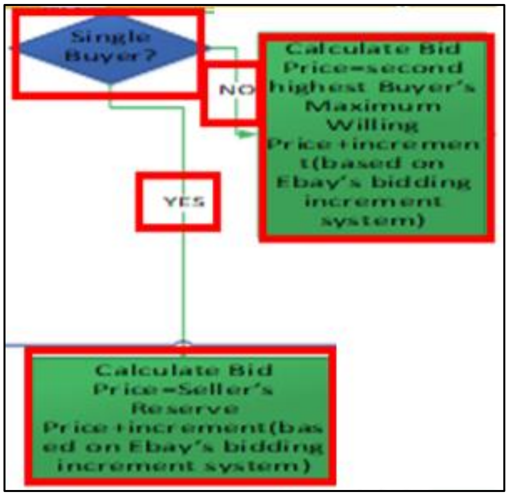



**Figure 3-22** Bid price calculation step in Swim lane process map.

19. If the first buyer's demand is less than the first seller's overstock, then the seller is removed from the 'Sorted Seller List' after meeting the buyer's demand. The first seller is listed as a new seller into the 'Sorted Seller List' as the first seller with updated stock. This updated stock is calculated by subtracting the first buyer's demand from the first seller's stock. In this step, the first buyer's demand is fulfilled, and the first buyer is removed from the 'Sorted Buyer list'.The 'Sorted Buyer list' updates. Red marked boxes represent this step.

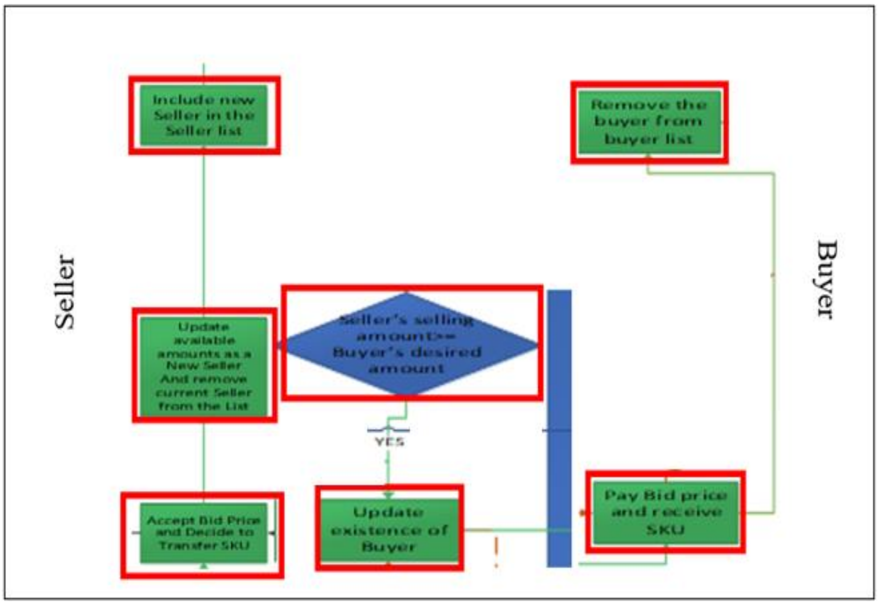



**Figure 3-23** Seller buyer update step in Swim lane process map when Seller's amount>=Buyer's amount

20. For that first buyer in the list, if the first buyer's demand is greater than the first seller's overstock, the first Seller is removed from the 'Sorted Seller List' (figure 3-24). 'Sorted Seller List' updates.


**Figure 3-24** Step of removing seller after meeting demand in Swim lane process map

The first buyer is removed from the buyer list after receiving a partial amount of the desired amount. The first buyer is listed as a new buyer as the first buyer in the 'Sorted Buyer List' with updated stock needed (figure 3-25).

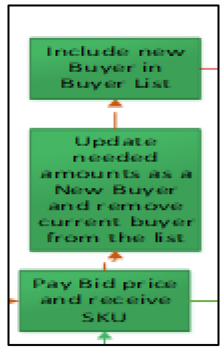



**Figure 3-25** Update Buyer list step in Swim lane process map

21. Then steps 13-21 continue. This process continues for all the buyers into the Sorted Buyer List for the first SKU.
22. After completion of bidding for the first SKU, it is removed from the SKUs list. Bidding is terminated for the selected SKU (figure 3-26).


**Figure 3-26** Terminating bidding step in swim lane process map.

23. For the next SKU in the Q-1 number SKUs list, steps 5-22 are followed. This process continues for all the SKUs (figure 3-27).

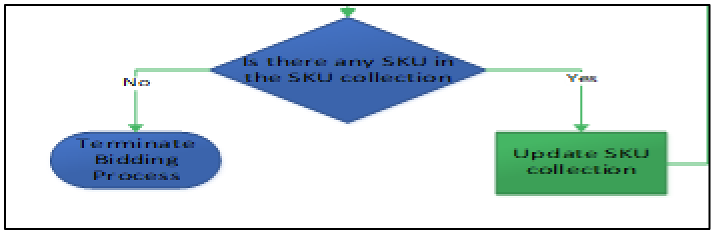



**Figure 3-27** Updating SKU collection step in Swim lane process map

24. Inventory will be updated after receiving and transferring products for respective outlets. The full algorithm has also been presented in swim lane process map in figure 3-10

$$I_{q,i,t+1} = I_{qi,t} + \sum_{j\neq i}^{j=N} X_{q,ji,t} - s'_{q,i,t}$$

$$I_{q,j,t+1} = I_{q,j,t} - \sum_{i\neq j}^{N} X_{q,ij,t} - s'_{q,j,t}$$

**Imbalance Amount-Based Unsupervised Bidding Redistribution Model-Process**

Bidding will start simultaneously for all stores when the regular shopping hours are closed. Most of the steps are similar to price based unsupervised bidding redistribution model. Steps that are primarily different have been discussed with the relevant part of the total swim lane process flow map. The algorithm of the model has been demonstrated here with the swim lane process flow in figure 3-29. Steps are illustrated in details in the following section:

1. All the Q number SKUs list is created.
2. Outlets with overstocks and outlets with low stocks are checked.
3. For each outlet, every SKU's stock is checked. If any SKU's inventory meets the criteria

   $I_{q,i} < (D_{q,i} * d)/30$ [Here, $i$=1, 2, 3, .., $n_1$]

then the store is listed in the Buyer store's list. Buyers needed amount is calculated as Amount needed=

$(D_{q,i} * d)/30 - I_{q,i} + (V_q/U) * J$. The maximum willing price is set as the MRP for the stock needed SKU for that buyer's store.

4. Outlets are also checked for overstock SKUs. If any outlet's any SKU's stock meets the criteria

   $I_{q,j} > (D_{q,j} * d_1)/30$ [ Here j=1,2,3,..,$n_2$]

then the store is listed in the Seller store's list.

The Reserve price of the overstock product is set based on shelf life and time remaining of the SKU number q in that store.

Reserve price= $P_{qj,t}$

amount overstock= $I_{q,j} - (D_{q,j} * d_1)/30$

5. From the list of all the SKUs, the first selected SKU is taken.
6. From the Buyer's list, the first buyer is taken and checked whether this buyer is a buyer of the first SKU taken from the SKUs list or not. If the selected buyer is the first SKUs buyer, then

he is listed in another list called ‘Selected SKUs Buyer’. This process continues for all the buyers on the buyer’s list for the first SKU.

7. If there is no buyer for the selected SKU, SKU is removed from the SKU collection list.
8. From the Seller’s list, the first seller is taken and checked whether this seller is a seller of the first SKU taken from the SKUs list or not. If the selected seller is the first SKUs seller, then he is listed in another list called ‘Selected SKUs Seller’. This process continues for all the sellers on the seller’s list for the first SKU.
9. If there is no Seller for the selected SKU, SKU is removed from the SKU collection list.
10. ‘Selected SKUs Seller’ list is rearranged by sorting the sellers with their overstocks in descending order. Sorted sellers are listed in a new list ‘Sorted Seller List’.
11. ‘Selected SKUs Buyer’ list is rearranged by sorting the buyers with their needed stock, in descending order. Sorted buyers are listed in a new list ‘Sorted Buyer List’.
12. From the ‘Sorted Buyer List’, the first buyer store i where i is equal to 1, is taken. Needed stocks are checked for the first buyer selected from the ‘Sorted Buyer List’.
13. For the first buyer from the ‘Sorted Buyer List’, from the ‘Sorted Seller List’, the first seller store j where j is equal to 1, is taken. Overstock is checked for the first seller selected from the ‘Sorted Seller List’.
14. Transportation cost, $T_{q,ji}$ is calculated for the transferrable stock from the seller j to the buyer i for SKU q where q is 1 (first SKU).
15. The feasibility of biding is checked on two criteria for the first SKU (q=1)

    First criterion (Price based):

    $$B_{q,i,t} * P_{q,j,t} \leq ((Y_{q,i}) * B_{q,i,t} - T_{q,j,i}) \; if \; B_{q,i,t} \leq W_{q,ji,t}$$

    $$W_{q,ji,t} * P_{qj,t} \leq ((Y_{qi}) * X_{q,ji,t} - T_{qji}) \quad if \; B_{q,i,t} > W_{q,ji,t}$$

    Second criterion (Shelf life based):

    $$f_q - l_{q,t} \geq Z_q$$

16. If the first criterion is not feasible, then the rest of the sellers are checked following their orders till the criterion is fulfilled (figure 3-28).

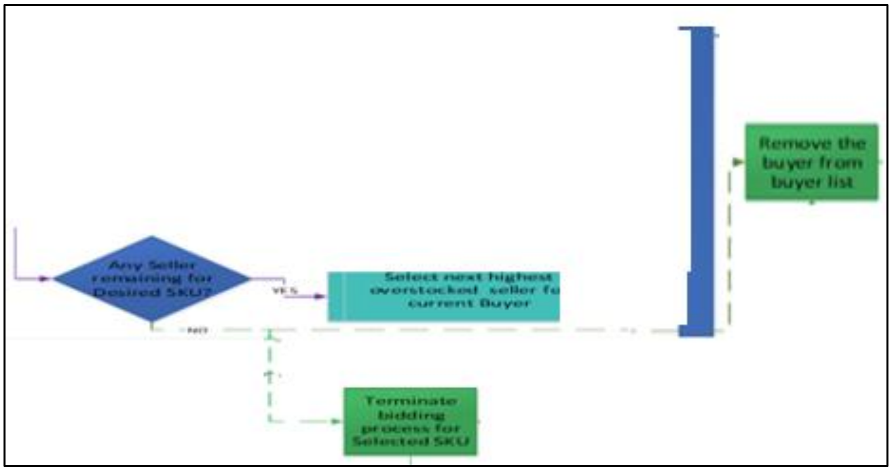



**Figure 3-28** Steps for checking feasibility in Swim lane process map.

17. If the second criterion is not feasible, the rest of the sellers are checked following their orders till the criterion is fulfilled (figure 3-28).
18. If feasible to bid, the first buyer will offer a bid price. This price will be equal to the next highest feasible buyer's price plus an increment. For our model, we are using the bid increments used by eBay.

    The bid price as a final transaction price for the first buyer by the system:

    $B_{p,1}$=$Y_{i-1}$ + Bid increment.

    Bid price $^{n}$th outlet:

    $B_{p,n}$=$Y_{n-1}$+Bid increment.

If there is only one buyer, then the final transaction price or bid price will be calculated by adding the bid increment to the seller's reserve price.

19. If the first buyer's demand is less than the first seller's overstock, then the seller is removed from the 'Sorted Seller List' after meeting the buyer's demand. The first seller is listed as a new seller into the 'Sorted Seller List' as the first seller with updated stock. This updated stock is calculated by subtracting the first buyer's demand from the first seller's stock. In this step, the first buyer's demand is fulfilled, and the first buyer is removed from the 'Sorted Buyer list'. The 'Sorted Buyer list' updates.
20. For that first buyer in the list, if the first buyer's demand is greater or equal to the first seller's overstock, the first Seller is removed from the 'Sorted Seller List'. 'Sorted Seller List' updates. The first buyer is removed from the buyer list after receiving a partial amount of the desired amount (if buyer's demand>seller's overstock). The first buyer is listed as a new buyer as the first buyer in the 'Sorted Buyer List' with updated stock needed.
21. Then steps 11-20 continue. This process continues for all the buyers into the Sorted Buyer List for the first SKU.
22. After completion of bidding for the first SKU, it is removed from the SKUs list.
23. For the next SKU in the Q-1 number SKUs list, steps 5-22 are followed. This process continues for all the SKUs.
24. Inventory will be updated after receiving and transferring products for respective outlets:

$$I_{q,i,t+1} = I_{qi,t} + \sum_{j\neq i}^{j=N} X_{q,ji,t} - s'_{q,i,t}$$

$$I_{q,j,t+1} = I_{q,j,t} - \sum_{i\neq j}^{N} X_{q,ij,t} - s'_{q,j,t}$$

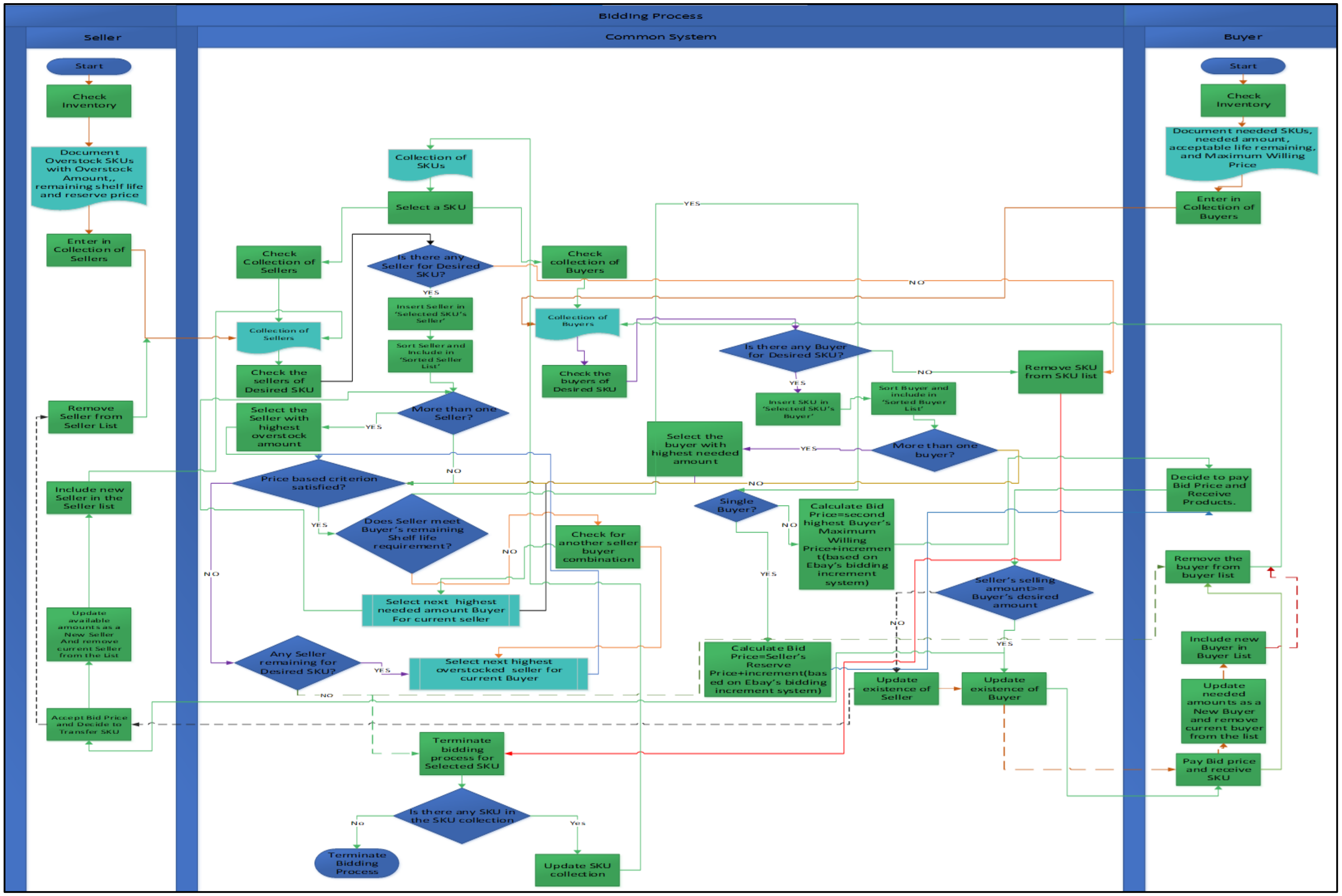



**Figure 3-29** Swim lane process map of Imbalance amount-based unsupervised bidding redistribution model

### *3.6.2 Supervised Redistribution Model*

In this model, the enterprise will check whether the stores that are acquiring products by bidding are worthy of selling those or not. Enterprise will check the past performance of the stores based on the ratio of revenue to purchasing cost. It will explain what percentage of the cost was generated to revenue by the buyer stores from the SKUs they received via bidding. In this way, buyer stores will be liable, and there will be control from the enterprise for not overbidding. If a store wants to bid, its previous bidding history will be observed. If it's selling to receiving value ratio for the previously bided same SKU is less than a certain percentage (will be decided by the enterprise), that bidder will not be allowed to get the desired amount of SKU from bidding. For modeling the supervised bidding redistribution model, some extra parameters have been used including unsupervised model parameters. Two models have been developed for the supervised bidding redistribution model, like the unsupervised bidding redistribution model. These are the price-based supervised bidding redistribution model and the Imbalance amount-based supervised bidding redistribution model.

**Parameters for Supervised redistribution:**

| | | |
|---|---|---|
| $B_{p,q,t-1}$ | = | Total cost of purchasing SKU q via bidding from time 0 to t-1 |
| $A_{q,t-1}$ | = | Total purchasing cost of SKU q for the buyer store via DC from time 0 to t-1 |
| $SL_{q,t-1}$ | = | Revenue earned from the bided product from time 0 to t-1 |
| $H_q$ | = | Ratio of SKU revenue earned to the total cost of purchasing by DC and through bidding of bidding SKU q. |
| $AH$ | = | Value of H ratio that will allow the buyer outlet to bid the amount they desire (based on needed stock calculation). |

$y$ = If the H ratio is less than AH, then the buyer outlet will be allowed to bid y percentage of their desired bid amount.

$$H_{q,t} = \frac{SL_{\mathrm{q,t-1}}}{B_{\mathrm{q,t-1}} + \mathrm{A}_{\mathrm{q,t-1}}}$$

**Price Based Supervised Redistribution Model-Process**

Algorithm for this model has been represented here with a swim lane process flow map (figure 3-30)

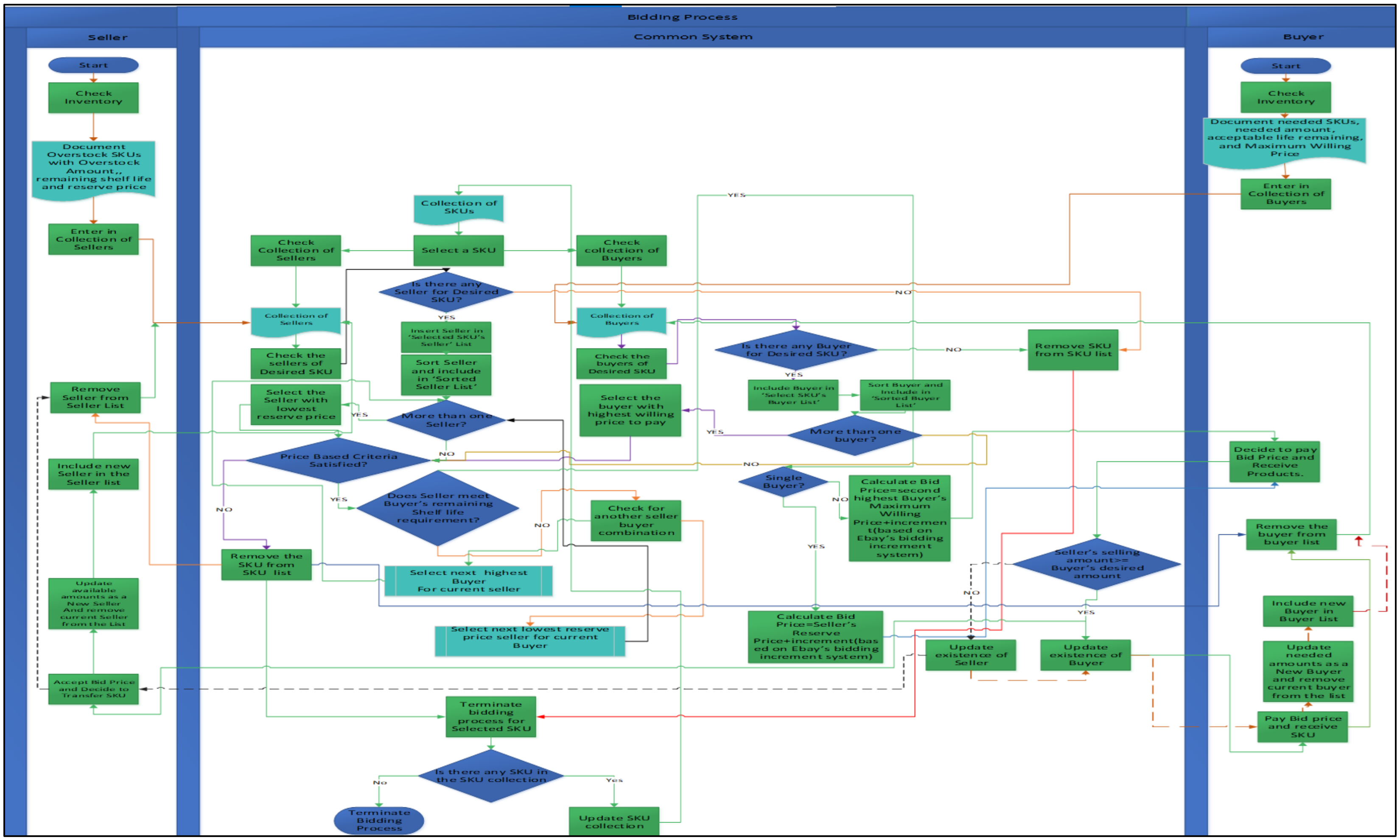



**Figure 3-30** Swim Lane Process Map of Price-Based Supervised Bidding Redistribution Mode

The detail process has been discussed by the following steps. The steps which are different from the price-based unsupervised bidding-based redistribution model, have been illustrated with the relevant part from the total swim lane process flow map (figure 3-30).

1. All the Q number SKUs list is created.
2. Outlets with overstocks and outlets with low stocks are checked.
3. For each outlet, every SKU's stock is checked. If any SKU's inventory meets the criteria

   $I_{q,i} < (D_{q,i} * d)/30$ [Here, $i$=1, 2, 3, .., $n_1$]

then the store is listed in the Buyer store's list. Buyers needed amount is calculated as Amount needed=

$(D_{q,i} * d)/30 - I_{q,i} + (V_q/U) * J$. The maximum willing price is set as the MRP for the stock needed SKU for that buyer's store.

4. Outlets are also checked for overstock SKUs. If any outlet's any SKU's stock meets the criteria

   $I_{q,j} > (D_{q,j} * d_1)/30$ [ Here j=1,2,3,..,$n_2$]

then the store is listed in the Seller store's list.

The Reserve price of the overstock product is set based on shelf life and time remaining of the SKU number q in that store.

Reserve price= $P_{qj,t}$

amount overstock= $I_{q,j} - (D_{q,j} * d_1)/30$

5. From the list of all the SKUs, the first SKU is taken.
6. From the Buyer's list, the first buyer is taken and checked whether this buyer is a buyer of the first SKU taken from the SKUs list or not. If the selected buyer is the first SKUs buyer, then he is listed in another list called 'Selected SKUs Buyer'. This process continues for all the buyers on the buyer's list for the first SKU.
7. If there is no buyer for the selected SKU, SKU is removed from the SKU collection list.

8. From the Seller's list, the first seller is taken and checked whether this seller is a seller of the first SKU taken from the SKUs list or not. If the selected seller is the first SKUs seller, then he is listed in another list called 'Selected SKUs Seller'. This process continues for all the sellers on the seller's list for the first SKU.
9. If there is no Seller for the selected SKU, SKU is removed from the SKU collection list.

10. 'Selected SKUs Buyer' list is rearranged by sorting the buyers with their maximum willing price in descending order. Sorted buyers are listed in a new list 'Sorted Buyer List'.
11. 'Selected SKUs Seller' list is rearranged by sorting the sellers with their reserve price in ascending order. Sorted sellers are listed in a new list 'Sorted Seller List'.
12. From the 'Sorted Buyer List', the first buyer store i where i is equal to 1, is taken. Needed stocks are checked for the first buyer selected from the 'Sorted Buyer List'.
13. For the first buyer from the 'Sorted Buyer List', from the 'Sorted Seller List', the first seller store j where j is equal to 1, is taken. Overstock is checked for the first seller selected from the 'Sorted Seller List'.
14. Ratio H is checked for the first buyer for the first SKU. If it is less than AH, then the allowed amount to bid will be $B_{i,t}$ *y. This amount is the buyer's modified demand as $B_{q,i,t'}$ (figure 3-31). If the ratio is equal or greater than the desired ratio, then this step is avoided, and the next steps are followed. Red marked circles represent this step.

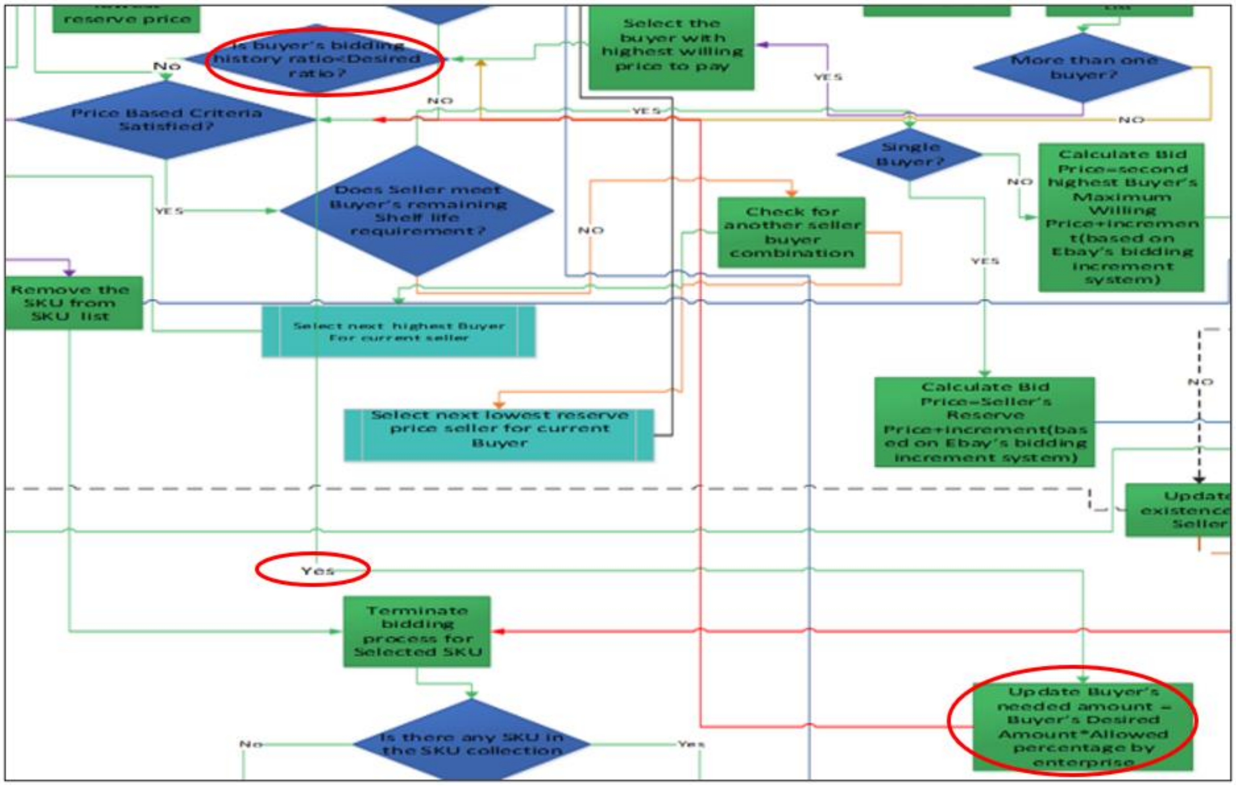



**Figure 3-31** Buyer's needed stock update step in swim lane process map

15. Transportation cost, $T_{qji}$ is calculated for the transferrable stock from the seller j to the buyer i for SKU q where q is 1 (first SKU).

16. The feasibility of biding is checked on two criteria for the first SKU (q=1)

    First criterion (price based):

    $$B_{q,i,t}{'} * P_{q,j,t} \leq ((Y_{q,i}) * B_{q,i,t'} - T_{q,j,i}) \quad if\ B_{q,i,t}{'} \leq W_{q,ji,t}$$

    $$W_{q,ji,t} * P_{qj,t} \leq ((Y_{qi}) * X_{q,ji,t} - T_{qji}) \quad if\ B_{q,i,t}{'} > W_{q,ji,t}$$

    Second criterion (shelf life based):

    $$f_q - l_{q,t} \geq Z_q$$

17. If the first criterion is not feasible, the first buyer and first seller are removed from the respected lists. The first SKU is removed from the SKU list.
18. If the second criterion is not feasible, then the second next lowest reserve price seller is selected and steps 13-17 are repeated for the second seller. This continues for all the sellers of the first SKU for the current buyer till the feasibility is achieved. The value of 'j' changes based on the rank of the seller in the 'Sorted Seller List'
19. If feasible to bid, the first buyer will offer a bid price. This price will be equal to the next highest feasible buyer's price plus an increment. For our model, we are using the bid increments used by eBay.

    The bid price as final transaction price for the first buyer by the system:

    $B_{p,1}$=$Y_{i-1}$ + Bid increment.

    Bid price $^{n}$th outlet:

    $B_{p,n}$=$Y_{n-1}$+Bid increment.

    If there is only one buyer, then the final transaction price or bid price will be calculated by adding the bid increment to the seller's reserve price.
20. If the first buyer's demand is less than the first seller's overstock, then the seller is removed from the 'Sorted Seller List' after meeting the buyer's demand. The first seller is listed as a new seller into the 'Sorted Seller List' as the first seller with updated stock. This updated stock is calculated by subtracting the first buyer's demand from the first seller's stock. In this step, the first buyer's demand is fulfilled, and the first buyer is removed from the 'Sorted Buyer list'. The 'Sorted Buyer list' updates.
21. For that first buyer in the list, if the first buyer's demand is greater than the first seller's overstock, the first Seller is removed from the 'Sorted Seller List'. 'Sorted Seller List' updates. The first buyer is removed from the buyer list after receiving a partial amount of the desired amount. The first buyer is listed as a new buyer as the first buyer in the 'Sorted Buyer List' with updated stock needed.

22. Then steps 10-21 continue. This process continues for all the buyers into the Sorted Buyer List for the first SKU.
23. After completion of bidding for the first SKU, it is removed from the SKUs list.
24. For the next SKU in the Q-1 number SKUs list, steps 5-23 are followed. This process continues for all the SKUs.
25. Inventory will be updated after receiving and transferring products for respective outlets:

$$I_{q,i,t+1} = I_{qi,t} + \sum_{j\neq i}^{j=N} X_{q,ji,t} - s'_{q,i,t}$$

$$I_{q,j,t+1} = I_{q,j,t} - \sum_{i\neq j}^{N} X_{q,ij,t} - s'_{q,j,t}$$

**<u>Imbalanced Amount Based Supervised Redistribution Model-Process</u>**

Imbalanced amount based supervised redistribution model is the combination of steps followed in imbalanced amount based unsupervised model and price based supervised model. Here we have represented the algorithm for the full model with swim lane process map (figure 3-32) and described the steps of the algorithm in details.

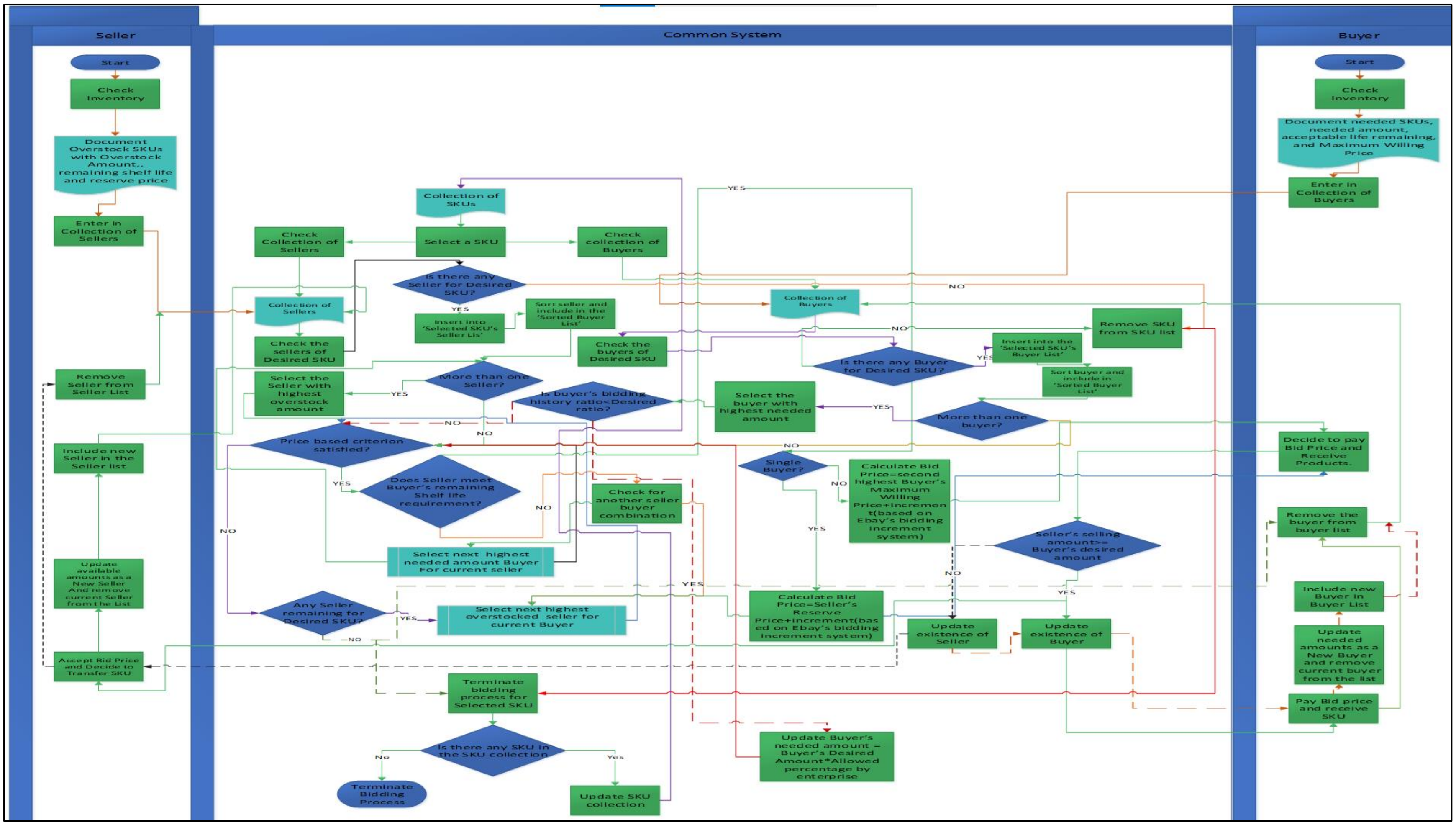



**Figure 3-32** Swim Lane Process Map of Imbalance Amount-Based Supervised Bidding Redistribution Model

Bidding will start simultaneously for all stores when the regular shopping hours will be closed. Steps are:

1. All the Q number SKUs list is created.
2. Outlets with overstocks and outlets with low stocks are checked.
3. For each outlet, every SKU's stock is checked. If any SKU's inventory meets the criteria

$I_{q,i} < (D_{q,i} * d)/30$ [Here, $i$=1, 2, 3, .., $n_1$]

then the store is listed in the Buyer store's list. Buyers needed amount is calculated as Amount needed=

$(D_{q,i} * d)/30 - I_{q,i} + (V_q/U) * J$. The maximum willing price is set as the MRP for the stock needed SKU for that buyer's store.

4. Outlets are also checked for overstock SKUs. If any outlet's any SKU's stock meets the criteria

$I_{q,j} > (D_{q,j} * d_1)/30$ [ Here j=1,2,3,..,$n_2$]

then the store is listed in the Seller store's list.

The Reserve price of the overstock product is set based on shelf life and time remaining of the SKU number q in that store.

Reserve price= $P_{qj,t}$

amount overstock= $I_{q,j} - (D_{q,j} * d_1)/30$

5. From the list of all the SKUs, the first SKU is taken.
6. From the Buyer's list, the first buyer is taken and checked whether this buyer is a buyer of the first SKU taken from the SKUs list or not. If the selected buyer is the first SKUs buyer, then he is listed in another list called 'Selected SKUs Buyer'. This process continues for all the buyers on the buyer's list for the first SKU.
7. If there is no buyer for the selected SKU, SKU is removed from the SKU collection list.

8. From the Seller's list, the first seller is taken and checked whether this seller is a seller of the first SKU taken from the SKUs list or not. If the selected seller is the first SKUs seller, then he is listed in another list called 'Selected SKUs Seller'. This process continues for all the sellers on the seller's list for the first SKU.
9. If there is no seller for the selected SKU, SKU is removed from the SKU collection list.
10. 'Selected SKUs Buyer' list is rearranged by sorting the buyers with their maximum needed stock in descending order. Sorted buyers are listed in a new list 'Sorted Buyer List'.
11. From the 'Sorted Buyer List', the first buyer store i where i is equal to 1, is taken. Needed stocks are checked for the first buyer selected from the 'Sorted Buyer List.'
12. 'Selected SKUs Seller' list is rearranged by sorting the sellers with their maximum overstock in descending order.
13. For the first buyer from the 'Sorted Buyer List', from the 'Sorted Seller List', the first seller store j where j is equal to 1, is taken. Overstock is checked for the first seller selected from the 'Sorted Seller List'.
14. Ratio H is checked for the first buyer for the first SKU. If it is less than AH, then the allowed amount to bid will be $B_{q,i,t}$*y. This amount is the buyer's modified demand, $B_{q,i,t'}$. If the ratio is equal or greater than the desired ratio, then this step is avoided and the next steps are followed.
15. Transportation cost, $T_{qji}$ is calculated for the transferrable stock from the seller j to the buyer i for SKU q where q is 1 (first SKU).
16. The feasibility of biding is checked on two criteria for the first SKU (q=1)

    First criterion (Price based):

    $$B_{q,i,t'} * P_{q,j,t} \leq ((Y_{q,i}) * B_{q,i,t'} - T_{q,j,i}) \quad if\ B_{q,i,t'} \leq W_{q,ji,t}$$

    $$W_{q,ji,t} * P_{qj,t} \leq ((Y_{qi}) * X_{q,ji,t} - T_{qji}) \quad if\ B_{q,i,t'} > W_{q,ji,t}$$

    Second criterion (shelf life based):

$f_q - l_{q,t} \geq Z_q$

17. If the first criterion is not feasible, then the rest of the sellers are checked from "Sorted Seller List" following their orders till the criterion is fulfilled.
18. If the second criterion is not feasible, then the rest of the sellers are checked from "Sorted Seller List" following their orders till the criterion is fulfilled.
19. If feasible to bid, the first buyer will offer a bid price. This price will be equal to the next highest feasible buyer's price plus an increment. For our model, we are using the bid increments used by eBay.

    The bid price as final transaction price for the first buyer by the system:

    $B_{p,1}=Y_{i-1}$ + Bid increment.

    Bid price $^{n}$th outlet:

    $B_{p,n}=Y_{n-1}$+Bid increment.

If there is only one buyer, then the final transaction price or bid price will be calculated by adding the bid increment to the seller's reserve price.

20. If the first buyer's demand is less than the first seller's overstock, then the seller is removed from the 'Sorted Seller List' after meeting the buyer's demand. The first seller is listed as a new seller into the 'Sorted Seller List' as the first seller with updated stock. This updated stock is calculated by subtracting the first buyer's demand from the first seller's stock. In this step, the first buyer's demand is fulfilled, and the first buyer is removed from the 'Sorted Buyer list'. The 'Sorted Buyer list' updates.
21. For that first buyer in the list, if the first buyer's demand is greater or equal to the first seller's overstock, the first Seller is removed from the 'Sorted Seller List'. 'Sorted Seller List' updates. The first buyer is removed from the buyer list after receiving a partial amount of the desired

amount (if buyer's demand>seller's overstock). The first buyer is listed as a new buyer as the first buyer in the ' Sorted Buyer List' with updated stock needed.

22. Then steps 12-21 continue. This process continues for all the buyers into the Sorted Buyer List for the first SKU.
23. After completion of bidding for the first SKU, it is removed from the SKUs list.
24. For the next SKU in the Q-1 number SKUs list, steps 5-23 are followed. This process continues for all the SKUs.
25. Inventory will be updated after receiving and transferring products for respective outlets:

$$I_{q,i,t+1} = I_{qi,t} + \sum_{j \neq i}^{j=N} X_{q,ji,t} - s'_{q,i,t}$$

$$I_{q,j,t+1} = I_{q,j,t} - \sum_{i \neq j}^{N} X_{q,ij,t} - s'_{q,j,t}$$

## 3.7 Donation Process in Our Model

We have included the donation option in our model with the redistribution option. Based on the SKUs' stock levels and the remaining shelf life, the enterprise will donate the SKUs. The main idea here is to reduce disposal costs and earn tax benefits. In this section, only the donation process of the total redistribution-donation system has been illustrated. For this donation process, we have assumed that the enterprise can donate every thirty days. For each SKU, the donation can be done to a certain amount. When calculating the donation amount available for each SKU, we have considered the remaining shelf life of an SKU. We have checked based on the forecast whether an SKU's existing stock can be sold before it expires. If it cannot be sold, then it is considered for donation. For calculating the amount available for donation, we also used one day's stock based on the forecast as safety stock. The details have been discussed in the latter part of this chapter. To develop the algorithm of donation, we have considered some parameters listed below:

**Nomenclature of parameters**

| | | |
|---|---|---|
| $Q$ | = | Number of SKUs |
| $q$ | = | SKU index |
| $f_q$ | = | Shelf-life |
| $l_q$ | = | Life passed |
| $I_q$ | = | Inventory of SKU q |
| $UT_q$ | = | Untransferable stock |
| $D_q$ | = | Forecasted demand/day of SKU q |
| $C_q$ | = | MRP of SKU q |
| $G_q$ | = | Purchasing cost of SKU q |

| | | |
|---|---|---|
| DR | = | Donation cycle |
| $DM_q$ | = | Limit amount for donation |
| $DA_q$ | = | Amount can be donated |
| $DA_{q'}$ | = | Final donation amount |
| $TaxD_q$ | = | Tax deduction |
| $s'_{q,t}$ | = | Total sales of SKU q at time t |

**Eligibility for donation**

If an SKU cannot be sold based on the sales trend before it expires, then that SKU will be eligible for donation. Here we have considered one day's extra sales while considering an SKU for donation.

$I_q > \left(D_q * \left(f_q - l_q + 1\right)\right)$

**Donation Process**

1. Every day All SKU stocks and remaining shelf lives are checked at every store. The donation process is conducted for each outlet.
2. If $I_q$> ($D_q$*($f_q$-$l_q$+1)), then the eligibility of donation amount is calculated as Iq- Dq*(fq-lq).
3. Eligible SKUs are checked in the list of redistributable SKUs. If any SKUs are considered for redistribution, then the redistributable amount is checked. Un-redistributable amount is calculated by subtracting the redistributable amount from the overstock amount calculated for redistribution.
4. If $UT_q$>= $I_q$ $-$($D_q$*($f_q$-$l_q$+1)) then the donatable amount DAq= $I_q$ $-$($D_q$*($f_q$-$l_q$+1)) Otherwise, the donatable amount is DAq=UTq.
5. If the SKU is not in the list of redistribution, then the donatable amount $DAq$ = $I_q$- $D_q$*(fq-lq).
6. If $DA_q$<= $DM_q$, then donates $DA_q$ as $DA_q{}'$. Otherwise, donate $DM_q$ as $DA_q{}'$.

7. Every DR day, check the updated donation amount if stock status changed or not

8. Donate SKUs and Update Inventory after donation

$I_{q,t+1} = I_{q,t} - s'_{q,t} - DA_{q,t}$

9. Itemized Tax deduction is calculated as,

$TaxD_q = G_q + 0.5*(C_q - G_q)$ for tax year

10. Decrease in tax bill calculated as = $(\sum_{q=1}^{Q} TaxDq) * tax\ rate$

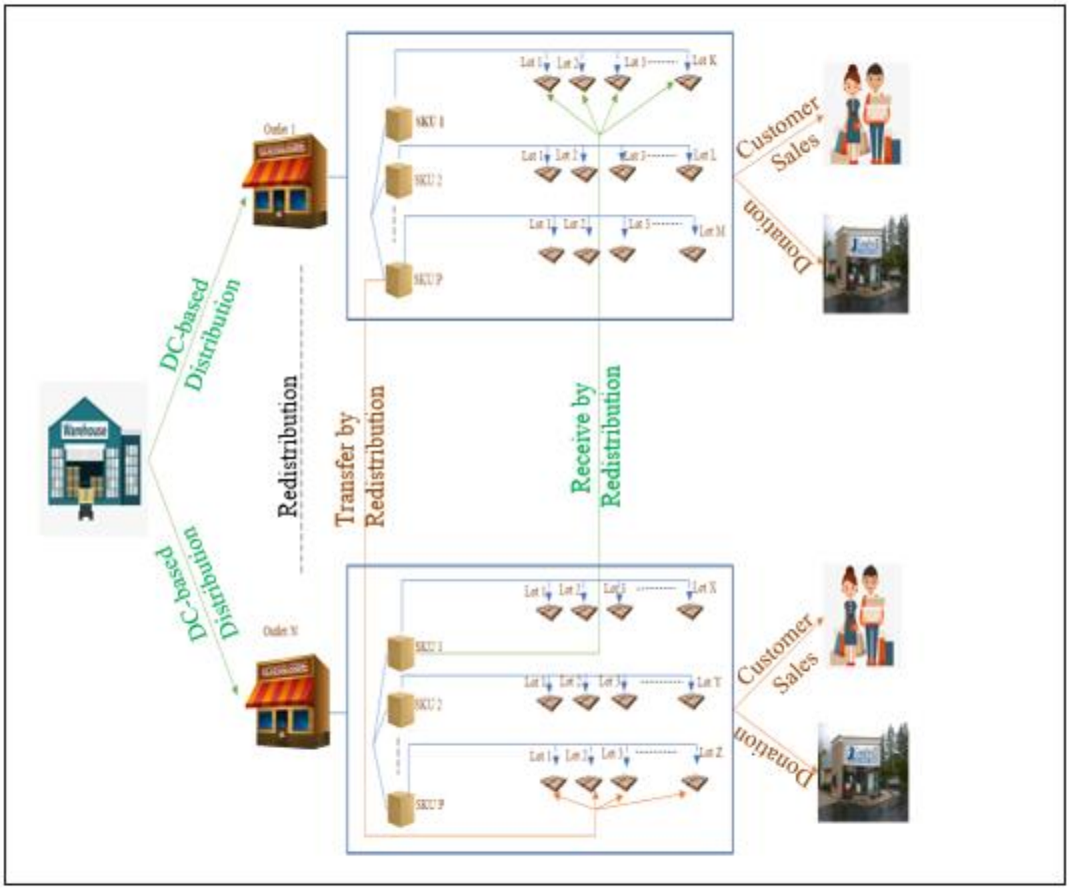



**Figure 3-33** SKU flows considering redistribution and donation option.

*Green arrows represent SKU inflow in the outlet; orange arrows represent SKU outflow from outlets, blue lines and arrows represent parts of a component.

## 3.8 Performance Measures

A performance measure is a numeric number and based on data to describe how an agency or activity is working and whether it is achieving its objective or not [24]. For our model, we are using three performance measures. These are Net cash inflow, fill rate and cash inflow over cost ratio. The definition and reason for choosing these performance measures have been illustrated below.

### *3.8.1 Net Cash Inflow*

This study has considered net cash inflow as the difference between the summation of expected revenue and a decrease in the tax bill and all the costs (purchasing, disposal, holding, transportation, and lost sales). The net cash inflow will provide the enterprise with an idea about its financial status. For the next year, the retail enterprise will be able to plan for its' financial investment.

Net cash inflow= Revenue + Decrease in Tax Bill-Purchasing cost-Holding Cost-Disposal Cost-Transportation cost-Lost Sales.

### *3.8.2 Fill Rate*

Customer satisfaction is the main motto for a business's success. It is necessary to know how much a retail chain is meeting the customer's demand. The more the number of customers becomes dissatisfied, the more will be the impact on future sales. To measure this we have used the following formula:

$$\text{Fill Rate } \% = \frac{Total\ Met\ Demand}{Total\ Demand} \times 100$$

*3.8.3 Cash inflow over cost ratio (COCR)*

The ratio of summation of revenue and the tax bill's decrease to costs (summation of purchasing, holding, disposal cost, transportation cost, and lost sale) has been addressed as cash inflow over cost ratio.

Cash inflow over cost $= \frac{Revenue + Decrease\ In\ Tax\ Bill}{Purchasing\ Cost + Holding\ Cost + Disposal\ Cost + Transportation\ Cost + \ Lost\ Sales}$

# Chapter 4 Model Development and Implementation

## 4.1 Introduction

Based on the methodology discussed in chapter 3, our redistribution model and donation process has been developed. This model has been developed using hybrid simulation with Anylogic 8.7 personal version software. Based on their behavior, process of work, and interaction, each agent has been developed. This model's main components are outlets, multiple SKUs, DC, DC vehicles, and customers. Four redistribution models have been developed with the option of donation. In this chapter's later section, input data analysis, agent development, model development, implementation of models, and results analysis have been demonstrated.

## 4.2 Input Data

For observing a model's behavior, input data are required. We have collected data from one of the largest retail chains situated in Bangladesh, Dhaka. The total number of SKUs was seven thousand two hundred and twenty-nine. The sales amounts are different for each SKU over the outlets. Data selected includes mainly the IDs of SKUs, their weight, volume, shelf life, average sales amount, the average number of customers coming to the outlets, purchasing prices, and selling prices. Ten outlets and a single distribution center are the stock movement points among where the SKUs move. As our model's behavior evolves based on the SKUs' lives, we consider shelf life as an important factor within our simulated system.

Table 4-1 Data used for SKUs (Stock keeping units)

| Data Field | Source of Data | Data attributesName | Description of Data |
|---|---|---|---|
| SKU | Database of the selected Retail | Master Category | Eleven different Categories |
| | | Product Code | SKU Identification number |
| | | Product Name | SKU Name |
| | | Outlet Id | Outlet Identification number |
| | | Customer Purchased | Number of customers purchased |
| | | Sales Amount | Average monthly sales |
| | | Price | Market retail price (the price the customer pays) |
| | | Total Customer count at the outlet | Number of Customer coming to the outlet where the SKU is |
| | | Tprice | Trade Price (the price the retailer pays to the supplier to purchase) |
| | | life (Days) | The shelf life of SKUs in days (45,60,120,180,365,730,1095) |
| | Calculated Based on the database of the selected retail-chain | Percent Customer B | Percentage of total customer buying the SKU |
| | | Number of Integer Amount | Integer amount of an SKU buying by a Customer |
| | | Probability of buying another | Probability of buying another SKU by a customer who bought an integer amount |
| | Based on the selected retail' | Life threshold for full price | Age of an SKU before when it can be sold to other outlets at Full retail price |
| | From Internet and assumption | Weight | Weight of the SKU |
| | | Volume | The volume of the SKU |

Our data source retail outlet has eleven different SKUs, excluding the highly perishable categories (meat, fish, and vegetables). Based on the SKUs' use and characteristics, they have been categorized.

Table 4-2 Different Categories of SKUs

| Master Category (MC) | Description |
|---|---|
| 21 | Baby Care |
| 22 | Baby Food |
| 23 | Beverage & Tobacco |
| 24 | Commodities |
| 25 | Dairy |
| 26 | Home Care |
| 27 | Kitchen Additives |
| 28 | Packaged Foods |
| 30 | Personal Care |
| 35 | Electronics & Appliances |
| 42 | Gift & Toys |

Stock sales points are the outlets. Our model is capable of running for any number of outlets. Here, we have considered ten outlets situated in different places. Outlets' names represented the location of the outlets on the map. Location is required for transporting SKUs from the distribution center (DC) to the outlets. Zones are required to set the delivery cost for lateral transshipment/redistribution.

Table 4-3 Outlet Data

| Data Field | Source of Data | Data attributes | Description of Data |
|---|---|---|---|
| Outlet | Database of selected Retail | Outlet ID | Outlet Identification number |
| | | Outlet Name | Name of the Outlet |
| | | Number of Customers | The average number of customer coming into the outlet/ month |
| | Assumed | Zone | 1,2,3,4 |

*4.2.1 Input Data Analysis*

For our model development, we need to know how the SKUs' sales vary over the outlets. Knowing the sales variation will help identify the SKUs that contribute to the total revenue most and least. This knowledge can help later to analyze the impact of the redistribution for different SKU class contributions. As shelf-life is an important part of our redistribution model, knowing about different shelf-lives can contribute to develop the model.

*4.2.1.1 ABC analysis of SKUs*

ABC analysis is a popular method to segregate SKUs based on their contribution to sales. By doing this, high-contributing SKUs can be identified and monitored to ensure their stock availability remains high. On the other hand, low-performing SKUs can be investigated to determine the reasons for their performance. ABC analysis has been conducted on the collected SKUs. 80% of the total revenues have been earned from around 37% of the total SKUs. These are class A SKUs.

15% of the total revenues earned by 40% of the total SKUs and 5% of the total revenues earned by 23% of the total SKUs.

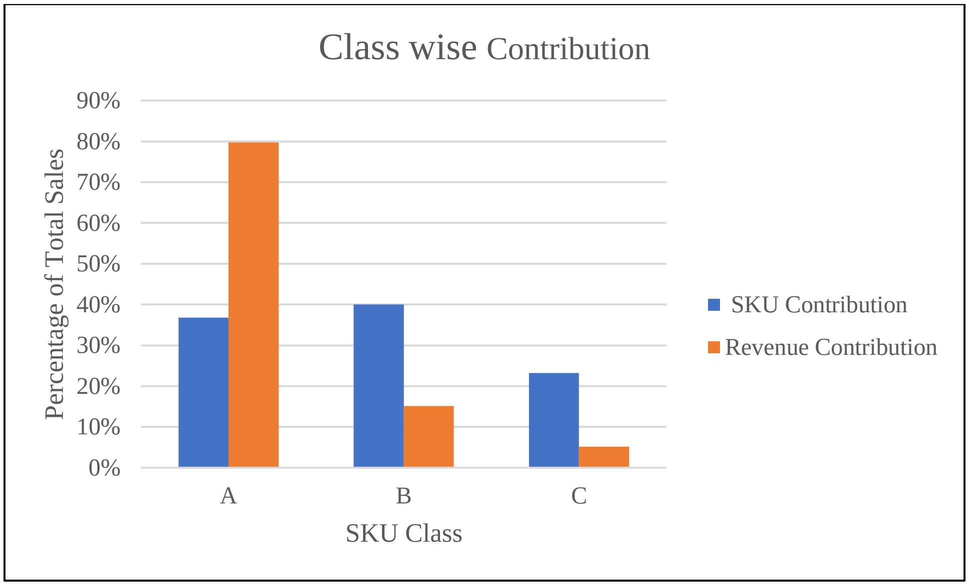



**Figure 4-1** ABC Classification of SKUs

*4.2.1.2 Shelf life*

The shelf-life of a product is the period of time until it is consumable, suitable to use, or saleable. In our model, the flow of stocks by lateral transshipment is controlled by a SKUs' shelf life-based value. Based on our collected data, SKUs in a retail environment can have different shelf lives. Observed SKUs shelf lives vary in seven different lives. Most of our collected SKUs have shelf lives of seven hundred- and thirty-days life. The smallest group of SKUs have a shelf-life of one thousand and ninety-five days.

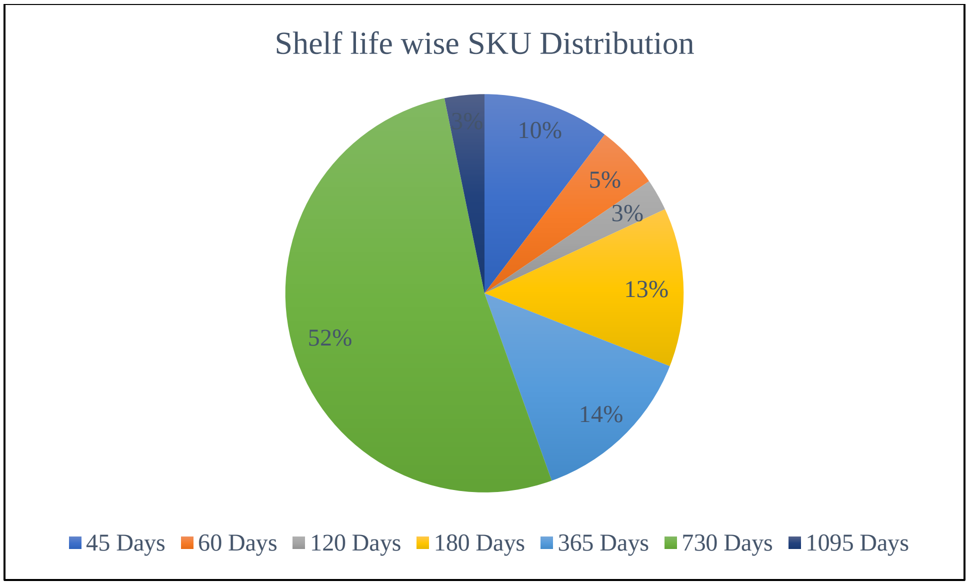



**Figure 4-2** Distribution of SKUs with different shelf lives

4.3 Development of Hybrid Model in AnyLogic Software

An agent-based model is a simulation modeling approach that simulates different simultaneous interactions of multiple agents to predict a complex system at a microscale level. AnyLogic is a simulation modeling tool that can utilize multi-methods. In discrete-event simulation (DES) models, system operates in a sequence. System state changes when events occur at a particular time in (DES) model. The agent-based, discrete event and system dynamics are three different methodologies that Anylogic can support. Our model is a combination of agent-based and discrete event simulation. Most of the process of the model work in agent-based environment. There are mainly two classes in Anylogic. One is the agent class and another one is experiment class. For developing a model in Anylogic, we need to develop the process and interactions under the agent class. Experiment class is used to observe the response of model output for different experiments.

*4.3.1 Main Agent*

A default agent named “Main” is created when a new model is opened in the AnyLogic application. Normally, the outputs of the simulation run, environment, GIS space are some of the features that exist under the main agent after the model is developed and run.

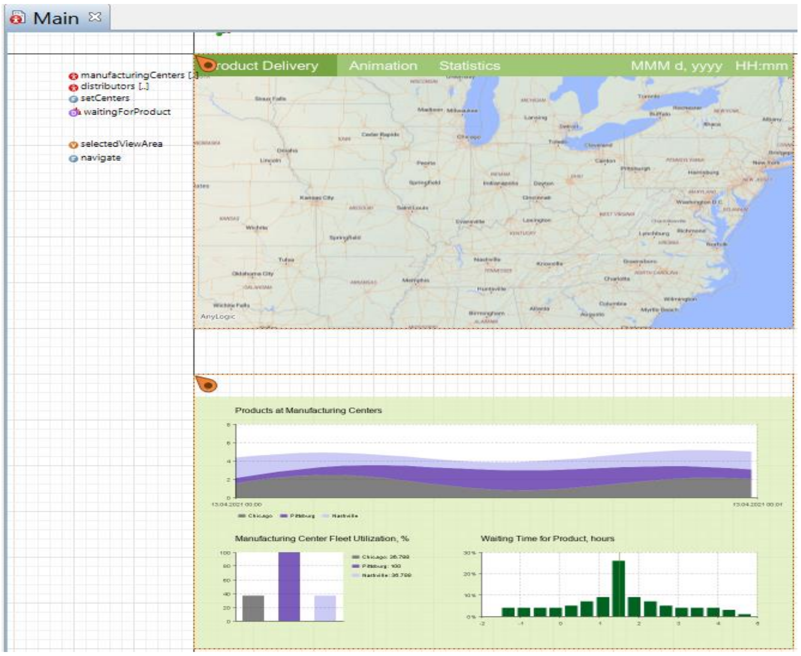
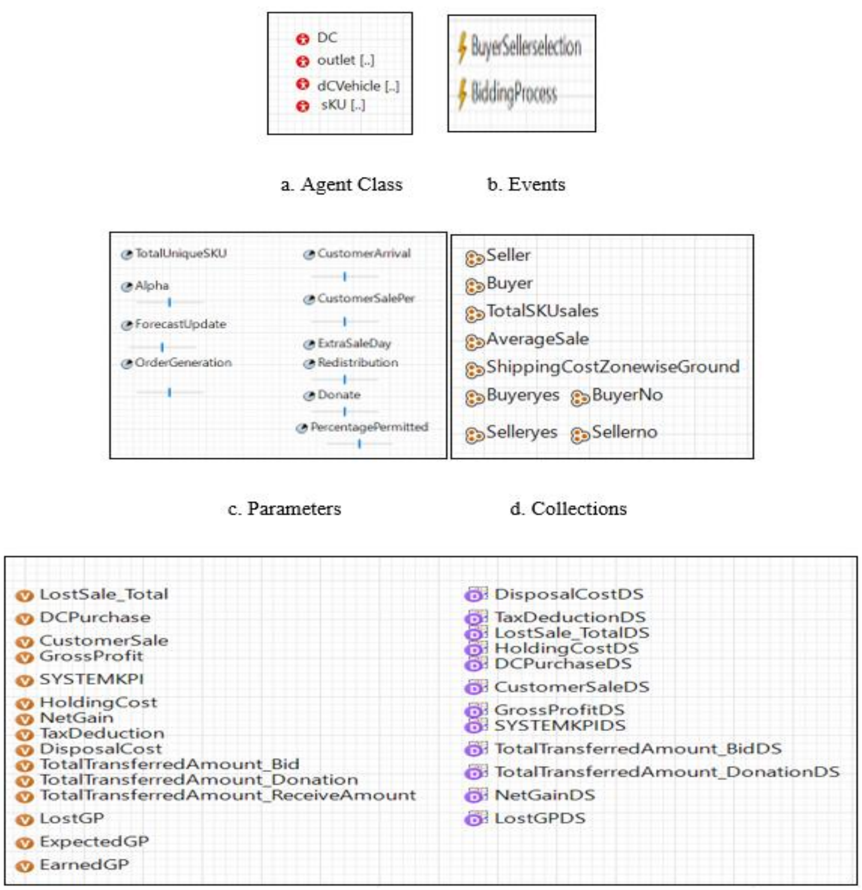



**Figure 4-3** Main Agent in Anylogic (An example from Anylogic Software)

For an animation of the outlets, DC, and DC vehicles, we used GIS space for locating these places in our model. GIS map helps to see these agents' location and how DC vehicle agents moves over the GIS space responding to the model run.


**Figure 4-4** GIS Space of our model

We have developed ten agent classes. Four of them are also placed on the main agent class(SKU, Outlet, DC, and DC Vehicles). To observe the DC Vehicle agent's movement from DC to outlets on the GIS Map, we need to put these three agents on the Main agent class. SKU agent is required for the action chart ( Figure 4-6). 'TotalUniqueSKU' parameter of our model captures the number of unique SKUs. All our outlets do not necessarily have demands for all the SKUs. This parameter addresses an aggregated number of unique SKUs for all the outlets (Figure 4-5). 'ForecastUpdate' is used to set the period for demand forecast. We have used exponential smoothing forecasting for our model. 'Alpha' has been used as the smoothing constant. 'OrderGeneration' parameter has been used as the inventory review period. For our model, we have used the number of customers arriving will follow a normal distribution. This normal distribution will have a mean value of average number of customers arriving in a store and a standard deviation of a certain percentage of average number of customers. For capturing this deviation, 'CustomerArrival' parameter has been used. In our model, outlets are allowed to bid for more amount than needed based on the forecast. This will allow them to act based on the most recent sales trends. The forecast is not perfect. The forecast is modified after a certain period. But before that period comes, outlets can ask for more products by bid, based on the most recent sales trend. 'CustomerSalePer' parameter considers the number of most recent days which has been considered to track the actual sales for those days. 'ExtraSaleDay' is the number of days stock considered to ask for bids based on the most recent days sales. The bid's total amount will be the summation of this amount and stock needed based on the forecast.




a. Agent Class b. Events

c. Parameters d. Collections

e. Model Output

**Figure 4-5** Part of Main Agent Window of our Model

‘Redistribution’ and ‘Donate’ are the binary parameters for including redistribution and donation options in the model respectively. For the Supervised model, outlets’ bidding amount is controlled by the enterprise. ’Percentage Permitted’ parameter will set the control on how much of the desired amount a buyer outlet can bid. Collections have been used to store the related components of the model. For example, the ‘Selleryes’ collection stores the sellers who are willing to sell a certain SKU. This has been done for all the SKUs after running them in a loop. (Figure 4-6). Events will generate an action in the model. Model outputs are used to store the simulation results.

Based on the interactions of the agents, we have developed an action chart under the main agent. This action chart will take all agents' information and run the bidding process (Figure 4-6). From this process's outcome, stocks will be transferred, and SKUs’ inventories will be updated.

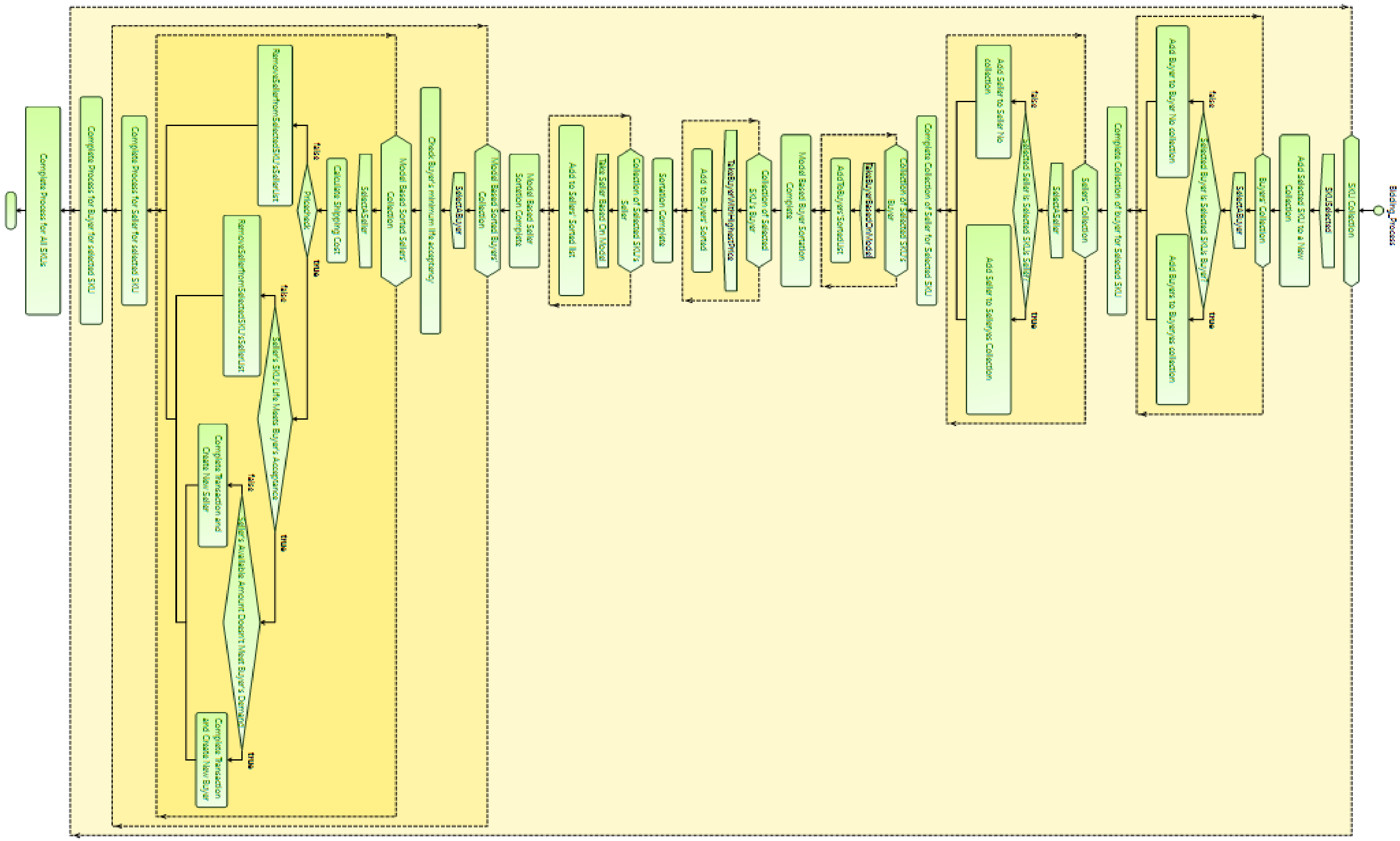


**Figure 4-6** Action Chart of Unsupervised Process

### *4.3.2 SKU Agent*

SKU agent has been developed based on some attributes. Some of these attributes are the same for all the outlets. Like Master Category, Product Code, Product Name, Weight, Volume, and Trade price. The rest of our SKU agent attributes listed in the table(Table 4-4) vary depending on which outlet it is.

Table 4-4 Attributes of SKU agent

| **Attributes** | **Details** |
|---|---|
| Master Category | Eleven different Category |
| Product Code | SKU Identification number |
| Product Name | SKU Name |
| Outlet Id | Outlet Identification number |
| CustomerPurchased | Number of customers purchased |
| SalesAmount | Average monthly sales |
| Stock | Inventory of SKU |
| Price | Market retail price (the price the customer pays) |
| Total Customer at Outlet | Number of Customer coming to the outlet where the SKU is |
| Tprice | Trade Price (the price the retailer pays to the supplier to purchase) |
| life (Days) | The shelf life of SKUs in days (45,60,120,180,365,730,1095) |
| PercentCustomerB | Percentage of total customer buying the SKU |
| Number of IntegerAmount | Integer amount of an SKU buying by a Customer |
| Probability of buying another | Probability of buying another SKU by a customer who bought an integer amount |

Table 4-4 Continued

| | |
|---|---|
| Life threshold for full price | Age of an SKU before when it can be sold to other outlets at Full retail price |
| Weight | Weight of the SKU |
| Volume | The volume of the SKU |

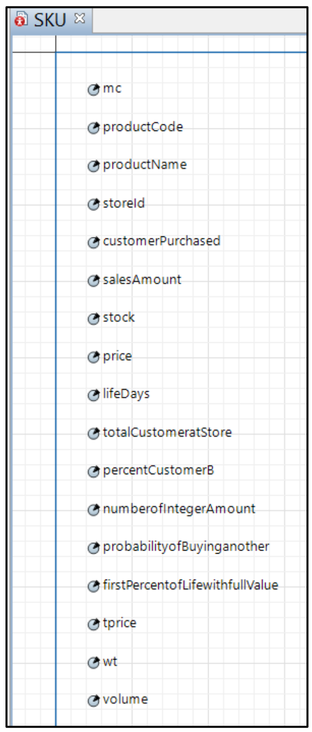



**Figure 4-7** Parameters of SKU agent

*4.3.3 Outlet Agent*

Outlets have been built in our model from spatial and non-spatial perspectives. The population of outlet agents is ten and each outlet agent has its attributes. To place our outlets in the GIS MAP, we have used the name of the location. For identifying the outlets, unique numerical numbers have been used as Outlet Id. The number of Customers has been used to address the average number of customers coming to a certain outlet in a month.

Table 4-5 Attributes of Outlet agent

| Attributes Class | Details |
|---|---|
| **1.** Spatial | Store Name has been used as a Spatial attribute for the outlet agent. |
| **2.** Non-Spatial | Store Id has been used for identifying outlets, number of Customers is the average number of customers coming to the relevant outlet. Zone defines the zone number of the outlet for transportation cost calculation. |

Like the main agent, outlet agents also have some events and collections with some variables. 'StockAttheBeginningofSimulation' event sets the stock of different SKUs at different Outlets.'DailyStockCount' event updates all SKUs related process and variables. 'GenerateOrder',' UpdateForecast', and 'StockTransfer' events place orders to DC (distribution center) based on forecast and stocks, updates forecast, and transfer stocks based on bid respectively. 'CMevent' triggers the calculation of customer purchase value. 'TotalFinalTransfer' and 'TotalFinalReceive' variables are used for addressing stock transfer amount and receive the amount by the bid. 'ScheduledDelivery' is used to measure the remaining time to get delivery from DC. After an SKU is donated, the tax deduction amount is calculated. This value is displayed here as 'Valuegainfrom_donation' variable. 'ValuegainedbyBid' and 'Valuelostbybuyingbid' are used to capture the value received and lost from the outlet's bidding process.

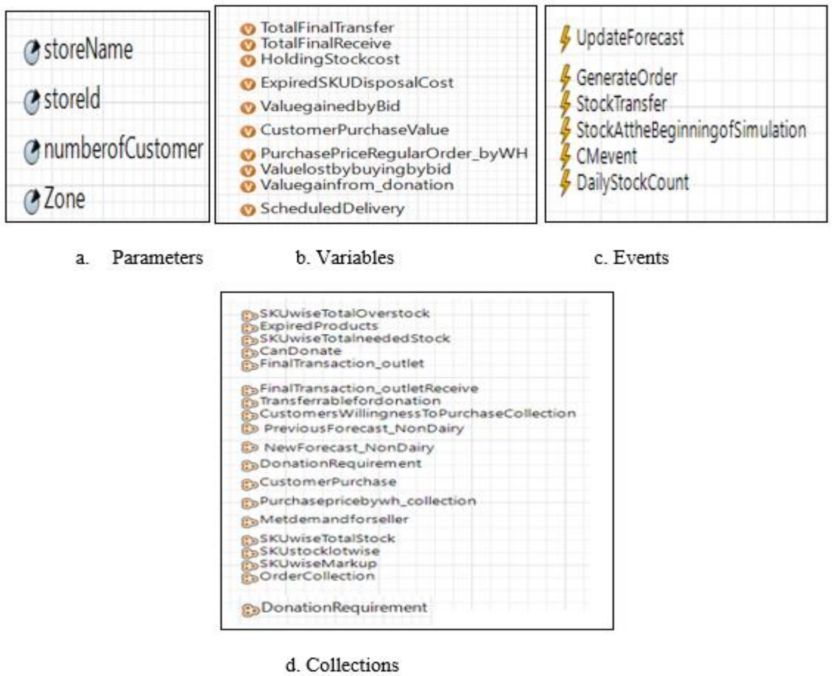



**Figure 4-8** Parameters, variables, events, and collection of Outlet Agent

Collections are used to store related information of the collection items. The flow of customer agents is developed in outlet agents through process flow (Figure 4-9). The process flow is composed of customer arrival in-store, purchase, and the customer leaving the store.

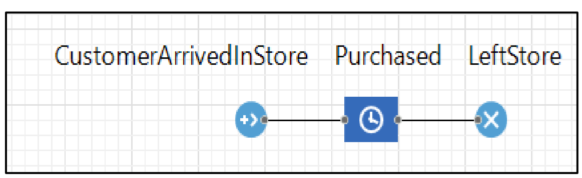



**Figure 4-9** Customer Process Flow in outlet agent

Every day customer comes to the outlets. This number is normally distributed with a mean number of customers (average number of customers coming to a certain outlet) and standard deviation of a certain percentage of this mean number. After coming to the outlets, the purchase action follows the action chart (Figure 4-10)

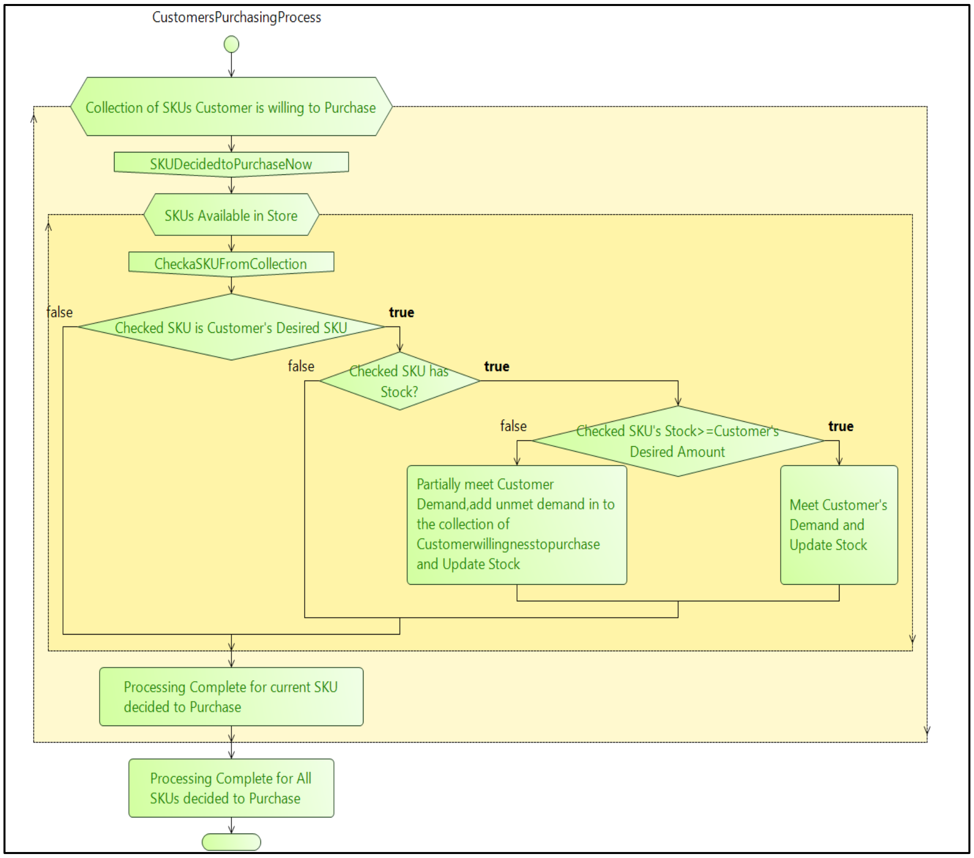



**Figure 4-10** Action Chart for Customer's purchasing process

The action chart works based on codes. A sample code (Figure 4-11) has been demonstrated here related to this action chart (Figure 4-10)

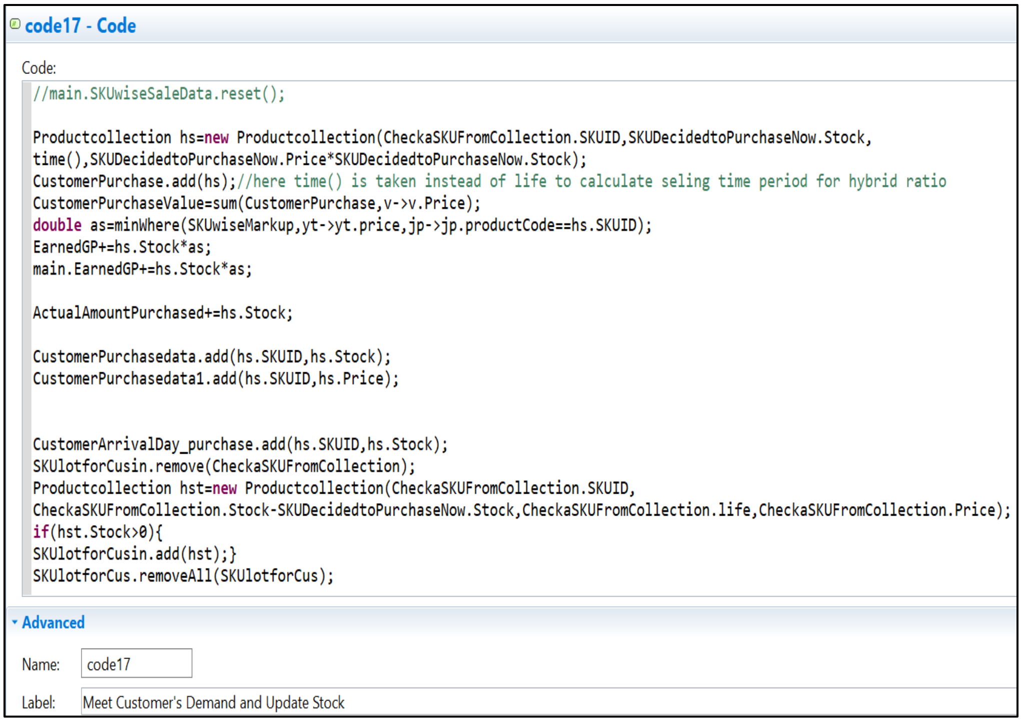



**Figure 4-11** Sample Code for Customers Purchasing Process

Stock transfer via redistribution and donation are triggered by the stock levels. 'DailyStockCount' event selects the SKUs having overstock and needed stock conditions. After identifying the overstock amount, it is required to find out which lot of a certain SKU has how much overstock. This is very important to know lot wise overstock so that necessary actions can be taken for the oldest lot's overstock. Action chart has been used in outlet agent to deal with SKU and Lot wise overstock calculation Process (Figure 4-12)

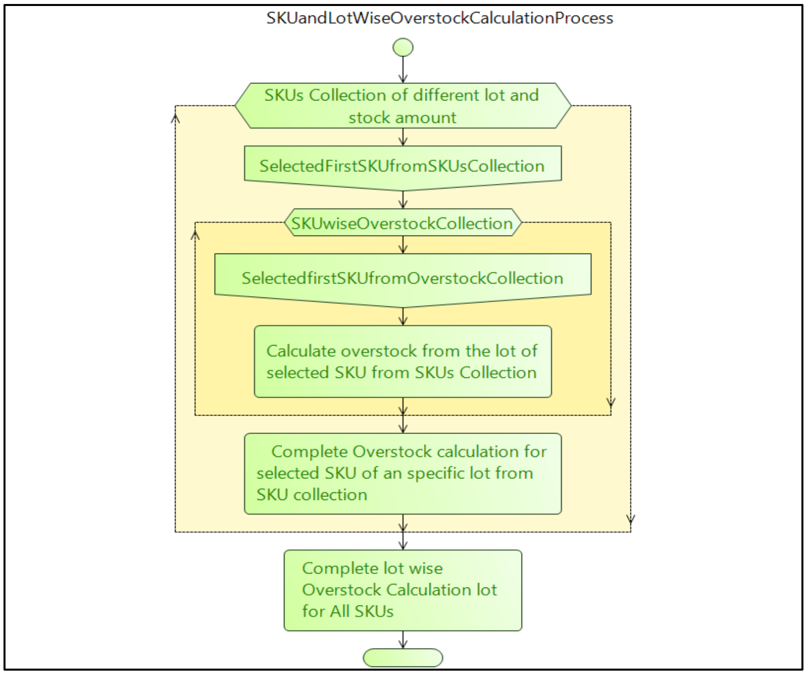



**Figure 4-12** Action Chart for SKU and Lot wise Overstock Calculation Process

```
if(sku.SKUID==overstock.SKUID){
if(overstock.Stock>0){if(sku.Stock<overstock.Stock){
Imbalance sb=new Imbalance(storeId,overstock.SKUID,sku.Stock,sku.life,sku.Price);
Productcollection oc=new Productcollection(overstock.SKUID,sku.Stock,sku.life,sku.Price);

STOCKOVER.add(oc);
main.Sellervisible.add(oc);

main.Seller.add(sb);
}
else {Imbalance pb=new Imbalance(storeId,overstock.SKUID,overstock.Stock,sku.life,
sku.Price);
Productcollection jc=new Productcollection(overstock.SKUID,overstock.Stock,
sku.life,sku.Price);

main.Seller.add(pb);

STOCKOVER.add(jc);
main.Sellervisible.add(jc);//}

}
Productcollection pb=new Productcollection(overstock.SKUID,(overstock.Stock-sku.Stock),0,0);

if(pb.Stock>0){
SKUwiseTotalOverstockintermediate.add(pb);

}

}}
else {
SKUwiseTotalOverstockintermediate.add(overstock);
}
```

**Figure 4-13** Sample code for SKU and Lot wise Overstock Calculation Process Action Chart

Based on stock levels, the bidding process is done. If an outlet is accepted in a bid to transfer stocks or receive stocks, some processes are required to follow in Anylogic.'Stock Transfer' event triggers the stock transfer and stock receiving process. The first process is carried out through an action chart (Figure 4-14). The stock receiving process is done only under 'Stock Transfer' event.

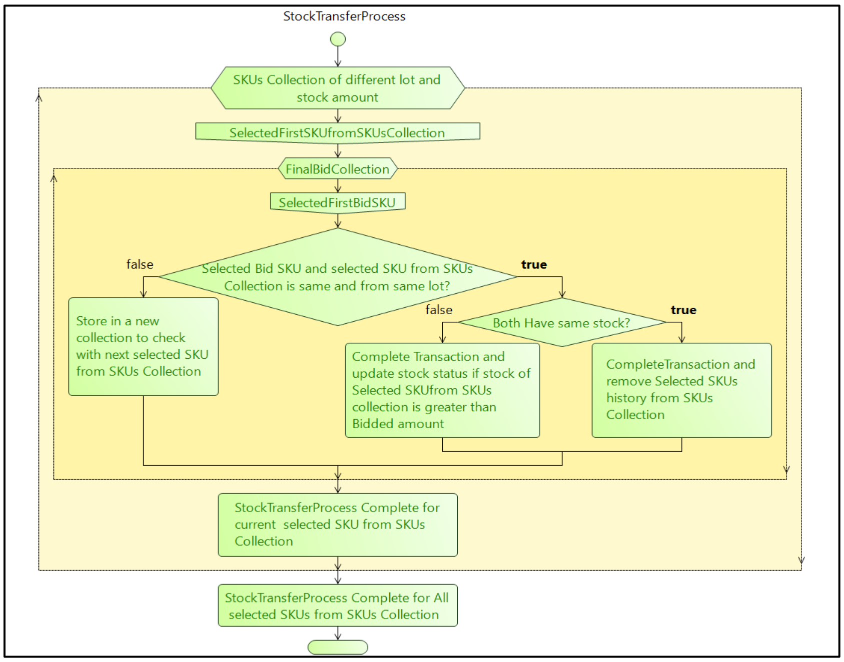



**Figure 4-14** Action Chart for Stock Transfer Process

Code:

```
SkustocklotwiseIntermediate.remove(SelectedFirstSKUfromSKUsCollection);
if(NewSkustocklotwise.size()>0){
if(NewSkustocklotwise.get(0).SKUID==SelectedFirstBidSKU.SKUID){
if(NewSkustocklotwise.get(0).Stock>SelectedFirstBidSKU.Stock){
Productcollection pc=new Productcollection(SelectedFirstBidSKU.SKUID,
NewSkustocklotwise.get(0).Stock-SelectedFirstBidSKU.Stock,SelectedFirstBidSKU.life,SelectedFirstBidSKU.Price);

if (!SkustocklotwiseIntermediate1.isEmpty()){
SkustocklotwiseIntermediate1.removeFirst();}
SkustocklotwiseIntermediate1.add(0,pc);
NewSkustocklotwise.clear();
NewSkustocklotwise.add(pc);
SKUstockLotandAmount.add(pc.SKUID,pc.Stock);
}

else{
Productcollection pc=new Productcollection(SelectedFirstBidSKU.SKUID,0,
SelectedFirstBidSKU.life,SelectedFirstBidSKU.Price);

if (!SkustocklotwiseIntermediate1.isEmpty()){
SkustocklotwiseIntermediate1.removeFirst();}
SkustocklotwiseIntermediate1.add(0,pc);
NewSkustocklotwise.clear();
NewSkustocklotwise.add(pc);
SKUstockLotandAmount.add(pc.SKUID,pc.Stock);
}
}
else
{
if(SelectedFirstSKUfromSKUsCollection.Stock>=SelectedFirstBidSKU.Stock){
Productcollection pc=new Productcollection(SelectedFirstBidSKU.SKUID,
SelectedFirstSKUfromSKUsCollection.Stock-SelectedFirstBidSKU.Stock,SelectedFirstBidSKU.life,SelectedFirstBidSKU.Price)
if(pc.Stock!=0){SkustocklotwiseIntermediate1.add(0,pc);
NewSkustocklotwise.clear();
NewSkustocklotwise.add(pc);SKUstockLotandAmount.add(pc.SKUID,pc.Stock);}}
else{
Productcollection pc=new Productcollection(SelectedFirstBidSKU.SKUID,0,SelectedFirstBidSKU.life,
SelectedFirstBidSKU.Price);
SkustocklotwiseIntermediate1.add(0,pc);
NewSkustocklotwise.clear();
NewSkustocklotwise.add(pc);SKUstockLotandAmount.add(pc.SKUID,pc.Stock);
}
}}
else
{if(SelectedFirstSKUfromSKUsCollection.Stock>=SelectedFirstBidSKU.Stock){
Productcollection pc=new Productcollection(SelectedFirstBidSKU.SKUID,
SelectedFirstSKUfromSKUsCollection.Stock-SelectedFirstBidSKU.Stock,SelectedFirstBidSKU.life,SelectedFirstBidSKU.Price)
SkustocklotwiseIntermediate1.add(0,pc);
//NewSkustocklotwise.clear();
NewSkustocklotwise.add(pc);SKUstockLotandAmount.add(pc.SKUID,pc.Stock);}
else{
Productcollection pc=new Productcollection(SelectedFirstBidSKU.SKUID,0,SelectedFirstBidSKU.life,
SelectedFirstBidSKU.Price);
SkustocklotwiseIntermediate1.add(0,pc);
//NewSkustocklotwise.clear();
NewSkustocklotwise.add(pc);SKUstockLotandAmount.add(pc.SKUID,pc.Stock);
}
}
```

**Figure 4-15** Sample Code for Stock Transfer Process

For finalizing the amount of donation, we have used an action chart 'Donation Amount Finalizing Action Chart'. Based on donation requirements and available stocks for donation, this action has been conducted.

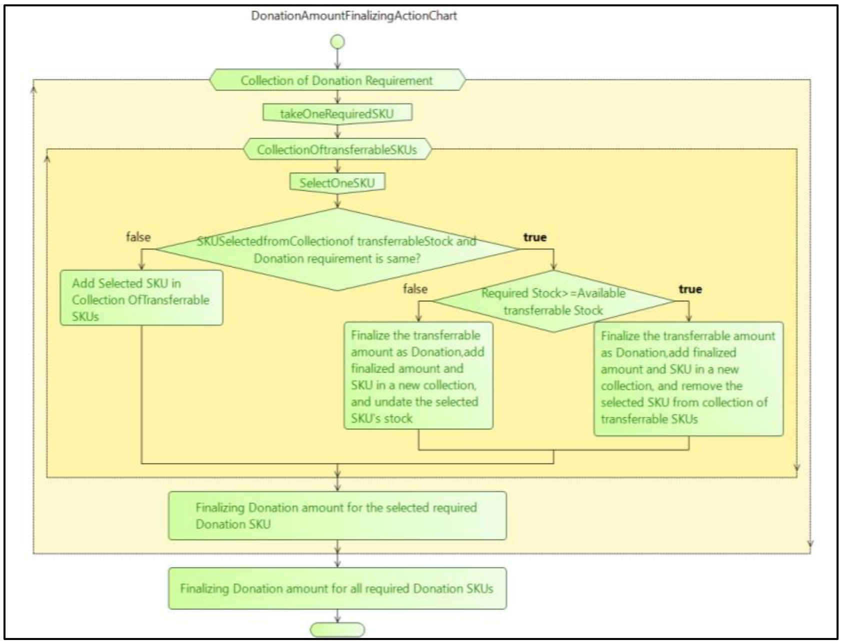



**Figure 4-16** Action Chart of Donation Amount Finalization

```
if(NewCharity.size()>0){
if(NewCharity.get(0).Stock==0){
DonationRequirement.remove(TakeaRequirement);
NewCharity.clear();
}
else{
//if(NewCharity.get(0).SKUID==SelectOneSKU.SKUID)
Productcollection ch=new Productcollection(TakeaRequirement.SKUID,
NewCharity.get(0).Stock-SelectOneSKU.Stock,SelectOneSKU.life,
TakeaRequirement.Price);
Metdemandforseller.add(SelectOneSKU);
Metdemandforsellercopyfortaxcalc.add(SelectOneSKU);
Metdemanddataset.add(SelectOneSKU.SKUID,SelectOneSKU.Stock);
Metdemanddatasetlife.add(SelectOneSKU.life,SelectOneSKU.Price);

NewCharity.clear();
NewCharity.add(ch);
}}
else{
Productcollection ch=new Productcollection(TakeaRequirement.SKUID,
(TakeaRequirement.Stock-SelectOneSKU.Stock)*0,SelectOneSKU.life,
TakeaRequirement.Price);
Metdemandforseller.add(SelectOneSKU);
Metdemandforsellercopyfortaxcalc.add(SelectOneSKU);
Metdemanddataset.add(SelectOneSKU.SKUID,SelectOneSKU.Stock);
Metdemanddatasetlife.add(SelectOneSKU.life,SelectOneSKU.Price);

NewCharity.add(ch);}
```

**Figure 4-17** Sample code of Donation Amount Finalization

After finalizing the donation amount, the product donation process has been carried out by using 'Donated Product Transfer' action chart (Figure 4-18).

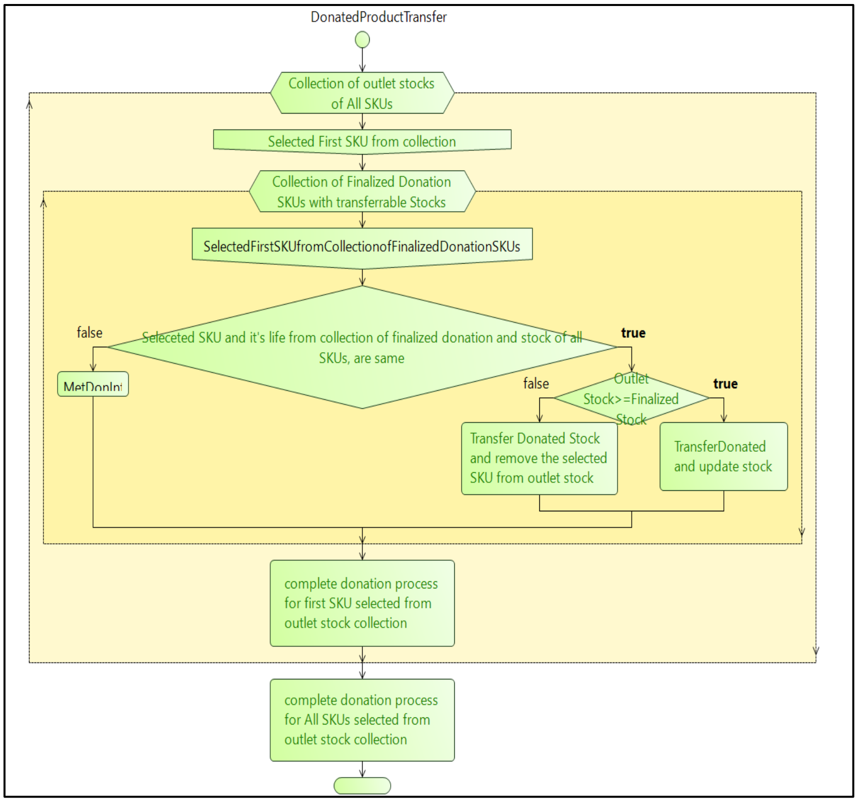



**Figure 4-18** Action Chart of Donated Product Transfer Process

'Tax Deduction Calculation' action chart has been used to calculate the amount of tax that can be deducted.

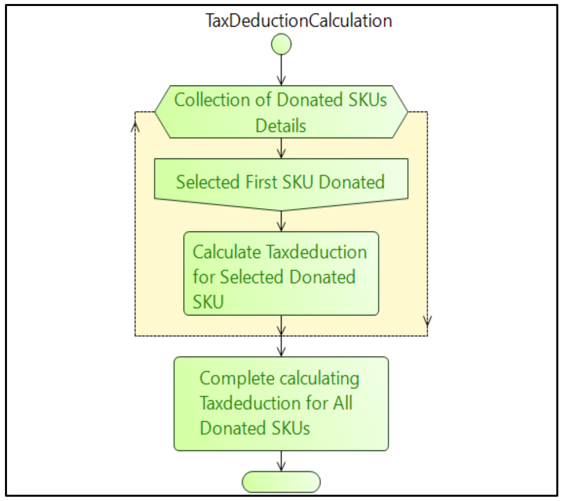



**Figure 4-19** Action Chart of Tax Deduction Calculation

*4.3.4 Order agent*

The order agent worked based on the ordered amount of the outlets and the outlets respectively for each order. Based on stock levels, the order is generated under the outlet agent.

Table 4-6 Attributes of Order Agent

| Attributes | Details |
|---|---|
| SKUID | Identification number of SKUs in an Order |
| Amount | Order amount of each SKU for a certain outlet |
| Outlet | The outlet for which the order has been created |

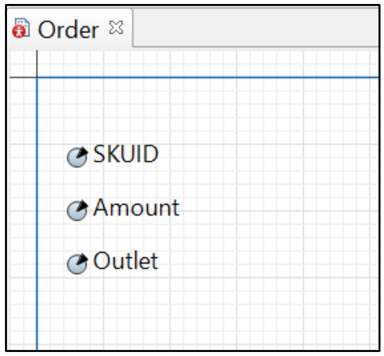



**Figure 4-20** Attributes of Order Agent

*4.3.5 Customer agent*

Customer agents are the source of sales. It has been assumed that the arriving customers will all buy products and generate sales. The reason for the stock imbalance of not having sales as predicted demand. When customer agents come to outlets, they purchase and leave the outlets. The time they spend in outlets is assumed negligible. Customers' activity in the outlets has been developed by using the process modeling library of Anylogic. This has been developed in the Outlet agent (Figure 4-9)

*4.3.6 DC_Vehicle agent*

Products flow from DC to outlets according to the delivery schedule of every review period plus the lead time to send it from DC to the outlet. After the DC gets the order from outlets, it is processed and the DC vehicle as the truck takes the orders send from the DC as a message 'order' and start working by 'loading'.

Table 4-7 Attribute of DC_Vehicle agent

| Attribute class | DC_Vehicle Agents |
|---|---|
| Mobility attributes | Spatial |

According to the order's destination and amount, it start 'moving to outlets'.'Unloading' of order start after it reaches the destined outlet and then left for dc as 'moving to DC' state. After order completion, finally the DC vehicle is 'AtDC' and stays as long as it doesn't receive any message of order from DC.

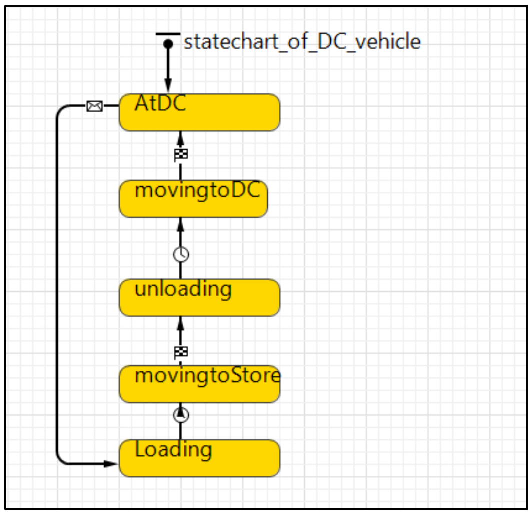



**Figure 4-21** State Chart of  DC vehicle agent

*4.3.7 DC agent*

Order generated by outlets every inventory review period according to their forecasted demand is sent to the DC which later processes it and deliver with a lead time of two days. This process follows receiving the order, the order in the queue, seizing the order with a resource pool of DC vehicle as a truck. Until the orders are taken and delivered, the resource pool will not delay, after arriving in DC they will delay. It will be followed by the release of the vehicles and disposal of these vehicles from the model. Order processing in the DC is a discrete event.

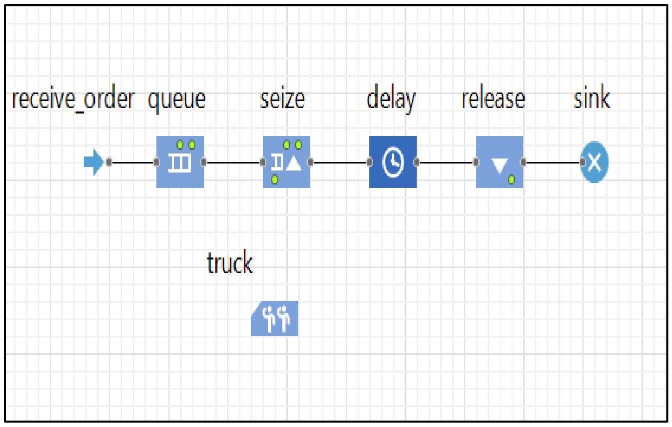



**Figure 4-22** Process flow at DC

*4.3.8 Imbalance agent*

For starting the bidding process, an imbalance agent is important. This agent stores the outlets, SKUs with imbalance amount, the life of the SKUs, and reserve price. Reserve price is calculated based on the life of the SKUs.

Table 4-8 Attributes of Imbalance Agent

| **Attributes** | **Details** |
|---|---|
| StoreID | Outlet Identification number |
| SKU | SKU ID of an SKU having an imbalanced stock level |
| Imbalance Amount | Surplus stock or needed stock of an SKU |
| Life Passed | Life passed of an SKU |
| Price | Reserve price of an SKU |

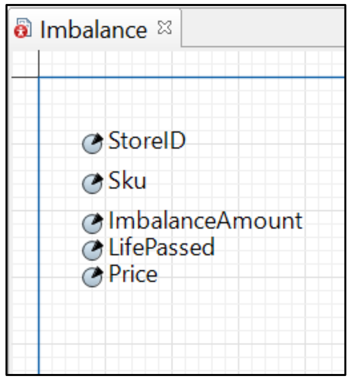



**Figure 4-23** Parameters of Imbalance Agent

*4.3.9 Product Collection agent*

Product collection agent stores SKUs' identification number, their stock, life, and selling price of the SKUs. For stock status update, stock transfer, stock receiving, this agent has been used.

Table 4-9 Attributes of Product Collection Agent

| Attributes | Details |
|---|---|
| SKUID | SKU Identification number |
| Stock | The stock of an SKU |
| life | The shelf life of an SKU |
| Price | Selling/MRP of an SKU |

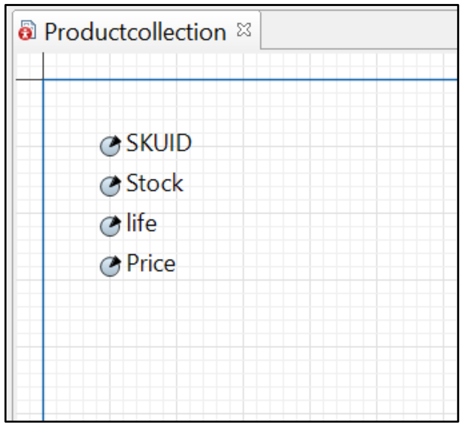



**Figure 4-24** Parameters of Product collection Agent

*4.3.10 Negotiation agent*

The bidding finalization process is done with the negotiation agent. By following the bidding process discussed in the methodology chapter, the bid amount and price is finalized with the Negotiation agent.

Table 4-10 Attributes of Negotiation Agent

| Attributes | Details |
|---|---|
| Seller ID | Seller outlet's identification number |
| Buyer ID | Buyer outlet's identification number |
| Amount | Final Bid amount |
| Price | Bid Price |

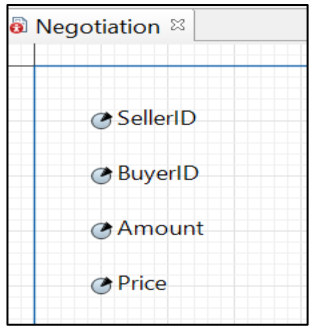



**Figure 4-25** Parameters of Negotiation Agent

## 4.4 Implementation Results and Discussion

In this section, we will discuss running our model for some specific inputs and analyzing the outputs. Model run time is for three hundred and sixty-five days. For running the model, we have assumed that the number of customer arrival will follow the normal distribution of the mean of the number of daily customer arrival with the standard deviation of a certain percentage of the mean daily number of customer arrival. As discussed in the methodology, we have implemented our model in two steps. We have categorized our whole SKU data based on the demand variability over the outlets (Table 4.11). After categorizing the SKUs based on their demand variability, we took SKUs from all three categories.

Table 4-11 SKU Category based on demand variability.

| SKU Category Based on Demand Variability | Description |
|---|---|
| High Demand Variability | (Standard Deviation/Average)>0.8 |
| Medium Demand Variability | 0.8>=(Standard Deviation/Average)>0.4 |
| Low Demand Variability | (Standard Deviation/Average)<=0.4 |

We ran our model for the selected forty-five SKUs with different inventory review periods (10 Days, 15 Days, and 20 Days) and standard deviations of the number of customer arrival (5%,10%,15%,20%). Net Cash Inflow has been considered to analyze the differences between different categories. From figure 4-26, we can see that the impact of redistribution compared to no redistribution, on the SKUs of high demand variability is the highest. Based on this result, we have selected one hundred and fifty-five SKUs from our SKU database, which have high demand variability. The reason to choose the SKUs from the high demand variable category is to better analyze the impact of redistribution.

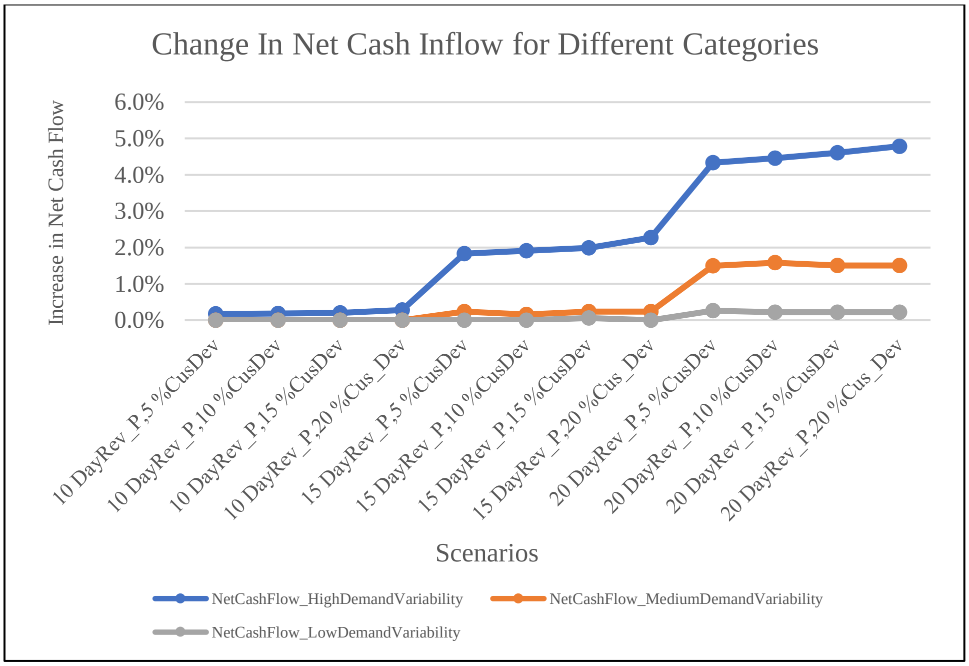



**Figure 4-26** Change in Net Cash Inflow by redistribution for categories of different demand variability.

We have implemented our model for these one hundred and fifty-five SKUs. All the detailed analysis has been performed for these SKUs. The main outputs which will be discussed are the impact of redistribution and donation, separately and combined, on the net cash inflow of the total system, customer fill rate, cash inflow over cost ratio, disposal, holding, purchasing cost, and Lost Sales. The inventory review period for this case was considered as 20 days with a customer arrival deviation of 20%. In our base model, outlets receive stocks from only one source, the distribution center (DC). And the selling point is only the end consumer. Products are delivered at a fixed regular interval. We have observed and analyzed the system's performances and important parameters, for different scenarios.

The model output data has been examined for four different basic scenarios. These scenarios are:

1. The base model (with no Redistribution and Donation option available)
2. The base model with only donation option available
3. The base model with only redistribution option available
4. The base model with both option available

Scenarios 3 and 4 have four sub-scenarios because of our four different redistribution models (Unsupervised price-based bidding redistribution, Unsupervised Imbalance stock-based bidding redistribution, Supervised price-based bidding redistribution, Supervised Imbalance stock-based bidding redistribution). We have developed our model based on some assumptions:

1. We followed orders up to the level-inventory policy. At every inventory review period, an order will be generated based on twenty-two days' demand considering on-hand inventory.

2. Daily Number of Customers coming to the outlets follow a normal distribution.

3. Outlets have stocks of one month's average demand at the starting of simulation.

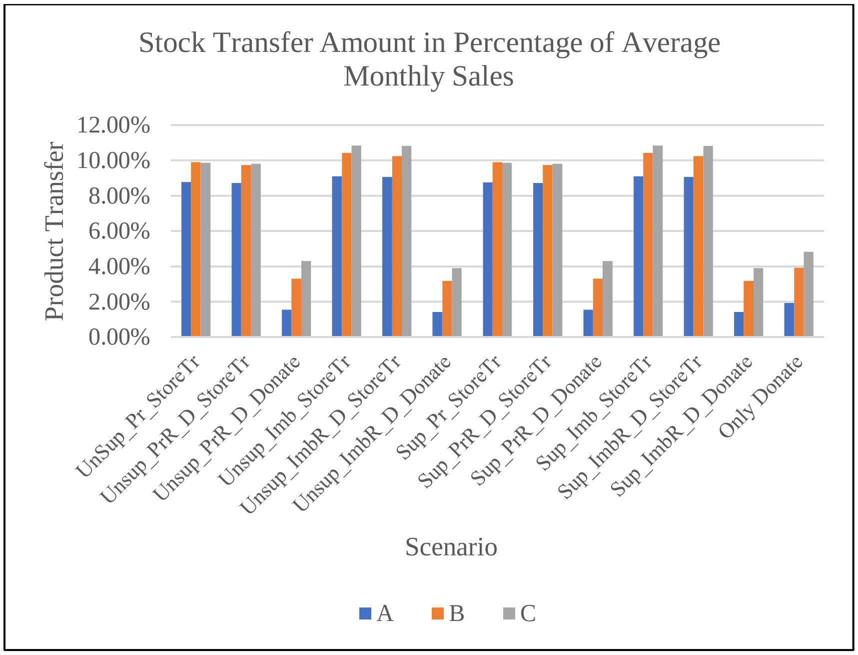
4. Outlets have been divided into four shipping zones used to establish model transportation costs.

5. Forecast updated every thirty days.

6. The donation takes place every thirty days.

7. The tax rate is 25%

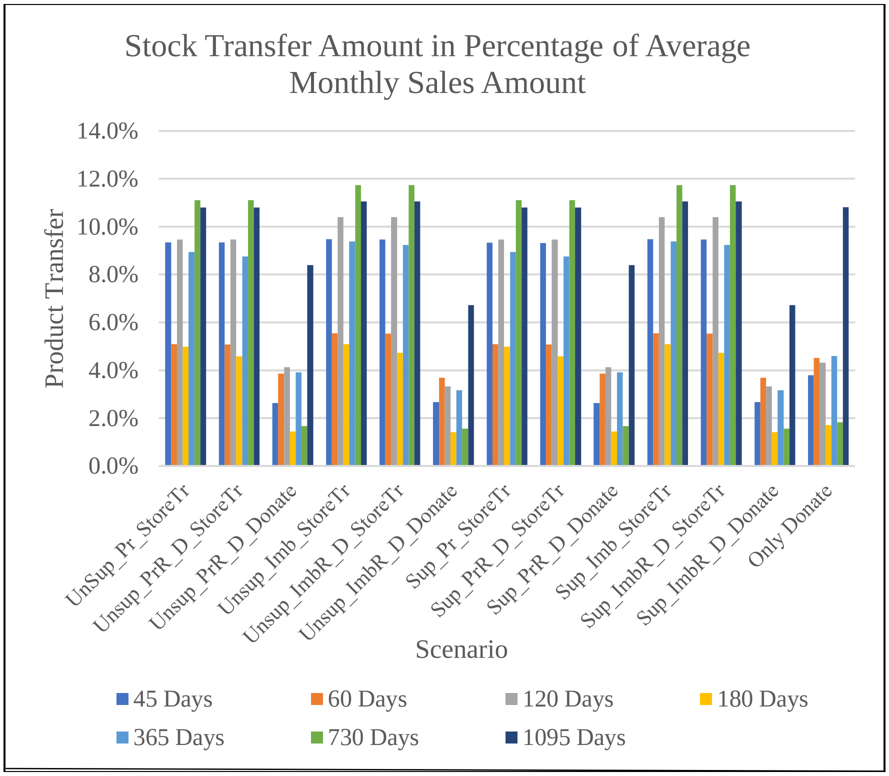
To test the impact of redistribution, we need to analyze first the amount transferred for scenarios 2, 3, and 4.




**Here 'Pr' is used for representing price-based model, 'Imb'for imbalance stock-based model, 'R_D' for the availability of both redistribution and donation in the model, 'Tr' for transfer

**Figure 4-27** Stock transferred for different scenarios.

From figure 4-27 we can see that SKUs from class C have been transferred more than SKUs from class A and class B as percentage of these classes' average monthly sales. Imbalance stock-based models transfer more amount than the price-based models. Stock transferred from the donation is much smaller than the stock transfer from redistribution. While considering the stock transfer amount from a shelf-life perspective, we do not see any correlation between the order of shelf life and the transfer amount (figure 4-28).



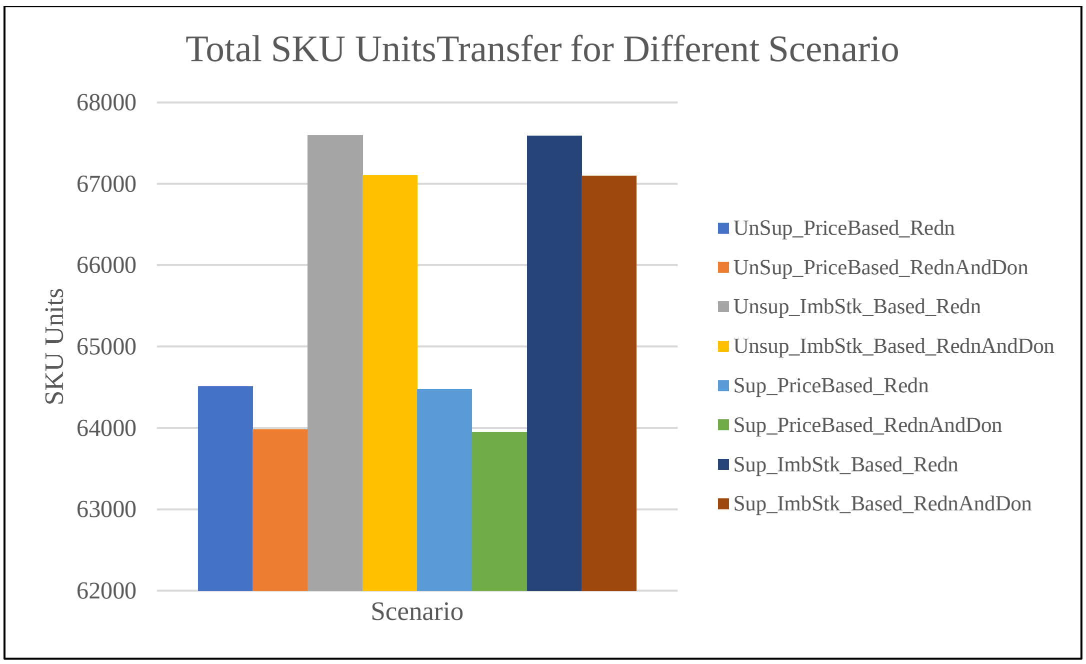

**Here 'Pr' is used for representing price based model, 'Imb'for imbalance stock-based model, 'R_D' for the availability of both redistribution and donation in the model, 'Tr' for transfer

**Figure 4-28** Stock transferred for different scenarios (Shelf life-wise)

The next section will discuss how the SKUs transfer impacts different areas of a retail chain and overall performance measures.

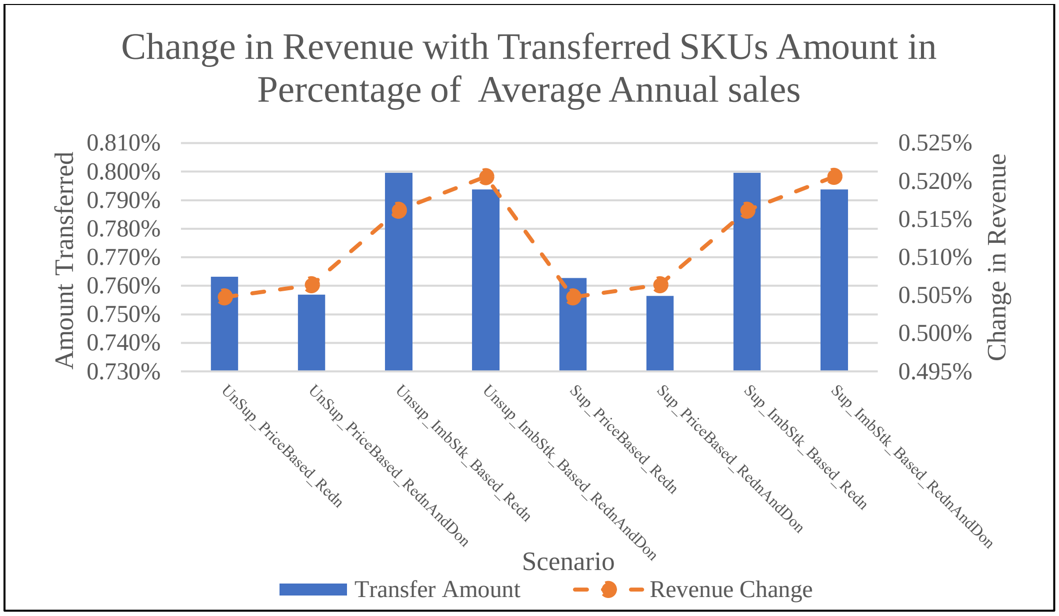
### *4.4.1 Change in Revenue (Sales)*

We used the base model (with no redistribution or donation option available) output to compare with the outputs of the models with only redistribution option available and both donation and redistribution option available in the base model. From Figure 4-29, we can see that from imbalanced stock-based models, the amount of SKU units transfer is higher than the price-based model. This variation of transfer amount impacts the revenue in the same way (Figure 4-30). That means that the transfer amount has a positive correlation with the change of revenue. On the other hand, supervised and unsupervised models generate almost the same amount of transfer. The transfer amount for supervised models is slightly smaller than the unsupervised models. The revenue increase is almost 0.52% for the imbalanced stock-based models and it is the highest among all the scenarios. When a model has both redistribution and donation options available, revenue earned is lower than the model with only redistribution options available. This may happen because the donated SKUs cannot contribute to the increase of revenue.




**Here 'UnSup' is used for representing unsupervised model, 'Sup' for supervised model,'ImbStk'for imbalance stock-based model, 'Redn' for the availability of redistribution, 'Don' for the availability of donation option in the model.

**Figure 4-29** Total SKU units transferred for different scenario.




**Here 'UnSup' is used for representing unsupervised model, 'Sup' for the supervised model,'ImbStk'for imbalance stock-based model, 'Redn' for the availability of redistribution, 'Don' for the availability of donation option in the model.

**Figure 4-30** Change in Revenue with the amount transferred for different scenario.

Based on the ABC classification, we examined the number of products transferred from each class. For this, we measured the ratio of total product transferred amount to average annual sales amount for each class. This ratio represents the percentage of the average annual sales amount transferred by redistribution. The total transferred amount for C class SKUs concerning average annual total C class SKUs sales is the highest where for class A SKUs, it's the lowest. Change in revenue for Class A SKUs is the lowest than class B and class C SKUs.

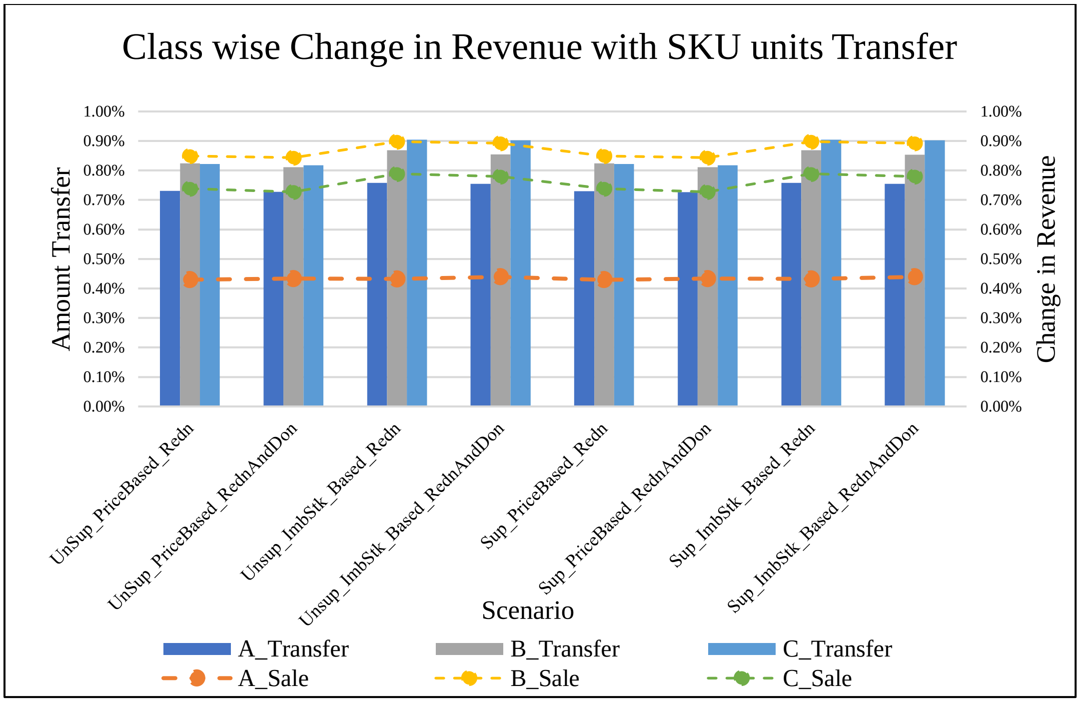



**Figure 4-31** Class wise Change in Revenue concerning SKU units transfer in percentage.

These results depict that redistribution positively impacts the increase in revenue compared to the base model.

### *4.4.2 Change in Purchasing Cost*

In our model assumption, we assumed that orders will be placed to a certain level after a certain interval based on the forecast. When products are redistributed, two scenarios can emerge:

a. After the seller outlet transfers SKUs to the buyer outlet, an unpredicted number of customers arrive in the seller outlet for the same transferred SKUs. Stocks decrease for meeting this unpredicted demand. So, the forecast for these SKUs increase. For the next order cycle, the seller outlet has to purchase SKUs based on the forecast.

b. After receiving SKUs in buyer outlets, customer sales increase which contributes to an increase in the next period's forecast for those SKUs for buyer outlets. This leads buyer outlets to purchase more amount of these SKUs for the next order cycle.

For the Redistribution model and redistribution model with donation options available, purchasing cost increased by around 0.35% where the latter is slightly higher (figure 4-32)

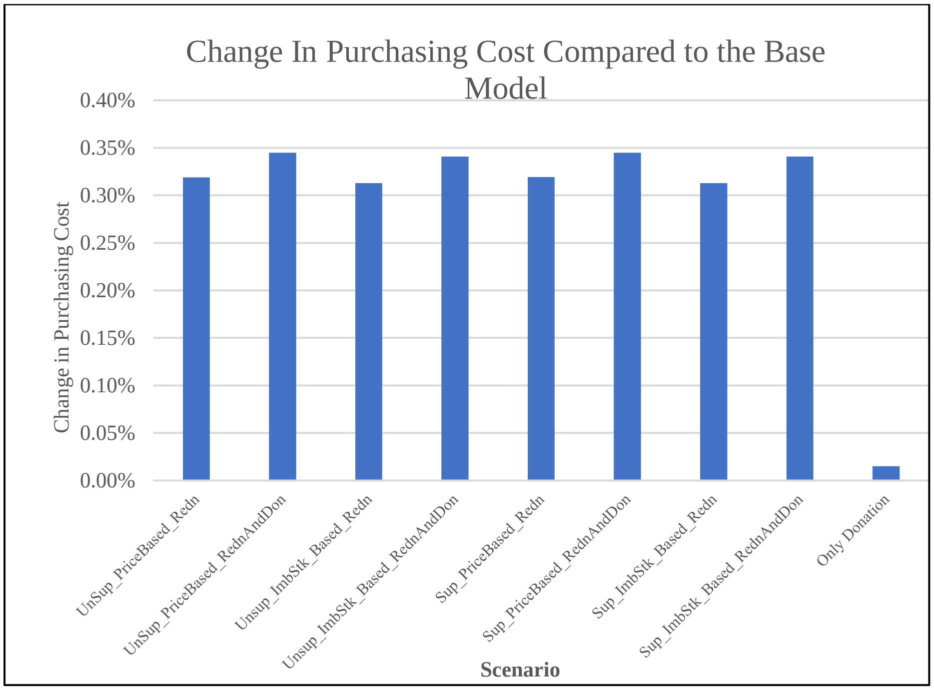



**Figure 4-32** Change in Purchasing Cost Compared to the Base Model

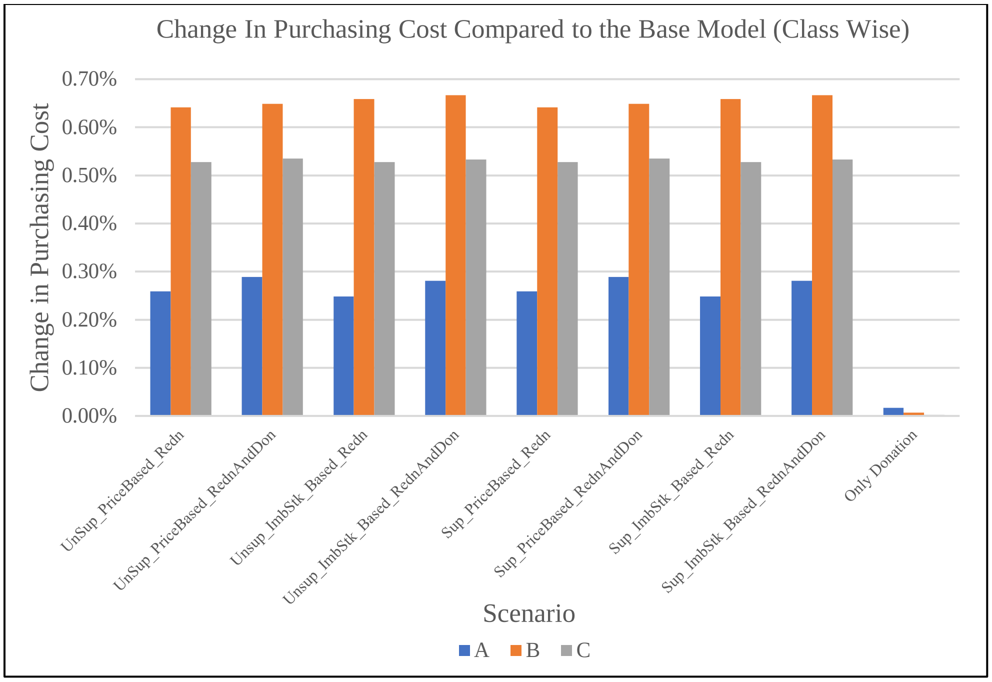



**Figure 4-33** Change in Purchasing Cost Compared to the Base Model (Class Wise)

From the perspective of ABC classified SKUs, A class SKUs purchasing cost increase is the lowest where for class B, it is the highest. This is because transferred stocks of class A SKUs did not contribute much to the percentage of revenue increase or consumption than the other two classes to require further purchase (Figure 4-31).

*4.4.3 Change in Holding Cost*

In the model where there has only the donation option available, the decrease in holding cost is the highest. Instead of adding up to holding costs and later being expired, donations help avoid extra holding costs. On the other hand, for the redistribution models, SKUs are transferred among the outlets but not removed from the system. Because of that, a decrease in holding cost is smaller for redistributing the SKUs than donating. The combination of redistribution and donation options in the model also contributes to the decrease in holding cost and more significant than only redistribution options.

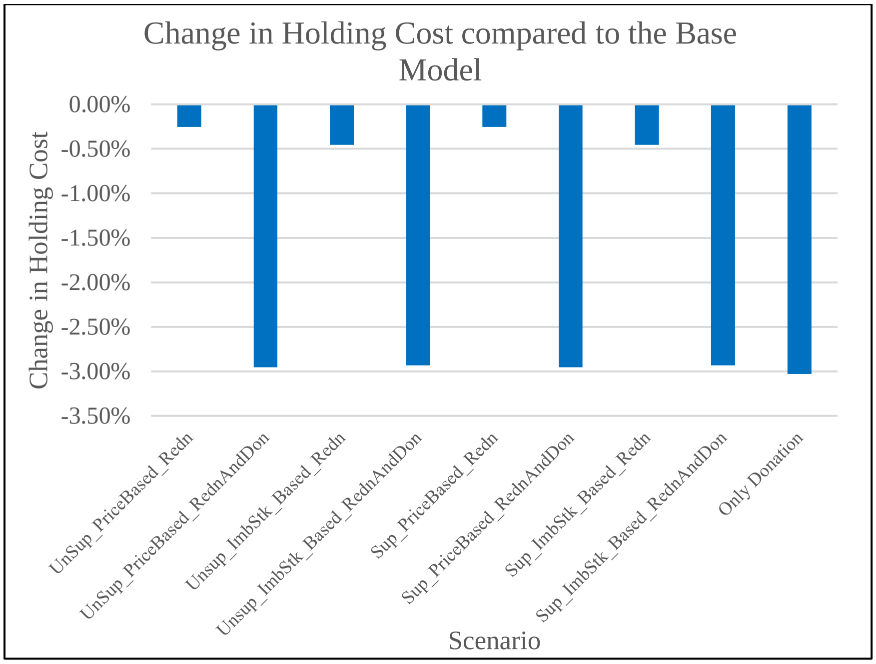



**Figure 4-34** Change in Holding Cost Compared to the Base Model.

We can see that holding cost decreased to the highest for C class SKUs from the ABC classification perspective and the lowest for A-class SKUs (Figure 4-35). We know that SKU class C is the least contributing class to the total revenue of a company. This means the consumption of this class is not that much like other classes. So when there is an overstock situation in class C, redistribution cannot necessarily reduce the total system's stock level because of not having enough demands over the outlets. The donation option can help to reduce stock levels and as a result, the holding cost.

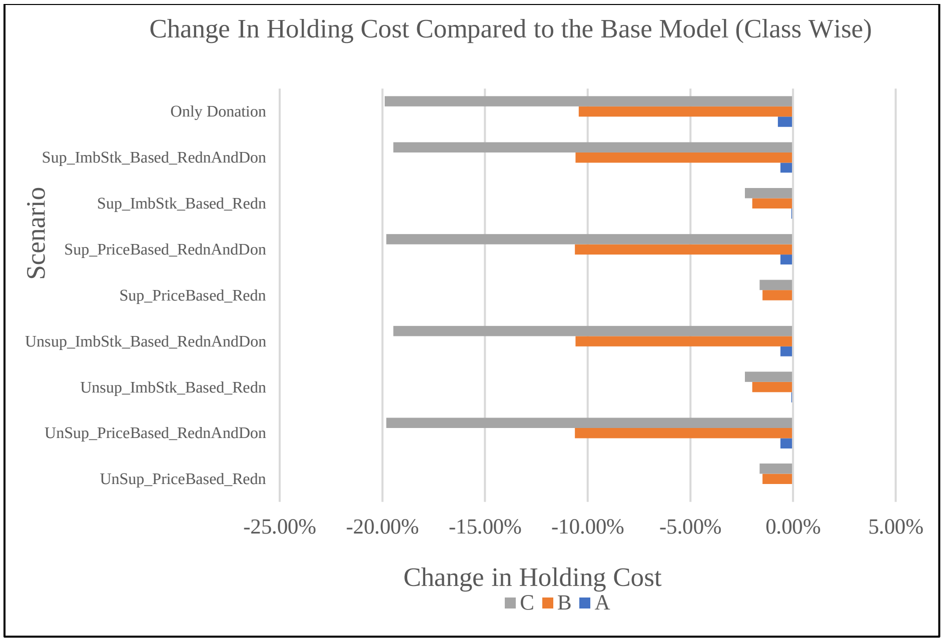



**Figure 4-35** Change in Holding Cost Compared to the Base Model (Class Wise)

*4.4.4 Change in Lost Sales*

Redistributing SKUs to the stock needed outlets generates sales due to decreased lost sales compared to the base model. The total retail chain's lost sales have decreased around 35% compared to the base model by adopting only redistribution option and both redistribution and donation option (Figure 4-36)

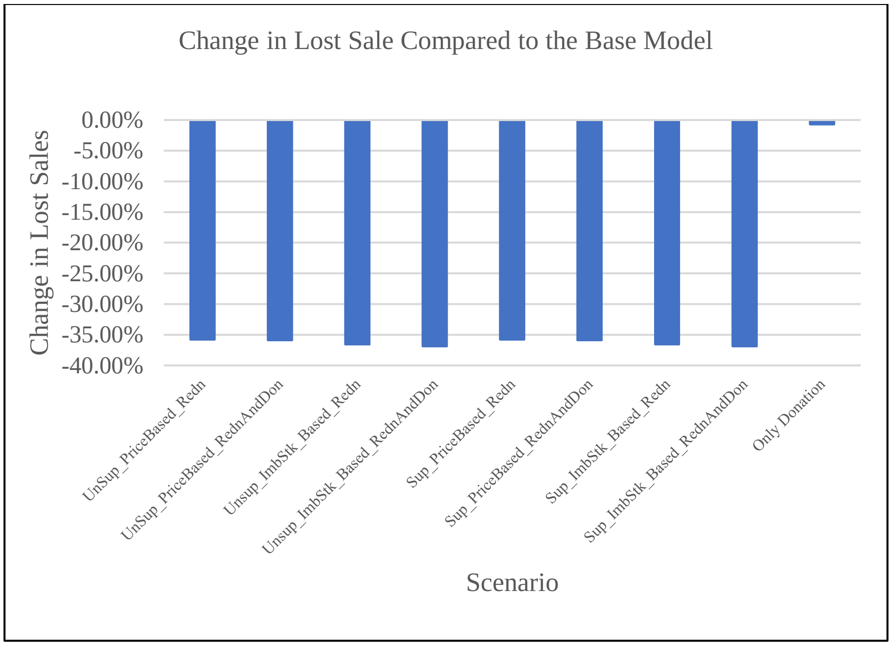



**Figure 4-36** Change in Lost Sales Compared to the Base Model

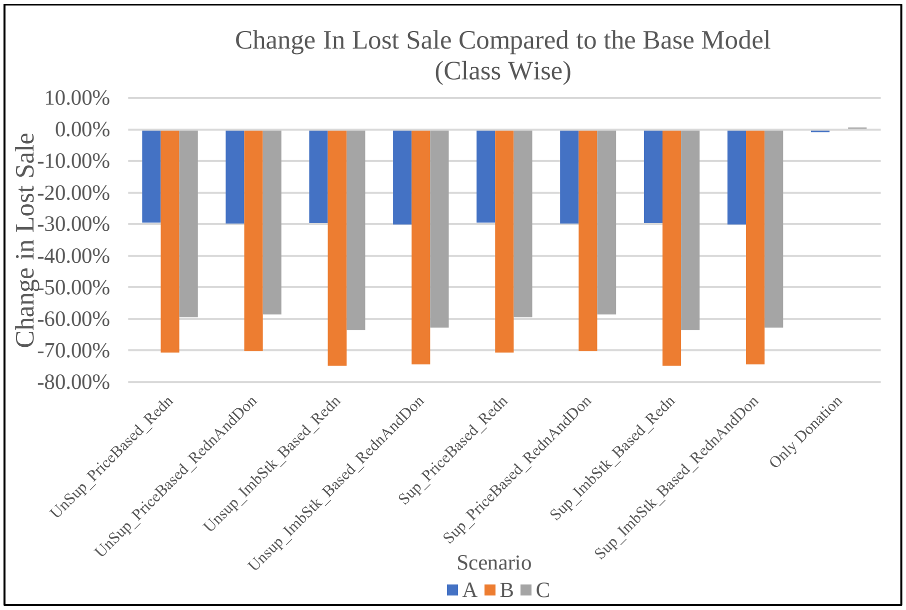



**Figure 4-37** Change in Lost Sale Compared to the Base Model (Class Wise)

Class A SKUs' lost sales did not decrease much when the available option includes redistribution, compared to the rest of the classes. As from Figure 4-27, we can see that the transfer percentage is less for Class A than the rest of the classes.

*4.4.5 Change in Disposal Cost*

In the scenarios where the models have both donation and redistribution options available, a decrease in disposal cost is the highest. The models with individual options of donation and redistribution also decrease the disposal cost but the percentage is less than having both options available in the model. This is easy to understand that with the increase of the number of transfer points, disposal cost will decrease more. While doing redistribution, we have transferred the old SKUs first to be sold to other outlets having demands. The same strategy has been followed for donation-Overstock, near expiry but consumable SKUs have been donated. This has resulted in a decrease in disposal cost ranging from around 25% to around 50% (Figure 4-38) based on the models and options we take.

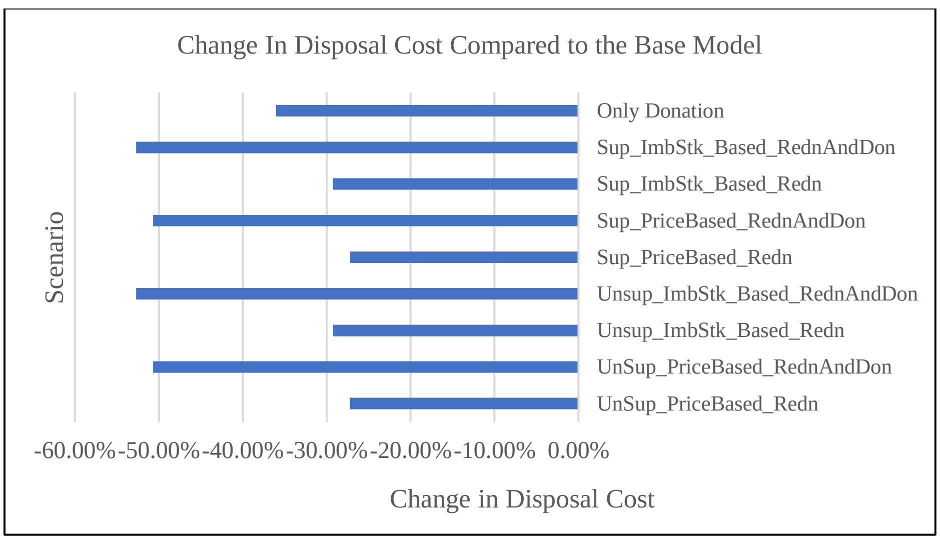



**Figure 4-38** Change in Disposal Cost Compared to the Base Mod

*4.4.6 Change in Fill Rate*

Extra stock from another outlet can meet customer demand which could be unmet because of not having products from the distribution center. Fill rate is the percentage of demand met from the available stocks. In our models, using the redistribution option increased the fill rate by around 55% (Figure 4-39). C class SKUs contribute most to increase the fill rate of its class (Figure 4-40). As we have seen before, the percentage of SKU units transfer for C class SKUs is the highest, contributing to increasing the fill rate more than the other classes.

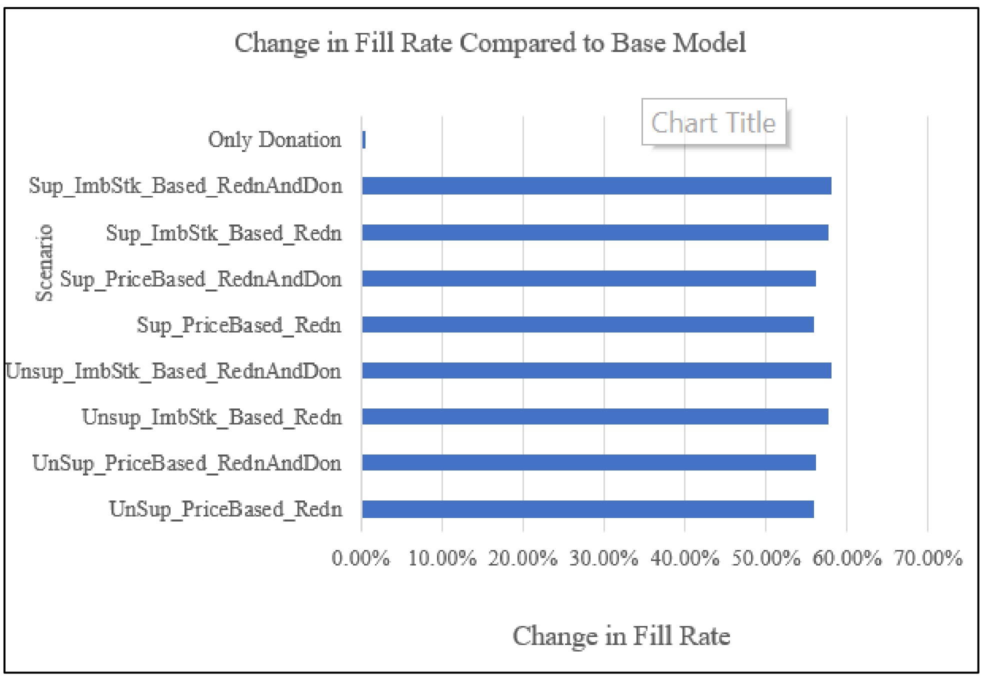



**Figure 4-39** Change in Fill rate Compared to the Base Model

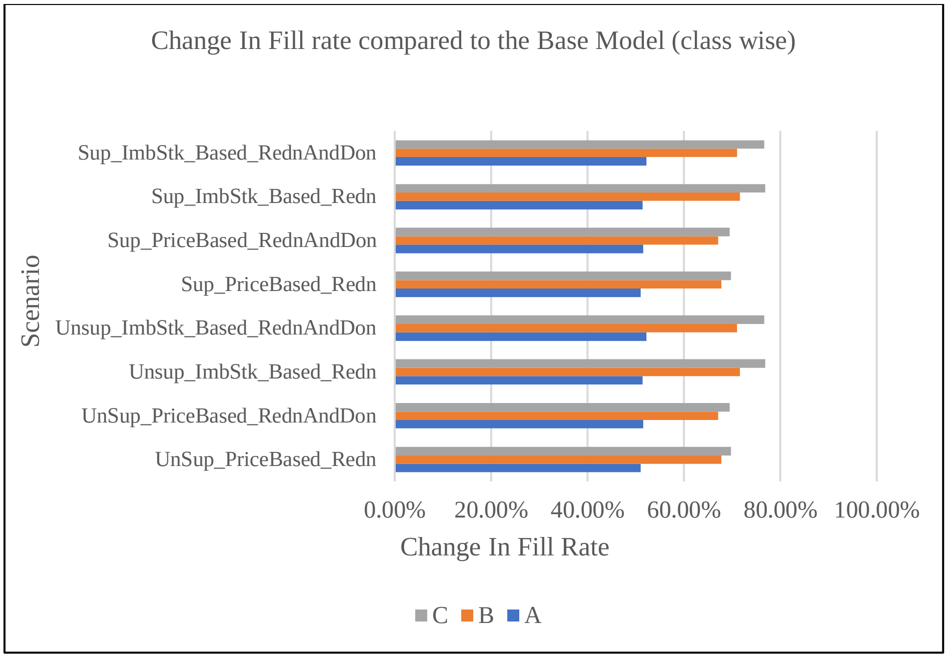



Figure 4-40 Change in Fill rate Compared to the Base Model (Class Wise)

### *4.4.7 Net Cash Inflow*

One of our performance measures is the Net cash inflow of the total system. Here, the Net Cash Inflow

=Revenue+Tax_deductable(for donation option available in the model)-Purchasing cost-Holding cost-Disposal Cost-Redistribution transportation cost-Lost Sale.

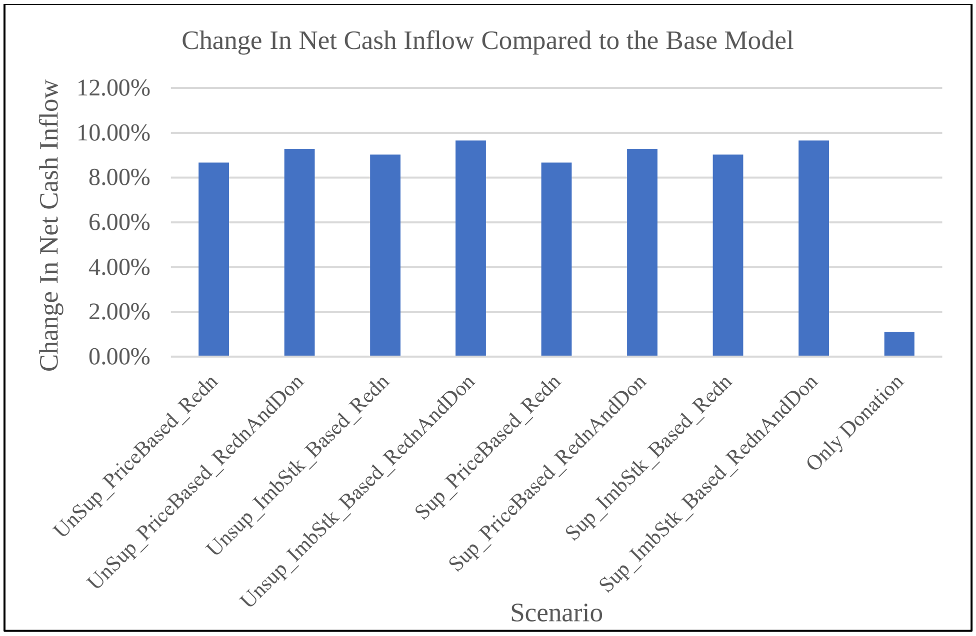



**Figure 4-41** Change in Net Cash Inflow Compared to the Base Model

For the scenarios where the models have a redistribution option, the net cash inflow is higher than only having a donation option. Price-based models generated low net cash inflow than imbalanced stock-based models. If any scenarios have models with both redistribution and donation options, then these generate more net cash inflow than the other scenarios. We can also see that Class A SKUs can increase their class's net cash inflow more than the rest two classes.

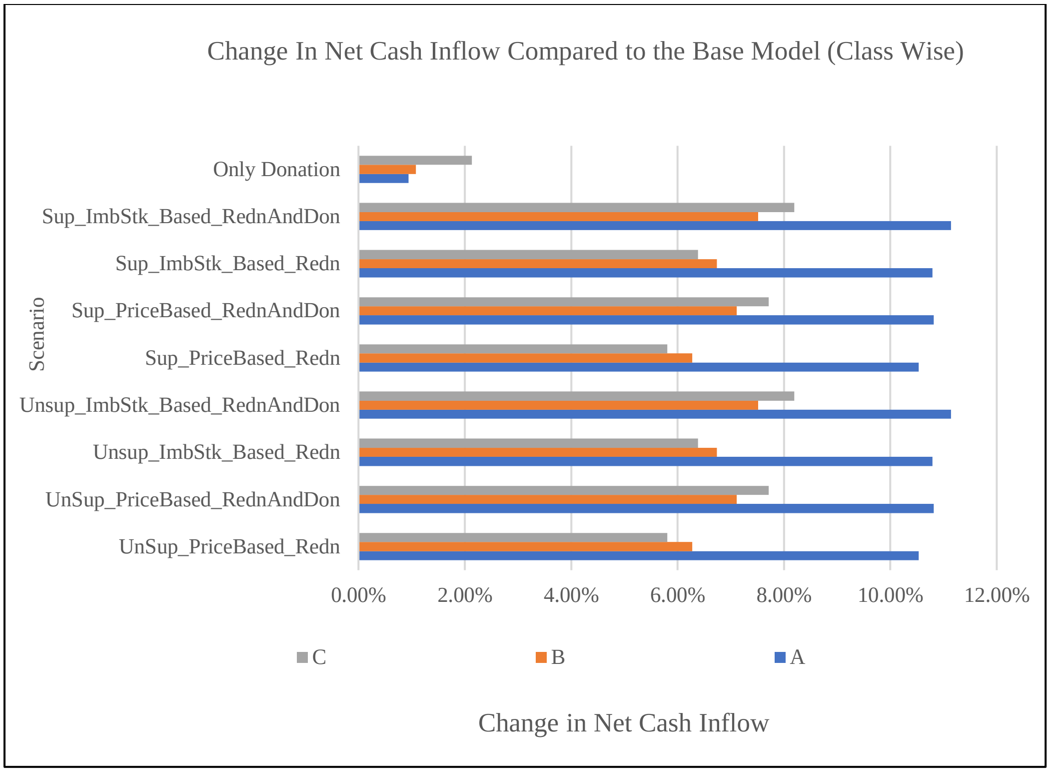



**Figure 4-42** Change in Net gain Compared to the Base Model (Class Wise)

*4.4.8 Cash Inflow Over Cost Ratio (COCR)*

Cash Inflow Over Cost Ratio can explain what percentage of costs have been covered by cash inflows. We have compared the impact of redistribution and donation with the base model.

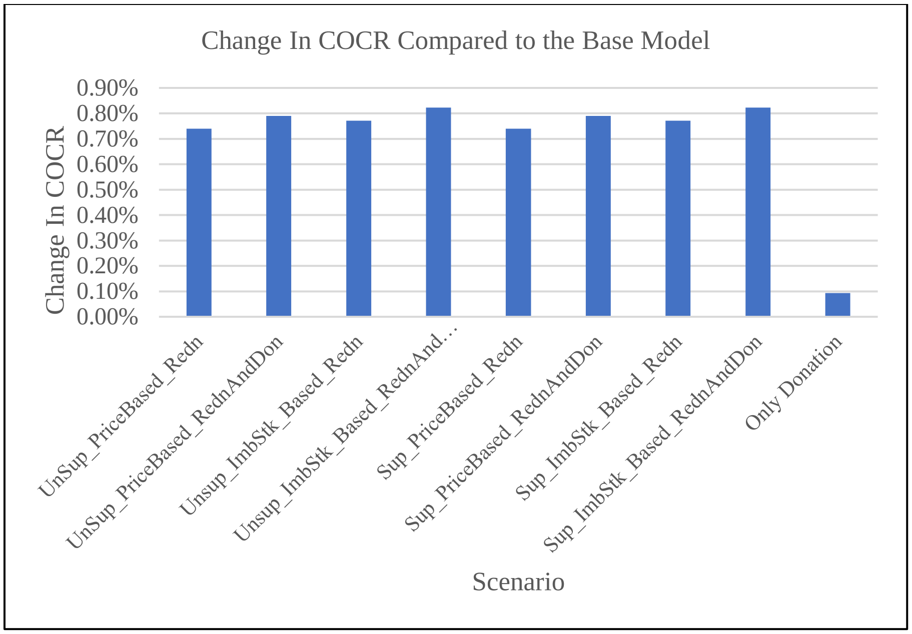



**Figure 4-43** Change in COCR Compared to the Base Model

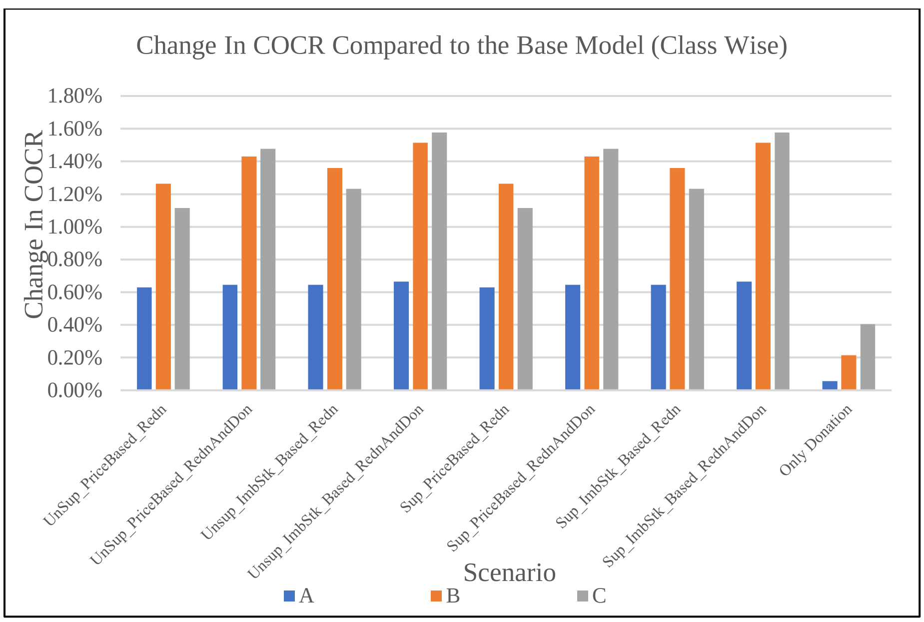



**Figure 4-44** Change in COCR Compared to the Base Model (Class Wise)

With redistribution, Cash Inflow over cost ratio has increased by 0.70% (figure 4-43) . For class C SKUs, COCR increased up to nearly 1.6% where it's around 0.6% for class A SKUs (figure 4-44). These scenarios are excluding the only donation option. If we consider only donation option available in our model, we can see that class C SKUs contribute most to increasing COCR here. However, the increase is much lower than the model having redistribution option.

From the above analysis, we can say that redistribution positively impacts a retail network's performance. We can see that donation also impacts the performance measure but less compared to the redistribution option. Disposal cost decreased significantly for both the redistribution and donation option. As products are transferred by redistribution to the needy outlets, fill rates also increased by incorporating redistribution in the retail system. When analyzing from the SKU classes perspective, we can say that we can see a different performance from these three classes for these one hundred and fifty-five SKUs. The total system's performance is mainly related to the supply of the SKUs and their consumption. For donation option only, the C class SKU group benefitted most. In class C, SKUs are relatively slow-moving than Class A, and Class B. Demands are less than the other two classes. Because of this reason, Class C got the most benefit from donation than the rest of the classes. This chapter has considered SKUs with seven different shelf lives (45 days,60 Days, 120 Days, 180 Days, 365 Days, and 1095 Days). In the later chapter, we will examine the impact of different shelf lives on the retail system's performance considering the same SKU demand. We will also examine the impact of different factors like the inventory review period and different standard deviations in the number of customers arriving at the outlets on the model's performance.

## 4.5 Price-Based and Imbalanced Stock-Based Model preference

There is a basic difference between the price-based and imbalanced stock-based models. We know from chapter three that the price-based model arranges the outlets in a way that product is transferred to the highest buyer from the seller with the lowest price. On the other hand, for the imbalanced stock-based model, outlets are arranged in a way that products can transfer from the seller outlet with the highest overstock to the buyer outlet with the highest needed stock. After implementing our models with one hundred and fifty-five products, we found out that the Imbalanced stock-based model outperformed the price-based model. To address these two models' differences, we have conducted a detailed analysis in SKU levels for two different scenarios. For this, we have run both the models for 365 days with two SKUs.

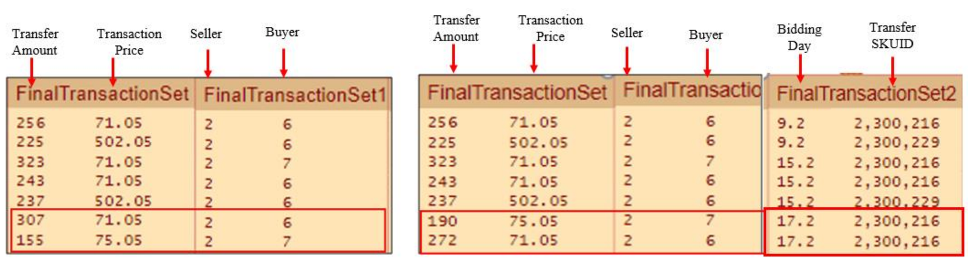
<u>Competitor sellers' prices are less than all competitor buyers' prices (scenario 1)</u>

Generally, by using a price-based model, SKUs are transferred to the Buyer Outlets where they can be sold to the highest value among the available options (buyers). So, the system's total revenue will be higher than transferring the SKUs to the outlets with lower sales value. But, an important thing here is to check the supply and demand of the SKUs throughout the outlets. The seller competitors' reserve prices and buyer competitors' maximum willing price to pay are also important to decide to choose the models. We ran our model with ten days inventory review period and a 10% deviation in the number of customers arriving at the stores. Both of our models in this section are unsupervised redistribution models. In this scenario, we can see from table 4.12 that the total number of SKU Units transferred by both models is the same 3160 units.

Table 4-12 SKU Units Received amount from Price –Based and Imbalanced Stock-Based Models

| Outlet ID | Transfer Amount by Price Based Model | Transfer Amount of Imbalanced Amount Based Model |
|---|---|---|
| Outlet 2 | 739 | 739 |
| Outlet 5 | 172 | 172 |
| Outlet 6 | 1705 | 1740 |
| Outlet 7 | 525 | 490 |
| Outlet 9 | 19 | 19 |
| Total Amount | 3160 | 3160 |

In this case, for both models, only two transactions were different. In figure 4-45(a), we can see that for both models, the seller is only one and buyers are two. Seller outlet 2 has its reserve price of $71 and buyer outlets 6 and 7 have their maximum willingness to pay prices are $75 and $76 respectively. For both the models, the total transfer amount within the system is the same but most revenue is earned from the price-based model as it helped to send more SKUs to outlet 7 where it can be sold at a higher price than outlet 6.




(a) (b)

**Figure 4-45** (a) Imbalanced Stock-based Model (b) Price based Model for scenario 1

Not all the Competitor sellers' prices are less than all competitor buyers' prices (scenario 2)

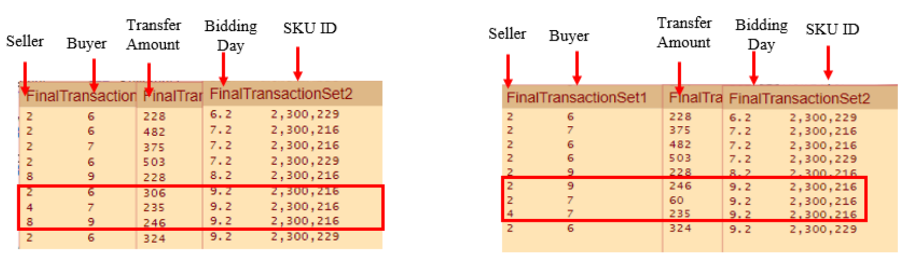
We ran both the models with an inventory review period of 20 days and a customer arrival deviation of 20% of the mean number of customers coming to the outlets. After running the models, we observed that the imbalanced stock-based model transferred more SKU units than the price-based model. We also observed several transaction different transactions from the two models compared to scenario one.

Table 4-13 Table SKU Units Received amount from Price –Based and Imbalanced Stock-Based Models

| Outlet ID | Transfer Amount By Price Based Model | Transfer Amount of Imbalanced Amount Based Model |
|---|---|---|
| Outlet 2 | 476 | 476 |
| Outlet 3 | 628 | 628 |
| Outlet 5 | 2780 | 3007 |
| Outlet 6 | 9612 | 10451 |
| Outlet 7 | 670 | 610 |
| Outlet 9 | 3528 | 2751 |
| Outlet 10 | 199 | 199 |
| Total | 17893 | 18122 |

To analyze SKU levels, we are taking the example of figure 4-46. For the transaction of SKUID 2300016 at time 9.2 days, for an imbalance stock-based model, there are three sellers and three buyers. On the other hand, for price based model, the number of sellers and buyers are two respectively. In our models, outlet ID also indicates the price trends of the SKUs. Low outlet ID represents a low price, and high outlet ID represents a high price. figure 4-46 indicates that not all the sellers' prices are less than all the buyers' prices’. Seller ID 8 is greater than buyer ID 6 and 7. It indicates that the price of outlet 8 is greater than the prices of outlets 6 and 7.

For an imbalanced stock-based model, the matching criteria between seller and buyer outlets are based on stocks. The total stock transfer from the imbalanced stock-based model is 787 (figure 4-46(a)). The transfer amount is 541 units for the price-based model (figure 4-46(b)). The main principle is to match the lowest price seller to the highest price buyer for price-based model. Based on this criteria, seller 2 outlets transferred its stocks to outlet 9 first and then outlet7. The next lowest seller is 4 and it transferred stocks to the next highest buyer who needs the products. When comparing the imbalanced stock-based model, we can see that another seller outlet 8 and buyer outlet 6 are still remaining to participate in product transfer. As the price of seller outlet 8 is greater than the price of buyer outlet 6, it's not possible to complete the stock transfer.




| FinalTransaction | | FinalTrar | FinalTransactionSet2 | |
|---|---|---|---|---|
| 2 | 6 | 228 | 6.2 | 2,300,229 |
| 2 | 6 | 482 | 7.2 | 2,300,216 |
| 2 | 7 | 375 | 7.2 | 2,300,216 |
| 2 | 6 | 503 | 7.2 | 2,300,229 |
| 8 | 9 | 228 | 8.2 | 2,300,216 |
| 2 | 6 | 306 | 9.2 | 2,300,216 |
| 4 | 7 | 235 | 9.2 | 2,300,216 |
| 8 | 9 | 246 | 9.2 | 2,300,216 |
| 2 | 6 | 324 | 9.2 | 2,300,229 |

| FinalTransactionSet1 | | FinalTra | FinalTransactionSet2 | |
|---|---|---|---|---|
| 2 | 6 | 228 | 6.2 | 2,300,229 |
| 2 | 7 | 375 | 7.2 | 2,300,216 |
| 2 | 6 | 482 | 7.2 | 2,300,216 |
| 2 | 6 | 503 | 7.2 | 2,300,229 |
| 2 | 9 | 228 | 8.2 | 2,300,216 |
| 2 | 9 | 246 | 9.2 | 2,300,216 |
| 2 | 7 | 60 | 9.2 | 2,300,216 |
| 4 | 7 | 235 | 9.2 | 2,300,216 |
| 2 | 6 | 324 | 9.2 | 2,300,229 |

(a) (b)

**Figure 4-46** (a) Imbalanced Stock-based Model (b) Price based model for scenario 2

Suppose in a system, the above scenario happens for several transactions, and stocks cannot be transferred because the seller's price greater than the buyers' price In that case, the system will not be able to transfer overstock amounts largely if it chooses to use price-based model. Finally, the retail system will not get benefit from redistribution if it choose price based instead of imbalanced stock based mode.

When comparing the two scenarios, we found out that for scenario one, the price-based model outperformed the imbalanced stock-based model where the opposite happened for scenario 2 (Figure 4-47).

We cannot decide which model should be used for SKU transfer before implementing it. The choice varies from transaction to transaction and SKU to SKU. For each bidding day, for each SKU, it is required to calculate the anticipated sales value-form transaction based on both models. Whichever will provide the highest total sales value from the transaction, that model should be chosen for that transaction. This indicates the need of developing a hybrid of price and Imbalanced stock-based models. The development of hybrid model is out of scope for this study.

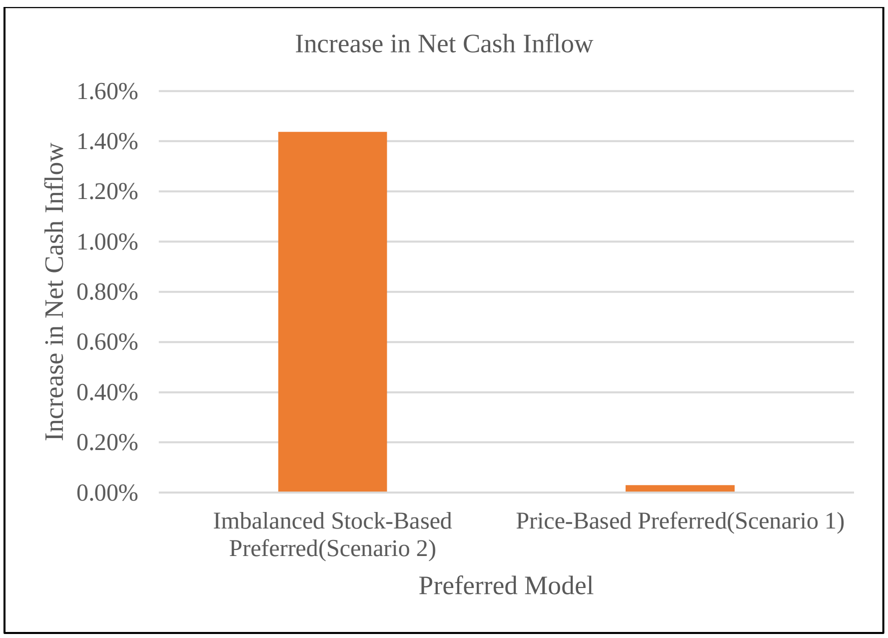



**Figure 4-47** Scenario-based model preference between Imbalanced Stock-Based and price-based redistribution model.

# Chapter 5 Model Verification

## 5.1 Introduction

Model verification and validation are crucial parts of simulation models. For a model developer, it is necessary to check the model's output with the expected output. This ensures the model developer that the progression of model development is in the right direction. On the other hand, to check the model's acceptance in the practical field, it is required to compare the model's output with real-world data. As there does not exist any redistribution model as we developed, it is not possible to validate our model. We will discuss our model verification process in detail in the next section.

## 5.2 Verification

The agent-based simulation model is complex. It is required to develop the agents separately and also develop their interactions correctly. With the agents' development, verification of that agent and the agents' interactions can make it easier to verify the model. Our model is a hybrid of both agent-based and discrete event simulation. To verify the model, we have used different techniques. These are illustrated below.

### *5.2.1 Checking the development of agents.*

In the process of building the complex full model, we had to check the development of the agents. We have developed our SKU agent based on a database. This database comprises the SKUs, their sales, location of the SKU, and many other parameters. We ran our model after building the SKU agent to see whether same SKU under the outlet agent have different sales amounts based on the database or not. This is an example to verify the model by checking the development of the agents based on the database.

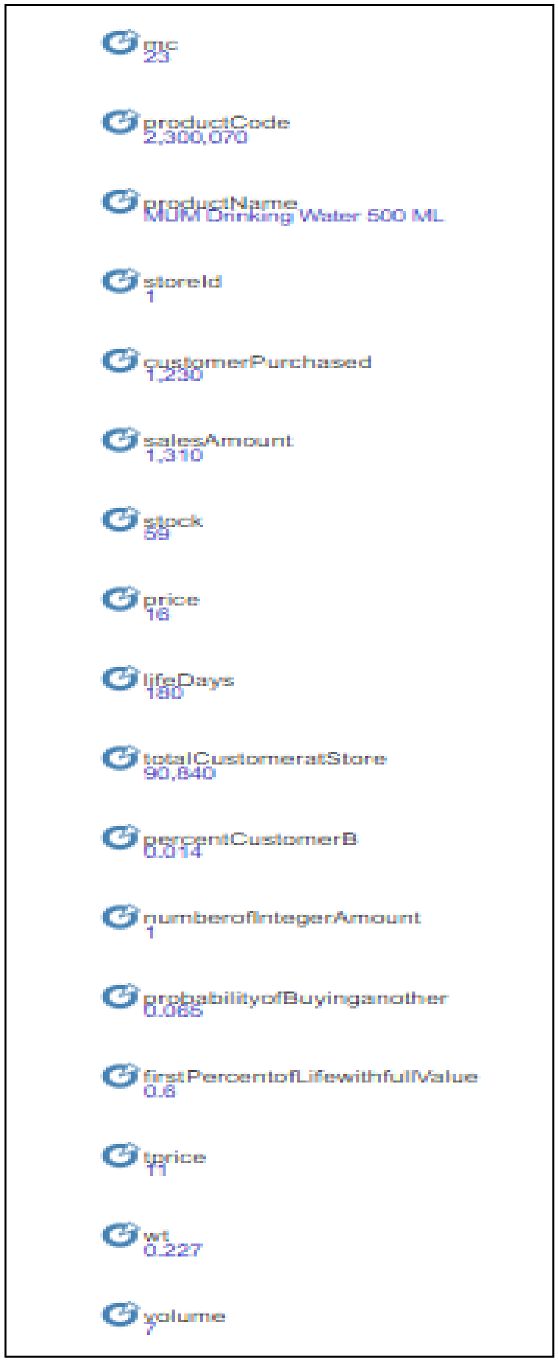



**Figure 5-1** One SKU agent creation for outlet one

*5.2.2 Comparing simulation results of subsystems with analytical results.*

We have verified sub-systems of our model in various ways. We have explained some of them in this section. Verification of order generation, seller identification, buyer identification, transportation cost calculation, and bid finalization have been explained here.

*5.2.2.1 Order Generation*

It is necessary to check the sub-system's output with the analytical results to know that the model is working as predicted. For example, in our model, SKUs are delivered from the DC to the outlets at every specific interval. This amount is calculated based on the outlets' stock level, the forecasted amount, and the safety stock. For an outlet having Q SKUs, beginning inventory levels $I_q$ (j=1,2,…, q), monthly forecast amount of $F_q$ (j =1,2,…., q), and sales amounts $S_q$(j=1,2,…, q) of each SKU are required to calculate order amount. Here q has been considered as SKU index.

For the inventory review period of T days and Safety Stock for T' days, the following criteria were checked for generating order to the distribution center (DC)

$$If \;\; \mathrm{I_q} - \mathrm{S_q} \geq \mathrm{F_q} * (\mathrm{T} + \mathrm{T'})/30$$

$$Then \; 0$$

$$Else \; \mathrm{F_q} * (\mathrm{T} + \mathrm{T'})/30 - (\mathrm{I_q} - \mathrm{S_q}) \ldots\ldots (5.1)$$

We have used the dataset (Figure 5-2) to verify our model by checking the order amount.

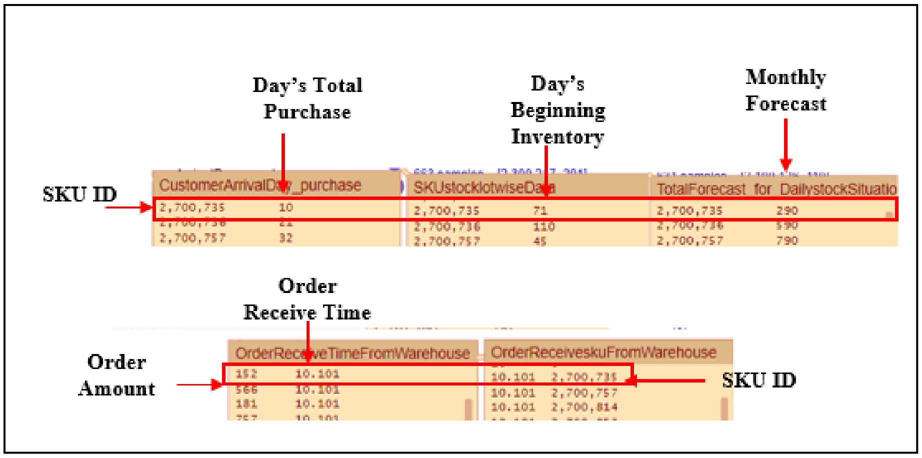



**Figure 5-2** Dataset for verifying generated Order.

For the above example, we are considering SKUID 2700735. From the figure 5.2, we can say that the values of parameters related to generate order are:

I=71, S=10, F=290. Here we are considering inventory review period , T=10 days. As order up to level is for 22 days, so, T'=12. We are considering here that the lead time to get product from DC to store is zero. So, the generated amount is calculated as $(290 * 22)/30$-$(71 - 10) \approx 152$

*5.2.2.2 Seller Selection*

For the bidding process, first it is required to identify the sellers and the buyers. All the sellers and buyers are listed in different collection. For an outlet with SKU stock $I_q$ and Forecast of $F_q$, over stock is calculated based on the following criteria. Here, $d_1$ represents the number of days considered for overstock and $d_1$>=30.

$$\text{If } I_q > F_q * d_1/30$$

$$Then\ I_q - (F_q * d_1/30) \ \ldots\ldots (5.2)$$

To verify our model, we have created different data set for sellers. In figure 5.3 (a) SKUID and overstock amounts are listed in "sellerset" dataset. In "Sellerset1", the outlet ID and price of those SKUs are listed. Here, we are going to give example for only one SKU and for one outlet. It is marked in red frame. In figure 5.3 (b), we can see the dataset for monthly forecast and Stock levels of outlet ID-8. Here we are using SKUID 2300070 for verification.

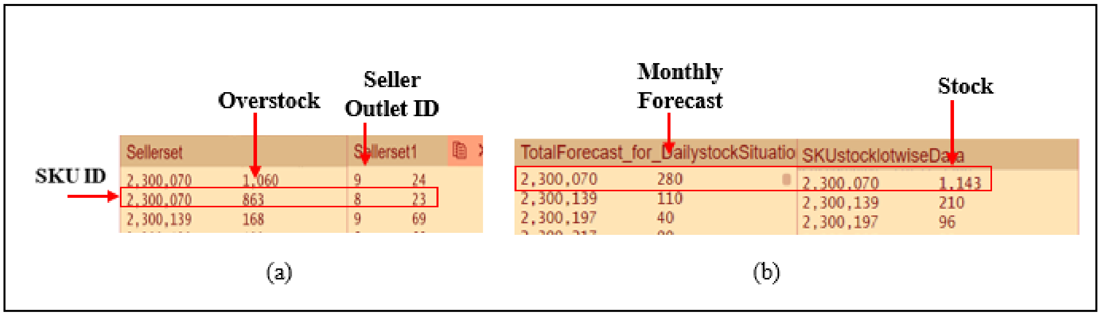



**Figure 5-3** Figure 5.3 (a) All Seller dataset (b) Forecast and stock dataset for Outlet ID-8

From the figure 5.4 (b) I=1143, and F=280. Here we used $d_1$=30. So the overstock will be 1143-280=863. We can see from figure 5.4 (a) that SKU with ID-2300070 has been listed as overstock in "sellerset" for outlet ID-8.

*5.2.2.3 Buyer Selection*

Considering whether an outlet needs stock for any SKUs or not depends on various factors as described in chapter 3. Every day, time remaining to get the stock from the DC is calculated. If the inventory review period is 20 days, and current day is 12$^{th}$ day. Then the time remaining to get the product is 20-12=8 days. Here, we will use "d", to represent the time remaining to get the product from the DC. Here, d<30. "I" has been used for inventory level and "F" as monthly forecast. To address the impact of recent actual sales, we have used "U" for number of recent days and "V" as the total sales amount in "U" days. "J" has been used to represent the number of days considered to calculate extra amount needed based on recent sales. The criteria to become a buyer is based on the current stock level and stock required for remaining days to get products from the DC based on forecast.

$$If\ I_q < (F_q * d)/_{30}$$

$$Then\ (F_q * d)/30 - I_q + (V_q/U_q) * J \ \ldots\ldots\ (5.3)$$

The amount required has been calculated based on equation 5.3.

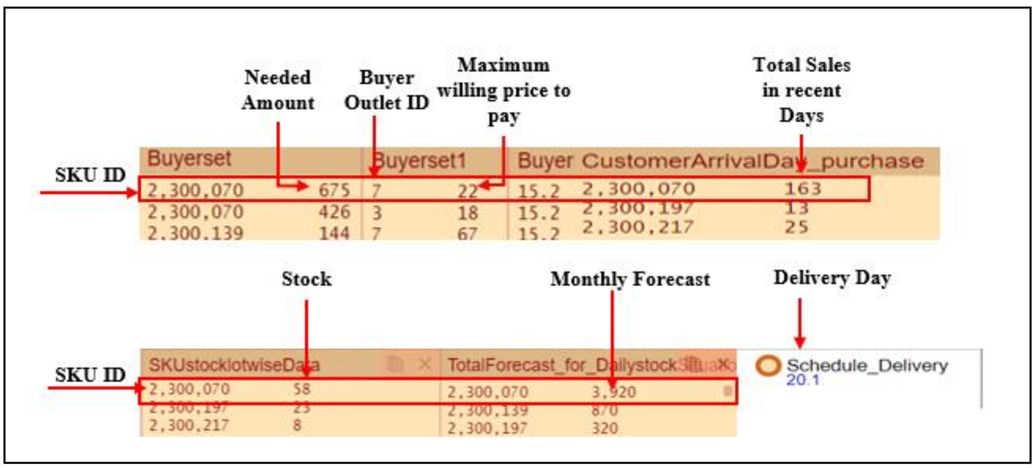



**Figure 5-4** Dataset for verifying Buyer Selection.

For example, we have used SKUID 2300070 and related dataset from Figure 5.5. Here, U =2 days, V=163 units (Total sales in recent two days), and J=1 day (considered). Delivery will take place at 20.1 days. Current time is 15.2th Day. Calculation will be done for Buyer outlet ID-7. Current stock of SKUID 2300070 at Outlet 7 is 58 and monthly forecast is 3920 units. Based on the data from figure 5.5, d=20.1-15.2=4.9 days. Based on equation 5.3, Outlet 7 is a buyer for SKUID 2300070 and amount required is approximately 675 units. This calculated amount 675 matches the amount generated by the model as “Needed amount” in the dataset (Figure 5.4).

*5.2.2.4 Transportation Cost calculation*

In our model, we have used the basic way to calculate transportation cost based on USPS's modified method. In our model, we have divided our outlets in four zones. From the chapter 3, we know that to calculate shipping cost/transportation cost, it is required to know the total weight (lb) and total volume (inch$^3$). After that, it is required to know the zone of seller outlet and buyer outlet. For verification, we are going to use the dataset of figure 5.5 The SKUID for this example is SKUID 2400103. Zone for buyer outlet is 1 and seller outlet is 2. Transfer zone is (2-1) =1. The amount selected to transfer was 79 units. From the figure 5.6, we can see that the per unit weight is 0.455 lb and per unit volume is 120 inch$^3$. Total transfer weight will be (0.455*79) =35.9lb ($W_q$). Total transfer volume will be (120*79) = 9480 inch$^3$($V_q$). Weight considered from dataset based on figure 5.6, is 1lb as immediate weight (W′) less than the actual weight of the SKU we are considering. The price for (W′) is $W_p'$. We have calculated the average price/lb based on the shipping cost chart of USPS for zone 1 and considered it for all our calculation as average price/lb. Here this price has been presented as $W_a$. The flat rate price has been addressed as Fr. The algorithm for calculating shipping cost (SC) has been demonstrated in chapter 3. As the transfer zone is one, the transportation cost has been calculated based on the following algorithm.

$$If\,(\,V_q > 1720\,)\{$$

$$SC = W_p' + (W_q - W') * \ W_a;\}$$

$$else\{$$

$$if\ (W_q > 70)\{$$

$$SC = \ W_p' + \left(W_q - W'\right) * \ W_a;\}$$

$$else\{F_r;\}$$

$$\}$$

In this example, the total volume 9480 inch$^3$>1720 inch$^3$. Zone difference is 1(2-1=1). Weight less than the desired weight 35.9 lb, available is 1 lb in our base dataset (Figure 5.6). So, $W_q$=35.9lb and W'=1 lb. From figure 5.6, shipping cost zone wise ground-dataset, we can see that the shipping cost for 1 lb in zone 1 is 69.2. Based on shipping cost algorithm, $W_p'$=69.2 here. Our calculated average increase in shipping cost for each 1 lb increase is $4.6 based on modified USPS (actually $0.46). Here, $W_a = \$4.6$.

By doing the calculation based on the algorithm,

Transportation cost, $SC = W_p' + (W_q - W') * W_a$

$$= 69.2 + (35.9\text{-}1) *4.6 = \$229.7814$$

we get the value of shipping cost as $229.7814. This is close to the generated shipping cost from our model (Figure 5.5). So, our shipping cost/transportation cost calculation have been verified.

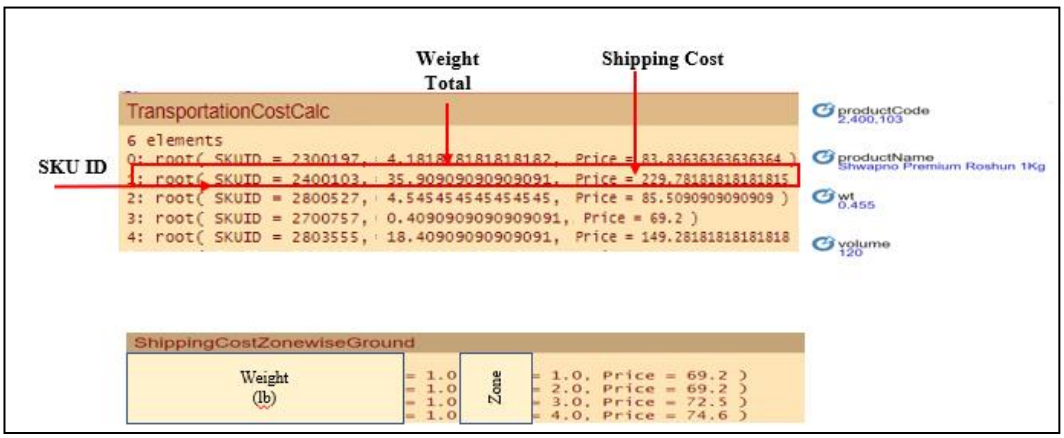



**Figure 5-5** Dataset for verifying transportation cost calculation process.

*5.2.2.5 Bid Finalization*

For verification of finalized bid price, we have used price-based bidding unsupervised model. After the two constraints (price based and life based) are fulfilled as mentioned in detail in chapter 3, it is required to finalize the price that the seller is going to get from the buyer. Based on our model's bidding strategy, buyer will give the seller, the maximum willingness to pay price by the next highest buyer plus an increment. This increment amount has been considered as the increment strategy followed by eBay (Appendix). We are going to use SKUID 2300070 for verification. From figure 5.6 (c), we can see that for the first transaction.

Seller is outlet 2 and Buyer is outlet 7. From figure 5.6 (a), we can see that seller 2 has reserve price for SKU 2300070 as 17. Buyer outlet 7's maximum willingness to pay is 22 (figure 5.6 (b)). Next highest Buyer is outlet 3. It's maximum willingness to pay is 18. Based on the model's bidding strategy, buyer outlet 7 will pay the seller outlet 2 the price 18 plus increment.

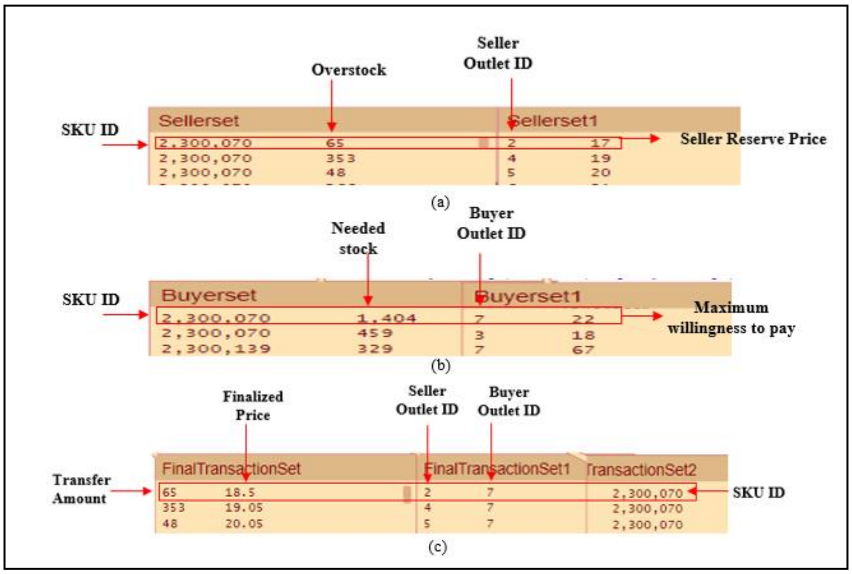



**Figure 5-6** Dataset for verifying final transaction price from buyer to seller. (a) Seller Dataset (b) Buyer Dataset (c) Final transaction

From figure 5.7 we can see that for a price range between \$5 to \$24.99, will get an increment of \$0.50. As \$18 falls in this range, buyer outlet 7 will give seller outlet 2 the final price as =\$18+\$0.50=\$18.50.

| Current price | Bid increment |
|---|---|
| $0.01–$0.99 | $0.05 |
| $1.00–$4.99 | $0.25 |
| $5.00–$24.99 | $0.50 |

**Figure 5-7** Bid Increment chart (partial) of eBay

From figure 5.6 (c), we can say that the finalized price generated by our model matched our analytical result.

*5.2.3 Checking animation of the model*

The movement of the agent is an interesting feature of an agent-based simulation model. An agent's movement at an anticipated time verifies that a model is running the way it was predicted. In our model, we used a GIS map for locating the outlets and the DC (figure 5-8). Orders are processed in the DC and send to the outlets via DC vehicle. Here the movement of delivery vehicles has been observed and time has been tract. Then the delivery time is checked with the anticipated time. The movement of the vehicle and the checking of time is another way of verifying the model other than the two ways mentioned before.


**Figure 5-8** Vehicle movement between DC and Outlets to complete order

# Chapter 6 Experimentation

## 6.1 Introduction

Simulation models are developed based on input data. To predict the behavior of the model, it is required to run the model with multiple sets of values of the input parameters. Using 'What-If' experimental analysis, the impact of a range of input parameter values on simulation output can be measured. While taking any strategic decision about the retail business, it is necessary to know the influence of these parameters on the model's performance. In this chapter, the model has been run for different important inputs and the model's performance has been analyzed. Our model has considered Net Cash Inflow, Fill Rate, and Cash inflow over cost ratio as performance measures. After conducting the 'What-if' analysis, the model's performance will be evaluated based on these performance measures. Our main aim is to see whether the performance measures changed significantly for adopting the redistribution model or not.

## 6.2 Factors and Hypothesis Testing

Selecting factors for the "What- If" analysis is critical. These factors help to identify their impact on the response of the model. For taking strategic decisions for the business on which the model is built, significant factors play a crucial role.

### *6.2.1 Factors*

Factors are independent variables which can influence the response variable. For this study, the dependent variable or response variables are the system's performance measures (Net cash inflow, fill rate, and cash inflow over cost ratio). Selected factors are described in the following section.

#### *6.2.1.1 Inventory Review Period*

The enterprise determines SKU delivery cycle to the outlets. In this study, we are assuming the inventory review period is periodic. This review period can be the same for all the SKUs or different depending on the retail enterprise's policy. We have assumed that the inventory review period is the same for all the SKUs for our study. If the products are not supplied at the right time, revenue will be lost. This will impact the performance of our model. Hypothesis for this factor can be depicted by the following.

Hypothesis 1

H0: Increase in the review period has no impact on net cash inflow.

H1: Increase in the review period has an impact on net cash inflow.

Hypothesis 2

H0: Increase in the review period has no impact on the fill rate.

H1: Increase in the review period has an impact on the fill rate.

Hypothesis 3

H0: Increase in the review period has no impact on the cash inflow over cost ratio.

H1: Increase in the review period has an impact on the cash inflow over cost ratio.

#### *6.2.1.2 Deviation of Number of Customer Arrival*

Stock flow in retail is customer oriented. Customers generate the revenue in the system. Because of the uncertainty of customer arrival, revenue deviates from expected. The deviation of the number of customer arrival is an important factor for our model's performance.

Hypothesis 4

H0: Increase in the deviation of the number of customer arrival has no impact on net cash inflow.

H1: Increase in the deviation of the number of customer arrival has an impact on net cash inflow.

Hypothesis 5

H0: Increase in the deviation of the number of customer arrival has no impact on the fill rate.

H1: Increase in the deviation of the number of customer arrival has an impact on the fill rate.

Hypothesis 6

H0: Increase in the deviation of the number of customer arrival has no impact on the cash inflow over cost ratio.

H1: Increase in the deviation of the number of customer arrival has an impact on the cash inflow over cost ratio.

*6.2.1.3 Shelf life*

SKUs shelf life is an important factor. An SKU with long shelf life doesn't expire earlier than low shelf life SKUs. If an SKU is a slow-moving SKU in one outlet and has demand in another outlet, disposal cost can be avoided if that SKU is redistributed to the needy outlet. The performance of the system will be affected because of the reduction of the disposal cost. To analyze this effect, we have developed the hypothesis as follows:

Hypothesis 7

H0: Difference in the Shelf Life has no impact on net cash inflow.

H1: Difference in the Shelf Life has an impact on net cash inflow.

Hypothesis 8

H0: Difference in the Shelf Life has no impact on the fill rate.

H1: Difference in the Shelf Life has an impact on the fill rate.

Hypothesis 9

H0: Difference in the Shelf Life has no impact on the cash inflow over cost ratio.

H1: Difference in the Shelf Life has an impact on the cash inflow over cost ratio.

### *6.2.2 Hypothesis Testing For Evaluating The Effect of Redistribution*

To check whether the inclusion of redistribution option in the retail system impacts the system's performance or not, we have conducted hypothesis testing. For all the factor-level experiments, this testing has been performed.

Hypothesis Testing for Net Cash Inflow

H0: Redistribution does not have any impact on the system's net cash inflow.

H1: Redistribution has an impact on the system's net cash inflow.

Hypothesis Testing for Fill Rate

H0: Redistribution does not have any impact on the Fill Rate.

H1: Redistribution has an impact on the Fill Rate.

Hypothesis Testing for Cash inflow over cost ratio

H0: Redistribution does not have any impact on the cash Inflow over cost ratio.

H1: Redistribution has an impact on the cash inflow over cost ratio.

*6.2.3 Design of Experiment*

After careful identification of the factors, we have set the levels for different factors. Inventory review period's levels have been selected as 10 days, 15 days, and 20 Days. The number of customers arrival have been considered to have four levels. We have assumed that the daily arrival of customer numbers is normally distributed with the mean number of customers coming to the stores daily with a standard deviation of 5% of the mean,10% of the mean,15 % of the mean, and 20% of the mean. For SKUs shelf life, the shelf life of 60 days and 180 days have been considered as two levels for experimental purposes.

Table 6-1 Factors for Experiments

| Factor | Levels | Details |
| --- | --- | --- |
| Review Period | 3 | 10 Days, 15 Days, 20 Days |
| Number of Customer Arrival Deviation | 4 | 5% Deviation,10% deviation,15% deviation,20% deviation |
| SKU Shelf life | 2 | 60 Days and 180 Days |

Total Number of experiments=Review Period (3 levels) * Number of Customer Arrival Deviation (4 levels) * SKU Shelf life (2 levels)=24

For the design of the experiment, we have chosen the unsupervised imbalanced stock-based model. As all the redistribution models have impacts on the increase of performance measures based on Chapter 4's implementation results, instead of experimenting with all the four redistribution models, we chose one. To observe whether there is any impact of redistribution on the retail system's performance, we have conducted paired t-test for each experiment with 15 replications. With a 95% confidence level, we found out that the redistribution has a significant impact on the retail system's net cash inflow, fill rate, and cost over net cash inflow (Table 6.2).

Table 6-2 Summary of Paired t-test

| Inventory Review Period (Days) | Customer Deviation (%) | Shelf Life | Null Hypothesis | Net Cash Inflow | | Fill rate | | COCR | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | T-value | P-Value | T-value | P-Value | T-value | P-Value |
| 10 | 5 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 481.46 | <0.0001 | 411.60 | <0.0001 | 50.41 | <0.0001 |
| 10 | 10 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 420.69 | <0.0001 | 569.58 | <0.0001 | 104 | <0.0001 |
| 10 | 15 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 418.15 | <0.0001 | 382.88 | <0.0001 | 106 | <0.0001 |
| 10 | 20 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 336.29 | <0.0001 | 368.28 | <0.0001 | 51.64 | <0.0001 |
| 15 | 5 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 557.37 | <0.0001 | 929.26 | <0.0001 | 179.04 | <0.0001 |
| 15 | 10 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 617.01 | <0.0001 | 1167.52 | <0.0001 | 163.54 | <0.0001 |
| 15 | 15 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 639.96 | <0.0001 | 1092.10 | <0.0001 | 129.31 | <0.0001 |
| 15 | 20 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 522.65 | <0.0001 | 1189.20 | <0.0001 | 200.81 | <0.0001 |
| 20 | 5 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 455.43 | <0.0001 | 1081.56 | <0.0001 | 521.82 | <0.0001 |
| 20 | 10 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 397.92 | <0.0001 | 774.75 | <0.0001 | 428.69 | <0.0001 |
| 20 | 15 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 525.29 | <0.0001 | 1331.12 | <0.0001 | 729.48 | <0.0001 |
| 20 | 20 | Low | $\mu_{No\ Red} - \mu_{Red=0}$ | 360.52 | <0.0001 | 778.53 | <0.0001 | 531.47 | <0.0001 |
| 10 | 5 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 5.83 | <0.0001 | 407.04 | <0.0001 | 74 | <0.0001 |
| 10 | 10 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 438.87 | <0.0001 | 588.02 | <0.0001 | 74 | <0.0001 |
| 10 | 15 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 366.54 | <0.0001 | 405.87 | <0.0001 | 48.51 | <0.0001 |
| 10 | 20 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 483.83 | <0.0001 | 359.07 | <0.0001 | 44.56 | <0.0001 |
| 15 | 5 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 658.65 | <0.0001 | 921.36 | <0.0001 | 210.60 | <0.0001 |
| 15 | 10 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 601.27 | <0.0001 | 1156.38 | <0.0001 | 210.60 | <0.0001 |
| 15 | 15 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 481.44 | <0.0001 | 1072.94 | <0.0001 | 301 | <0.0001 |
| 15 | 20 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 569.85 | <0.0001 | 1166.74 | <0.0001 | 229.68 | <0.0001 |
| 20 | 5 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 1172.62 | <0.0001 | 1086.56 | <0.0001 | 330.56 | <0.0001 |
| 20 | 10 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 1351.71 | <0.0001 | 1179.18 | <0.0001 | 549.67 | <0.0001 |
| 20 | 15 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 1577.04 | <0.0001 | 1264.91 | <0.0001 | 518.07 | <0.0001 |
| 20 | 20 | High | $\mu_{No\ Red} - \mu_{Red=0}$ | 1099.52 | <0.0001 | 950.31 | <0.0001 | 517.25 | <0.0001 |

After identifying that the mean values of performance measures are different for redistribution and no redistribution (base model) in the system, we want to know which experiment/experiments have/have a significant impact on the percentage change of the performance measures. Instead of absolute value change, we have considered the percentage change for measuring the significant impact of redistribution. Mean values of the percentage change of performance measures for redistribution compared to the base model, have been listed in Table 6.3-Table 6.5, for different experiments.

Table 6-3 Mean of Net cash inflow (%) increase for different experiments

| Customer Deviation | Shelf life-Low | | | Shelf life-High | | |
|---|---|---|---|---|---|---|
| | Inventory Review Period | | | Inventory Review Period | | |
| | 10 | 15 | 20 | 10 | 15 | 20 |
| 5 | **1.18%** | **4.48%** | **51.69%** | **0.86%** | **3.58%** | **26.39%** |
| 10 | **1.20%** | **4.50%** | **51.67%** | **0.88%** | **3.60%** | **26.38%** |
| 15 | **1.25%** | **4.55%** | **53.08%** | **0.91%** | **3.66%** | **26.72%** |
| 20 | **1.42%** | **4.60%** | **56.88%** | **1.04%** | **3.70%** | **28.77%** |

Table 6-4 Mean of Fill Rate (%) increase for different experiments.

| Customer Deviation | Shelf life-Low | | | Shelf life-High | | |
|---|---|---|---|---|---|---|
| | Inventory Review Period | | | Inventory Review Period | | |
| | 10 | 15 | 20 | 10 | 15 | 20 |
| 5 | **57.05%** | **58.53%** | **48.7%** | **61.95%** | **59.59%** | **36.83%** |
| 10 | **56.41%** | **58.45%** | **48.5%** | **61.11%** | **59.52%** | **36.67%** |
| 15 | **54.77%** | **58.39%** | **48.3%** | **58.99%** | **59.46%** | **36.21%** |
| 20 | **56.38%** | **58.16%** | **45.1%** | **60.28%** | **59.24%** | **33.98%** |

Table 6-5 Mean of Cash Inflow over cost ratio (%) increase for different experiments.

| Customer Deviation | Shelf life-Low | | | Shelf life-High | | |
|---|---|---|---|---|---|---|
| | Inventory Review Period | | | Inventory Review Period | | |
| | 10 | 15 | 20 | 10 | 15 | 20 |
| 5 | **0.19%** | **0.68%** | **3.56%** | **0.14%** | **0.54%** | **2.51%** |
| 10 | **0.19%** | **0.71%** | **3.59%** | **0.14%** | **0.54%** | **2.51%** |
| 15 | **0.20%** | **0.70%** | **3.61%** | **0.16%** | **0.56%** | **2.52%** |
| 20 | **0.24%** | **0.67%** | **3.65%** | **0.15%** | **0.59%** | **2.55%** |

One-way ANOVA has been performed with a 95% confidence level to check the significant differences in the different experiments' means. Same colors represented insignificant differences, where different color represents significant differences in the mean value. Table 6.3 and table 6.5 show that with a customer arrival deviation of 20% of the average number of customers and the inventory review period of 20 days, low shelf-life products get the highest benefit from the redistribution. From table 6.4, we can see that for high shelf-life SKUs, lowest customer deviation, and most frequent inventory review period results in the highest system performance for fill rate. When customer deviation is low and the inventory review period is more frequent, then the need for redistribution is less as the number of unsatisfied customers is less. Suppose any store needs to get any SKU by redistribution in this situation. In that case, it can find more supply points than when the situation is with high customer deviation and less frequent inventory review period. As customers’ demands can be fulfilled better for a low customer deviation and more frequent inventory review period situations, the percentage increase in fill rate is higher than the opposite situation.

To check the main effects and interaction effects of the factors on performance change, we have conducted General Linear Modeling (GLM) Analysis with a 95% confidence level. We found out that all the factors can significantly affect the percentage of the fill rate change and Net Cash Inflow. Cash Inflow over cost ratio (COCR) changes significantly with the levels of factors- Inventory Review Period and Shelf life of SKU. Interaction effect of factors (Inventory review period*Shelf Life) is present for all the performance measures and interaction effect of Inventory review period* Customer deviation is present for % Fill rate change and % increase in Net Cash Inflow. We will discuss the interactions separately in the later section.

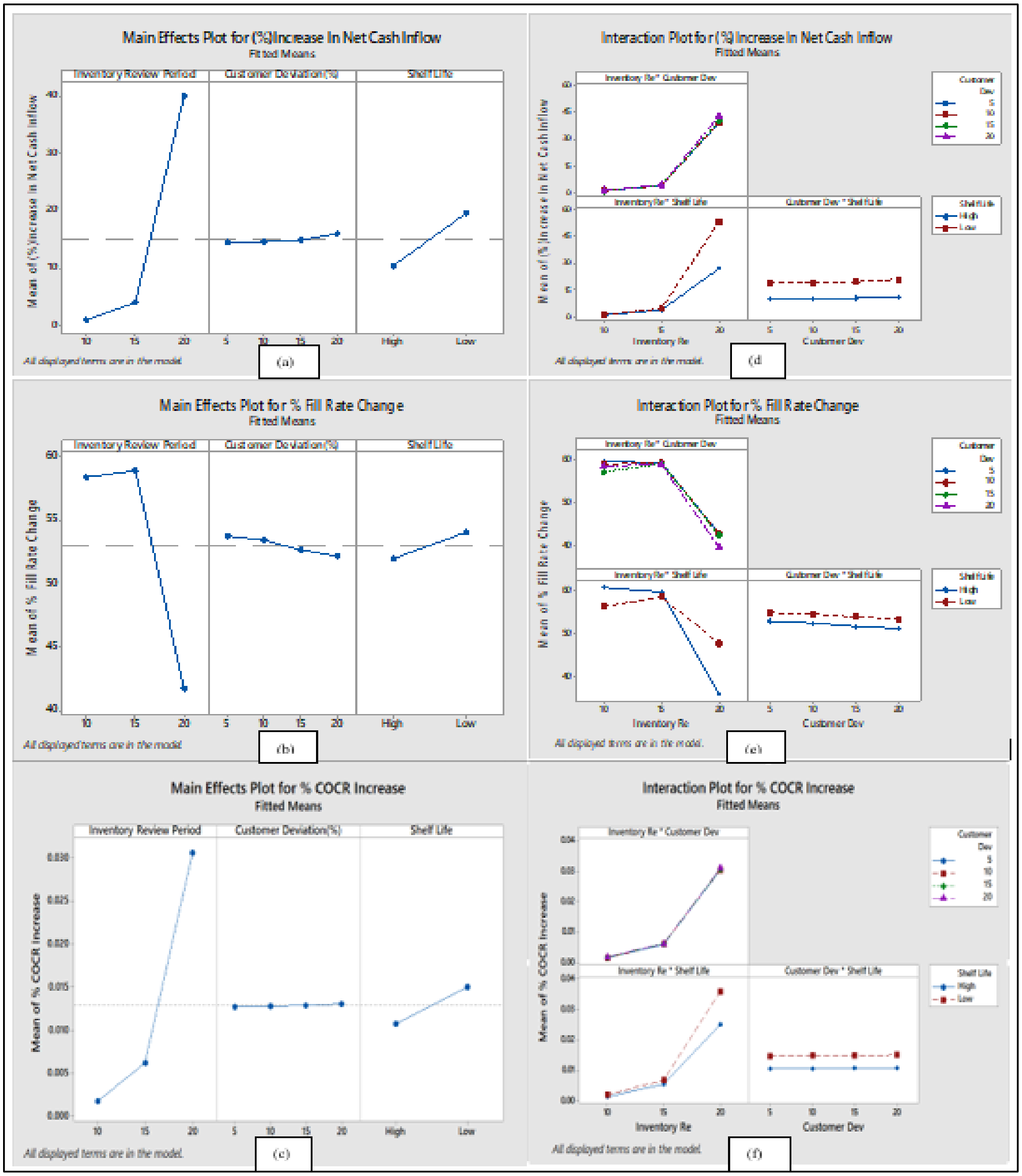



**Figure 6-1** Main Effect plot for % increase in Net Cash Inflow (a), % increase in Fill rate (b), % increase in CIOC (c), Interaction Plots for % increase in Net Cash Inflow (d), % increase in Fill rate (e), and % increase in CIOC (f).

#### *6.2.3.1 Main Effect of Inventory Review Period*

When comparing the different levels of the inventory review period, we can see from table 6.6, the impact is highest for 20 days inventory review period. As a stock up to level policy, in this study, we have considered that at every review period, orders will be generated in a way that the system will have twenty-two days stock. So longer review period means the stock will be received less frequently, and the chance of using redistribution is high. This means that for any imbalanced stock situation, outlets will have to wait for a longer period for getting products from the DC. By this time they can use redistribution for meeting their customer demands. As in this study stock up to level is twenty-two days stock, for ten days inventory review period the order amount will be generated every 10 days in a way that there will be ten days plus another twelve days stock in the outlet. For fifteen days review cycle it will be an extra seven days stock and for twenty days it will be an extra two days stock. Based on figure 6.1 (a) and table 6.6, we can say that if the review period is close to stock up to level days, the impact of redistribution is highest. With a long review period with fewer extra days stock ( it acts like safety stock), to meet customer demand, outlets get more benefit from redistribution. This is true for our performance measure Net Cash Inflow and Cash inflow over cost ratio (COCR). Instead of absolute change, we have compared percentage change for our performance measures. The absolute value does not represent the actual impact. Sometimes seemingly a large value changes because a system's change can be a very small percentage of actual value. That may represent that the system change is not significant. On the other hand, the opposite situation can happen with seemingly low absolute value change can be a large percentage of actual value. We have also provided the absolute change of performance measures for different levels of the inventory review period in figure 6.2-figure 6.4.

Table 6-6 Descriptive statistics of Impact of Inventory Review Period on Performance measures

| Inventory Review Period | Change in Net Cash in Flow | | |
|---|---|---|---|
| | Mean | Standard Deviation | 95% CI |
| 10 | 1.10% | 0.20% | (1.05%,1.13%) |
| 15 | 4.10% | 0.50% | (4.00%,4.16%) |
| 20 | 40.20% | 13.30% | (37.70%,42.60%) |
| Inventory Review Period | Change in COCR | | |
| | Mean | Standard Deviation | 95% CI |
| 10 | 0.20% | 0.00% | (0.17%,0.18%) |
| 15 | 0.60% | 0.10% | (0.61%,0.64%) |
| 20 | 3.10% | 0.50% | (2.96%,3.16%) |
| Inventory Review Period | Change in Fill Rate | | |
| | Mean | Standard Deviation | 95% CI |
| 10 | 58.40% | 2.50% | (57.91%,58.82%) |
| 15 | 58.90% | 0.60% | (58.81%,59.03%) |
| 20 | 41.80% | 6.00% | (40.69%,42.88%) |

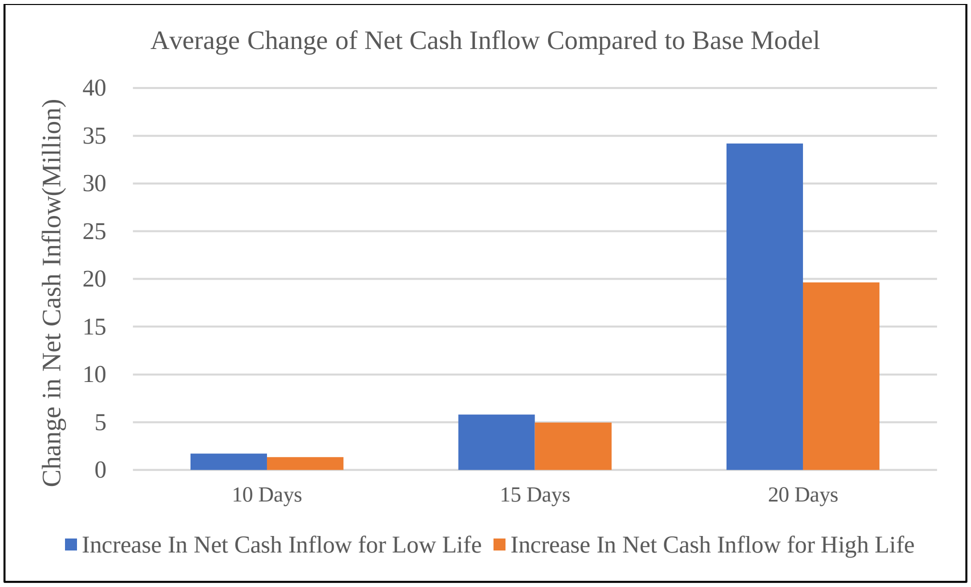



**Figure 6-2** Average Change of Net Cash Inflow for redistribution compared to Base Model.

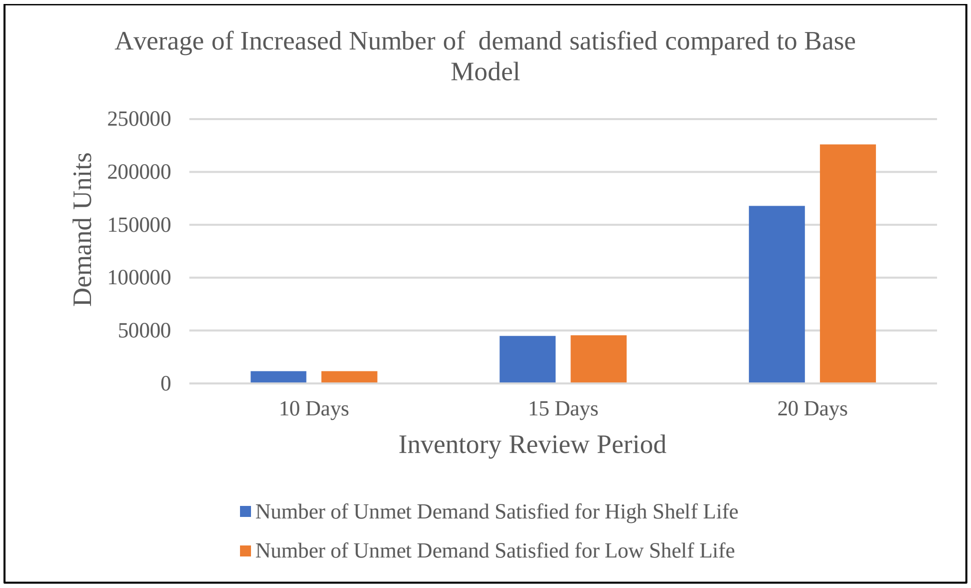



**Figure 6-3** Average Increase of Satisfied demand for redistribution compared to Base Model.

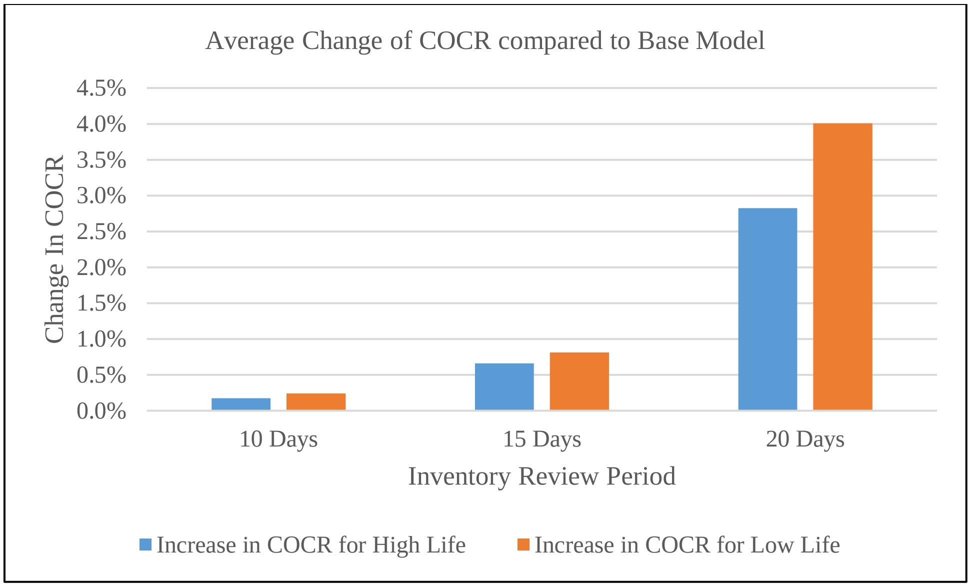



**Figure 6-4** Average Change of COCR for redistribution compared to Base Model

While observing the effect of the inventory review period on the % Change of fill rate, we can see that there is a negative trend between the inventory review period and % change of fill rate. From figure 6.3, we can see that the system can meet more demands of the customers because of redistribution compared to the system with no redistribution (base model). We can also see from figure 6.3 that the amount is the highest for the twenty-day inventory review period. For high shelf life SKU, redistribution satisfied around 17000 more demand units compared to the base model. For low shelf life SKUs, it is around 23000. When considered the percentage increase of fill rate, we found out that for 20 days review period, it is the lowest. When the inventory review period and the stock up to level days have a large difference, the need for redistribution is smaller compared to the small difference between the inventory review period and stock up to level days.

For the former case, outlets have more days extras stocks to meet uncertain demand so the need for redistribution is low. But if there is any necessity, the possibility of meeting the demand through redistribution is high as there will be more supply sources and fewer demand sources because most of the stores should have enough days of stock. As a result, the percentage of change/increase in fill rate is greater with a low inventory review period than a higher inventory review period which is close to stock up to level days.

#### *6.2.3.2 Main Effect of Number of Customer Arrival Deviation*

Deviation of the number of customer arrival creates variations in demands. It is obvious from table 6.7 that the change in all the three performance measures changes linearly with an increase in the deviation of the number of customer arrival. The impact of the difference of different levels of the number of customer arrival deviation is less than the impact of the difference of different Inventory review period levels.

Table 6-7 Descriptive statistics of Impact of Number of Customer Arrival Deviation on Performance measures

| Number Of Customer Arrival Deviation(%) | Change in Net Cash In Flow | | |
|---|---|---|---|
| | Mean | Standard Deviation | 95% CI |
| 5 | 14.70% | 18.90% | (10.75%,18.65%) |
| 10 | 14.70% | 18.80% | (10.76%,18.65%) |
| 15 | 15.00% | 19.30% | (10.98%,19.07%) |
| 20 | 16.10% | 20.70% | (11.72%,20.41%) |
| Number Of Customer Arrival Deviation(%) | Change in COCR | | |
| | Mean | Standard Deviation | 95% CI |
| 5 | 1.27% | 1.31% | (1.00%,1.54%) |
| 10 | 1.28% | 1.31% | (1.00%,1.55%) |
| 15 | 1.29% | 1.31% | (1.01%,1.57%) |
| 20 | 1.31% | 1.33% | (1.03%,1.59%) |
| Number Of Customer Arrival Deviation(%) | Change in Fill Rate | | |
| | Mean | Standard Deviation | 95% CI |
| 5 | 53.80% | 8.70% | (52.0%,55.6%) |
| 10 | 53.50% | 8.60% | (51.7%,55.2%) |
| 15 | 52.70% | 8.40% | (50.9%,54.4%) |
| 20 | 52.20% | 9.60% | (50.2%,54.2%) |

The absolute value of change in Net Cash Inflow is presented in figures 6.5-6.7. For a certain inventory review period, how the changes in deviation of customer arrival impact Net cash inflow can be seen from figure 6.5-figure 6.7.

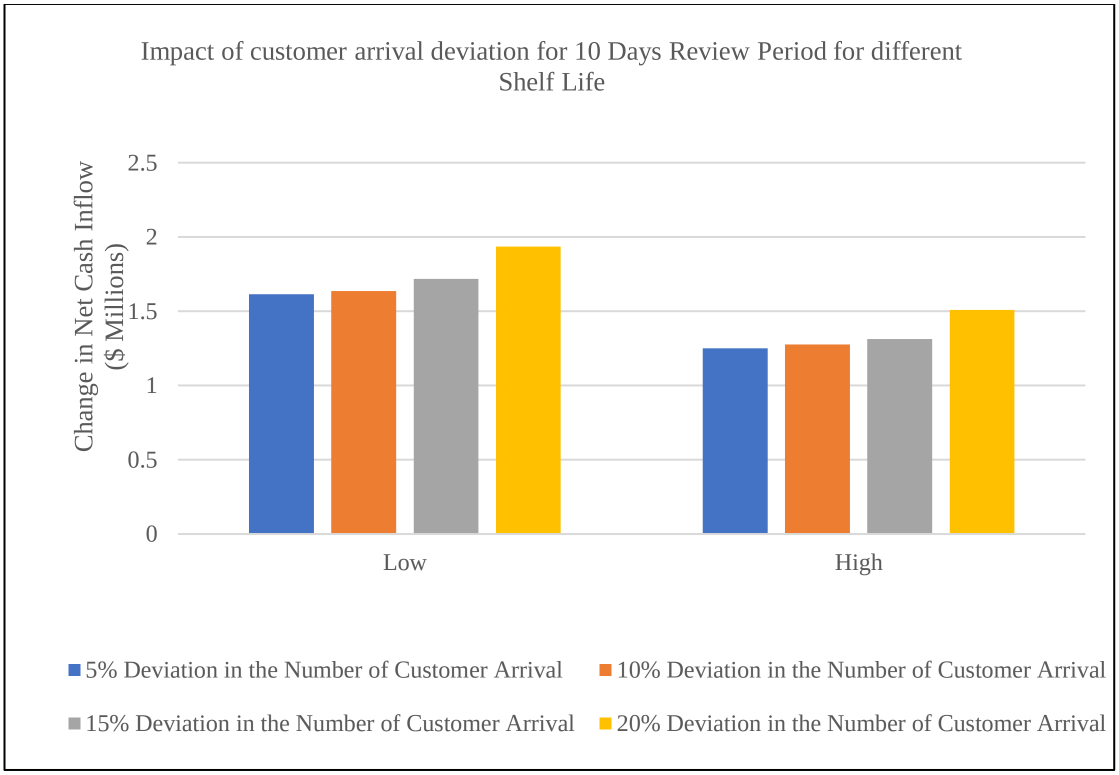



**Figure 6-5** Impact of customer arrival deviation on Net Cash Inflow for 10 Days Review Period for different Shelf Life

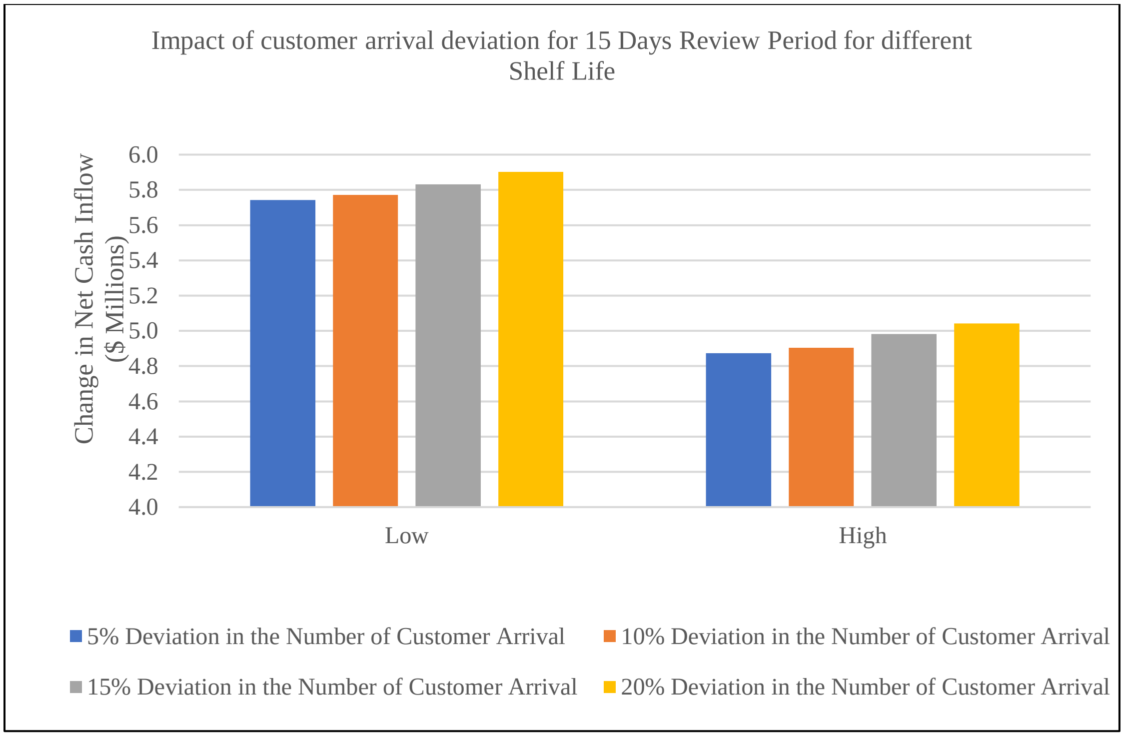



**Figure 6-6** Impact of customer arrival deviation on Net Cash Inflow for 15 Days Review Period for different Shelf Life

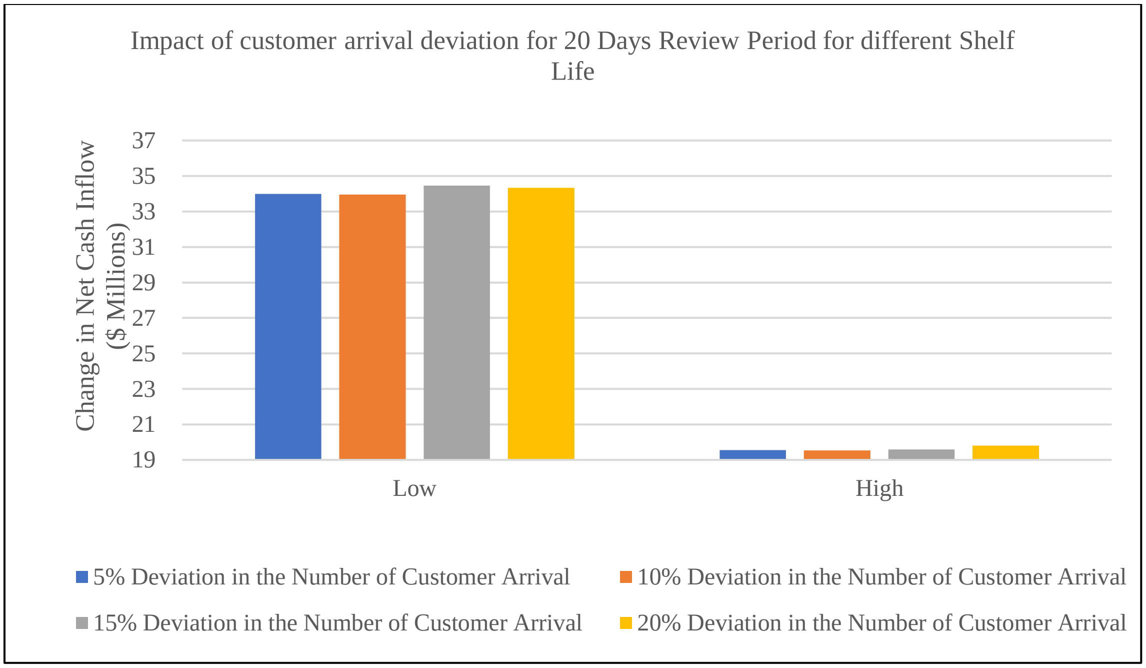



**Figure 6-7** Impact of customer arrival deviation on Net Cash Inflow for 20 Days Review Period for different Shelf Life

#### *6.2.3.3 Main Effect of Shelf Life*

From table 6.8, we can see that the low shelf life products can get more benefit from redistribution than the high shelf life SKUs. Changes in Net Cash Inflow for different levels of shelf life are less compared to that of the inventory review period. From the perspective of cost, low shelf-life products tend to prone faster than high shelf life. This results in extra costs related to their disposal.

Another point is that the SKUs' reserved prices are related to their shelf life. Less shelf life means the seller can offer less price which increases the chance of being redistributed.

So, if these products get redistributed, they can positively impact cash flow. As products got redistributed more, so change of fill rate increase for low life SKUs. The same impact can be seen on the cash inflow over cost ratio.

Table 6-8 Descriptive statistics of Impact of Shelf Life on Performance measures

| Shelf Life | Change In Net Cash In Flow | | |
|---|---|---|---|
| | Mean | Standard Deviation | 95% CI |
| High | 10.50% | 11.80% | (8.8%,12.3%) |
| Low | 19.70% | 23.90% | (16.2%,23.2%) |
| Shelf Life | Change In COCR | | |
| | Mean | Standard Deviation | 95% CI |
| High | 1.10% | 1.00% | (0.9%,1.2%) |
| Low | 1.50% | 1.50% | (1.3%,1.7%) |
| Shelf Life | Change In-Fill Rate | | |
| | Mean | Standard Deviation | 95% CI |
| High | 52.00% | 11.40% | (50.30%,53.60%) |
| Low | 54.10% | 4.80% | (53.30%,54.70%) |

#### *6.2.3.4 Interaction Effect on Performance measures*

To understand better the interaction effects of different factors, we have created graphs for the interaction of inventory review period and customer arrival deviation separately for high and low shelf life. We can observe the same trend for both low and high shelf life from figure 6.8 and figure 6.9. When the inventory review period changes from 10 days to 15 days, there is no significant difference in the change of Net Cash inflow for different customer arrival deviation levels. The change in net cash inflow is almost the same for all levels of the number of customer arrival deviation. Changing the inventory review period from 15 days to 20 days creates a high increase in Net Cash Inflow change. At 20 days review period, though there is no significant difference for 5%,10%, and 15% customer arrival deviation, for 20% customer arrival deviation, we can see that there exists a difference in the change in Net Cash Inflow. This difference of 2.1% (average) is between 20% customer arrival deviation and other customer arrival deviation at 20 Days review period.

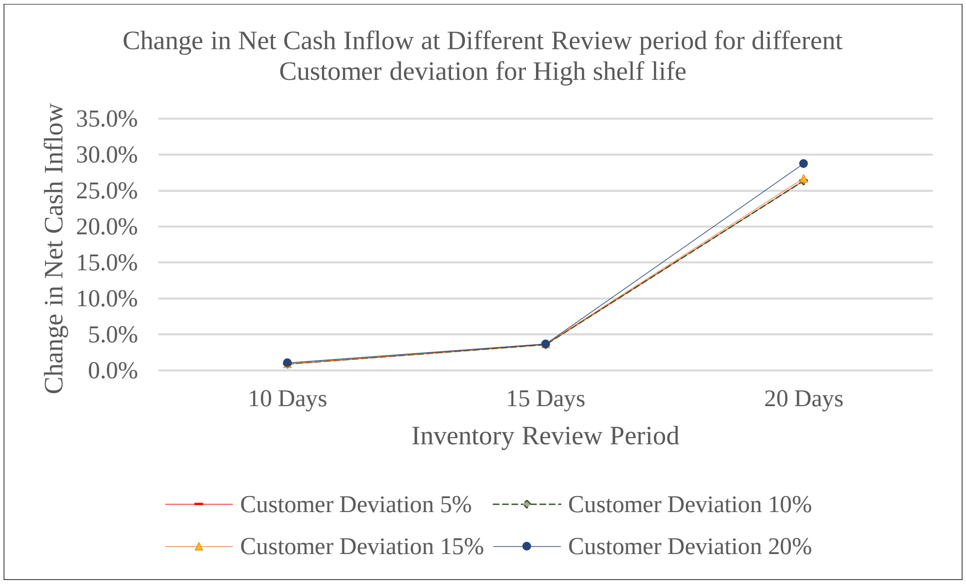



**Figure 6-8** Interaction effect of the inventory review period and customer arrival deviation on Net Cash Inflow for High Shelf life

For low shelf life, the differences in net cash inflow changes for different levels of customer deviation are more observable at the 20 days inventory review period than for high shelf life. The difference of change in net cash inflow at 20 days inventory review period, for low shelf life SKUs, is 1.4% between 10% deviation in customer arrival and 15% deviation in customer arrival where it is 3.8% between 15% deviation and 20% deviation in customer arrival.

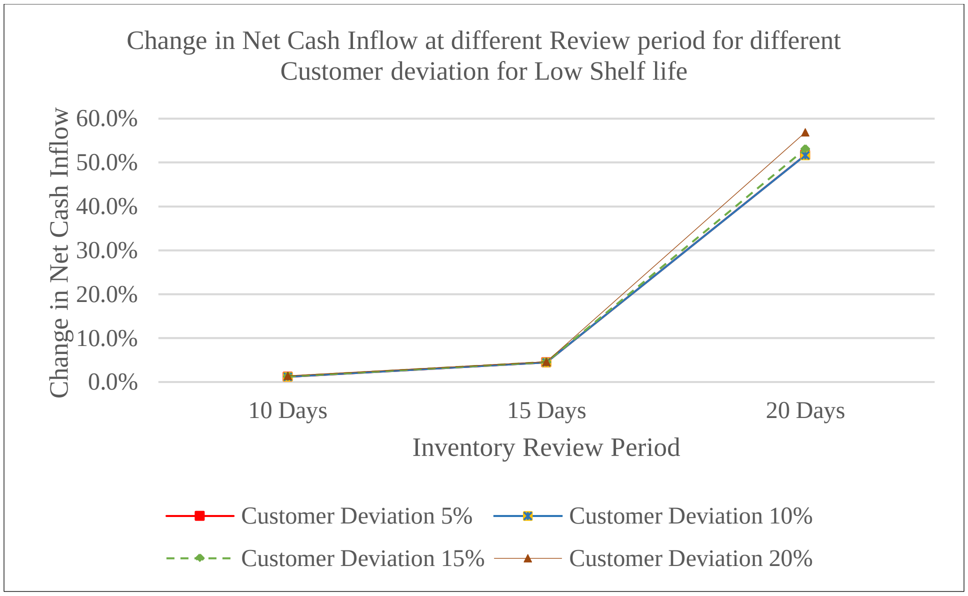



**Figure 6-9** Interaction effect of the inventory review period and customer arrival deviation on Net Cash Inflow for Low Shelf life

Based on the above discussion we can say that with the decrease of the difference of inventory review period and stock up to level days, the impact of customer deviation on the change of net cash inflow increases. The higher the customer deviation, the larger the percentage increase of net cash inflow. The change is higher for low-life SKUs than high-shelf life SKUs.

For the performance measure fill rate, we can see from figure 6.10 and figure 6.11 that with the increase of the inventory review period, the change in the percentage of fill rate is negative for most of the customer deviation levels. When the inventory review period is twenty days, the decrease is the highest. For high shelf-life SKUs, the impact of 20% customer arrival deviation is more than the SKUs with Low shelf life.

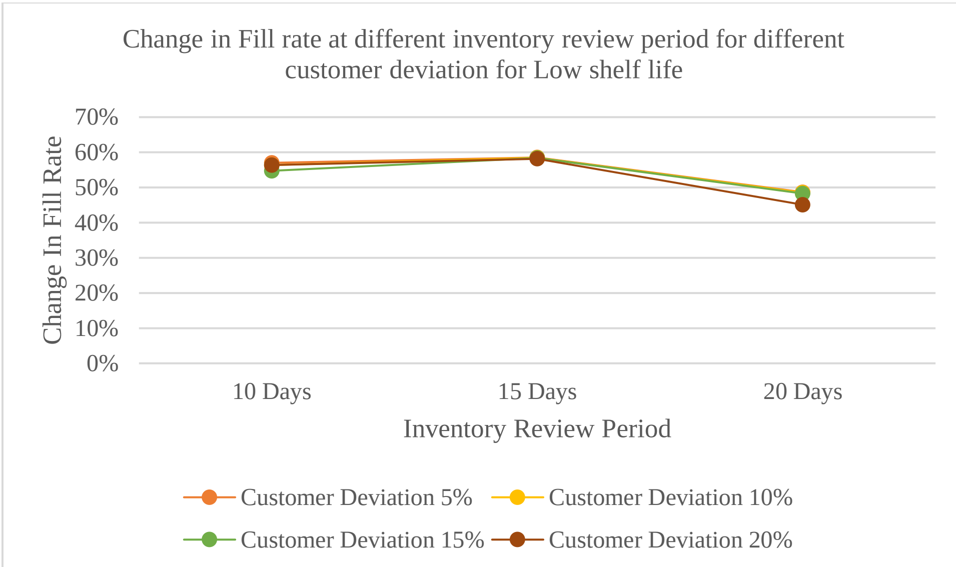



**Figure 6-10** Interaction effect of the inventory review period and customer arrival deviation on Change in Fill Rate for Low Shelf life

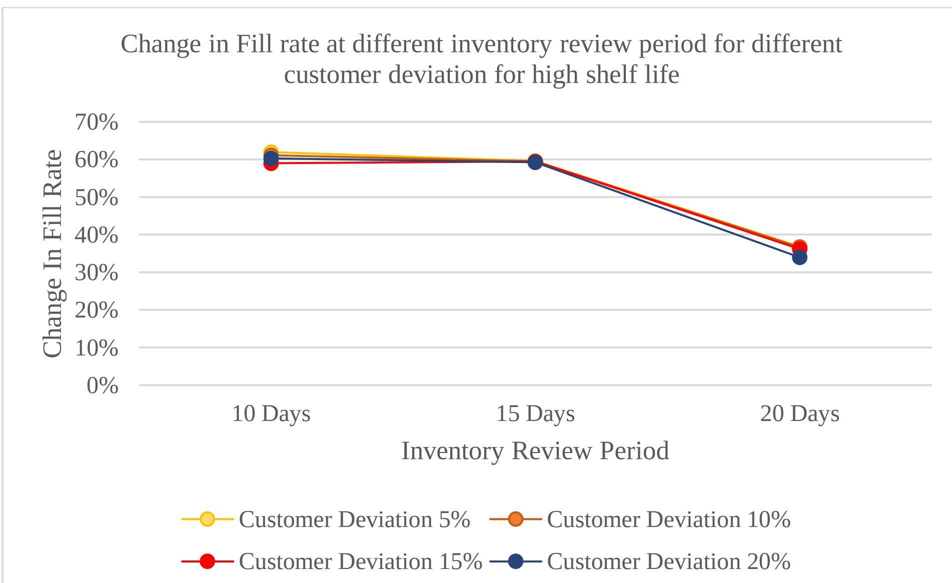



**Figure 6-11** Interaction effect of the inventory review period and customer arrival deviation on Change in Fill Rate for high Shelf life

To understand the impact of the redistribution for different levels of customer arrival deviation, we can see the change of fill rate in absolute value from figure 6.12-6.14. From these figures, we can see that with the increase of customer arrival deviation, the number of satisfied demands increases for redistribution than no redistribution. But the increased percentage decrease with the increase of the inventory review period. As mentioned earlier, when the inventory review period is long (less difference between review period and stock up to level days), outlets cannot meet the demands as required. As a result, though redistribution takes place and the number of satisfied demands is bigger than the short inventory review period, the percentage change is low.

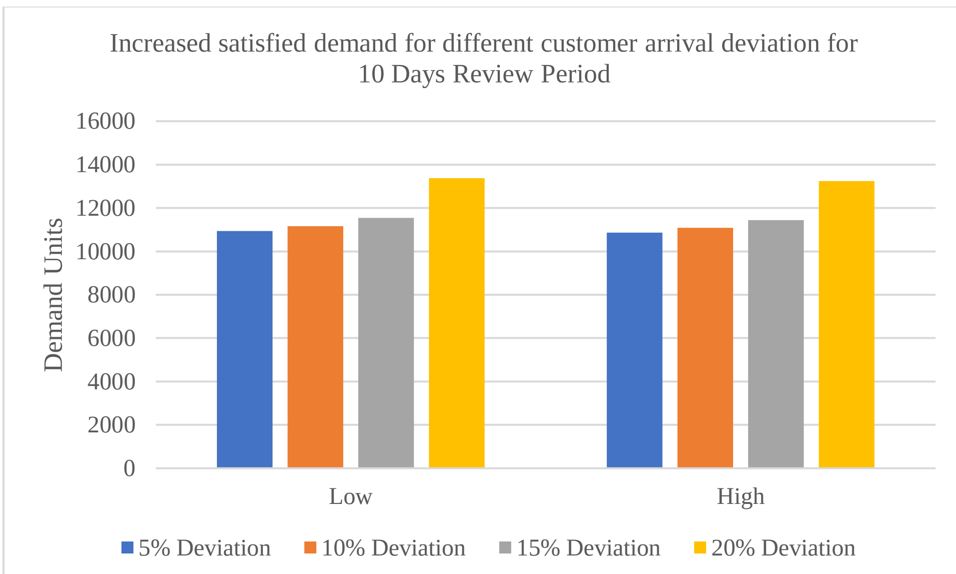



**Figure 6-12** Increase in satisfying demand compared to no redistribution for different levels of customer arrival at 10 days review period.

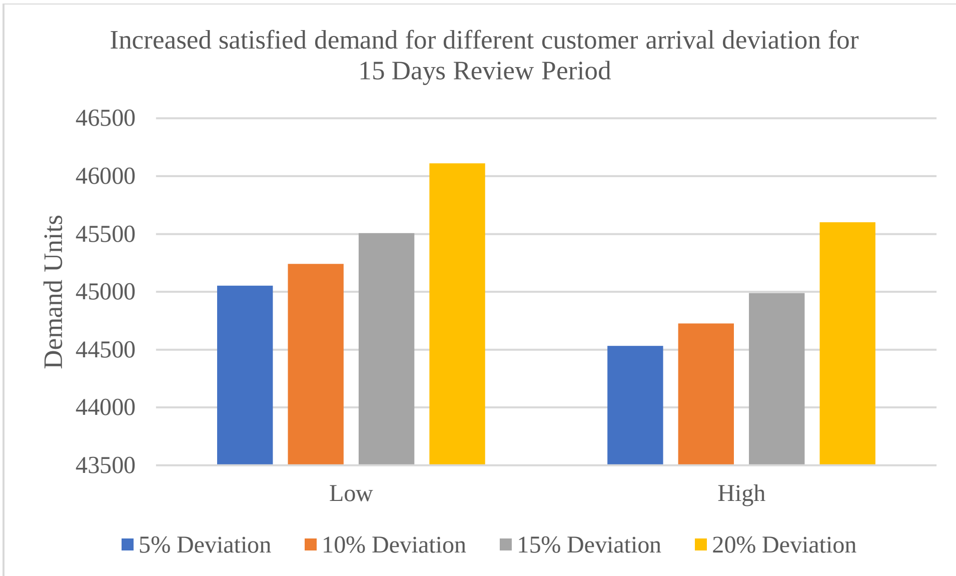



**Figure 6-13** Increase in satisfying demand compared to no redistribution for different levels of customer arrival at 15 days review period.

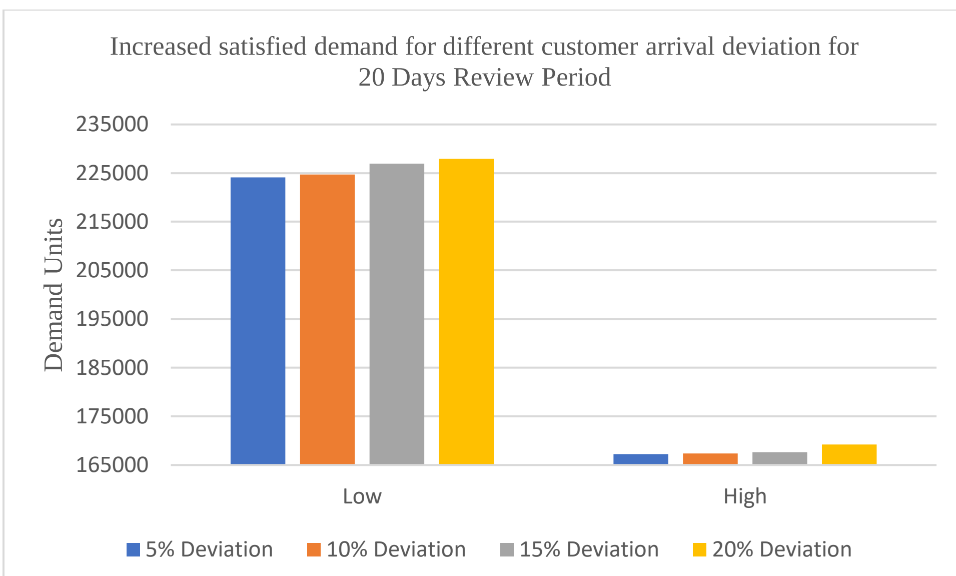



**Figure 6-14** Increase in satisfying demand compared to no redistribution for different customer arrival levels at 20 days review period.

For different customer arrival deviation levels, with the change of inventory review period, we cannot see any significant difference (figure 6.15- 6.16) on the change of COCR.

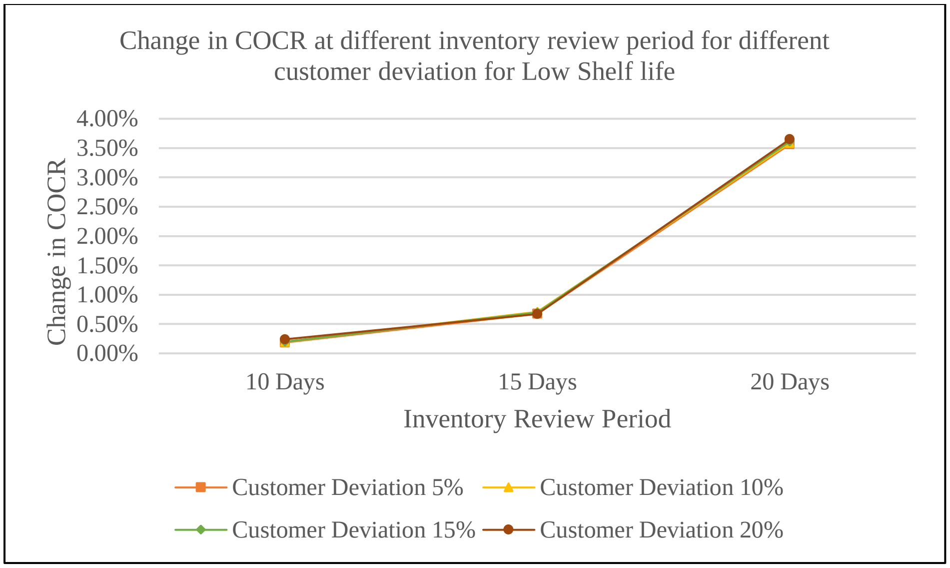



**Figure 6-15** Interaction effect of the inventory review period and customer arrival deviation on COCR for Low Shelf life

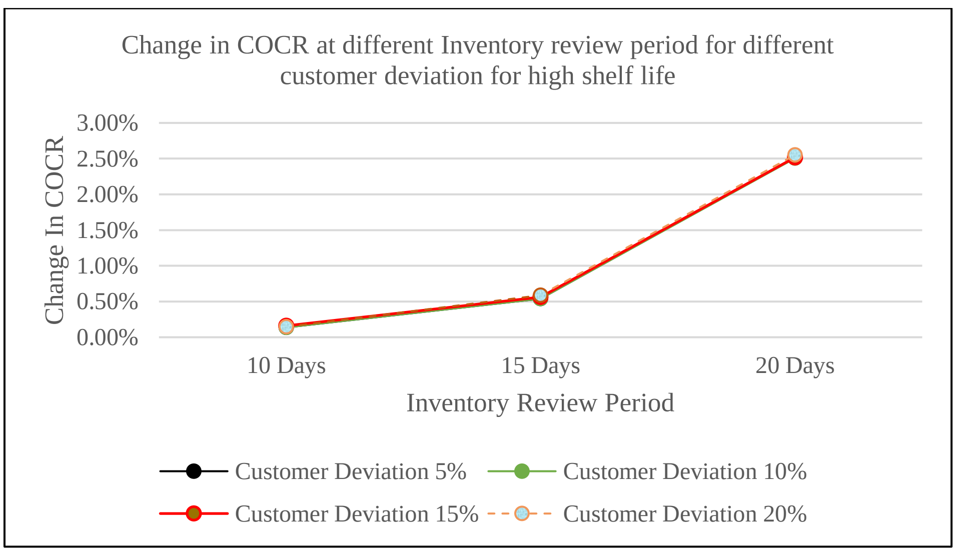



**Figure 6-16** Interaction effect of the inventory review period and customer arrival deviation on COCR for high Shelf life

From the above discussion, we can say that the highest impact of redistribution on the performance measures have been identified for the situation when the retail system has the highest deviation of customer arrival, the lowest difference between inventory review period and stock up to level, and for the SKUs with low shelf life.

### 6.2.4 *Experiments on SKU Classes*

The standard way to classify any inventory is based on ABC classification. In chapter 4, we have observed that different classes of inventories are impacted differently after introducing only redistribution, only donation, and both in the retail system. As our model is stochastic, we ran our model with different seeds for 15 replications to see the impact in this section. We have conducted a paired t-test to check whether there is any meaningful difference between the base model's performance measures and the inclusion of donation option and redistribution option separately in the base model. For this experiment, we have considered the same shelf-life (180 Days), inventory review Period (10 Days), and deviation in the number of customers (20%). The performance measure considered here is the Net cash inflow.

With a 95% confidence interval, we can say that there is a significant difference between the base model's performance measures and the inclusion of donation option and redistribution option separately in the base model for all three classes.

Table 6-9 Summary of hypothesis testing (Class wise)

| SKU Class | Hypothesis | T-Value | P-Value | 95% CI for the mean difference |
|---|---|---|---|---|
| A | $\mu_{BaseModelA}$-$\mu_{DonationA} = 0$ | 84.05 | <0.0001 | (96798 ,  101868) |
| B | $\mu_{BasedModelB}$-$\mu_{DonationB} = 0$ | 122.54 | <0.0001 | (109385 ,  113282) |
| C | $\mu_{BaseModelC}$-$\mu_{DonationC} = 0$ | 78.52 | <0.0001 | (69385, 73282) |
| A | $\mu_{BaseModelA}$-$\mu_{RedistributionA} = 0$ | 287.6 | <0.0001 | (909831, 923505) |
| B | $\mu_{BasedModelB}$-$\mu_{RedistributionB} = 0$ | 238.65 | <0.0001 | (449920, 458080) |
| C | $\mu_{BaseModelC}$-$\mu_{RedistributionC} = 0$ | 116.2 | <0.0001 | (134798, 139868) |

From table 6.10, we can see that C-class gets the most benefit from donation compared to the other two classes. On the other hand, redistribution provides the lowest benefit to C-class compared to the other two classes.

Table 6-10 Descriptive analysis of the class-wise experiment.

| SKU Class | Base Model | | Donation | | | Redistribution | | |
|---|---|---|---|---|---|---|---|---|
| | Mean (Net Cash Inflow)($) | Standard Deviation ($) | Mean (Net Cash Inflow)($) | Standard Deviation ($) | Increase in Net Cash Inflow compared to Base Model | Mean (Net Cash Inflow)($) | Standard Deviation ($) | Increase in Net Cash Inflow compared to Base Model |
| A | 86,853,333 | 61,283 | 86,952,667 | 60,273 | 0.11% | 87,770,000 | 65,727 | 1.06% |
| B | 43,420,000 | 5,164 | 43,531,333 | 4,976 | 0.26% | 43,874,000 | 7,838 | 1.05% |
| C | 14,464,667 | 4,782 | 14,536,000 | 4,781 | 0.49% | 14,602,000 | 3,384 | 0.95% |

# Chapter 7 Conclusion and Future work

## 7.1 Introduction

To make our model more real retail business-oriented, we have considered multiple factors- SKUs' shelf life, lot-based life, multiple pricing of the same SKUs are some of them. To develop this complex model, a hybrid simulation model has been developed. This hybrid simulation model is a combination of agent-based and discrete event simulation. Overall, this decision-based model can help retail organizations best utilize their stocks and project retail companies' performance.

## 7.2 Research Contribution

Our model can contribute from two perspectives. The first one is academic, and the second one is the industrial contribution.

### *7.2.1 Academic Contribution*

Using a bidding mechanism is not new for lateral transshipment or product redistribution, using the change of product value with its remaining shelf life while bidding will contribute to the current bidding mechanism research work. This product value will dynamically change with time. In our study, we have used a modified ebay bidding mechanism. Reserve price is an essential component of this bidding process. We have used the life-based dynamic value of the product to calculate the reserve price. The development of the dynamic value function will add a mark in current bidding-based redistribution research works.

A strategy has been developed to identify and segregate the redistributable products based on their demand variations over the outlets of a retail chain. Based on this strategy, the most benefitted product groups from redistribution can be identified. This strategy has not been studied before as far as our knowledge.

Consideration of both redistribution and donation options for balancing inventory and increasing retail chain's performance needs importance in today's retail-based research works. In our model, we have integrated both options based on stock, demand, life, and life-based dynamic value.

*7.2.2 Industrial Contribution*

Increased cost in the retail industry is a great concern for this business. Product sales, space utilization, inventory turnover ratio improves when costs decrease. Selecting appropriate ways for inventory utilization can contribute to decreasing the retail system's cost. Our model can identify the products with imbalanced inventory and the opportunity to balance the inventory by redistributing, donating, or both. Expired product disposal costs have also been considered in our model for measuring the retail system's performance. Our model is an integrated tool for evaluating a retail chain daily which can account for the revenue from regular sales without redistribution, revenue generation from redistribution, expected tax savings for donation, disposal costs for dumping expired products, and other related costs. This integrated tool can help the retailers to take care of their imbalanced stock and near expiry products, in a profitable way.

Our model can continuously monitor the stocks and based on the stock/inventory levels and the age of the products; an outlet can automatically participate in bidding for product redistribution. The bidding process has been developed based on ebay bidding process with a little modification. This will eliminate the need for an employee to be present all time to check the bidding progress and the condition of his bid. But if any outlet wants to change the bid amount, remove the product from redistribution, it will have the options to do those.

The transportation cost calculation process for product redistribution has been developed based on the USPS shipping cost calculation process. This is the first redistribution model to do the transportation cost calculation based on the USPS cost calculation mechanism. Our model considers products' physical weights and volumes and divided the outlets into different zones where zone-wise transportation cost varies. The transportation cost calculation process is in practical use (USPS).

We have also developed a strategy to segregate the products to identify the most profitable groups of products for redistribution. This will help the retailers with thousands of products, to get more benefit when the facility for redistribution is limited.

Overall, our model can help a retail chain to identify the ways of utilizing their inventories, leading to increased performance and reduced cost.

Overall, our model will help a retail chain to identify the ways of utilizing their inventories leading to increased performance and reduced cost.

## 7.3 Findings

From this study, we found out that redistribution and donation can contribute to increasing the retail system's performance. Our main focus in this study was to develop a redistribution model. The experimental design has identified that for an order up to level-periodic review inventory system; the inventory review period plays an important role while adapting redistribution in the retail system. Here, order up to level is equal to predetermined days stocks based on forecasted sales. We found out that when the review period and order up to level days are close, then the system gets more benefit from redistribution than when the difference between the review period and order up to level days is big. Suppose any retail enterprise needs to review their inventory less frequently and cannot keep large safety stock because of facility constraints. In that case, redistribution can increase the net cash inflow, fill rate, and cash inflow over cost ratio. The deviation in the number of customer arrival has also an impact on the retail systems' performance. When the retail system's inventory review period and order up to level days are close and the customer number deviation is high, the system gets more benefit from redistribution. Our study shows that for the same stock and sales combination, low shelf-life SKUs get more benefit from redistribution than high shelf-life SKUs. The problem with low-life SKUs is their tendency to expire fast, leading to disposal costs for the retail. By doing redistribution, this disposal cost can be minimized. From SKU classes' perspective, class C gets more benefit from donation than redistribution compared to Class A and Class B. As slow-moving items, this class's transfer amount is less than the rest of the two classes. For this reason, a donation can help to overcome the overstock situation of Class C overstock items.

## 7.4 Limitations and Future Work

We have developed a complex supply chain network in our model. But there are some limitations to our model. The customer arrival data we have collected for our model was the total average number of customers to the outlets per month. As we ran our model for one year, it would be more useful if we could know this number for different times and days of a year. Supplier is an important part of supply chain network. To avoid complexity, we didn't consider suppliers in our model. We have considered that DC can provide the outlets the products they need based on the forecast. We have considered the exponential forecasting method for our study. For future work, an optimized forecasting method can be studied for this model. In retails, inventory review policies sometimes vary based on different categories of SKUs. For example, some products are delivered every month, where others are delivered every week. In this study, we have considered the same review period for all types of SKUs. To get rid of overstock and near expiry SKUs, the use of promotion options can be seen to be practiced. Using the promotion option with the donation and redistribution option in our current model can make our model more applicable in the real environment. We have built four different types of redistribution models. Identification of choosing the models based on different situations can be studied as a part of future work. For categorizing the SKUs to identify the most beneficial SKUs for redistribution, machine learning method like cluster analysis can be conducted. Where we considered only the demand variability ratio, cluster analysis considering multiple attributes can lead to more accuracy for this SKU categorization for redistribution.

Appendix

Table A1: SKUs (155) used for detail analysis.

| SKU Name | Shelf Life (Days) |
|---|---|
| (Promo) Radhuni Chilli Regular 200 gm | 730 |
| Aarong Ghee 900 gm | 45 |
| Aarong white Curd 500 ml | 45 |
| ACI Pure Beson 450 gm | 730 |
| Aci Pure Halim Mix 200 gm | 730 |
| ACI Pure Maida 1 Kg | 120 |
| ACI Pure Maida 2 Kg | 120 |
| Aci Pure Morich Powder 200 gm | 730 |
| Aftab Tandori Chicken Nuggets 250 gm | 60 |
| Ahmed Tomato Sauce 1000 gm(S.Mg) | 730 |
| Ambassador Olive Oil 150 gm Tin | 365 |
| Badhan Show Piece 10 | 1095 |
| Badhan Show Piece 2 | 1095 |
| Badhan Show Piece 9 | 1095 |
| Badhan Sticker Regular | 1095 |
| BALACHAW DRY PRAWN CHUTNEY 250 gm | 730 |
| Bangla Paper Napkin (80 Sheet/Pack) | 730 |
| Bangla Toilet Tissue Super Gold | 730 |
| Basundhara Toilet Tissue Regular Pink | 730 |
| BD Garam Masala 50gm | 730 |
| Bebem Baby Diaper 3 Midi 4-9kg (27pcs) | 730 |
| Bombay Chanchur 200gm(Dalmoth) | 730 |
| Cadbury Dairy Milk 140Gm(U.K) | 730 |
| Cadbury Dairy Milk 49Gm(U.K) | 730 |
| Cadbury Fruit & Nut 49GM(U.K) | 730 |
| Canped Adult Large Diaper 8pc PK | 730 |
| Chip Choc Pkt 180gm | 730 |
| Clear Men Cool Sport-2010 380ml | 365 |
| Coca-Cola 500 ml pet | 180 |
| Comot Brush(Flat) | 730 |
| Dabur Honey 500 gm | 730 |
| Dano - 2 Kg (Regular) Tin | 45 |
| Denim body spray 150ml | 365 |

| SKU Name | Shelf Life (Days) |
|---|---|
| Doux Chicken Franks 340 gm | 730 |
| Dove bar pink 100 gm | 365 |
| Dove Beauty Moisture Facial Foam 100g | 365 |
| Duracell AA Battery 4+2 promo pack | 1095 |
| Fanta 500 ml pet | 180 |
| Farlin Cotton Buds (100 PCs) BF - 113 | 730 |
| Farm Fresh Pasteurized Milk 500 ml | 45 |
| Farm Fresh PasteurizedMilk 1000 Ml | 45 |
| Farmland Gold instant 400gm | 45 |
| Fay Cotton Buds 140 Pcs | 365 |
| Fay Facial Tissue 120x2 Sheet | 365 |
| Fay Facial Tissue 130x2 Sheet | 365 |
| Fay Toilet Paper | 730 |
| Fram Fresh yugurt (Sour) 500 ml | 45 |
| Fresh Milk Powder BIB 400 gm | 730 |
| Fun Chanachur Hot&Spicy 340 gm | 730 |
| Gillette Foam 196 gm Regular | 365 |
| Gillette Foam 418gm Regular | 365 |
| Hajmola regular 120 tabs | 730 |
| Harpic Flushmatic - 50 gm | 730 |
| Harpic Total Power - 200 gm | 730 |
| Huggies Dry Pants L.20 (8-13Kg) | 730 |
| Int. Lux white 75gm | 365 |
| Ispahani Green spot 400 gm ( Poly Bag) | 180 |
| Ispahani Mirzapur Best RD400gm(PolyBag) | 180 |
| IspahaniMirzapur best quality bop 500 gm | 180 |
| Jharu (Big) | 730 |
| Johnsons Baby Pink Lotion 200 ml(Ind | 730 |
| Johnsons Baby Pink Lotion Ita 500 ml | 730 |
| Johnsons Gift Box Medium | 730 |
| Johnsons Milk Lotion Ma 100 ml | 730 |
| Johnsons NMT Shampoo Ind 475 ml | 730 |
| Johnsons Pink Lotion Ma 500 ml Pump | 730 |
| Kazi & Kazi Green Tea Bag 60 gm | 180 |
| Kings Pure Sunflower Oil 2ltr Pet Bottle | 180 |
| Kishan Cheese 200 gm | 45 |
| Knorr Soup Combo(buy3Get1Free) | 730 |

| SKU Name | Shelf Life (Days) |
|---|---|
| Lactogen 1 400 gm Tin | 730 |
| Lifebuoy care 200ml pump | 365 |
| Lini Baby Set Small | 730 |
| Lipton taaza danadar Tea 400gm | 180 |
| Luxsoap Peach&Cream 175gm (impi) | 180 |
| Maggi Healthy Soup Vegetable 25 gm | 730 |
| Moury Shahi Borhani 1500ml | 45 |
| Moury Sour curd 500g | 45 |
| MUM Drinking Water 500 ML | 180 |
| MUSK Hand&Body Lotion 625ml | 365 |
| Nature`s Scrt Cucumber FcWash(Tube)100ml | 365 |
| Nestle Coffee Mate Original 400 gm Jar | 45 |
| Nestle Corn Flakes 275 gm BIB | 730 |
| No.1Sweetened condensed milk 400 gm | 45 |
| Pantene 350 ml smooth&Silky Shampoo | 365 |
| Pran Haleem Mix- 200 gm | 730 |
| pran mango juice Pack 1 litre | 180 |
| Pran Pasteurized Liquid Milk 1000ml | 45 |
| Pran Pasteurized Liquid Milk 500ml | 45 |
| Pran Premium Ghee- 900gm | 45 |
| Pran Turmeric 200 gm | 730 |
| Pran UHT Milk 500ml | 45 |
| PRINGLES 40 gm ORIGINAL | 730 |
| PRINGLES Cheddar Cheese 181 gm | 730 |
| PRINGLES ORIGINAL 181 gm | 730 |
| PRINGLES Sourcream & Onion 40gm | 120 |
| Probhati Mixed Fruits150gm | 730 |
| Provati Chira 500gm | 730 |
| Provati kaju badam Polypack 100 gm | 730 |
| Provati kaju badam Polypack 50gm | 730 |
| Provati Kishmish Granular Polypack 100gm | 730 |
| Provati Pesta Granular Polypack 25 gm | 730 |
| Provati Rice Flour 1 kg | 120 |
| Purno Low GI Rice 1 Kg | 730 |
| Pusti Soyabean Oil 1 Ltr Pet btl | 180 |
| Pusti Soyabean Oil 2 Ltr Pet btl | 180 |
| Pusti Soyabean Oil 8 Ltr Pet btl | 180 |

| SKU Name | Shelf Life (Days) |
|---|---|
| Radhuni Chotpoti Masala 50 gm | 730 |
| Radhuni Cumin 200 gm | 730 |
| Radhuni Cumin 50 gm | 730 |
| Radhuni Easy Mix  Roast Masala 35gm | 730 |
| Radhuni Firni Mix 150Gm | 730 |
| Rashana Bilash Almond?100gm | 730 |
| Rashana Bilash Chick Peace Flour?500gm | 730 |
| Rashana Bilash Cumin?200gm | 730 |
| Rashana Bilash Dry Apricot?100gm | 730 |
| Rexona Roll-On Free Spirit 40ml | 365 |
| Rich  Cheese & Potato Finger 200 gm | 730 |
| Rich  French Fries 300gm | 730 |
| Rich Beef Jumbo Nugget 250g | 60 |
| Rich Beef Sausage 250g | 60 |
| Rich Chicken Jumbo Nugget 250g | 60 |
| Rich Chicken Kievs 250g | 730 |
| Rich Chicken Samucha 12 pcs | 730 |
| Rich Chicken Sausage 250g | 60 |
| Rich Chiken Sausage 340g | 60 |
| Rich Roti Paratha 300gm | 730 |
| Richi Prawn Spring Roll 10 pcs | 730 |
| RomaniaLexusOriginal energy 230(+/-10gm) | 730 |
| Rupchanda Soyabean Oil 5 LtrPet  btl | 180 |
| Sajeeb Bar-B-Q Noodles 180 gm | 730 |
| Sajeeb Lachha Semai 200 gm | 730 |
| Savlon Active Antiseptic Handwash 1000ml | 365 |
| savlon freedom regular flow wings 10pads | 365 |
| SHAN BOMBAY BIRIANY MIX 65gm | 730 |
| Shawpnil Cumin Polypack 50 gm | 730 |
| Shawpnil Garammasala Polypack 50 gm | 730 |
| Shwapnil Chola Boot  1 Kg Pack | 730 |
| Shwapno Premium Alu 1Kg (When Packed) | 60 |
| Shwapno Premium Roshun  500gm(When Packed) | 60 |
| Shwapno Premium Roshun 1Kg (When Packed) | 180 |
| Sunsilk Thick and Long Shampoo 400ml | 365 |
| Tang 750gm Foil Pack (Orange) | 180 |
| Teer Soyabean Oil 5 Liter bottle | 180 |

| SKU Name | Shelf Life (Days) |
|---|---|
| Teer Suji 500 gmPack | 180 |
| Tetley Premium Leaf 200 gm | 180 |
| TIBET 570 SOAP 130 gm (6 pcs pack) | 730 |
| TIBET BALL SOAP 130 gm (6 pcs pack) | 730 |
| Tong Garden Ordn saltd Cashew Nuts150Gm | 365 |
| Tova Jam Starwberry 450 gm | 730 |
| Vanish Quick Action Toilet Cleaner 500ml | 730 |
| VIM Dishwash Powder 500 gm | 730 |
| WHISPER ULTRA CLEAN 8pad WINGS | 365 |
| win2 Mini pocket Black vs White 60gm | 730 |
| win2 Mini pocket choco egg roll 60 gm | 730 |

Table A2. Bid increment used in eBay bidding.

| Current price | Bid increment |
|---|---|
| \$0.01–\$0.99 | \$0.05 |
| \$1.00–\$4.99 | \$0.25 |
| \$5.00–\$24.99 | \$0.50 |
| \$25.00–\$99.99 | \$1.00 |
| \$100.00–\$249.99 | \$2.50 |
| \$250.00–\$499.99 | \$5.00 |
| \$500.00–\$999.99 | \$10.00 |
| \$1000.00–\$2499.99 | \$25.00 |
| \$2500.00–\$4999.99 | \$50.00 |
| \$5000.00 and up | \$100.00 |

Table A3 Class wise Paired t-test with and without inclusion of donation in the based model

## Paired T-Test and CI: Don_1, N

Paired T for Don_1 - N

| | N | Mean | StDev | SE Mean |
|---|---|---|---|---|
| Don_1 | 15 | 86952667 | 62389 | 16109 |
| N | 15 | 86853333 | 63434 | 16378 |
| Difference | 15 | 99333 | 4577 | 1182 |

95% CI for mean difference: (96798, 101868)
T-Test of mean difference = 0 (vs ≠ 0): T-Value = 84.05 P-Value = 0.000

Class A

Paired T for Don_1 - N

| | N | Mean | StDev | SE Mean |
|---|---|---|---|---|
| Don_1 | 15 | 43531333 | 5164 | 1333 |
| N | 15 | 43420000 | 5345 | 1380 |
| Difference | 15 | 111333 | 3519 | 909 |

95% CI for mean difference: (109385, 113282)
T-Test of mean difference = 0 (vs ≠ 0): T-Value = 122.54 P-Value = 0.000

Class B

Paired T for Don_1 - N

| | N | Mean | StDev | SE Mean |
|---|---|---|---|---|
| Don_1 | 15 | 14536000 | 5071 | 1309 |
| N | 15 | 14464667 | 5164 | 1333 |
| Difference | 15 | 71333 | 3519 | 909 |

95% CI for mean difference: (69385, 73282)
T-Test of mean difference = 0 (vs ≠ 0): T-Value = 78.52 P-Value = 0.000

Class C

Table A4. Class wise Paired t-test with and without inclusion of Redistribution in the based model

```
Paired T for Red - N

              N      Mean  StDev  SE Mean
Red          15  87770000  68034    17566
N            15  86853333  63434    16378
Difference   15    916667  12344     3187


95% CI for mean difference: (909831, 923503)
T-Test of mean difference = 0 (vs ≠ 0): T-Value = 287.60  P-Value = 0.000
```

Class A

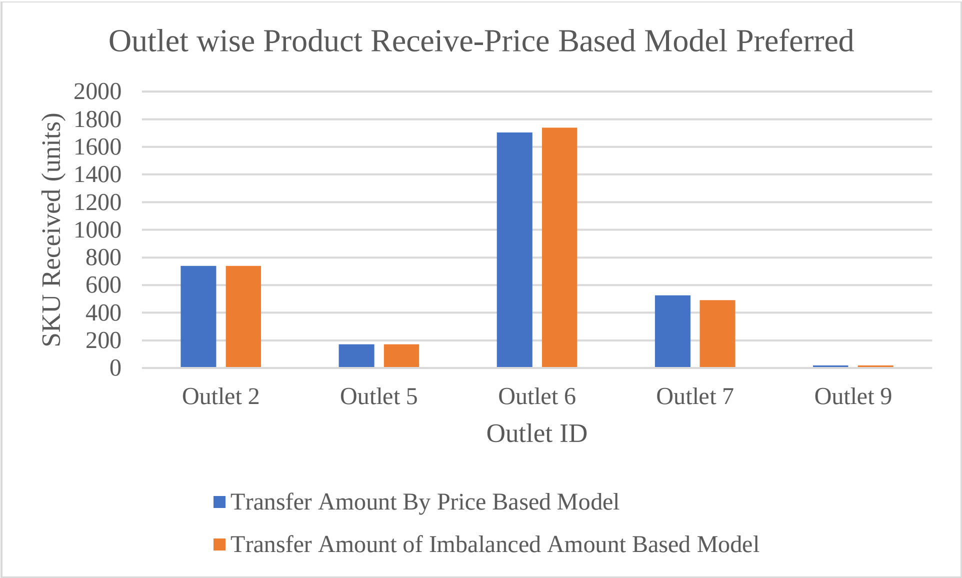
```
Paired T for Red - N

              N      Mean  StDev  SE Mean
Red          15  43874000   8281     2138
N            15  43420000   5345     1380
Difference   15    454000   7368     1902


95% CI for mean difference: (449920, 458080)
T-Test of mean difference = 0 (vs ≠ 0): T-Value = 238.65  P-Value = 0.000
```

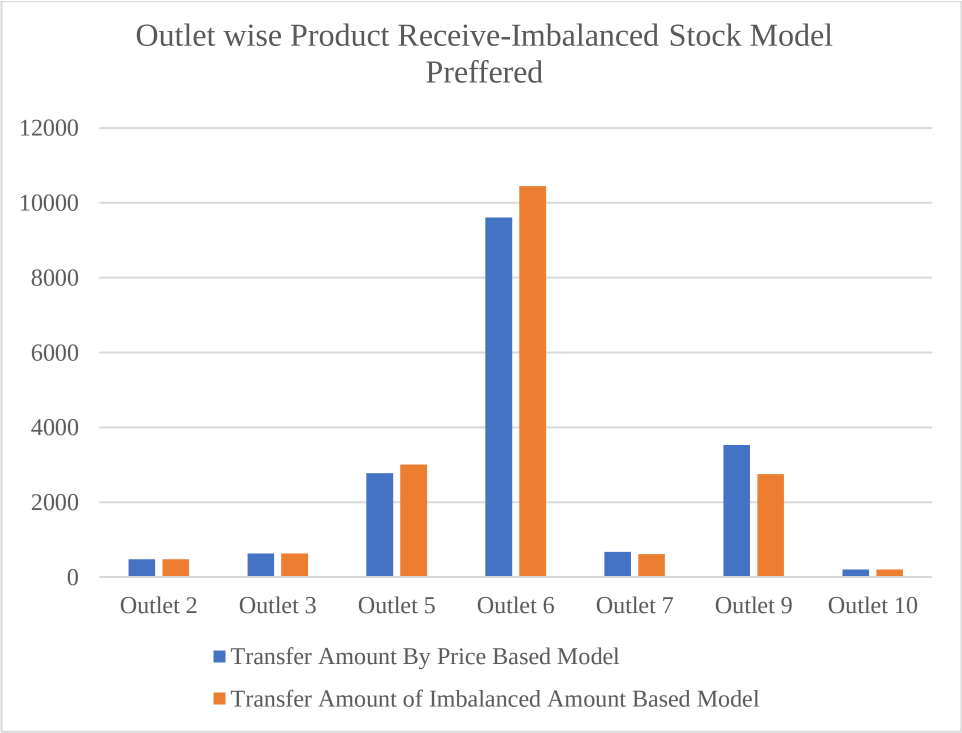
Class B

```
Paired T for Red - N

              N      Mean  StDev  SE Mean
Red          15  14602000   4140     1069
N            15  14464667   5164     1333
Difference   15    137333   4577     1182


95% CI for mean difference: (134798, 139868)
T-Test of mean difference = 0 (vs ≠ 0): T-Value = 116.20  P-Value = 0.000
```

Class

Figure A1. Number of SKU units received for Price based and Imbalanced stock based preferred model.



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