Multi-Echelon Inventory Management for a Fresh Produce Retail Supply Chain

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Abstract

Perishability presents a challenging problem in inventory management for the fresh produce industry since it can lead to higher inventory costs and lower service levels. If a supply chain has multiple echelons, that further complicates the issue since companies have an added risk of not having the right amount of product at the right location at the right time. We conduct our research on Chiquita's Fresh Express supply chain. We analyze the impact of perishability on total relevant costs. Our research focuses on determining the optimal inventory policy for the system considering inventory holding costs, shrinkage costs, lost sales costs, forecast accuracy and service levels. We test the sensitivity of the system with respect to forecast errors and the transportation lead time. We developed a discrete-event simulation model using Arena software to conduct the research.

Our research demonstrates that by lowering the current target on-hand inventory levels at the distribution center and retail stores, inventory holding costs and shrinkage costs are reduced significantly. Under the optimal inventory policy, the system can save 31% in costs, improve the item fill rate at the distribution center, reduce the total shrinkage volume, and maintain high service levels of more than 95% at the retail stores. Our sensitivity analysis shows that the system is very sensitive to the forecast errors. Additionally, we recommend keeping the transportation lead time as low as possible to maximize the products' lifetime at the retail stores. Reducing the forecast errors or the transportation lead time would reduce the total relevant cost of the system while improving the item fill rates across the supply chain.

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1 Introduction

Chiquita Brands International, Inc. is a leading international marketer and distributor of fresh food products including bananas, various other fruits, and blends of packaged green salads. The company markets its products under the Chiquita ® and Fresh Express ® brands and other related trademarks. The perishable nature of Chiquita's products presents a challenge in managing the inventory as keeping track of the age of inventory is challenging. The multiple layers of inventory locations throughout the supply chain further complicate the issue of inventory management. Additionally, the volatile demand of the Fresh Express line and the inexperienced produce buyers at the retail level make the issue even more challenging. Developing better order and inventory policies requires an understanding of the impacts of the product's limited lifetime, the interactions of multiple inventory locations, and the trade-off between the relevant costs and the customer service levels.

The objective of our research is to quantify these impacts and trade-offs to help Chiquita's management to develop a better inventory policy that minimizes the costs and at the same time achieves the desired customer service levels. The management at Chiquita is considering changing the existing inventory and order policies in order to minimize out-of-stock and spoilage for its Fresh Express line of packaged green salads. Due to confidentiality concerns, all the numbers used throughout the thesis are for illustrative purposes only and are not necessarily indicative of actual performance at Chiquita.

1.1 Problem Description

While most inventory models assume that items can be stored indefinitely to meet future demand, in reality not all items have an infinite lifetime. Perishable inventory is defined as items that decay in storage; as time elapses, the items gradually become partially or entirely unsuitable for consumption. Typical examples of perishable inventories include fresh produce, photographic films, drugs, and blood. Perishability is typically classified into two categories: fixed lifetime and random lifetime. A product with a fixed lifetime has a pre-determined lifetime, meaning after a specific number of periods, the product becomes unusable and must be discarded. In reality, many products have random lifetimes because the exact lifetime cannot be pre-determined. For example, a product with a random lifetime could decay exponentially, implying that a fraction of the inventory is lost each period. Products could also have a random lifetime, a variable with a specific probability distribution (Nahmias, 82).

Perishability presents a challenging problem for inventory management. Perishability can lead to increases in four costs:

- Inventory shrinkage costs: costs due to inventory that must be discarded because of spoilage
- Shortage costs: lost sales costs due to inventory stock out caused by perishability
- Ordering costs: higher ordering costs due to more frequent purchases to counter the perishable nature of the products
- Inventory carrying costs: higher inventory holding costs due to the lack of understanding for the proper inventory level

In order to effectively manage inventory costs, supply chain managers must keep track of each age level of the inventories. However, keeping track of the age of each unit at each period may be difficult and impractical for most companies due to extensive computations that are involved. Given this complexity, optimizing the system is incredibly difficult.

Most supply chain networks have a series of inventory locations; rarely is there only one inventory location that ships to the final destination. Supply chain networks with multiple layers of inventory locations are referred to as multi-echelon supply chains. Having inventory in multiple layers may have benefits, such as shorter lead time for the final destinations, better service for the final destinations, and lower transportation cost through shipment consolidation. However, since available inventory is divided and stored at more than one location, a multi-echelon system may have a higher risk of not having the right amount of product at the right location at the right time (Taylor, 2004). In order to have an effective inventory policy, one must determine the dependencies between echelons and the proper inventory level required at each echelon.

1.2 The Case of Chiquita's Fresh Express

Chiquita's Fresh Express network represents a complex multi-echelon perishable supply chain. The raw materials of Fresh Express products are harvested from either California or Arizona, depending on the season, and then shipped across the United States to Chiquita's plants to be processed and packaged. The cycle time for raw materials to be turned into packaged salads is typically two or three days. Once the salads are packaged, they are usually shipped to Chiquita's customers' distribution centers (DC) within two days. Typically, the products stay in customers' DCs no longer than two days before they are shipped again to the retail locations. The total lead time is merely four to six days for Chiquita to harvest the vegetables from the field, ship the vegetables across the nation to be processed into packaged salads, ship the packaged salads to customers' distribution, and deliver them to the retail locations.

Additionally, the high demand volatility of packaged salads further complicates the issue of managing Fresh Express inventories. The sales volume of packaged salads is heavily influenced by retail promotions; a high percentage of Fresh Express' volume is sold under promotions. The retailers frequently lower the prices for two purposes: to increase sales volume and store traffic as a part of the marketing efforts, and to clear out aging inventory to minimize the risk of potential loss of unusable inventories.

These three issues (perishability, the multi-echelon system, and the high demand volatility) combine together make inventory management for Fresh Express extremely difficult. Inventory is often managed based on buyers' experience and intuition, which is by nature subject to human error. As a result, Chiquita and the retailers often carry excessive inventories to try to achieve a high service level. A large percentage of the inventory at the retailers' warehouses and the retail stores is considered no longer fresh for consumers to purchase and needs to be discarded. Hence, Chiquita would like to know whether or not a better multi-echelon inventory management system can be developed for its Fresh Express products. Specifically, Chiquita is interested in answering the following questions:

1) What are the parameters for optimal inventory management depending upon forecast accuracy, inventory carrying cost, product perishability, lost sales and inventory shrinkage costs?
2) What is the trade-off between service level and inventory costs?
3) What is the impact of increased forecast accuracy on inventory-related costs?

1.3 Research Motivation

The analysis of multi-echelon perishable systems is not as well developed as that of single-echelon perishable systems. Most research for multi-echelon perishable systems has assumed that the product has a fixed lifetime at each echelon, the system uses a continuous review inventory policy (inventory is reviewed continuously, and an order is placed whenever the inventory reaches below a particular level), and the system allows backorders (unfilled orders can be fulfilled in the future). However, Chiquita's Fresh Express supply chain is a multi-echelon system with products that have random lifetimes. Also, the system uses a periodic review inventory policy (inventory is reviewed periodically, and an order may be placed based on the inventory level after each review) and unfilled orders are considered lost sales. Therefore, the assumptions used in most research are not applicable to Chiquita's Fresh Express supply chain.

In this thesis we develop an inventory management system that simulates Chiquita's Fresh Express supply chain. Our research focuses on identifying ways to minimize out-of-stock and inventory shrinkage while maintaining high service levels, which are common goals that most companies share. The objective of this research is to address the three key questions posed in the previous section by Chiquita and provide recommendation on multi-echelon inventory systems for fresh produce supply chains.

1.4 Research Scope

This research uses Chiquita's Fresh Express supply chain as a case to develop a better understanding of the challenges that fresh produce companies may face in managing their inventories. In order to simulate Chiquita's supply chain, the research assumes that all products have random lifetimes that decay according to a shrinkage probability and have maximum lifetimes of 14 periods (days). The system uses a periodic review and all backorders in the system are considered lost sales. These assumptions are based on system descriptions provided by Chiquita personnel.

Our analysis focuses on one supply chain of Chiquita's Fresh Express line, which starts at Chiquita's plant in Georgia. This plant is located across the nation from the sources of raw materials. We chose this location because it serves one of Chiquita's biggest customers, which we refer to as ABC, Inc. (ABC). For the next echelon, we chose ABC's DC located in Florida, because this DC is served by Chiquita's Georgia plant and has one of the highest sales volumes. Figure 1.1 illustrates the physical locations of the sources of raw materials, Chiquita's plant in Georgia, and the customer's DC in Florida.

Figure 1.1: Chiquita's Fresh Express Supply Chain

Additionally, we chose two retail stores that have typical characteristics shared by most retail locations served by the customer's DC. We chose this supply chain because it represents a large portion of Fresh Express' volume and possesses common characteristics shared by Fresh Express' other supply chains with other customers. The physical structure of this supply chain (one plant, followed by one DC, followed by multiple retailers) is common for Chiquita. Therefore we expect the results of our research to be applicable to Fresh Express' other supply chains and to provide insights to other companies that have similar supply chain structures.

1.5 Thesis Structure

The thesis continues as follows. In Chapter 2, we provide a review of the relevant literature and methodology used in other research. In Chapter 3, we provide the methodology, various assumptions and the conceptual flow of our research and model. In Chapter 4, we document the model, the results of each simulation run, and a detailed analysis for each scenario in the testing plan. Finally in Chapter 5, we conclude by providing overall observations and implications of our research, key insights, and recommendations for future research.

2 Literature Review

In order to determine the best approach for modeling Chiquita's supply chain, we surveyed the academic literature to understand analytical approaches on how to develop an inventory policy for perishable products in multi-echelon systems. The literature available on inventory systems for perishable items varies by a combination of four assumptions or considerations: deterministic or stochastic demand, fixed or random lifetime, single period or multiple period of product lifetime, and single or multiple echelons. In Section 2.1, we review the analytical approaches for single echelon inventory management, and in Section 2.2, we review the analytical approaches for multi-echelon inventory management systems. Although the amount of literature on perishable inventory available is abundant, none of the models have assumptions that match well with the reality in Chiquita's business model.

Due to the complexity and limitations involved in implementing an analytical model for Chiquita's Fresh Express supply chain, we also surveyed literature on simulation methodologies to better understand whether a simulation model would be suitable for the scope of our research. This survey confirmed that simulation is a practical approach to model a complex system, and we present relevant literature on simulation methodology in Section 2.3.

2.1 Perishable Inventory Management for Single-Echelon Systems

The origin of all perishable inventory system analysis can be traced back to the simple Newsboy model, in which the product lifetime is exactly one period and the order quantity decision is independent in each period. Both Van Zyl (1964) and Nahmias and Pierskalla (1973) derived optimal policies for products with fixed lifetimes of two periods and stochastic demand. Van Zyl derived dynamic programming functional equations that consider ordering costs and shortage costs. Nahmias and Pierskalla approach the issue by considering the outdating and shortages costs. Fries (1975) and Nahmias (1975) extended the literature to consider products with lifetime beyond two periods with stochastic demand.

As Nahmias (1982) explains, the main challenge in managing perishable inventory lies in tracking inventories of different age-groups at each position in the supply chain. Thus, when a product lifetime becomes greater than three periods, models become multi-dimensional and computationally extensive. Because computation of optimal policies for such systems becomes impractical for everyday business decisions, approximations are potentially good alternative choices. Cohen (1976) developed an optimal critical number policy by using the stationary distribution of stock levels and then finding the critical number of periods' worth of demand to order that minimizes the expected cost. However, when the product lifetime is greater than three periods, obtaining the stationary distribution of the starting stock becomes very challenging. Nahmias (1976) eased the computation by developing a heuristic critical number approximation approach for products with fixed lifetime and stochastic demand. This approximation model was proven to result in costs that are generally less than one percent higher than the global optimal cost. Nahmias (1977) and Nahmias (1978) extended the approximation technique for products with random lifetimes and for systems with a set-up cost.

2.2 Perishable Inventory Management for Multi-Echelon Systems

Clark and Scarf (1960) were the first to model the optimal policy for a multi-period, multi-echelon inventory system subjected to stochastic demand. Since then extensive research has been done on multi-echelon inventory systems, yet research on multi-echelon inventory systems for perishable products is still limited due to its complexity. Yen (1965) was the first to consider a perishable inventory policy in a multi-echelon system using a stationary critical number order policy. Yen assumed that each regional location always receives the same proportional age of inventory according to its order quantity. Cohen, Pierskalla and Yen (1981) discussed periodic review policies which focus on inventory allocation for a multi-echelon system that differentiates products by age. Their model did not remove the over-age stock from the inventory, but the penalty cost associated with over-age stock was set sufficiently high to ensure small volumes of over-age stock in the system. Matta and Sinha (1995) investigated the periodic review of a two-echelon system for non-perishable products. Kanchanasuntorn and Techanitisawad (2006) extended Matta and Sinha's model to include perishable items with fixed lifetimes using an approximate periodic review policy.

There is limited research on multi-echelon inventory management systems for perishable products with a maximum fixed lifetime beyond three periods and a random lifetime with decay according to a probability distribution. To our knowledge, when the scope is further narrowed down to a multi-echelon system that uses periodic review and considers lost sales, shrinkage, stochastic demand, non-zero lead-times and forecast accuracy, no relevant models have been published. Because of this and the fact that analytical approaches are generally complex and difficult to implement for day-to-day operations, we felt that simulation would be a better approach to capture Chiquita's supply chain. In Section 2.3, we discuss the simulation modeling briefly.

2.3 Simulation

Although an analytical approach is generally the preferred method in developing inventory policies, it becomes intractable when the states of the inventory are too complex to be expressed in equations. While analytical approaches may be impractical for a complex inventory system, computer simulation modeling can help to keep track of the states of the inventory and monitor the interaction between the changes in each echelon of the supply chain.

White and Ingalls (2009) define a model as an entity that is used to represent some other entity for some defined purpose. Models are used when direct investigation of the actual system is impractical or expensive. They describe simulation as an experimental approach to studying models. A simulation modeler first creates a model that imitates the behaviors of the actual system, then experiments with the models with different inputs to observe the behavior, and at last tries to understand, summarize, and generalize that behavior. Because simulation modeling helps researchers understand the behavior of complex models in a cost-effective way, simulation has gained popularity and been widely used for academic research as well as for solving real-world problems. For example, Snyder and Shen (2006) used simulation models to gain insights on the differences between supply uncertainty and demand uncertainty in multi-echelon supply chains. Schmitt and Singh (2009) constructed a model that helps a large consumer products company to understand its vulnerability to disruption risk and the potential impact to customer service.

Using a simulation model also helps to test the impact of increases in variability, widely known as the *bullwhip effect* phenomenon, on the forecast-driven multi-echelon system. Simchi-Levi (2000) defines the *bullwhip effect* as the increase in demand variability as the demand travels up in a supply chain. The *bullwhip effect* is caused by multiple factors, including order batching and miscommunication of customers' true demand throughout the supply chain.

Law (2003) provided a concise yet comprehensive guide on conducting a successful simulation study. He discusses several key steps to developing a successful simulation study. These key steps are:

1. *Formulate the problem.* Simulation modeling typically starts with formulating the problem, defining the overall objective of the study and listing the specific questions that the study needs to address.
2. *Construct a conceptual simulation model.* Once the objective is clearly defined, modelers can begin constructing the conceptual model. Modelers first need to collect information to understand the system structure, and collect data to specify model parameters and probability distributions. With a good understanding of the system structure and model parameters, modelers can compile all the information to create a conceptual model.
3. *Validate the conceptual model.* Once a conceptual model is built, all parties involved should validate the model by walking through the conceptual model to ensure it is an accurate representation of the system.
4. *Program the model.* With the granted validity of the model, modelers can begin to program the conceptual model in programming language or in a commercial simulation-software product.
5. *Validate the programmed model.* While programming the model, modelers should validate the model with the existing system and perform sensitivity analyses to gain insights on the model factors
6. *Conduct and analyze simulation experiments.* This step is to determine the details on how to run the simulations, such as simulation run length, length of the warm-up period, and the number of independent runs. With all the steps completed, modelers can start conducting simulation runs and analyze the results of each run.

7. *Document and present the simulation results.* After an adequate number of simulation runs has been conducted, modelers should document the model and the simulation results in details and in a fashion that is easy to understand for the targeted audience.

2.4 Summary

Given the complex challenges that Chiquita's Fresh Express supply chain faces, we determined that a simulation approach is more suitable than an analytical approach for the purpose of this research. We used Law's approach as the reference guidelines for developing our simulation model and describe that process in Chapter 3, and we document and present the simulation results in Chapter 4. The details of the conceptual flow and user manual can be found in Appendix A and B respectively.

3 Methodology

In this chapter, we outline how we developed a simulation model using Arena Simulation Software developed by Rockwell Automation to capture Chiquita's Fresh Express multi-echelon supply chain. We explain how we used the simulation model to better understand the impact of perishability on costs and service levels. We include additional details on the conceptual flow of simulation model in Appendix A and the user guide in Appendix B.

In order to develop a simulation model that replicates the Fresh Express supply chain, we first investigated the standard practices, performance metrics, and challenges that exist in the supply chain. We determined the assumptions that we must make in order to develop the model and the data that we would use to run the simulation. After we gained a good understanding of the key elements and data available in the Fresh Express supply chain, we began to build a conceptual model to capture all the processes involved in this multi-echelon supply chain. Once the conceptual model was built and validated, we transformed the conceptual model into a simulation model in Arena. After we programmed the simulation model in Arena and created a testing plan, we were ready to conduct simulation runs to investigate the optimal inventory policy and the sensitivity of the costs.

We use several abbreviations throughout this chapter and subsequent chapters. The complete list of abbreviations and their definitions can be found in Table C.1 of Appendix C. Recall that due to confidentiality concerns, all the numbers used throughout the thesis are for illustrative purposes only and are not necessarily indicative of actual performance at Chiquita.

3.1 Problem Formulation

Using Law's approach as our reference guideline (Law, 2003), discussed in Section 2.3, we started our research by interviewing the supply chain managers at Chiquita to understand the business processes, the material and information flows, and the challenges facing the Fresh Express product line. As mentioned in the Introduction, we focused our analysis on Chiquita's plant in Georgia, ABC's DC in Florida, and ABC's retail stores served by the Florida DC. We gathered information on the existing inventory replenishment process and the performance metrics, namely the inventory shrinkage and the service levels, to understand the standard practices of this supply chain. We then determined the necessary assumptions that we needed to make to build our simulation model. We also mapped out what data is available and how the data should be used in the model. The details of these steps are discussed in the following sections.

3.1.1 Inventory Replenishment

At the end of each day, each retail store reviews its inventory position (IP) and places an order to maintain an inventory level of two or three days of on-hand inventory. If inventory is available, the DC typically will fulfill each order within 24 hours. The replenishment of the DC's inventory is managed directly by Chiquita through ABC's Vendor Management Inventory (VMI) system. Supply chain managers at Chiquita review the IP at ABC's DC five times a week and place appropriate orders to Chiquita's plant. Presently, Chiquita reviews the DC's IP every day except on Wednesdays and Fridays. For the purpose of further discussions, we will refer the activities that Chiquita performs (as a part of VMI) on behalf of the DC as the DC`s activities.

3.1.2 Inventory Shrinkage

All the Fresh Express products carry a production date stamp. After 14 days from the production date, the product is considered no longer fresh for a consumer to purchase. At the end of each day, each ABC store removes and disposes any products produced 14 days ago from the shelf or the inventory and considers the loss as inventory shrinkage costs.

Additionally, each store also removes and disposes any products that age more quickly than the expected 14-day of shelf life based on their appearance. The probability of a product needing to be disposed prior to reaching the full 14 days increases as it ages. Based on the inputs received from Chiquita supply chain managers and the results from our initial simulation runs, we determined that an exponential growth probability best matches the shrinkage that Chiquita experiences in reality. More information on this distribution is provided in Section 4.1.

The inventory shrinkage costs at the retail stores are absorbed by ABC itself, but high inventory shrinkage costs could potentially damage the business relationship between ABC and Chiquita. Currently, the total shrinkage at the retail stores is between 10 to 13% of the total shipment volume from the DC to the retail stores, the goal is to reduce the shrinkage volume to 8.5%.

At the DC, ABC has mandated an aging inventory shrinkage policy, in which ABC does not ship any products that have less than six days of shelf life remaining from the DC to the stores. ABC removes and discards any products produced eight days ago from inventory, and it charges the loss back to Chiquita. Thus both ABC and Chiquita share a common interest in controlling the inventory levels in a way that the potential inventory shrinkages are minimized at both the retail stores and the DC.

3.1.3 Service Levels

Although both Chiquita and ABC would like to minimize inventory shrinkage, they also need to maintain sufficient inventory levels as both of them strive for high customer service levels. The target average item fill rate (IFR) at the DC is 95%, which is calculated as the total demand fulfilled by the DC over the total quantity requested by each retail store on a daily basis. Any unfulfilled demand at the DC is recorded against Chiquita's performance, and any unfulfilled demand at the retail store is considered lost sales.

Presently ABC uses an "In Stock or Out of Stock" binary metric to measure the service levels at the retail stores. ABC considers an item at the store to be "In Stock" when the store has enough inventory to fulfill the daily average demand; otherwise, it is considered "Out of Stock". For example, if 85 stores out of 100 stores have enough inventory to cover their daily demand for an item, the service level for that item is 85%. However, for a store that does not have enough inventory to cover its daily demand, the current "In Stock or Out of Stock" binary metric does not capture the partial demand fulfillment by the store. After careful consideration and discussion with Chiquita supply chain managers, we believe that an IFR would be a more appropriate metric for measuring true service levels at the retail stores. Therefore we use an IFR metric in the model and assume that Chiquita would still require a 95% IFR at the retail level.

Given the high demand volatility for packaged salads, the current forecasts generated by each store and the DC each have a mean absolute percentage error of 25%. As a result, the DC and the retail stores often have to carry excessive inventory in order to ensure a high customer service level. The main challenge for the Fresh Express supply chain is how to balance the tradeoff between potential inventory shrinkage costs, potential lost sales costs, and inventory holding costs. In order to minimize these costs, Chiquita must understand how perishability impacts the inventory levels and the dynamics between all the factors in the system.

3.1.4 Assumptions

In our model, we include two retail stores served by ABC's DC in Florida. These two retail stores could represent actual stores, or they could represent two separate demand streams aggregated from multiple stores. We assume that the Chiquita plant does not have any raw material shortage or capacity constraints at the plant; in other words, Chiquita is always able to produce and supply the quantity required by ABC's DC. Hence, Chiquita's production plant is not part of our research.

Our model replicates ABC's and Chiquita's standard ordering practices, in which the DC and the retail stores use a base-stock policy for replenishments. A base-stock policy implies a periodic review policy, in which the DC and the retail stores each have an Order-Up-To-Level (OUL) for each product. The DC places orders five times a week and the retail stores place orders every period, where a period is one day.

Our model assumes the product demand to be stochastic and normally distributed with a known mean and variance. We feel justified this assumption because the normal distribution is commonly used in many models in the literature. Additionally, the demand used in the model can represent an aggregation of multiple individual products and/or stores, and the central limit theorem states that the mean sum of a large number of random variables will have a normal distribution. Additionally, we assume that the demand at each retail store is independent from each other.

We assume that a First-In-First-Out (FIFO) policy is followed for the inventory at the retail stores and the DC. A FIFO policy implies that older products are sold first to reduce possible shrinkage. Although at the retail stores certain consumers may pick younger products available from the back of the shelf over older products displayed in front, such consumer behavior is difficult to predict and too complicated to incorporate in the scope of this thesis. We also assume that the DC treats all the retail stores equally and does not prioritize a particular store over another.

The transportation lead time from the DC to the retail stores is assumed to be constant at one day (overnight), which means when the store places the order at the end of the day, if the stock is available, the order will arrive at the store the next morning, in time to be available for sale that day. The transportation lead time from the plant to the DC is assumed to be deterministic and constant for each simulation. However, it is formulated as an input parameter so that the model can test the sensitivity of the transportation lead time from the plant to the DC. Recall that the production lead time at the plant is 4 days.

3.1.5 Information Flow and Input Calculations

Figure 3.1 below illustrates the information flow and the calculations conducted using the input data specified by the user. We explain the logic below.

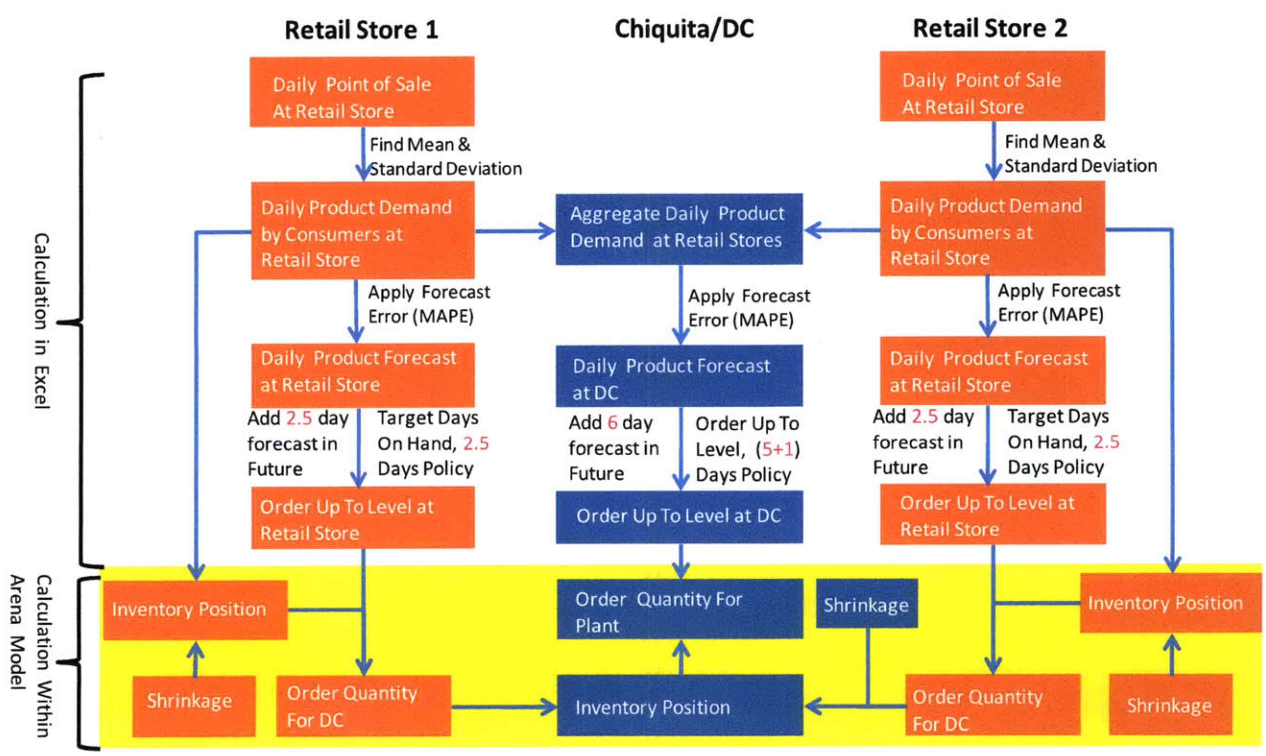

Figure 3.1: Information Flow and Input Calculations

We programmed Microsoft Excel to generate the random daily demands for each retail store using the mean and standard deviation obtained from the Point-Of-Sale (POS) data. The random daily demand is used as the actual daily demand realized at each store. We then apply the forecast error (mean absolute percentage error, MAPE) to this demand and errantly obtain the daily demand forecast.

We create the daily demand forecast using a uniformly-distributed random multiplier. We generate the multiplier using a minimum and maximum value range. Since the forecast errors can be either positive or negative, the maximum value is two times the given MAPE, and the minimum value is negative two times the given MAPE. Using Excel, uniformly-distributed random numbers are generated between the minimum and maximum values. This means the average of the multiplier is equal to zero but the average of the absolute value of the multiplier is equal to the MAPE. This random number is multiplied by the daily demand, thus providing the daily demand forecast. By measuring the forecast accuracy weighted across the total volume, we verify if the given forecast error was correctly translated. Even though in our calculation we use the daily demand to produce the demand forecast, this daily demand forecast is used in the model as the forecasts generated by each store prior to the arrival of the actual daily demand.

The OUL for each retail store is determined by the target days of on-hand inventory. The user inputs the target number of days of inventory, and then the actual daily OUL is calculated by adding the demand forecast for that number of days forward. For example, if the inventory policy at the retail store is 2.5 days of on-hand inventory, the OUL would be the sum of the demand forecast for the next 2.5 days. Depending on the IP at the time of the review, each retail store would place an individual order equal to the OUL minus the IP, or equal to zero if that subtraction yields a negative value. The IP is the on-hand inventory level after satisfying demand minus the shrinkage. Since the order placed at the end of the day would arrive the next morning, there is no shipment in transit needed to be included in calculating the IP for the retail stores.

To calculate the daily demand forecast at the DC, we apply the forecast error to the aggregated daily demand from the retail stores. The actual daily demand realized at the DC is the aggregated total of individual orders from each retail store.

The OUL for the DC is determined using the same technique used to calculate the OUL for the retail stores. The OUL for the DC is determined by the target days on-hand inventory at the DC and the total lead time from placing the order to Chiquita's plant to the delivery of the shipment. For example, if the target on-hand inventory at the DC is one day and the lead time for Chiquita to fulfill an order is five days, the OUL at the DC would be the sum of the demand forecast for the next six days. Depending on the IP, the DC would place an order equal to the OUL minus the IP, or again equal to zero if that subtraction yields a negative value. The IP for the DC is the on-hand inventory level after satisfying demand, minus the shrinkage, plus the shipments in transit to the DC.

In Figure 3.1, the numbers marked in red are input parameters that can be changed for each simulation run. The input data is generated by a user in an Excel file and the simulation model reads the data from this Excel file. The use of Excel file allows Chiquita to use the model to simulate other multi-echelon Fresh Express supply chains by simply changing the input parameters there.

3.2 Conceptual Model

The information captured during the Problem Formulation step was critical for us to understand Chiquita's supply chain system and decide the appropriate parameters, performance metrics, and level of detail for the model. Next we developed a generic conceptual model that details the logic of the system and would be applicable to most other multi-echelon systems within Chiquita.

3.2.1 Model Logic-Flow

We compiled the information captured during the interviews with Chiquita's Fresh Express supply chain managers and divided the processes into eight steps. Figure 3.2 provides a summary of the eight steps in the conceptual flow of our simulation model and we detail the logic for each step below. We explain more details of each step in Appendix A using additional flow charts.

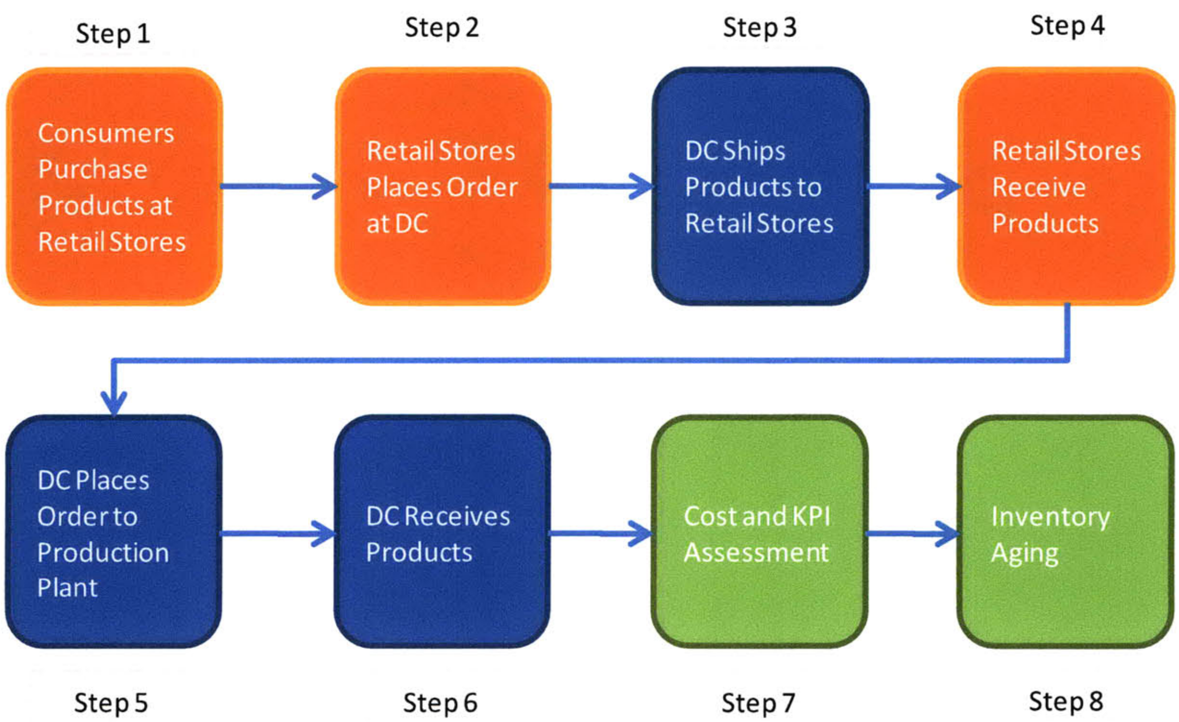

Figure 3.2: Overview of Conceptual Flow

Step 1

Consumers purchase products at the retail stores on any given day, depleting the inventory using a FIFO product policy. At the end of each day, the retail stores remove the perished products from their inventory. Since backorders are not allowed in the system, any unfulfilled consumer demand at the retail stores is considered lost sales.

Step 2

The retail stores operate on a daily periodic-review policy with an OUL. At the end of the day, each retail store checks its IP against the OUL and, if necessary, places an order to the DC.

Step 3

After aggregating the individual orders received from the two retail stores, the DC fulfills the orders using a FIFO product policy for the inventory depletion on any given day. The order fulfillment and inventory allocation for each retail store follows an order-splitting algorithm in order to allocate material logically. The detail of this algorithm used in the model can be found in Section A.1 of Appendix A.

Step 4

The products shipped from the DC are received by the retail stores the morning after the order is placed. Since the maximum shelf life of a Fresh Express product is 14 days, in the simulation model we created 14 virtual bins at the retail stores. Each bin contains Fresh Express products with distinct age-groups. For example, Bin 1 contains products that are one day old at the retail store, Bin 2 contains products that are two day old at the retail store, etc. Using the different inventory age bins, we ensure the accurate measure of shelf life, appropriate inventory transfers, and accurate calculation of shrinkage costs.

The bin age at the retail store does not include the transportation lead times; in other words, the actual shelf life of the product is its bin age at the retail store plus the transportation lead time from the plant to the DC and from the DC to the retail store. For example, if the DC has products that are 10 days old and it ships these products to the retail stores, we add that stock to the appropriate bin 11 at the retail stores as the actual shelf life must consider the one day transportation lead time from the DC to the retail store. This allows for flexibility of lead time input parameters; the model structure does not have to change in order to test different shipment lead times to the DC.

Each bin at the retail stores is assigned a shrinkage probability according to the true product age, so that every day a percentage of products in each bin may be discarded. These discarded products are unusable due to perishability.

Step 5

The DC periodically reviews its IP and creates an order to Chiquita`s plant if the IP at the DC is less than its OUL, as mentioned in Section 3.1.1.

Step 6

The DC receives a shipment from the plant according to production and transportation lead times. For example, if the total production and transportation lead time is five days, the DC will receive the shipment from the plant in the morning of the fifth day after the day when the order was placed. Using the same approach described for the retail stores, we created 14 virtual bins at the DC in the simulation model. The model conducts the inventory transfer in the same manner as was described for the retail stores in Step 4.

The model also provides flexibility for users to change the review schedule if needed. In other words, instead of reviewing the IP at the DC every day except Wednesday and Friday, the users may change the model to review the IP based on a different review schedule.

Step 7

At the end of each day, relevant costs and Key Performance Indexes (KPIs), as listed below, are captured and measured for each retail store and the DC. Lost Sales Cost is not considered at the DC because ABC operates its DC as a cost center, not a profit center. The DC charges a fee for products shipped to the retail stores, but the margin is only used to cover the warehousing and shipping expenses and not considered a sales profit. Hence, any unfulfilled demand at the DC is not charged a lost sales cost. However, as explained in Section 3.1.3, the DC does require that it maintains an average IFR of 95%.

Relevant Costs:

- Holding Costs
- Shrinkage Costs
- Lost Sales Costs

KPIs:

- Item Fill Rate
- Shrinkage Units
- Lost Sales Units
- Inventory Positions
- Inventory Levels

Different test scenarios are needed to compare these costs and KPIs, and to evaluate the trade-offs between them. The objective is to find the parameters that result in the lowest total relevant cost while satisfying the minimum IFR.

Step 8

At the end of each day, any inventory left at the retail stores and the DC ages by one day. In other words, the product shelf life remaining is reduced by one day. In the model, we shuffle inventory bins or transfer the inventory to the next bin to ensure accurate measure of product age and associated shrinkage costs. For example, at the end of the day, products that are 3 days old will now become 4 days old; products that are 4 days old will now become 5 days old, etc. Products that are 14 days old will no longer be considered fresh for consumers to purchase and will be discarded as shrinkage.

Additionally, as mentioned in Section 3.1.2, some products may age more quickly than the expected 14-day of shelf life. Thus a fraction of the products would be removed from the inventory according to the shrinkage profile.

3.2.2 Validation

After we mapped out the eight steps in the process, we presented the conceptual model to Chiquita's supply chain managers who validated that the model accurately represents the Fresh Express supply chain. We also validated the model flow with supply chain and simulation experts that include faculty and students at MIT.

3.3 Model Programming

We programmed the conceptual model using Arena, a discrete-event systems simulation software. We choose Arena because we have previous experience with the software and Chiquita already has licenses to Arena. In addition, Arena integrates well with Microsoft Office; the users can have Arena read and write from or to Excel spreadsheets, making Arena more user-friendly for day-to-day business operations.

Figure 3.3 below shows the screen shots of our simulation model programmed in Arena. The top section of the figure highlighted in red represents the logic for the retail stores. The middle portion of the figure represents the logic for the DC, The section of the figure highlighted in yellow represents the logic for the order creation process at the plant by the DC. Finally, the bottom section of the figure represents the process in Arena to read the input parameters from and write the outputs into the Excel file. Please refer to Appendix A for the more details of simulation model in Arena.

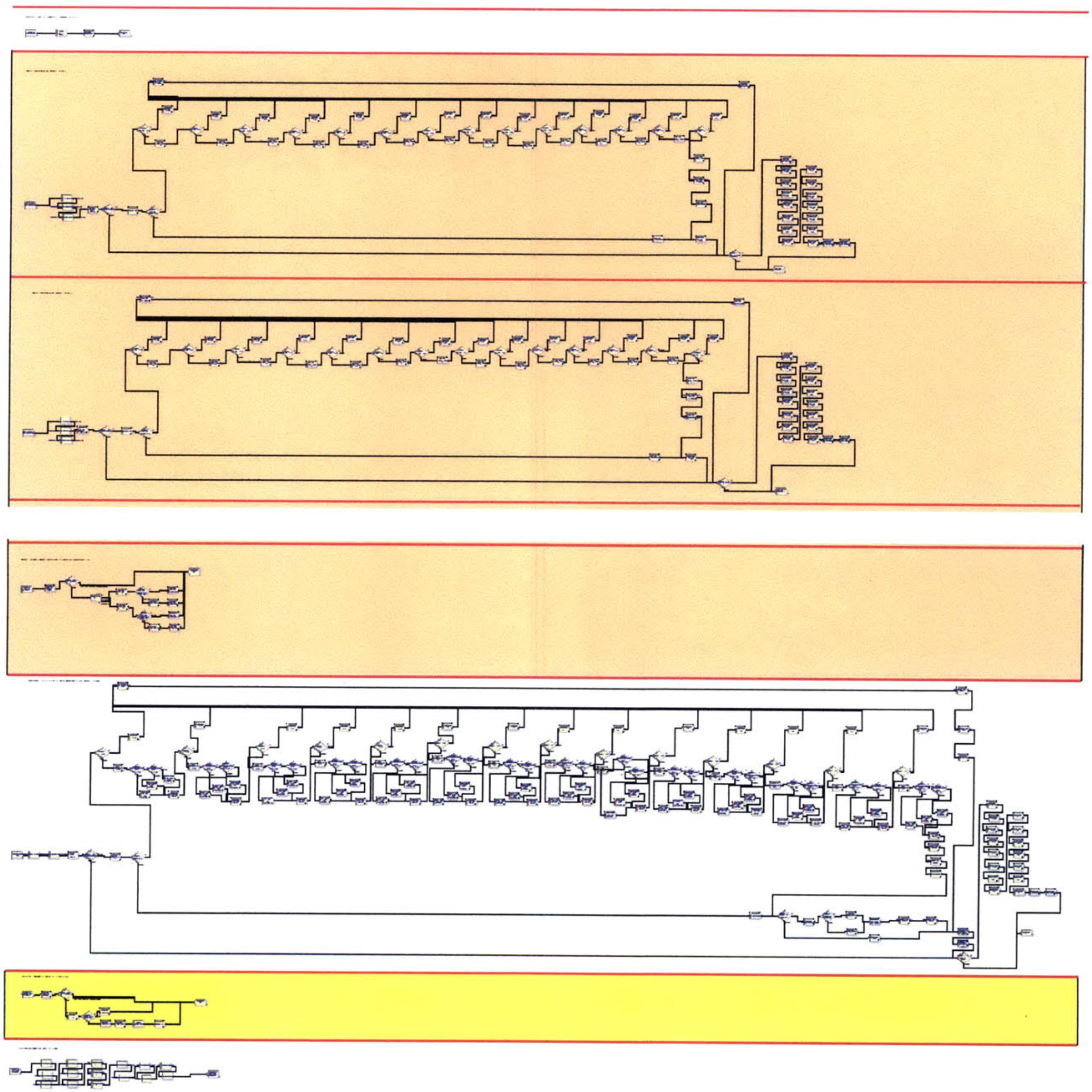

Figure 3.3: Arena Model Screen Shot

3.4 Arena Model Verification and Validation

We verified and validated the Arena model to ensure that the model sufficiently matches reality and performs according to the intended design. We verified the model by monitoring whether the model behaves as expected under different circumstances to ensure the conceptual model was correctly translated into the Arena model. For example, we raised the inventory level at the retails stores and subsequently saw higher shrinkage volumes and holding costs at the retail stores.

We validated the programmed model with supply chain managers from Chiquita and supply chain experts at the MIT. The experts were convinced that our programmed model sufficiently matches with the reality of Chiquita's Fresh Express supply chain system. Additionally, we validated the model by comparing outputs from the simulation model with historical performance metrics provided by Chiquita. We discuss the results in Chapter 4.

3.5 Simulation Testing

For our research, twenty independent simulation replications was deemed to be a sufficient number for producing results with tight enough 95% confidence intervals for performance metrics. The duration of each simulation run was 365 days, or one year. The system produced stable results after the simulation ran for thirty days, thus we determined the warm-up period for our model should be thirty days. For more details on the simulation run parameters, please refer to Appendix B.

We developed a testing plan containing different scenarios specifically to answer the three key questions described in Section 1.2. Our testing plan focused on finding the optimal inventory policies for the retail stores and the DC. Once we determined the inventory policies that resulted in the lowest total relevant costs while meeting the minimum IFR, we tested the sensitivity of the system to different percentage of forecasting errors and different transportation lead times from the plant to the DC.

We used the aggregated demands from one of Fresh Express' main product families to conduct all our simulation runs based on a suggestion by Chiquita's supply chain managers. The results generated from using this product family should provide a good overall representation of the whole Fresh Express product lines.

4 Results

In this chapter we discuss the results of our simulation runs and the interpretation of these results. Our objective was to find an optimal inventory policy that results in the lowest total relevant cost while satisfying the minimum IFR required at the retail stores and the DC. We also tested the sensitivity of the system to better understand the potential impact of some of the input parameters may have on the system under the optimal policy.

In Section 4.1 we describe the input parameters and the base scenario details. In Section 4.2 we discuss the simulation results under different inventory levels at the retail stores and at the DC and determine the optimal inventory solution. In Section 4.3 we test the sensitivity of the system under the optimal policy to the forecast errors, and in Section 4.4 we test the sensitivity of the system under the optimal policy to the transportation lead time from the plant to the DC. In Appendix D, we present additional results of the sensitivity analysis such as cost break-down at each echelon.

4.1 Input Parameters and Base Scenario

Table 4.1 lists the retail stores' input parameters and their definitions. Each of these input parameters is entered into the Excel spreadsheet by the user.

Table 4.1: Retail Stores Input Parameter Definitions

Input Parameter	Description
Demand Mean	Demand mean for product family
Demand Standard Deviation	Demand standard deviation for product family
Target days on-hand (in days)	Inventory policy/target days on-hand inventory at the retail store
Forecast Error (MAPE)	Mean absolute percentage error
Purchase Cost (per unit)	Average per unit cost for product family
Lost Sales Cost (per unit)	Average retail price per unit for product family
Inventory Holding Charge (per year)	Inventory holding cost per unit per year at the retail store
Shrinkage Cost (per unit)	Average per unit cost for product family
Order Cost (per order)	Cost to place an order to the DC
Shrinkage Probability on Day 14	% of inventory needing to be discarded at the end of day 14
Shrinkage Probability on Day 13	% of inventory needing to be discarded at the end of day 13
Shrinkage Probability on Day 12	% of inventory needing to be discarded at the end of day 12
Shrinkage Probability on Day 11	% of inventory needing to be discarded at the end of day 11
Shrinkage Probability on Day 10	% of inventory needing to be discarded at the end of day 10
Shrinkage Probability on Day 9	% of inventory needing to be discarded at the end of day 9
Shrinkage Probability on Day 8	% of inventory needing to be discarded at the end of day 8
Shrinkage Probability on Day 7	% of inventory needing to be discarded at the end of day 7
Shrinkage Probability on Day 6	% of inventory needing to be discarded at the end of day 6
Shrinkage Probability on Day 5	% of inventory needing to be discarded at the end of day 5
Shrinkage Probability on Day 4	% of inventory needing to be discarded at the end of day 4
Shrinkage Probability on Day 3	% of inventory needing to be discarded at the end of day 3
Shrinkage Probability on Day 2	% of inventory needing to be discarded at the end of day 2
Shrinkage Probability on Day 1	% of inventory needing to be discarded at the end of day 1

Table 4.2 lists the retail stores' input parameter values for the base scenario. The base scenario indicates the actual values presently observed or used in Chiquita's Fresh Express supply chain. As explained in Section 3.5, for our scenarios we use data from one of Chiquita's main product family, so the parameters are defined in Table 4.2 in terms of that product family. We conducted the simulation using these actual values, however, in Table 4.2, the pricing and cost information has been manipulated in the interest of confidentiality concerns. The existing inventory policy at the retail stores is to maintain 2.5 days of on-hand inventory. We choose one store with high demand volume and another store with low demand volume to capture the dynamics of different types of demands in the multi-echelon system. Retail Store 1 represents

the store with the high demand volume and Retail Store 2 represents the store with the low demand volume as Retail Store 1 has an average demand approximately two times that of Retail Store 2.

Table 4.2: Retail Stores' Base Scenario Parameter Values

	Retail Store 1	Retail Store 2
Input Parameters	Value	Value
Demand Mean	84	43
Demand Standard Deviation	29.2	16.4
Target days on-hand (in days)	2.5	2.5
Forecast Error (MAPE)	25%	25%
Purchase Cost (per unit)	4.88	4.88
Lost Sales Cost (per unit)	8.70	8.70
Inventory Holding Charge (per year)	12%	12%
Shrinkage Cost (per unit)	4.88	4.88
Order Cost (per order)	77.56	77.56
Shrinkage Probability on Day 14	100.0%	100.0%
Shrinkage Probability on Day 13	77.6%	77.6%
Shrinkage Probability on Day 12	60.2%	60.2%
Shrinkage Probability on Day 11	46.7%	46.7%
Shrinkage Probability on Day 10	36.3%	36.3%
Shrinkage Probability on Day 9	28.1%	28.1%
Shrinkage Probability on Day 8	21.8%	21.8%
Shrinkage Probability on Day 7	17.0%	17.0%
Shrinkage Probability on Day 6	13.2%	13.2%
Shrinkage Probability on Day 5	10.2%	10.2%
Shrinkage Probability on Day 4	7.9%	7.9%
Shrinkage Probability on Day 3	6.1%	6.1%
Shrinkage Probability on Day 2	4.8%	4.8%
Shrinkage Probability on Day 1	3.7%	3.7%

As discussed in Section 3.1.2, the shrinkage probabilities at the retail stores are best fit by an exponential growth model. This means that even for products that are less than 14 days old, an exponentially increasing fraction of inventory is discarded at the end of each day due to perishability. The exponentially growing shrinkage probabilities were obtained using Excel Solver to find the parameter that should result in 10-13% shrinkage, which is in the range of the shrinkage percentage experienced at the retail stores in reality. Equation 4.1 presents the formula for X, which is the shrinkage probability for a given age. The parameter a is determined in terms of k and the maximum value for t, the product shelf life, according to Equation 4.3. Thus Excel Solver finds only one unknown parameter, k. In our case, the maximum product shelf life is 14 days, resulting in 14 shrinkage probabilities.

$$X = ae^{kt} \text{ or } \ln X = kt + \ln a \qquad \text{(Equation 4.1)}$$

$$\mathrm{k} = \frac{\ln(\text{Maximum Shrinkage Probability}) - \ln(\text{Minimum Shrinkage Probability})}{\text{maximum } t - \text{minimum } t} \qquad \text{(Equation 4.2)}$$

$$a = \frac{\text{Maximum Shrinkage Probability}}{e\char`\^(k * \text{maximum } t)} \qquad \text{(Equation 4.3)}$$

where

t is the current age/time interval for the product (in our model, the minimum t =1 and maximum t= 14)
k is the growth constant determined according to Equation 4.2
a is determined according to Equation 4.3 and is the initial value of X

The maximum shrinkage probability is 100%. Seeking a 12% total shrinkage volume, using Excel Solver, we obtained k=0.2535 and a=0.0287, which produce the appropriate exponentially growing shrinkage probabilities from day 1 to day 14. Additionally, ABC's mandated inventory shrinkage policy at the retail stores is to discard 100% of any product that are 14 days old regardless the appearance of the product. Therefore, the value of parameter k obtained by Excel Solver is such that we have an exponentially growing shrinkage profile from day 1 to day 14 and we have 100% fixed shrinkage probability at day 14. The actual shrinkage probabilities obtained and used in the model are listed in Table 4.2.

We ran the simulation for the base scenario with these shrinkage probabilities and validated that these probabilities indeed produce aggregated total shrinkage volume at the retail stores within the valid range of 10% to 13%. Table 4.3 below indicates the observed and validated shrinkage volume for each store and their aggregate total.

Table 4.3: Retail Stores Base Scenario Shrinkage Volumes

Description	Retail Store 1	Retail Store 2	Total
Average Shipment to Store	111.34	58.92	170.26
Average Shrinkage Volume	13.09	7.77	20.86
Shrinkage %	11.76%	13.19%	**12.25%**

Table 4.4 list the DC's input parameters and definitions. Like the retailer inputs, these input parameters are also entered into the Excel sheet by the user.

Table 4.4: DC Input Parameter Definitions

Input Parameter	Description
Transportation lead time	Transportation lead time from the plant to the DC
Production lead time	Order processing and production lead time at the plant
Total Customer Lead Time (in days)	Transportation + Production lead time
Target days on-hand (in days)	Inventory policy/target days on-hand inventory at the retail store
Forecast Error (MAPE)	Mean absolute percentage error
Inventory Holding Charge (per year)	Inventory holding cost per unit per year at the DC
Purchase Cost (per unit)	DC's average per unit cost for product family
Lost Sales Cost (per unit)	Unfulfilled orders are not considered as lost sales at the DC
Shrinkage Cost (per unit)	Chiquita's average per unit cost to Chiquita for product family
Order Cost (per order)	Cost to place an order to the plant
Shrinkage Probability on Day 14	% of inventory needing to be discarded at the end of day 14
Shrinkage Probability on Day 13	% of inventory needing to be discarded at the end of day 13
Shrinkage Probability on Day 12	% of inventory needing to be discarded at the end of day 12
Shrinkage Probability on Day 11	% of inventory needing to be discarded at the end of day 11
Shrinkage Probability on Day 10	% of inventory needing to be discarded at the end of day 10
Shrinkage Probability on Day 9	% of inventory needing to be discarded at the end of day 9
Shrinkage Probability on Day 8	% of inventory needing to be discarded at the end of day 8
Shrinkage Probability on Day 7	% of inventory needing to be discarded at the end of day 7
Shrinkage Probability on Day 6	% of inventory needing to be discarded at the end of day 6
Shrinkage Probability on Day 5	% of inventory needing to be discarded at the end of day 5
Shrinkage Probability on Day 4	% of inventory needing to be discarded at the end of day 4
Shrinkage Probability on Day 3	% of inventory needing to be discarded at the end of day 3
Shrinkage Probability on Day 2	% of inventory needing to be discarded at the end of day 2
Shrinkage Probability on Day 1	% of inventory needing to be discarded at the end of day 1

Table 4.5 lists the DC's input parameter values for the base scenario. In Table 4.5, the pricing and cost information has been manipulated in the interest of confidentiality concerns as in case of the retail stores. However, we conducted the simulation using actual numbers for base scenario. The existing inventory policy at the DC is to maintain 1 day of on-hand inventory.

However, since the lead time from when the order is placed to Chiquita's plant until the order is delivered to the DC is five days, Chiquita must maintain a total six day worth of inventory in the pipeline. The DC does not check the appearance of the products, thus the shrinkage probability at the DC does not follow the exponentially growing shrinkage probability. The mandated inventory shrinkage policy at the DC is to discard 100% of any product that have less than six days of shelf life remaining regardless the appearance of the product. Therefore, any product that has less than six days of shelf life remaining has a shrinkage probability of 100%. The lost sales cost per unit is automatically zero at the DC, so it is not listed in table below.

Table 4.5: DC Base Scenario Parameter Values

	Customer DC
Input Parameters	Value
Transportation lead time (in days)	1
Production lead time (in days)	4
Total Customer Lead Time (in days, calculated by Excel)	5
Target days on-hand (in days)	1
Forecast Error (MAPE)	25%
Inventory Holding Charge (per year)	12%
Purchase Cost (per unit)	4.74
Shrinkage Cost (per unit)	4.74
Order Cost (per order)	77.56
Shrinkage Probability on Day 14	100%
Shrinkage Probability on Day 13	100%
Shrinkage Probability on Day 12	100%
Shrinkage Probability on Day 11	100%
Shrinkage Probability on Day 10	100%
Shrinkage Probability on Day 9	100%
Shrinkage Probability on Day 8	100%
Shrinkage Probability on Day 7	0%
Shrinkage Probability on Day 6	0%
Shrinkage Probability on Day 5	0%
Shrinkage Probability on Day 4	0%
Shrinkage Probability on Day 3	0%
Shrinkage Probability on Day 2	0%
Shrinkage Probability on Day 1	0%

4.2 Optimal Inventory Levels

We first determined the reasonable ranges of inventory levels at the retail stores and the DC separately. We then performed simulation tests by varying both target inventory levels simultaneously to determine overall optimal multi-echelon inventory levels. An optimal solution means the inventory levels resulted in the lowest total relevant costs for the system, which is the sum of the inventory holding costs, the lost sales costs, and the shrinkage costs, while satisfying the minimum IFR (95%) at the DC.

4.2.1 Inventory at the Retail Stores

We first ran the simulation with the base scenario inputs from Tables 4.2 and 4.5, then we held the DC inventory level constant and changed the days of on-hand inventory levels at the retail stores to understand at which values the inventory policy would result in reasonable costs yet still satisfy the minimum requirement of 95% IFR. We tested the target days on hand inventory levels at the retail stores in the increments of ½ integer values between ½ to 5 days. We tested the increments of ½ integer values because those are the smallest possible increments that ABC operates with, and we set the minimum at ½ of a day because the store would not accept complete stock-outs and always need some inventory on hand to satisfy demand.

Table 4.6 presents the total relevant costs at different values of target days on-hand inventory and Figure 4.1 and 4.2 graphs the results. We can see that if we only consider the retail stores, 1.5 days of on-hand inventory results the lowest cost and still satisfies the requirement of 95% IFR.

Table 4.6: Inventory Targets at the Retail Stores

Target OnHand Days at Retail Store	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5
DCIFR	99.1	99.6	98.4	95.3	91.7	85.9	80.5	73.3	66.1	58.2
DCIL	460.8	371.6	285.0	252.4	227.6	205.9	185.7	171.3	159.8	155.3
DCTotalRelevantCost	$144.76	$84.64	$60.06	$52.85	$47.28	$42.58	$38.25	$35.21	$32.80	$31.89
Retail1TotalRelevantCost	$130.44	$60.47	$26.99	$37.37	$50.64	$62.12	$72.27	$80.55	$87.57	$91.17
Retail2TotalRelevantCost	$67.17	$32.42	$15.05	$20.85	$28.36	$35.73	$42.56	$49.08	$55.13	$60.95
Retail1IFR	56.6	85.2	98.1	99.4	99.5	99.5	99.7	99.6	99.7	99.7
Retail1IL	3.2	27.8	53.5	89.3	123.9	153.5	181.7	204.0	223.4	234.1
Retail2IFR	57.6	85.5	98.3	99.7	99.9	99.9	99.9	100.0	100.0	100.0
Retail2IL	2.0	15.2	29.4	49.1	68.5	87.6	105.7	123.0	139.2	154.3
SystemTotalRelevantCost	$342.37	$177.53	$102.10	$111.07	$126.28	$140.43	$153.08	$164.84	$175.51	$184.02

Figure 4.1: Effects of Inventory Targets at the Retail Stores on IFR

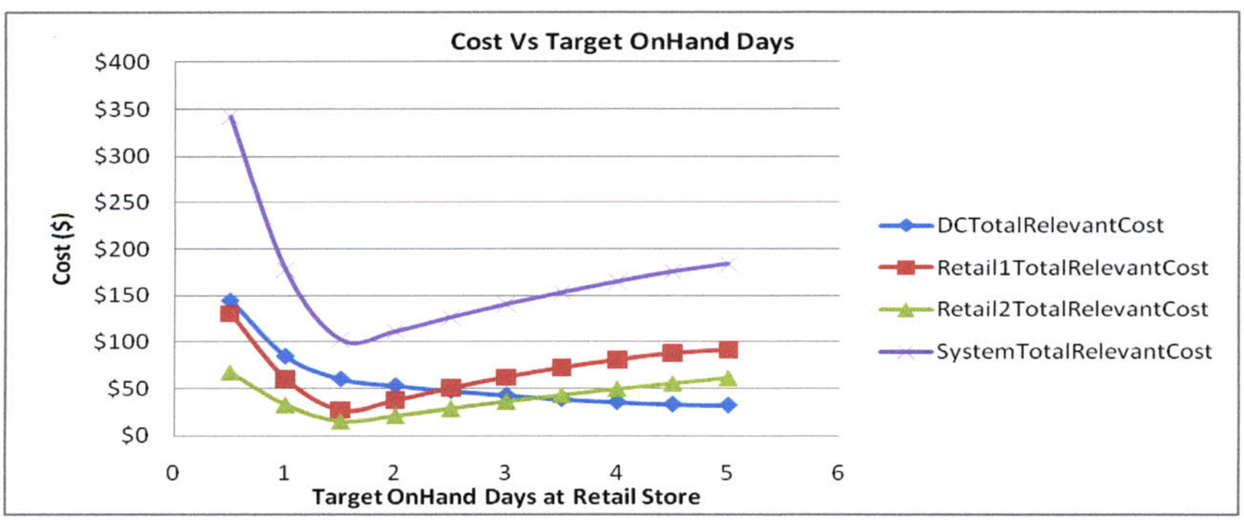

Figure 4.2: Effects of Inventory Targets at the Retail Stores on Cost

Figure 4.1 shows the effect of target on-hand inventory level at the retail stores on the IFR at each echelon. As the target on-hand inventory at the retail stores increases, the IFRs at the retail stores increases and the IFR at the DC decreases. Our analysis indicates that the IFR at the DC decreases with increasing target on-hand inventory levels at the retail stores because the stores order farther into the future with less accuracy which means the DC's ability to fill orders accurately is reduced. The shape of curve suggests that the IFRs at the retail stores remain above 95% for target on-hand days that are greater than 1.5 when the base on-hand inventory target of 1 day is used at the DC.

Considering Figure 4.2, we observe a clearly convex curve with the optimal solution achieved when the target on-hand inventory is equal to 1.5 days. For the target on-hand days less than 1.5 days, the total relevant cost for the system is higher due to higher lost sales costs at the retail stores and higher inventory holding costs at the DC. For the target on-hand days greater than 1.5, the total relevant cost for the system increases as a result of the increases of the inventory holding costs and the shrinkage costs.

Based on the costs and IFRs observed, we determined that the reasonable range for target on-hand inventory at the retail stores is between ½ to 4.5 days. This is because for target on-hand days greater than 4.5, the IFRs at the retail store remain relatively constant but the total relevant cost for retail stores and the system increases.

4.2.2 Inventory at the DC

Using the same approach described for the retails stores, we changed only the days of on-hand inventory at the DC and held the retailer levels constant at their base value (2.5 days). We tested the target inventory levels at the DC in the increments of ½ integer values between 0 to 5 days. Table 4.7 presents the total relevant costs at different values of target days on-hand inventory at the DC. Figures 4.3 and 4.4 graph the effects of inventory targets at the DC on the IFRs and the costs.

Table 4.7: Inventory Targets at the DC

Target OnHand Days at DC	0	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5
DCIFR	72.2	83.5	91.7	95.9	97.9	98.9	99.5	99.6	99.7	99.8	99.9
DCIL	138.2	172.3	227.6	280.9	340.6	397.2	456.0	511.3	568.5	622.0	675.8
DCTotalRelevantCost	$28.39	$35.49	$47.28	$58.54	$71.46	$83.96	$97.32	$110.32	$124.92	$138.24	$153.00
Retail1TotalRelevantCost	$48.69	$46.33	$50.64	$54.29	$57.87	$60.63	$63.28	$65.50	$67.65	$69.80	$71.81
Retail2TotalRelevantCost	$24.01	$25.72	$28.36	$30.26	$31.93	$33.38	$34.77	$35.95	$37.08	$38.24	$39.30
Retail1IFR	94.3	98.3	99.5	99.9	99.9	99.9	100.0	100.0	100.0	100.0	100.0
Retail1IL	87.8	109.7	123.9	129.4	131.0	131.0	130.2	129.0	127.5	126.2	124.9
Retail2IFR	98.5	99.6	99.9	99.9	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Retail2IL	58.9	65.2	68.5	69.5	69.4	68.9	68.0	67.2	66.4	65.6	64.8
SystemTotalRelevantCost	$101.09	$107.54	$126.28	$143.09	$161.26	$177.97	$195.37	$211.77	$229.65	$246.28	$264.11

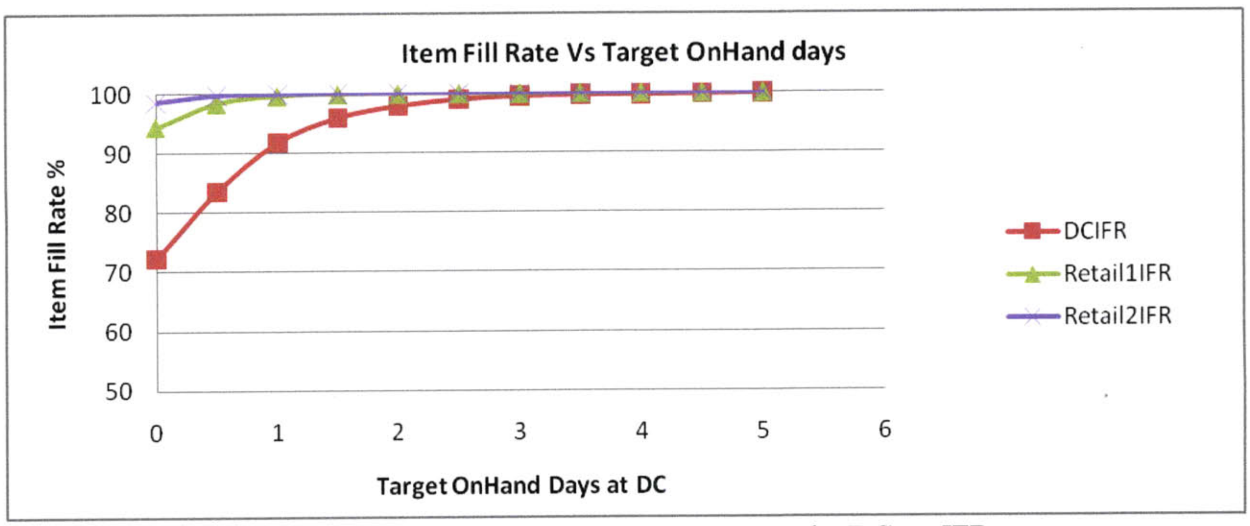

Figure 4.3: Effects of Inventory Targets at the DC on IFR

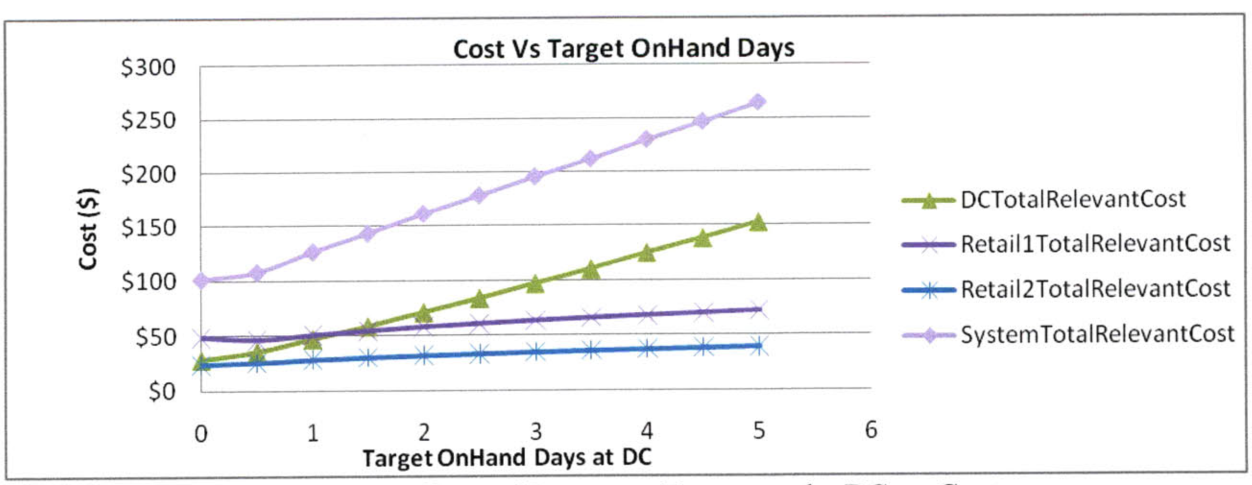

Figure 4.4: Effects of Inventory Targets at the DC on Cost

The IFRs at the DC and the retail stores both increase as the target on-hand inventory at the DC increases. The shape of curve suggests that the IFR at the DC remains above 95% for targets of on-hand days that are greater than 1.5 days.

The cost curves for both the DC and the system are increasing with the lowest-cost solution achieved when the target on-hand inventory at the DC is equal to 0 days. However, this lowest-cost solution is not feasible because it does not satisfy the constraint of a minimum 95% IFR at the DC. For the target on-hand days greater than 0, the total relevant cost for the system increases as a result of the increases of the inventory holding costs and the shrinkage costs at both the DC and the retail stores. As the target days on-hand inventory increases, the DC holds more inventory of an older age, which is then sent to the retail stores resulting in higher shrinkage costs at the retail stores.

Based on the costs and IFRs observed, we determined that the reasonable range for target on-hand inventory at the DC is between 0 to 4.5 days. This is because for target on-hand days greater than 4.5, the IFR at the DC remains relatively constant but the total relevant cost for the DC and the system shows an increasing trend. The major cost contribution comes from the increasing inventory holding cost at the DC.

4.2.3 Optimal Inventory at the Retail Stores and the DC

Although our simulation runs described in Sections 4.2.1 and 4.2.2 provide the optimal inventory policies at the retail stores and at the DC separately, these policies fail to consider the potential impact that the inventory levels have on each other. In order to find the global optimal inventory policy for the multi-echelon system, we must consider different combination of retail stores' and DC's inventory policies. As explained in Sections 4.2.1 and 4.2.2, we used the individual echelon optimization results to narrow down the number of possible combinations. We conducted simulation testing to seek the combination of inventory policies at the retail store and the DC that would result in the lowest total relevant cost for the system while still meeting the minimum 95% IFR required at the DC. Table 4.8 presents the total relevant costs at different values of target days on-hand inventory at the retail stores and the DC, with feasible solutions (those with IFRs greater than 95% at all echelons) highlighted in green. Table 4.9 presents the associated IFR at the DC. The base policy currently used by Chiquita is highlighted in red for these tables and all that follow. The results suggest that the optimal solution is for the retail stores and the DC to have target on-hand inventory levels of 1.5 days and 0.5 days, respectively. This yields the lowest total relevant costs while still having an IFR at the DC greater than 95%.

Table 4.8: Total Relevant Cost for the System

		Retail Stores								
	Target OnHand Days	0.5	1	1.5	2	2.5	3	3.5	4	4.5
	0	$305.15	$144.83	$87.47	$92.11	$101.09	$110.93	$118.47	$125.32	$131.96
	0.5	$321.63	$158.82	$87.51	$95.19	$107.54	$119.73	$129.84	$138.12	$145.11
	1.0	$342.37	$177.53	$102.10	$111.07	$126.28	$140.43	$153.08	$164.84	$175.51
	1.5	$359.43	$194.27	$116.96	$126.57	$143.09	$159.22	$174.40	$188.10	$201.55
DC	2.0	$380.02	$213.69	$134.29	$144.29	$161.26	$178.83	$195.41	$210.52	$225.36
	2.5	$397.53	$231.07	$149.78	$160.05	$177.97	$196.38	$214.01	$230.66	$246.95
	3.0	$418.13	$251.11	$167.81	$177.44	$195.37	$215.17	$232.95	$251.07	$267.95
	3.5	$435.50	$268.99	$184.18	$193.92	$211.77	$231.65	$250.54	$269.66	$287.15
	4.0	$455.81	$289.64	$203.10	$211.88	$229.65	$249.48	$268.22	$288.36	$305.88
	4.5	$474.11	$307.66	$220.06	$228.70	$246.28	$265.93	$284.97	$305.50	$323.17

Table 4.9: Item Fill Rate at the DC

		Retail Stores								
	Target OnHand Days	0.5	1	1.5	2	2.5	3	3.5	4	4.5
	0	98.9	98.4	89.0	80.4	72.2	63.2	53.9	44.6	36.8
	0.5	99.2	99.5	95.2	89.4	83.5	75.6	68.3	59.2	50.6
	1.0	99.1	99.6	98.4	95.3	91.7	85.9	80.5	73.3	66.1
	1.5	99.4	99.6	99.3	97.7	95.9	92.4	88.5	82.9	77.5
DC	2.0	99.5	99.7	99.5	98.8	97.9	95.9	93.3	89.2	84.9
	2.5	99.7	99.8	99.7	99.3	98.9	97.8	96.3	93.6	90.8
	3.0	99.7	99.8	99.8	99.5	99.5	98.9	98.0	96.4	94.5
	3.5	99.9	99.9	99.9	99.6	99.6	99.3	98.9	98.0	97.0
	4.0	99.9	99.9	99.9	99.7	99.7	99.5	99.4	98.9	98.2
	4.5	99.9	100.0	99.9	99.8	99.8	99.7	99.6	99.4	98.9

We observe that the total relevant cost for the system increases in general with respect to combination of higher target on-hand days at both the retail stores and the DC. This is because the inventory holding costs and shrinkage costs for the system increase while the lost sales costs decrease. The results for the optimal solution are highlighted in blue for all tables.

Table 4.9 also indicates other feasible solutions (cells marked in green) with more than 95% IFR at the DC, but these solutions do not yield the lowest total relevant cost for the system. Additionally, Table 4.9 indicates that at the current base policy, only a 91.7% IFR is achieved by the DC. This is consistent with current observations by Chiquita that their IFR values at the DC are not satisfactory.

Tables 4.10 and 4.11 indicate the IFRs at each retail store for different target on-hand levels. We observe that except for the combinations with cells marked in green (which indicate the feasible solution), the IFR at the retail stores deteriorates below 95%. Retail Store 2 has a higher IFR for lower values for target days on-hand inventory at the DC. This may be due to the fact that its demand is half that of Retail Store 1 and thus a larger proportion of its orders may be satisfied in full by the DC. Clearly, the target on-hand inventory policy of less than 1.5 days at the retail stores results in the higher lost sales cost for the system increasing the total relevant cost.

Table 4.10: Item Fill Rate at Retail Store 1

		Retail Stores								
	Target OnHand Days	0.5	1	1.5	2	2.5	3	3.5	4	4.5
DC	0	56.4	84.6	93.2	94.0	94.3	94.2	94.3	93.4	92.3
	0.5	56.6	85.3	97.1	98.1	98.3	98.2	98.5	98.5	98.3
	1.0	56.6	85.2	98.1	99.4	99.5	99.5	99.7	99.6	99.7
	1.5	56.8	85.1	98.3	99.7	99.9	99.9	99.9	99.9	99.9
	2.0	56.8	84.9	98.4	99.8	99.9	99.9	100.0	100.0	100.0
	2.5	56.9	85.0	98.4	99.9	99.9	100.0	100.0	100.0	100.0
	3.0	56.9	84.9	98.4	99.9	100.0	100.0	100.0	100.0	100.0
	3.5	57.0	84.9	98.4	99.9	100.0	100.0	100.0	100.0	100.0
	4.0	56.9	84.8	98.4	100.0	100.0	100.0	100.0	100.0	100.0
	4.5	56.9	84.8	98.4	99.9	100.0	100.0	100.0	100.0	100.0

Table 4.11: Item Fill Rate at Retail Store 2

	Target OnHand Days	Retail Stores 0.5	1	1.5	2	2.5	3	3.5	4	4.5
DC	0	57.6	85.6	96.1	98.0	98.5	98.9	99.0	99.3	99.6
	0.5	57.7	85.7	98.0	99.4	99.6	99.7	99.8	99.8	99.9
	1.0	57.6	85.5	98.3	99.7	99.9	99.9	99.9	100.0	100.0
	1.5	57.8	85.3	98.4	99.9	99.9	100.0	100.0	100.0	100.0
	2.0	57.8	85.2	98.3	99.9	100.0	100.0	100.0	100.0	100.0
	2.5	57.9	85.2	98.4	99.9	100.0	100.0	100.0	100.0	100.0
	3.0	57.9	85.1	98.4	100.0	100.0	100.0	100.0	100.0	100.0
	3.5	57.9	85.0	98.4	100.0	100.0	100.0	100.0	100.0	100.0
	4.0	57.9	84.9	98.3	100.0	100.0	100.0	100.0	100.0	100.0
	4.5	57.8	84.9	98.3	100.0	100.0	100.0	100.0	100.0	100.0

Table 4.12 indicates the retail stores' contribution to the total relevant cost of the system. We can see that for the cells marked in yellow, the retail stores have a bigger impact than the impact that DC has on the total relevant costs for the system. For these combinations, the major cost contribution comes from the higher inventory holding and shrinkage costs at the retail stores when each retail store's target on-hand inventory is high, or from lost sales costs when each retail store's target on-hand inventory is too low. The shrinkage costs at the retail stores become comparable to or even greater than the inventory holding costs for the combination of higher target on-hand days at both the retail stores and the DC. This holds true especially for combinations with target on-hand inventory greater than 3 days at the retail stores and 2 days at the DC.

Table 4.12: Retail Stores' Contribution to Total Relevant Cost for the System

	Target OnHand Days	Retail Stores 0.5	1	1.5	2	2.5	3	3.5	4	4.5
DC	0	65%	63%	59%	66%	72%	76%	78%	79%	80%
	0.5	61%	57%	48%	58%	67%	73%	77%	79%	81%
	1.0	58%	52%	41%	52%	63%	70%	75%	79%	81%
	1.5	55%	49%	37%	48%	59%	67%	73%	77%	81%
	2.0	52%	45%	34%	45%	56%	64%	70%	75%	79%
	2.5	50%	42%	31%	42%	53%	61%	68%	73%	77%
	3.0	47%	39%	29%	40%	50%	59%	65%	70%	75%
	3.5	45%	37%	27%	37%	48%	56%	63%	68%	73%
	4.0	43%	34%	25%	35%	46%	54%	61%	66%	71%
	4.5	42%	33%	24%	34%	44%	52%	59%	64%	69%

Table 4.13 indicates how the percentage of the shrinkage volume at the retail stores increases with respect to each combination of target on-hand days at the retail stores and the DC. The shrinkage volume for the optimal policy is 4.81% and for the base policy is 12.25%. The 4.81% of shrinkage volume under the optimal policy meets the goal of having shrinkage volume less than 8.5%. As the target days on-hand inventory at the retail stores and/or the DC increases, we observe an increasing trend in the shrinkage volume. For the combinations with target on-hand inventory greater than 3 days at the retail stores and 2 days at the DC, shrinkage volume ranges between 20 and 36%.

Table 4.13: Percentage of the Shrinkage Volume at the Retail Stores

		Retail Stores								
	Target OnHand Days	0.5	1	1.5	2	2.5	3	3.5	4	4.5
DC	0	1.38%	3.24%	3.91%	5.79%	7.44%	8.29%	8.93%	8.77%	8.84%
	0.5	1.46%	3.76%	4.81%	7.44%	9.81%	11.03%	12.40%	12.51%	12.61%
	1.0	1.48%	4.22%	5.71%	9.07%	12.25%	14.05%	16.04%	16.66%	17.47%
	1.5	1.55%	4.65%	6.42%	10.37%	14.11%	16.42%	19.02%	20.18%	21.79%
	2.0	1.59%	5.00%	7.13%	11.50%	15.70%	18.39%	21.45%	23.03%	25.03%
	2.5	1.66%	5.34%	7.76%	12.46%	16.98%	19.94%	23.51%	25.34%	27.81%
	3.0	1.68%	5.62%	8.37%	13.43%	18.24%	21.43%	25.21%	27.45%	30.21%
	3.5	1.73%	5.93%	8.91%	14.26%	19.31%	22.64%	26.69%	29.14%	32.11%
	4.0	1.76%	6.14%	9.45%	15.07%	20.35%	23.85%	28.04%	30.64%	33.72%
	4.5	1.87%	6.45%	9.96%	15.83%	21.31%	24.93%	29.20%	31.91%	35.12%

Tables 4.14 through 4.16 indicate the break-down of total relevant costs for the system across the inventory holding costs, the shrinkage costs and the lost sales costs separately. This analysis helps us to understand how the three costs are influencing the total relevant costs of the system for each combination of target on-hand days of inventory.

Table 4.14: Holding Cost for the System

	Target OnHand Days	Retail Stores 0.5	1	1.5	2	2.5	3	3.5	4	4.5
	0	$77.1	$60.1	$50.3	$54.4	$59.3	$64.5	$68.8	$71.7	$74.0
	0.5	$86.2	$72.5	$61.5	$66.6	$72.3	$78.0	$83.3	$87.7	$91.2
	1.0	$95.6	$85.3	$76.0	$81.0	$87.3	$93.2	$98.8	$104.2	$109.4
	1.5	$104.2	$96.2	$88.3	$93.4	$99.6	$105.7	$111.7	$117.5	$123.3
DC	2.0	$113.1	$107.0	$101.0	$106.0	$112.2	$118.3	$124.4	$130.3	$136.2
	2.5	$121.8	$117.2	$112.3	$117.4	$123.7	$129.7	$136.0	$141.7	$147.9
	3.0	$130.7	$127.4	$123.9	$129.0	$135.4	$141.7	$147.7	$153.6	$159.5
	3.5	$139.3	$136.9	$134.5	$140.0	$146.4	$152.3	$158.6	$164.7	$170.5
	4.0	$148.4	$146.6	$145.3	$151.1	$157.6	$163.5	$169.7	$175.7	$181.3
	4.5	$157.2	$156.2	$155.5	$161.5	$168.1	$174.0	$180.2	$186.2	$191.7

Table 4.15: Shrinkage Cost for the System

	Target OnHand Days	Retail Stores 0.5	1	1.5	2	2.5	3	3.5	4	4.5
	0	$32.8	$10.8	$11.1	$16.9	$22.6	$27.2	$30.8	$32.5	$33.8
	0.5	$40.9	$14.5	$14.2	$22.0	$29.6	$35.7	$41.7	$45.3	$48.2
	1.0	$52.2	$19.9	$18.2	$27.9	$37.3	$45.5	$53.1	$59.4	$64.9
	1.5	$61.1	$25.1	$21.7	$32.4	$43.1	$53.2	$62.5	$70.4	$78.1
DC	2.0	$72.9	$33.2	$26.2	$37.5	$48.8	$60.4	$70.9	$80.1	$89.2
	2.5	$82.1	$40.5	$30.6	$42.2	$54.0	$66.6	$78.0	$88.9	$99.0
	3.0	$93.8	$50.1	$37.0	$48.1	$59.8	$73.4	$85.2	$97.5	$108.4
	3.5	$102.7	$58.1	$43.0	$53.7	$65.3	$79.2	$91.9	$105.0	$116.7
	4.0	$113.9	$68.8	$50.9	$60.6	$72.1	$86.0	$98.5	$112.6	$124.5
	4.5	$123.2	$76.9	$57.7	$67.1	$78.1	$91.9	$104.8	$119.3	$131.5

Table 4.16: Lost Sales Cost for the System

	Target OnHand Days	Retail Stores 0.5	1	1.5	2	2.5	3	3.5	4	4.5
	0	$195.3	$73.9	$26.1	$20.8	$19.1	$19.2	$18.9	$21.2	$24.2
	0.5	$194.5	$71.8	$11.8	$6.6	$5.6	$6.0	$4.9	$5.1	$5.8
	1.0	$194.5	$72.3	$7.9	$2.1	$1.7	$1.8	$1.1	$1.2	$1.2
	1.5	$194.1	$72.9	$7.0	$0.8	$0.4	$0.4	$0.2	$0.2	$0.2
DC	2.0	$194.0	$73.5	$7.0	$0.7	$0.3	$0.2	$0.1	$0.1	$0.0
	2.5	$193.6	$73.4	$6.9	$0.4	$0.2	$0.1	$0.0	$0.1	$0.0
	3.0	$193.6	$73.7	$6.8	$0.3	$0.2	$0.1	$0.1	$0.0	$0.0
	3.5	$193.5	$73.9	$6.8	$0.2	$0.1	$0.1	$0.1	$0.0	$0.0
	4.0	$193.6	$74.3	$6.9	$0.2	$0.0	$0.0	$0.0	$0.0	$0.0
	4.5	$193.7	$74.6	$6.9	$0.2	$0.0	$0.0	$0.0	$0.0	$0.0

4.2.4 Comparison of Base and Optimal Solutions

In Tables 4.17 and 4.18 we compare the statistics for the KPI's for the base policy and the optimal policy. We ran the simulation for twenty independent replications or iterations to obtain reliable results. An explanation for the content of the columns is as follows:

i. **Average:** This value indicates the average for the output variable over all twenty iterations.

ii. **Half-Width:** This value helps to determine the reliability of the results for the output variable from all twenty iterations. This number is half of the 95% confidence interval for the true mean of the given KPI. Thus the output indicates that the true mean is within the range of the observed sample mean ± the reported half width.

iii. **Minimum Average:** This value indicates the minimum average value for the output variable from any of the twenty iterations.

iv. **Maximum Average:** This value indicates the maximum average value for the output variable from any of the twenty iterations.

v. **Minimum:** This value indicates the absolute lowest value observed for the output variable across all twenty iterations.

vi. **Maximum:** This value indicates the absolute highest value observed for the output variable across all twenty iterations.

Table 4.17: Results for Base Policy

	Base Policy Results (1 day at DC, 2.5 day at Retail Stores)					
VariableName	**Average**	**Half Width**	**Minimum Average**	**Maximum Average**	**Minimum Value**	**Maximum Value**
DCTotalRelevantCost	$47.28	$1.20	$41.35	$51.00	$0.00	$546.95
Retail1TotalRelevantCost	$50.64	$1.12	$46.04	$54.22	$0.03	$369.59
Retail2TotalRelevantCost	$28.36	$0.56	$26.00	$30.09	$0.41	$151.76
SystemTotalRelevantCost	$126.28	$2.77	$113.39	$134.68	$3.00	$595.31
DCHoldingCost	$46.71	$1.14	$41.29	$49.96	$0.00	$193.33
DCLostSalesCost	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
DCOutdateCost	$0.57	$0.29	$0.00	$2.05	$0.00	$472.10
Retail1HoldingCost	$26.16	$0.53	$24.19	$28.17	$0.00	$81.40
Retail1LostSalesCost	$1.45	$0.39	$0.05	$3.24	$0.00	$369.59
Retail1OutdateCost	$23.04	$0.59	$20.55	$25.04	$0.00	$83.24
Retail2HoldingCost	$14.47	$0.24	$13.63	$15.38	$0.00	$43.81
Retail2LostSalesCost	$0.22	$0.09	$0.00	$0.62	$0.00	$151.76
Retail2OutdateCost	$13.67	$0.31	$12.28	$14.68	$0.00	$56.92
DCIFR	91.74	0.59	89.45	93.94	0.00	100.00
Retail1IFR	99.53	0.12	99.07	99.98	0.00	100.00
Retail2IFR	99.85	0.06	99.52	100.00	0.00	100.00

Table 4.18: Results for Optimal Policy

	Optimal Policy Results (0.5 day at DC, 1.5 day at Retail Stores)					
VariableName	**Average**	**Half Width**	**Minimum Average**	**Maximum Average**	**Minimum Value**	**Maximum Value**
DCTotalRelevantCost	$45.57	$1.08	$42.01	$49.07	$0.00	$453.78
Retail1TotalRelevantCost	$27.46	$0.66	$24.69	$29.95	$0.00	$377.34
Retail2TotalRelevantCost	$14.48	$0.40	$13.01	$16.13	$0.00	$174.20
SystemTotalRelevantCost	$87.51	$1.79	$80.80	$94.13	$1.75	$585.66
DCHoldingCost	$45.05	$1.02	$41.82	$48.29	$0.00	$166.83
DCLostSalesCost	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
DCOutdateCost	$0.52	$0.24	$0.00	$1.66	$0.00	$453.78
Retail1HoldingCost	$10.48	$0.28	$9.31	$11.37	$0.00	$49.38
Retail1LostSalesCost	$8.62	$0.77	$5.43	$11.87	$0.00	$377.34
Retail1OutdateCost	$8.37	$0.26	$7.48	$9.19	$0.00	$49.00
Retail2HoldingCost	$6.02	$0.13	$5.52	$6.36	$0.00	$26.43
Retail2LostSalesCost	$3.14	$0.34	$2.03	$4.94	$0.00	$174.20
Retail2OutdateCost	$5.32	$0.15	$4.80	$5.78	$0.00	$32.70
DCIFR	95.24	0.45	93.38	96.75	0.00	100.00
Retail1IFR	97.05	0.26	96.22	98.14	0.00	100.00
Retail2IFR	97.97	0.22	96.95	98.73	0.00	100.00

By comparing the results in Table 4.17 and 4.18, we observe that the total relevant cost at each retailer and for the system is statistically significantly lower and the half-widths are smaller for the optimal policy as compared to the base policy. The DC total relevant costs are not statistically significantly different, yet the DC IFR is statistically significantly higher. The 95.24% IFR at the DC for the optimal policy with half-width of 0.45 is significantly is better than the 91.74% IFR with half-width of 0.59 for the base policy. Further, the smaller confidence intervals for the IFR at the DC and the total relevant cost for the system indicate that optimal policy would improve the reliability of the performance of the system and yield the lowest cost solution as compared to the base policy.

There is a small decrease in IFRs at the retail store under the optimal policy as compared to the base policy, although these IFRs under the optimal policy are still greater than 95%. This is because the optimal solution trades off the lost sales cost with the shrinkage costs and inventory holding costs at the retail stores in order to find the lowest cost solution for the whole system. For example, in the case of Retail Store 1, we see that the shrinkage cost is reduced from $23.04 to $8.37 and the inventory holding costs are reduced from $26.16 to $10.48 when comparing the base policy with optimal policy respectively. The lost sales cost increases from $1.45 for the base policy to $8.62 for the optimal policy. Overall, the total relevant cost at Retail Store 1 is now $27.46 for the optimal policy as compared to $50.64 for the base policy, which translates into cost reduction of $23.18. Additionally, the IFR under the optimal policy at the Retail Store 1 is 97.05% which is still greater than 95%. This means under the base policy, the major portion of the cost comes from the shrinkage costs and inventory holding costs.

Considering the cost reductions across the whole system, the optimal policy yields a 30.7% reduction in costs while maintaining the IFR greater than 95% at each echelon. The model optimizes the whole system by capturing the dynamic effects of perishability and inventory levels at each echelon, resulting in significant savings without sacrificing the service levels.

4.3 Sensitivity to the Forecast Errors

Using the optimal inventory policies obtained during the simulation runs described in Section 4.2.3, 0.5 days inventory target at the DC and 1.5 days inventory target at the retail stores, we tested the sensitivity of the system to the forecast errors. Testing the sensitivity of the optimal inventory policy with respect to the forecast errors demonstrates the potential benefits of increased forecast accuracy on reducing the inventory-related costs.

4.3.1 Forecast Error for DC's Demand Forecast

We conducted the sensitivity analysis by conducting simulation runs with the following inputs for forecast error for the DC's demand: 0, 5, 15, 25, 35, 50, 65, and 80%. Table 4.19 presents the results for the effects of DC's forecast error on the costs and IFRs at each echelon. Recall that the base value for forecast error is 25%.

Table 4.19: Forecast Error at the DC

DC Forecast Error	0%	5%	15%	25%	35%	50%	65%	80%
DCTotalRelevantCost	$30.68	$33.16	$38.77	$45.57	$53.53	$67.34	$83.29	$101.87
Retail1TotalRelevantCost	$28.68	$26.91	$26.56	$27.46	$29.03	$32.14	$34.97	$37.31
Retail2TotalRelevantCost	$13.61	$13.52	$13.94	$14.48	$15.17	$16.70	$18.01	$19.21
SystemTotalRelevantCost	$72.97	$73.59	$79.27	$87.51	$97.73	$116.18	$136.27	$158.39
DCHoldingCost	$30.65	$33.13	$38.69	$45.05	$52.05	$62.56	$73.25	$84.64
DCLostSalesCost	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
DCOutdateCost	$0.03	$0.03	$0.08	$0.52	$1.49	$4.78	$10.05	$17.23
Retail1HoldingCost	$8.60	$9.26	$10.08	$10.48	$10.64	$10.61	$10.50	$10.43
Retail1LostSalesCost	$14.38	$11.29	$9.05	$8.62	$9.16	$11.17	$13.22	$14.70
Retail1OutdateCost	$5.70	$6.36	$7.44	$8.37	$9.23	$10.35	$11.25	$12.18
Retail2HoldingCost	$5.60	$5.77	$5.96	$6.02	$6.01	$5.94	$5.85	$5.76
Retail2LostSalesCost	$3.98	$3.45	$3.14	$3.14	$3.38	$4.39	$5.31	$6.12
Retail2OutdateCost	$4.03	$4.31	$4.83	$5.32	$5.78	$6.38	$6.85	$7.33
DCIFR	88.77	91.15	93.86	95.24	95.66	95.29	94.59	94.22
Retail1IFR	95.17	96.23	96.98	97.05	96.79	96.01	95.22	94.62
Retail2IFR	97.46	97.79	97.99	97.97	97.76	97.01	96.31	95.71

Figure 4.5 shows that the total relevant cost for the DC and the system increases significantly as the forecast accuracy decreases. This is because the inventory holding cost at the DC increases significantly with respect to the decreasing forecast accuracy. Increasing the forecast accuracy by 10% or 20% would reduce the total relevant cost in the system by 9% or 16% respectively. Increasing the forecast error by 10% would increase the total relevant cost in the system by 12%.

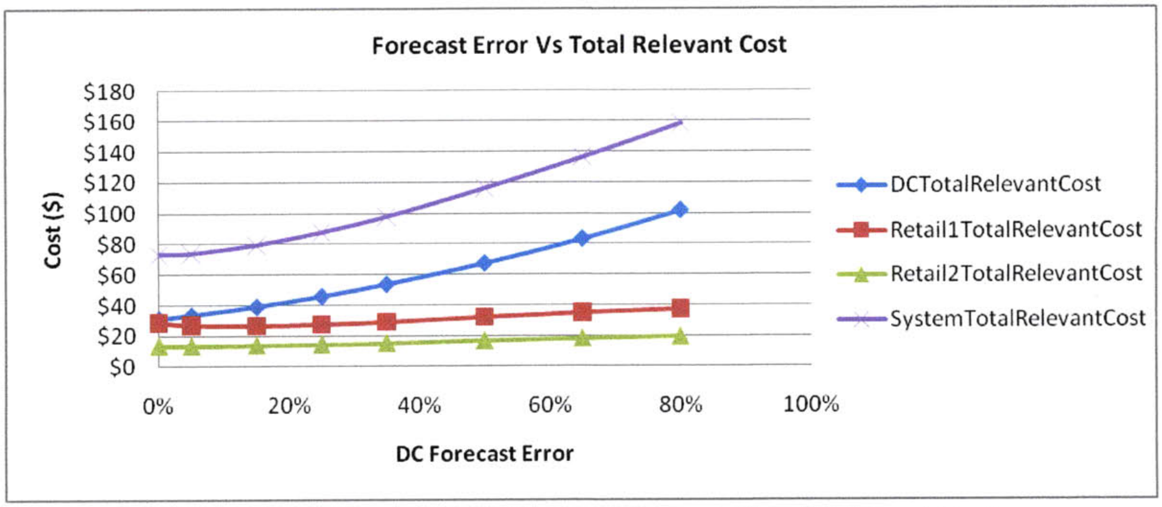

Figure 4.5: Effect of DC's Forecast Error on Total Relevant Cost

Figure 4.6 shows that the IFR at the DC is very sensitive to the DC's forecast error as compared to the IFR at the retail stores, and the IFRs at both the DC and the retail stores decrease as the forecast accuracy deteriorates beyond 25%. This occurs because the OUL for the DC, which is dependent upon DC's forecast, becomes less accurate and the shrinkage volume at the DC increases as forecast accuracy deteriorates. This affects the availability of the inventory at the DC and hence its ability to fulfill orders received from the retail stores. Thus IFRs at both the DC and the retail stores deteriorate for DC's forecast error beyond 25%.

For the DC's forecast error less than 25%, the inventory level at the DC is reduced but retail stores still have their own forecast error, so retail stores still tend to order more form the DC. Thus the IFR at the DC deteriorates because the retail stores order more than they need to, suggesting the presence of the bullwhip phenomenon.

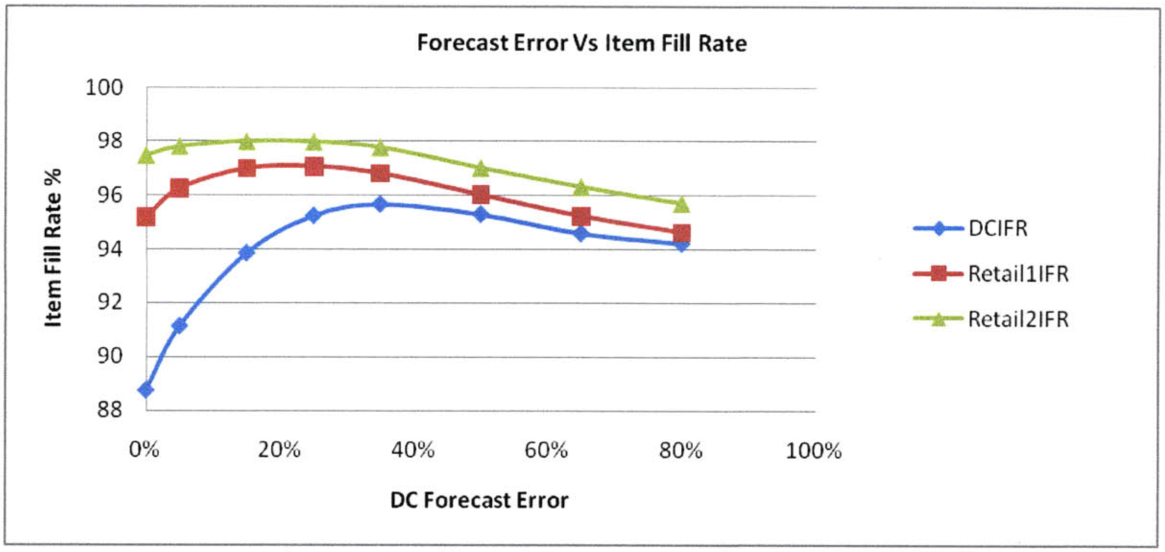

Figure 4.6: Effect of DC's Forecast Error on IFR

Figure 4.7 shows that the inventory level at the DC also increases as the forecast accuracy decreases. This occurs because when the demand forecast is higher than the actual demand, the DC would have excessive inventory. When the demand forecast is lower than actual demand, the inventory would be depleted but never go below zero (since sales are lost and not backordered). Thus, the increasing forecast error would ultimately increase the average inventory level.

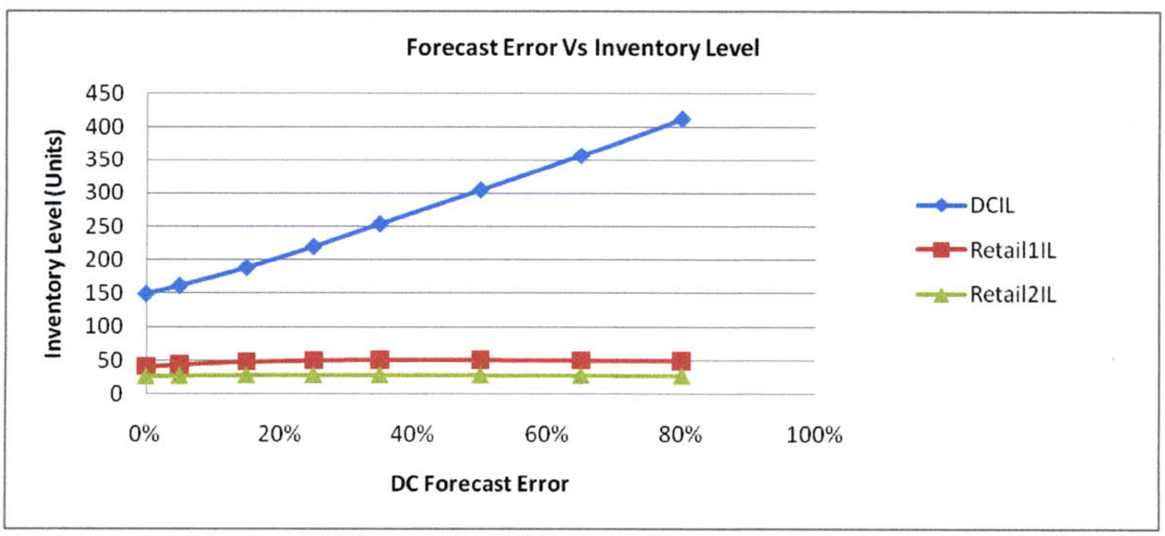

Figure 4.7: Effect of DC's Forecast Error on Inventory Level

We observe from Figure 4.8 that as the forecast accuracy deteriorates, the inventory at the DC begins to age more. Figure 4.8 (a) and (b) indicate the change in inventory and shrinkage volume by age distribution at the DC with respect to the DC's forecast error. Figure 4.8 (b) only shows shrinkage for the 8-days old inventory because of ABC's mandated policy for discarding any product once it reaches 8 days old. The aging inventory at the DC would eventually result in more inventory of older age distribution sent to the retail stores, thus higher shrinkage volume. Figure 4.8 (c) and (d) indicate the change in inventory and shrinkage volume by age distribution at the Retail Store 1 with respect to the DC's forecast error. Figure 4.8 (e) and (f) indicate the same for Retail Store 2. Please refer to Table C.2 in Appendix C for the legends of the terms used in Figure 4.8.

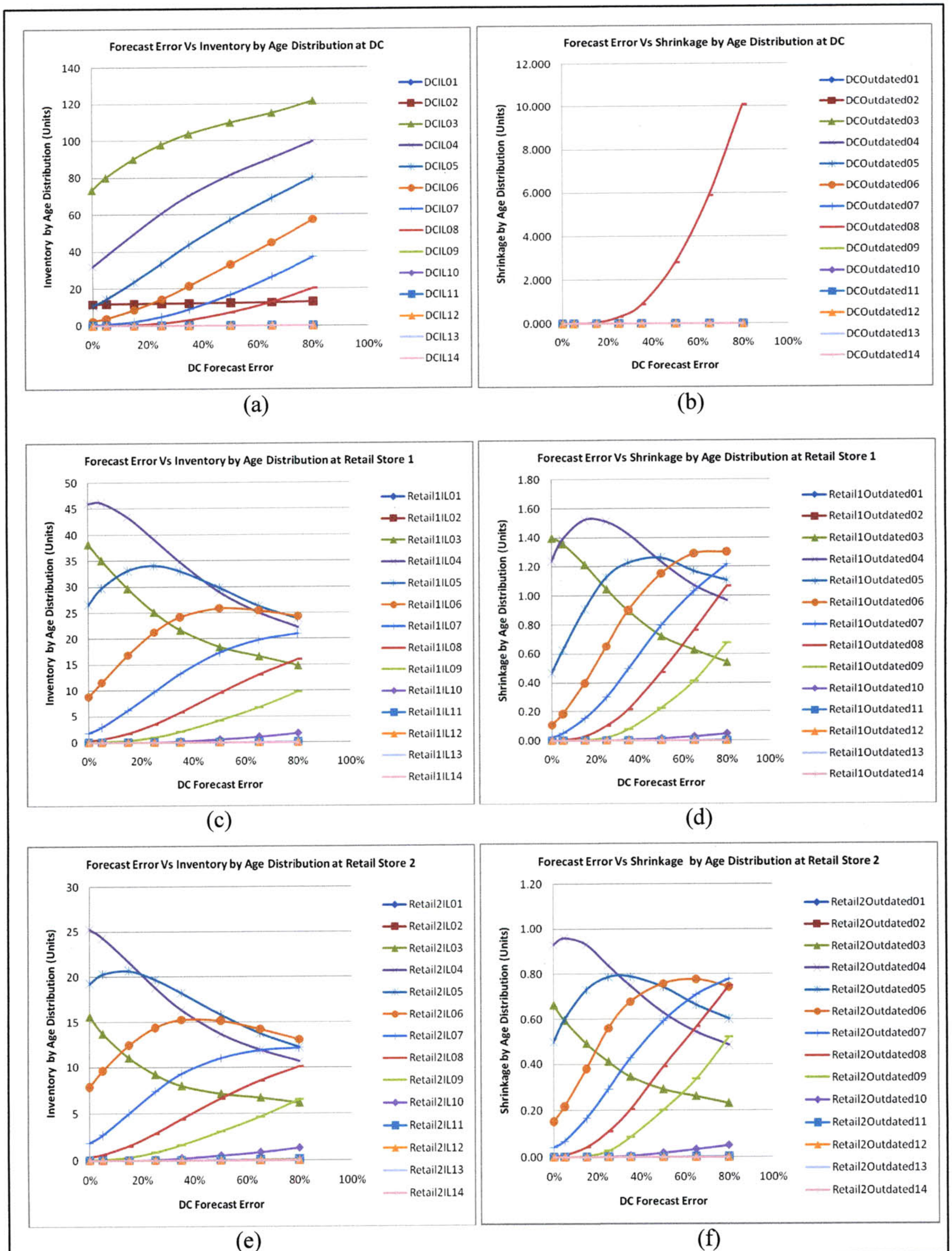

Figure 4.8: Impact of Forecast Error at the DC on Inventory

Figure 4.9 shows that the total shrinkage at the DC and the retail stores increase as the forecast accuracy deteriorates. This increases the shrinkage volume at each echelon in proportion with the inventory level. As the inventory levels increase at the DC, so does the amount of older inventory on hand there, and hence the age of the inventory shipped to the retailers also increases. It can be clearly seen that shrinkage volume at the DC is very sensitive to DC's forecast error as compared to the shrinkage volume at the retail stores. This increasing trend in DC's shrinkage volume is obvious for the forecast error greater than 40%. Thus the DC should invest its efforts in keeping the forecast error as low as possible.

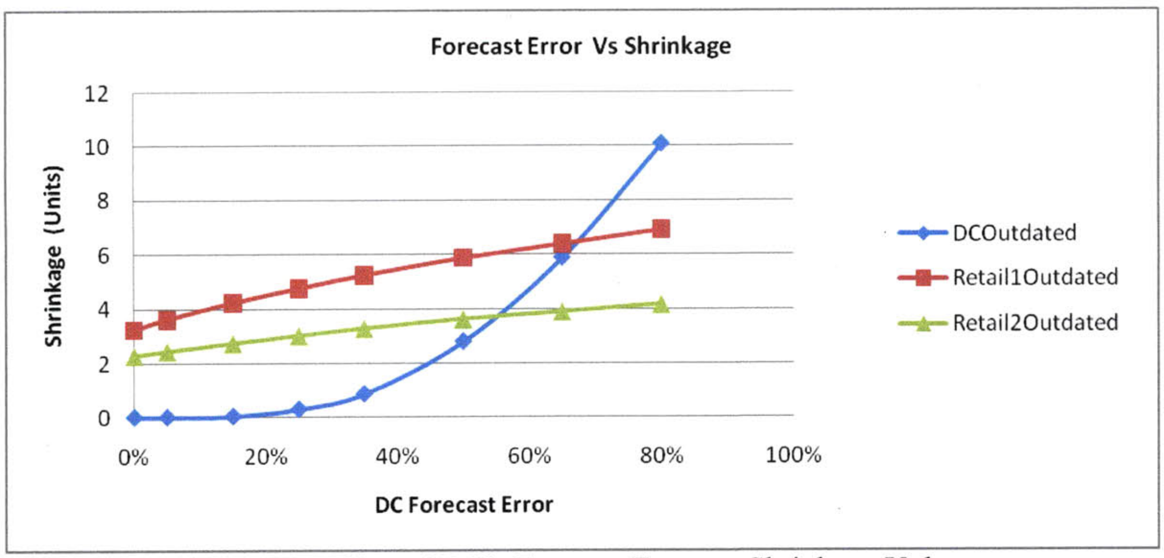

Figure 4.9: Effect of DC's Forecast Error on Shrinkage Volume

4.3.2 Forecast Error for Retail Stores' Demand Forecast

Using the same approach and the same set of forecast error values as those used for the DC forecast error in Section 4.3.1, we tested the sensitivity of the system to the retail stores' forecast errors. Table 4.20 presents the results for the effects of forecast error on system performance.

Table 4.20: Forecast Error at the Retail Stores

Retail Forecast Error	0%	5%	15%	25%	35%	50%	65%	80%
DCTotalRelevantCost	$46.83	$46.40	$45.91	$45.57	$45.54	$46.05	$45.94	$45.89
Retail1TotalRelevantCost	$22.35	$23.02	$24.79	$27.46	$30.49	$36.47	$41.67	$45.69
Retail2TotalRelevantCost	$11.73	$12.02	$13.07	$14.48	$16.08	$19.34	$22.63	$25.28
SystemTotalRelevantCost	$80.91	$81.44	$83.77	$87.51	$92.11	$101.87	$110.24	$116.85
DCHoldingCost	$46.71	$46.21	$45.60	$45.05	$44.74	$44.82	$44.44	$44.11
DCLostSalesCost	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
DCOutdateCost	$0.12	$0.19	$0.31	$0.52	$0.79	$1.23	$1.51	$1.78
Retail1HoldingCost	$7.94	$8.51	$9.45	$10.48	$11.50	$12.98	$14.34	$15.55
Retail1LostSalesCost	$7.80	$7.52	$7.73	$8.62	$9.93	$13.33	$16.14	$17.99
Retail1OutdateCost	$6.60	$6.99	$7.61	$8.37	$9.06	$10.17	$11.19	$12.15
Retail2HoldingCost	$4.31	$4.72	$5.33	$6.02	$6.76	$7.97	$9.21	$10.44
Retail2LostSalesCost	$3.50	$3.03	$3.00	$3.14	$3.38	$4.43	$5.43	$5.80
Retail2OutdateCost	$3.92	$4.26	$4.74	$5.32	$5.94	$6.94	$7.99	$9.04
DCIFR	96.98	96.61	95.96	95.24	94.32	92.61	90.72	88.67
Retail1IFR	97.64	97.68	97.53	97.05	96.38	94.80	93.36	92.39
Retail2IFR	98.07	98.29	98.20	97.97	97.60	96.54	95.52	95.00

Figure 4.10 shows that the total relevant costs for the retail stores and the system increase significantly as the forecast accuracy deteriorates. The major cost increase comes from the increased lost sales costs, shrinkage costs and inventory holding costs at the retail stores.

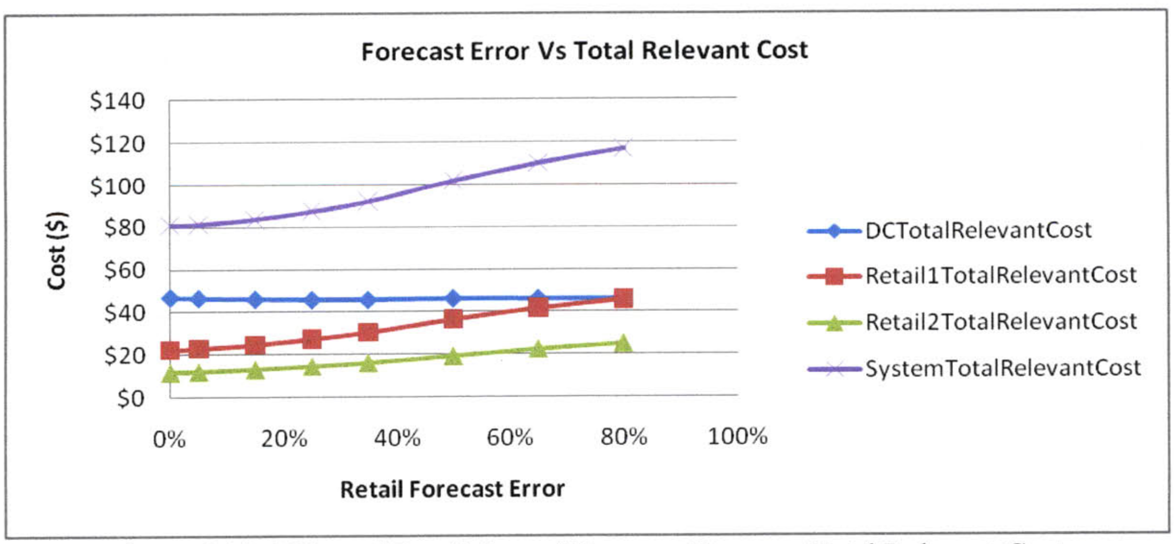

Figure 4.10: Effect of Retail Stores' Forecast Error on Total Relevant Cost

Considering the Figure 4.11, the IFRs at both the retail stores and the DC deteriorates as the forecast accuracy deteriorates. Again, the IFR at the DC is more sensitive to the forecast error as compared to the IFR at the retail stores due to the bullwhip effect, as explained in Section 4.3.1. This occurs because the inventory level at the DC becomes insufficient to fulfill orders from retail stores as the retail stores increasingly order more than they need with the increasing forecast error.

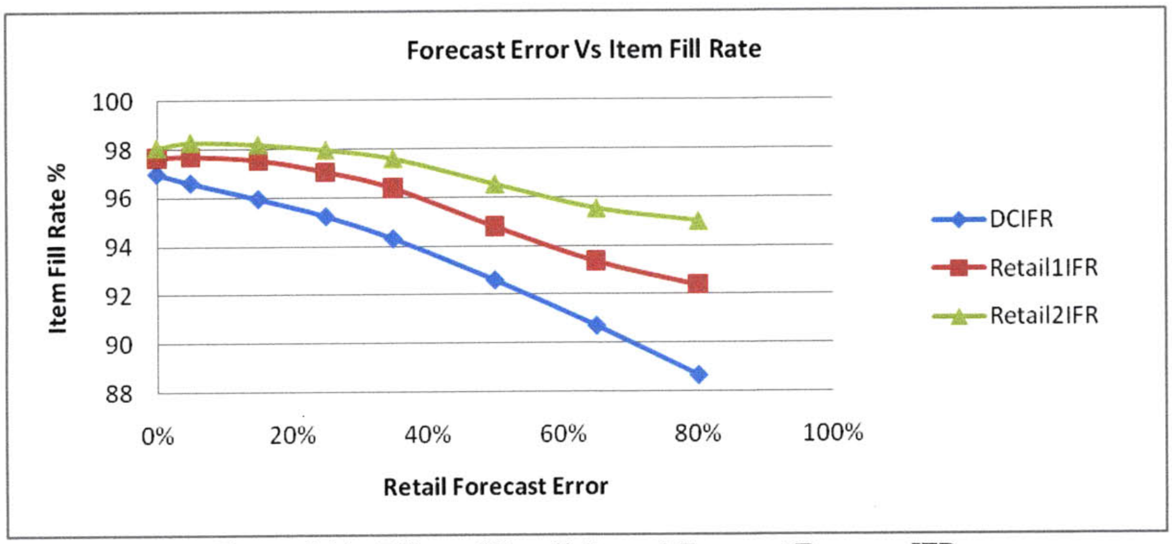

Figure 4.11: Effect of Retail Stores' Forecast Error on IFR

Figure 4.12 indicates that the inventory level at the retail stores increases as the forecast accuracy deteriorates. This occurs at the retailers because when the demand forecast is higher than the actual demand, the retail stores would have excessive inventory. When the demand forecast is lower than actual demand, the inventory would be depleted but never go below zero. Thus, the increasing forecast error would ultimately increase the inventory level.

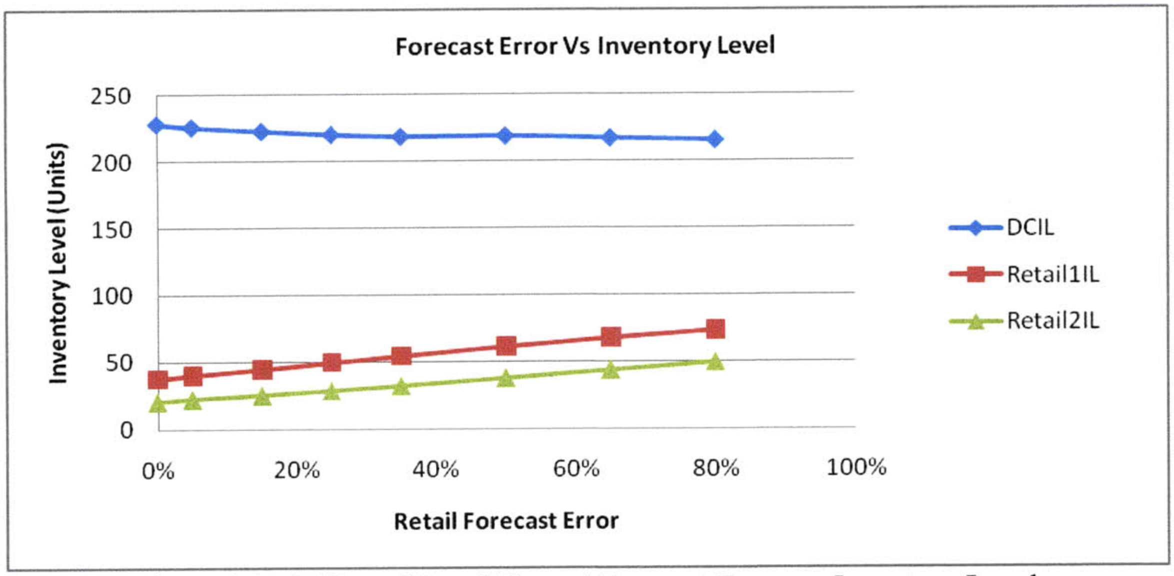

Figure 4.12: Effect of Retail Stores' Forecast Error on Inventory Level

We observe from Figure 4.13 (a) that as the forecast error increases, orders from retail stores deplete DC's inventory at a faster rate. Thus DC will not be holding inventory for long time periods. This results in less older age inventory at the DC and more older age inventory at the retail stores, as shown in Figure 4.13 (c) and (e). The distribution of older age inventory at the retail stores increases. This translates into higher shrinkage costs and lost sales costs at the retailers as compared to the impact of the DC's forecast error, given in Table 4.19 of Section 4.3.1. Please refer to Table C.2 in Appendix C for the legends of the terms used in Figure 4.13.

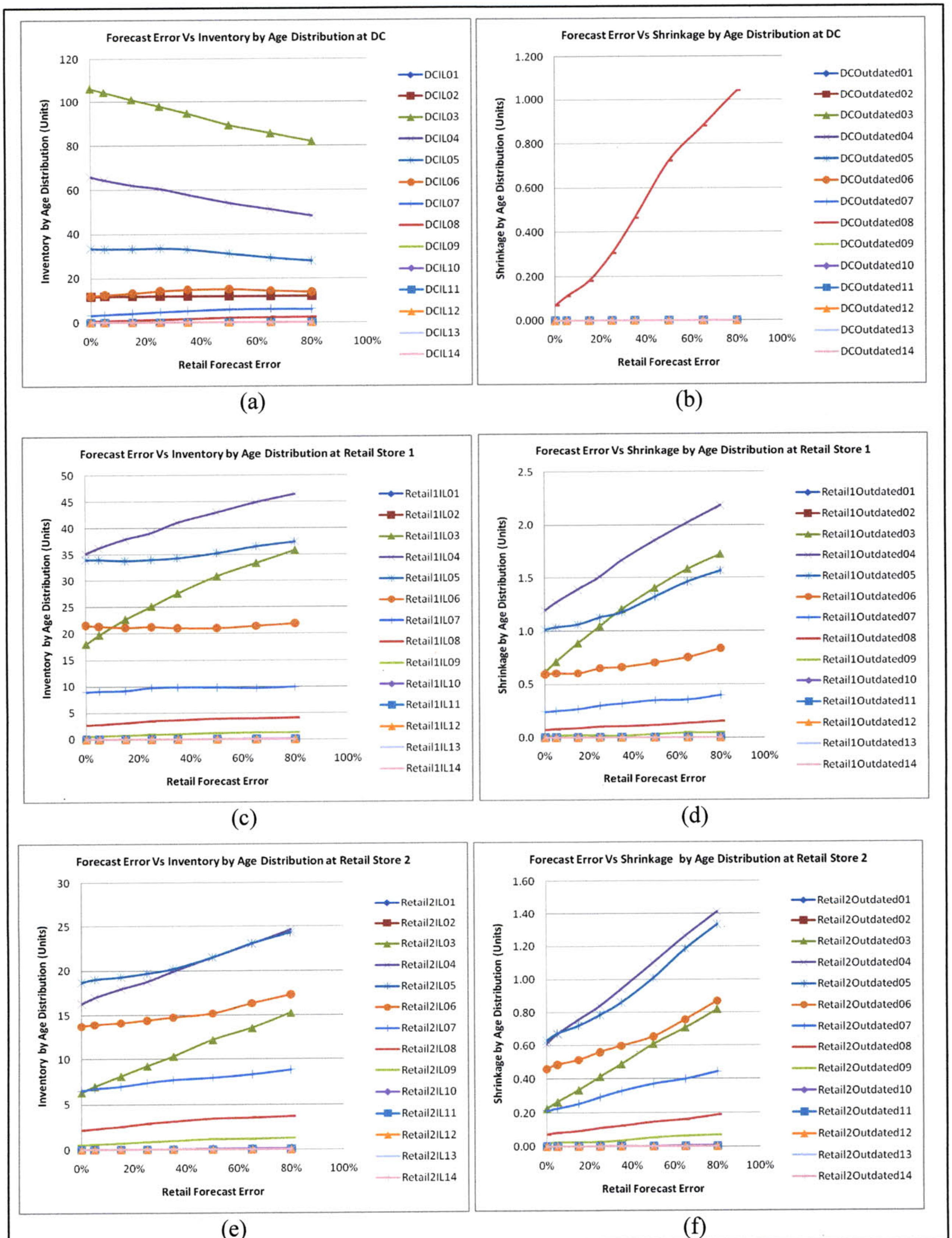

Figure 4.13: Impact of Forecast Error at the Retail Stores on Inventory

Figure 4.14 shows that the shrinkage volume at the retail stores increases as the forecast accuracy deteriorates. Due to the unpredictable order quantities from the retail stores, the DC's performance is affected. This causes slight increase in the shrinkage volume at the DC.

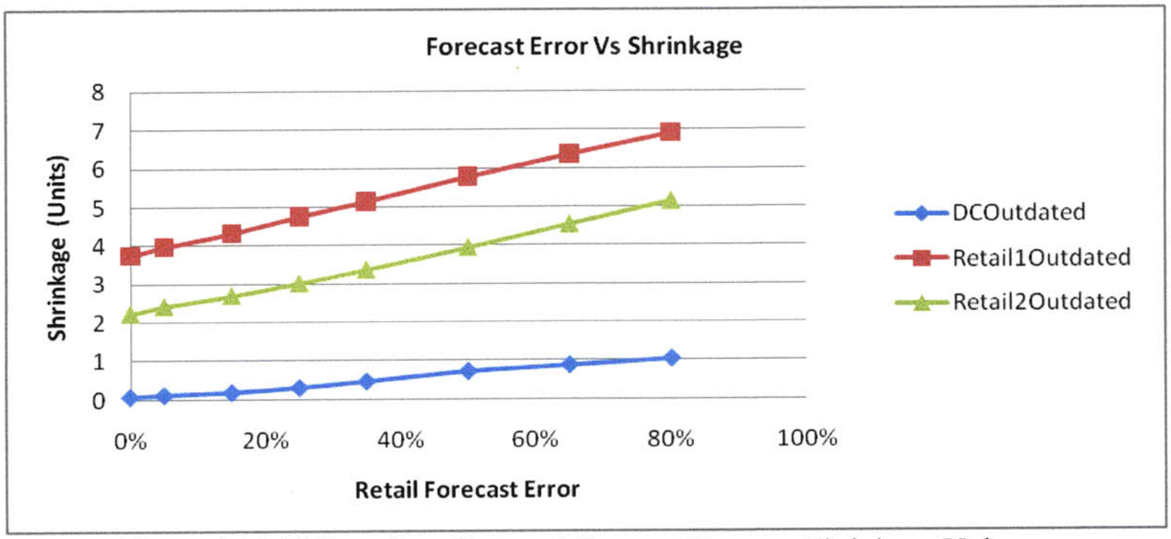

Figure 4.14: Effect of retail stores' Forecast Error on Shrinkage Volume

By comparing the results in this section and Section 4.3.1, we observe that improving forecast accuracy at the DC and the retail stores can reduce the costs significantly and improve the respective IFRs drastically. The forecast accuracy at the DC has greater impact than the forecast accuracy at the retail stores on the total relevant cost of the system. Because of the production and transportation lead time at the plant, the system is more sensitive to the DC's forecast error. The longer production and transportation lead time at the plant means more forecast error will be taken into account while calculating the DC's OUL as opposed to calculations with shorter lead times. This translates into the increased inventory holding cost at the DC.

However, the forecast accuracy at the retail stores has a greater impact than the forecast accuracy at the DC on DC's IFR. Even if the forecast accuracy at the DC is improved, if the retail stores have poor forecast accuracy then the DC's IFR will still suffer and the total relevant costs will increase. The cost benefits will be maximized if the forecast accuracies at both the retail stores and the DC are improved.

4.4 Sensitivity to Transportation Lead Time

Testing the sensitivity of the total relevant cost to the transportation lead time from the plant to the DC helps demonstrate the benefits of using expedited shipping services. We conducted this experiment with transportation lead times from the plant to the DC of 1 through 7 days. The production lead time is constant at 4 days which results in a cumulative lead time from the plant to the DC of 5 to 11 days. Recall that the cumulative lead time for base scenario is 5 days (4 days of production and 1 day of transportation lead time). Table 4.21 presents the numerical results of how this lead time impacts the KPIs.

Table 4.21: Impact of Transportation Lead Time

Plant To DC LeadTime	1	2	3	4	5	6	7
DCTotalRelevantCost	$45.57	$49.29	$47.31	$54.10	$55.89	$82.28	$164.57
Retail1TotalRelevantCost	$27.46	$30.97	$36.31	$41.44	$54.05	$81.62	$164.89
Retail2TotalRelevantCost	$14.48	$16.41	$18.47	$20.92	$25.97	$37.10	$73.85
SystemTotalRelevantCost	$87.51	$96.67	$102.10	$116.46	$135.91	$201.00	$403.31
DCHoldingCost	$45.05	$47.20	$41.52	$39.72	$30.01	$21.90	$6.47
DCLostSalesCost	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
DCOutdateCost	$0.52	$2.09	$5.79	$14.37	$25.88	$60.38	$158.10
Retail1HoldingCost	$10.48	$10.34	$9.39	$8.76	$7.56	$5.62	$2.00
Retail1LostSalesCost	$8.62	$9.66	$14.42	$17.65	$30.60	$60.77	$156.17
Retail1OutdateCost	$8.37	$10.97	$12.51	$15.04	$15.89	$15.23	$6.73
Retail2HoldingCost	$6.02	$5.87	$5.44	$5.13	$4.61	$3.69	$1.70
Retail2LostSalesCost	$3.14	$3.63	$5.13	$6.26	$11.14	$23.18	$66.39
Retail2OutdateCost	$5.32	$6.91	$7.90	$9.53	$10.22	$10.23	$5.76
DCIFR	95.24	95.38	92.67	90.83	84.62	70.68	31.03
Retail1IFR	97.05	96.77	95.09	93.77	89.26	77.40	41.56
Retail2IFR	97.97	97.66	96.64	95.72	92.45	83.26	51.56

Figure 4.15 demonstrates that the total relevant cost for each individual echelon and the system overall increases as the transportation lead-time increases. This increase is mainly due to

the increased lost sales cost at the retail stores and shrinkage costs at both the retail stores and the DC. As the transportation lead time increases, products' remaining life-time at the DC and retail stores decreases, in turn increasing the shrinkage volume. Additionally, the system is less responsive to demand due to the longer lead times, increasing the lost sales costs for the system.

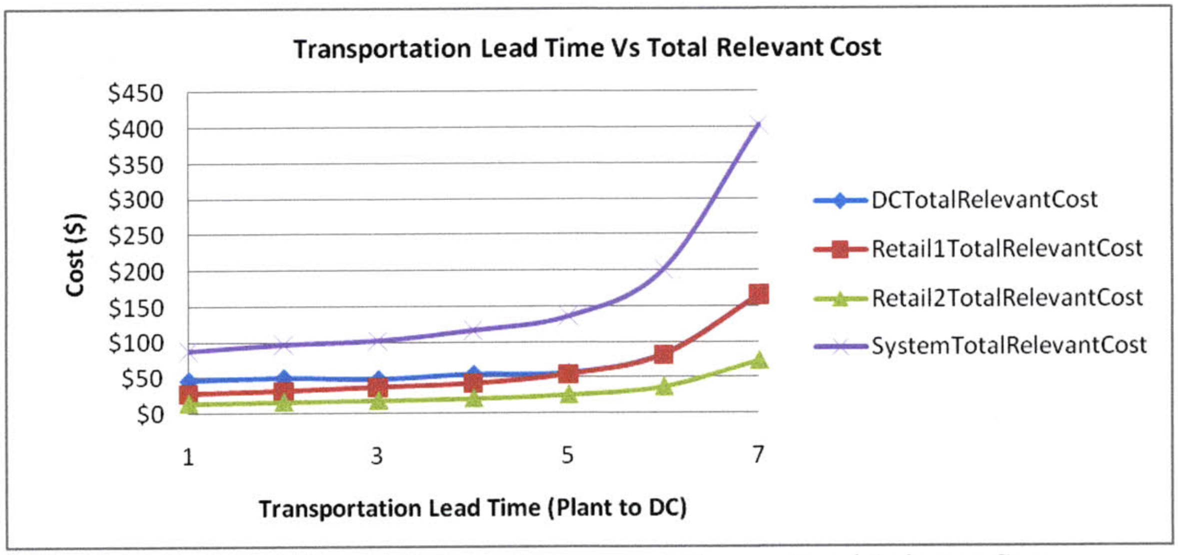

Figure 4.15: Effect of Transportation Lead Time on Total Relevant Cost

Figure 4.16 indicates the effect of transportation lead-time on the IFRs. As the inventory levels decrease with respected to increasing transportation lead-time, the IFRs at the DC and the retail stores decrease. The responsiveness of the system to the customer demand decreases with increasing lead-times, resulting in the poor IFR across the system.

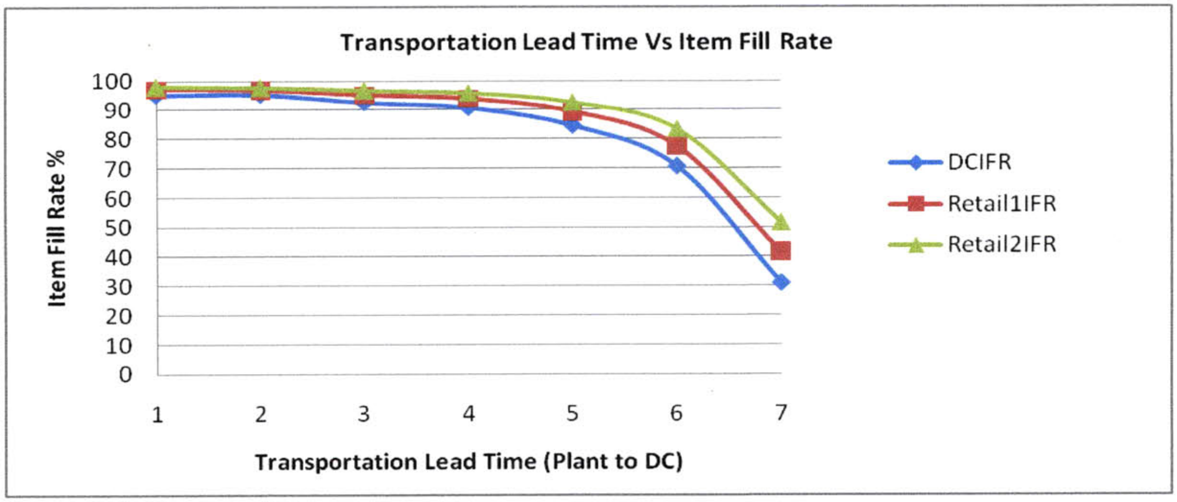

Figure 4.16: Effect of Transportation Lead Time on IFR

Figure 4.17 indicates that due to increasing transportation lead-time, the inventory level at the DC decreases. This primarily occurs because of increased shrinkage volume at the DC. This naturally affects the inventory level at the retail stores as DC will not be able to fulfill the orders from retail stores. This also means that the inventory holding costs at the DC and the retail stores decrease due to reduced inventory levels, as shown in Table 4.21.

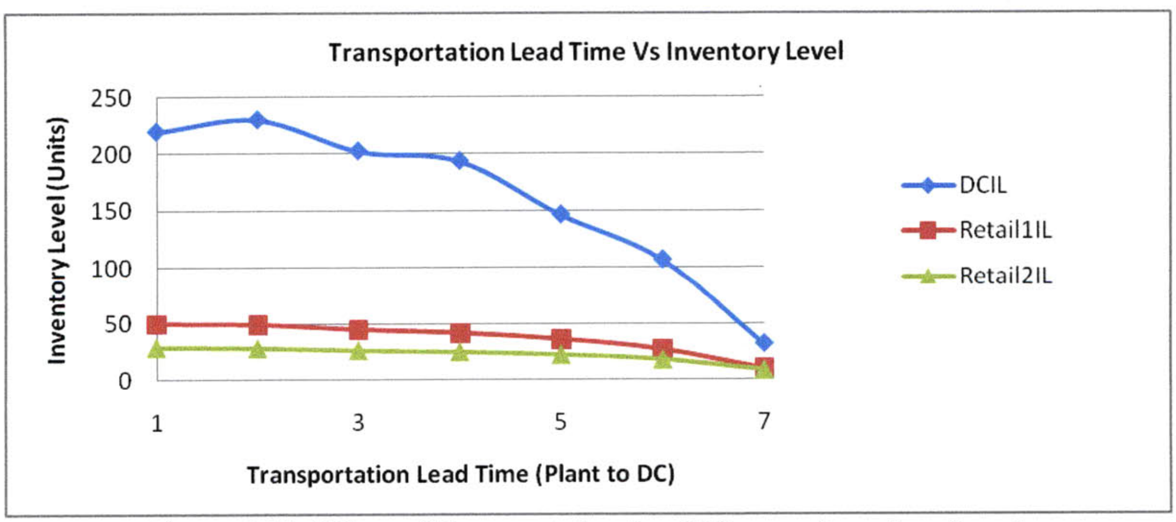

Figure 4.17: Effect of Transportation Lead Time on Inventory Level

Figure 4.18 (a) and (b) show that as the transportation lead time increases, the DC holds more inventory of an older age distribution, resulting in higher shrinkage costs at the DC. This means the retail stores also hold more inventory of older age distribution, which also translates into higher shrinkage costs at the retail stores. This can be seen in Figure 4.18 (c), (d), (e) and (f). Please refer to Appendix C.2 for definitions of the terms used in Figure 4.18.

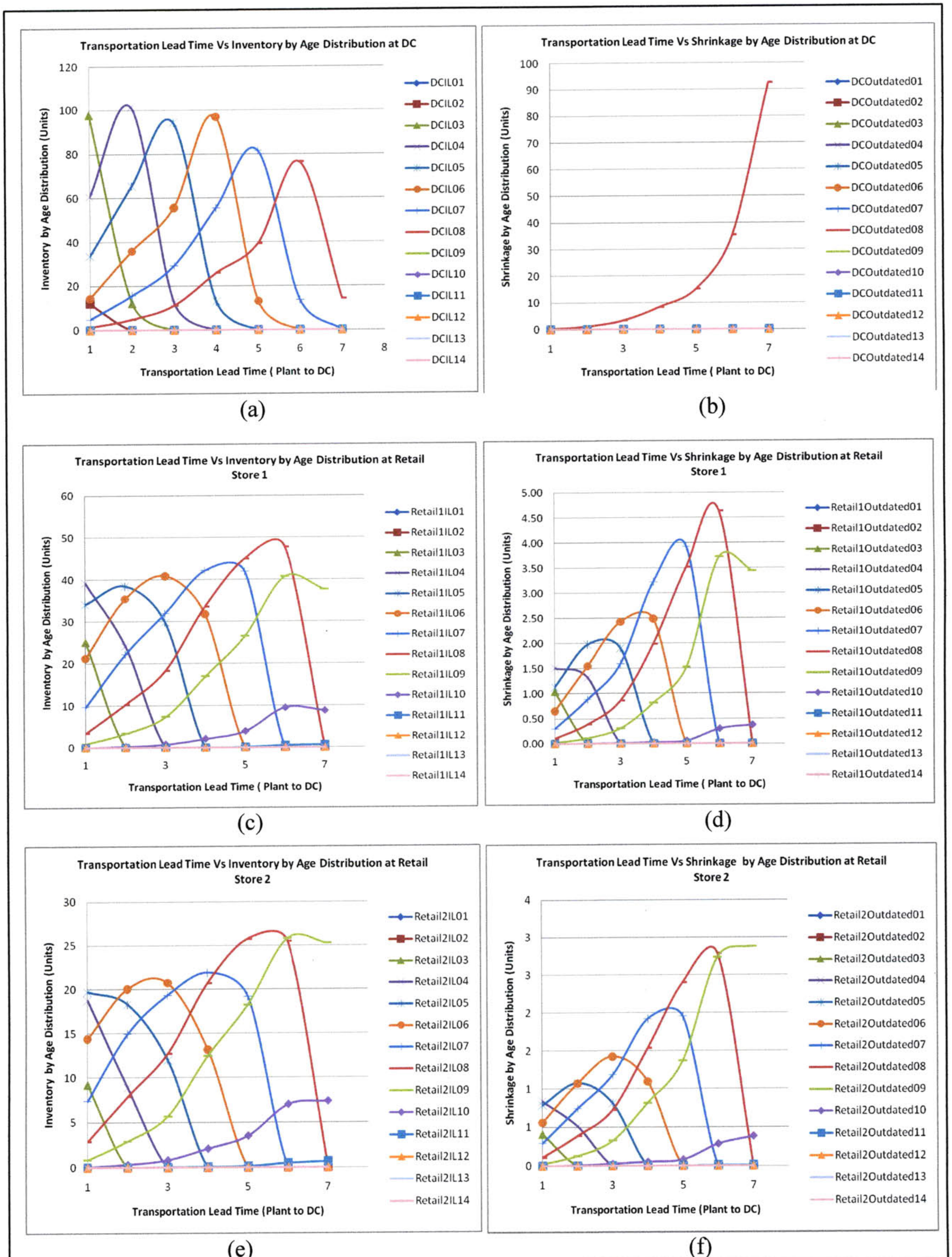

Figure 4.18: Impact of Transportation Lead Time on Inventory

We clearly observe in the Figure 4.19 that the shrinkage volume at the DC increases significantly for transportation lead times greater than 4 days. Increasing transportation lead times reduce the available lifetime of the products at the DC as products lose their useful lifetime during transit. Additionally, ABC's mandated shrinkage policy of discarding the products at the DC that have less than 6 days of lifetime remaining considerably reduces this useful lifetime of the product. This plays an important role in increased shrinkage volume.

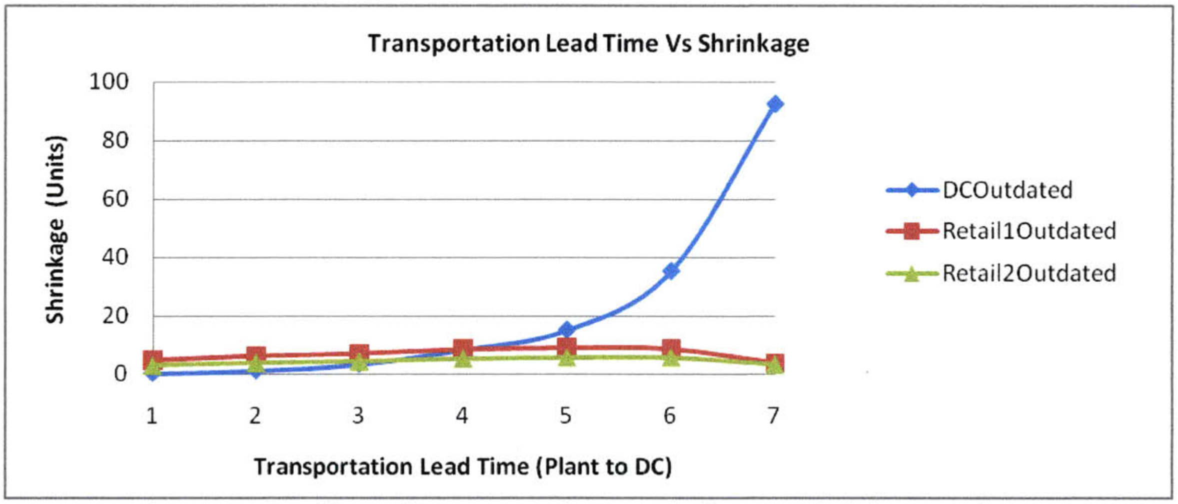

Figure 4.19: Effect of Transportation Lead Time on Shrinkage Volume

5 Conclusions

The objective of this thesis is to quantify the impact of perishability on total inventory costs and to establish the optimal inventory policy for the multi-echelon Fresh Express supply chain. In this chapter we present the challenges for perishable inventory system in a multi-echelon supply chain, the insights drawn from the use of our simulation model, and an outline for the future extensions.

5.1 Challenges for Perishable Inventory Systems in a Multi-Echelon Supply Chain

The major challenges in perishable inventory management systems reside in tracking the inventory distribution of different age-groups. The multi-echelon system further complicates the issue as the interaction between each echelon of the supply chain makes the issue dynamic and difficult to monitor and understand. Addressing these issues analytically requires extensive computations, thus analytical approaches are usually impractical for day-to-day operations in a complex inventory system.

Utilizing a simulation model is extremely useful in dealing with perishable inventory in multi-echelon supply chains because tracking the inventory distribution and the inventory transfer becomes relatively simple using computer software. A computer simulation model also helps the user to monitor the interactions and influence between each echelon of the supply chain. Additional benefits of a simulation approach are that we can test the sensitivity of the system to varying conditions, and that we can obtain 95% confidence intervals for the output variables, which indicate the reliability of the estimate.

5.2 Key Insights

We have discussed many of our key results in Chapter 4, and we highlight key insights in this section.

5.2.1 Service Level at the DC vs. Inventory at the Retail Stores

The simulations reveal that the IFR at the DC is sensitive to the target days on-hand inventory at the retails stores. As the target days on-hand inventory at the retail stores increases, the IFR at the DC decreases significantly. The dynamics of the demand variability, the forecast errors, and the shrinkage in the multi-echelon system amplify as the target days on-hand inventory at the retail stores increases. As a result of the dynamics of these three factors, the IFR at the DC deteriorates when the target days on-hand inventory at the retail stores increases past two days. The model suggests the retail store to keep its inventory less than two days to minimize the upstream impact of the demand variability, the forecast errors, the production schedule and the shrinkage.

5.2.2 Base Scenario Policy vs. Optimal Inventory Policy

One of the three key questions posed by Chiquita is what the optimal inventory levels are considering forecast accuracy, transportation lead-time, inventory carrying cost, lost sales costs and inventory shrinkage costs due to product perishability. Our simulation model considers all these factors and determines that the optimal inventory policy would be to set the target days on-hand inventory to be 0.5 days at the DC and 1.5 days at the retail stores. Comparing this optimal solution to the current inventory policy, the inventory policy determined by our simulation model reduces the total relevant cost by 30.7%, reduces the shrinkage below 8.5%, and maintains the IFR above the required 95% at all echelons.

Chiquita has been considering moving to a cross-dock policy at the DC, which means the DC will not carry any inventory. Our model indicates that by removing inventory from the DC, a cross-dock policy would reduce the total relevant costs by approximately 0.05%. Comparing with the 30.7% cost saving from the optimal policy, an additional 0.05% saving is relatively insignificant. In addition, our model shows that the cross-dock policy would reduce the IFR at both the retail stores. In particular, the IFR at the Retail Store 1 would be reduced from 97.1% to 93.2%, below the target IFR of 95%. Therefore, based on the results, we would not recommend Chiquita and ABC to introduce a cross-dock policy at the DC unless it makes other changes to its ordering and logistics to maintain sufficient IFRs.

5.2.3 Service Levels vs. Inventory Cost

Another question posed by Chiquita is the trade-off between service levels and inventory cost. As we expected, the service levels and inventory costs have a positive correlation. We determine our model's optimal inventory policy by selecting the policy that results in the lowest total relevant cost and still meets the minimum service level of 95% IFR. The optimal inventory policy improves the IFR at the DC from 91.74% to 95.24%, while the IFR at the retail stores decreases from 99% to 97%.

Although the IFR at the retail stores decreases by approximately 2%, 97% is still considered high customer service level. However, the impact of a reduction of 2% in IFR on consumer satisfaction and good-will are not captured in our model. Chiquita and ABC should gain a better understanding of the potential impact on consumer behavior and future sales before implementing the optimal inventory policy suggested by our simulation model.

Overall, the 30.7% cost savings are significant enough for Chiquita and ABC to consider replacing the current inventory policy with the optimal inventory policy found in our model. The majority of the cost reduction comes from the reductions in inventory holding costs and inventory shrinkage costs across the system, especially at the retail stores.

Additionally, the confidence intervals (95%) determined by our model for the IFR and the total relevant cost for the system are tighter in the case of the optimal inventory policy as compared to the confidence intervals in the base scenario policy. The tighter confidence intervals indicate less variability in the system performance.

5.2.4 Effect of Forecast Error on the Relevant Costs and the Service Level

The third question posed by Chiquita is the effect of forecast error on inventory-related costs. We found that the system is very sensitive to forecast errors, especially the forecast errors from the DC. In general, as the forecast accuracy deteriorates, the IFR at the DC and the retail stores decreases and the relevant cost of the system increases. Therefore, Chiquita and ABC should consider investing significant efforts to improve the forecast accuracies at the DC and the retail stores. Additionally, improving the forecast accuracy at the DC alone may not address the issue sufficiently because the DC's inventory is ultimately impacted by the orders and forecasts created by the retail stores. The IFR at the DC is more sensitive to the forecast error at the retail stores than to the DC's forecast error. To maximize the cost savings and improve the performance of the whole system, we recommend that Chiquita work with ABC to simultaneously improve the forecast accuracy at both the DC and the retail stores.

5.2.5 Effect of Transportation Lead Time on the Relevant Costs and Service Level

The system is sensitive to the transportation lead time since the transportation lead time directly impacts the products' lifetime at the DC and at the retail stores. Our model demonstrates that as the transportation lead time increases, the shrinkage in the system increases significantly. This further results in the increased lost sales at the retail stores and reduced IFR at the retail stores and the DC. Overall, the total relevant cost for the system increases and the IFR at each echelon deteriorates. Since the system is sensitive to the transportation lead time, Chiquita should not relax the current lead time and should continue to keep the transportation lead time as short as possible to maximize the products' available lifetime at the DC and the retail stores.

5.3 Extension of the Model and Future Research

Further research on perishable product supply chains can be conducted by relaxing the assumptions of our model. We have demonstrated the benefits of quantitative approach to improving the service levels at each echelon and reducing the total relevant cost of the system. Further extension of our research by exploring the following possibilities can extend the benefits to the perishable product supply chains.

5.3.1 Mandated Shrinkage Policy at the DC

Currently, ABC has mandated an inventory shrinkage policy at the DC, in which any product that has less than six days of shelf life remaining should be removed from the DC's inventory. Testing the sensitivity of the system with respect to this mandated inventory shrinkage policy at the DC could help Chiquita to understand the impact of this policy on the IFR at each individual echelon and the total relevant cost for the system.

5.3.2 Other Product Families

Our simulation is based on one of Fresh Express' main product families. The results generated from using this product family should provide a good overall representation of the whole Fresh Express product lines. However, Chiquita can use the simulation model to test other product families or each individual product to gain a deeper understanding of its supply chain.

5.3.3 Other Fresh Express Supply Chains

Our simulation is also based on one of Fresh Express' main customers, which we refer to as ABC Inc. This supply chain is similar to Chiquita's other supply chains for other customers. However, some of the inventory policies, such as ABC's mandated shrinkage policy at the DC, might be different for other customer's supply chains. Chiquita can conceivably change the input parameters in the model to determine the optimal inventory policy for its other supply chains.

5.3.4 Demand Correlation among Complementary Products

In our model, we assumed independent demand that is normally distributed for each product, but different demand distributions can be considered for further research. For example, it is possible to analyze and incorporate correlated demand for complementary products.

5.3.5 First In First Out Policy

Our model assumes a FIFO product policy; however, in reality if there are products with different lifetime displayed on the shelf, some consumers would look for and purchase the younger products. Such consumer behavior is not captured in our current model. Chiquita and its customers can either develop rules to expand our model to capture such behaviors or develop store shelf stocking policies to better control consumers' purchasing behaviors if needed.

5.3.6 Production Capacity of the Plant

In our model, we assumed that the plant has unlimited production capacity to fulfill DC's orders, but this assumption can be relaxed if an additional echelon is built into the model. This may be valuable since the plant serves other DC's if it has limited production capacity

5.4 Summary

We conclude that for multi-echelon perishable inventory management problems, simulation can be extremely helpful. Our research demonstrates that simulation modeling can quantify various trade-offs involved in making inventory management decisions for perishable products. It is extremely valuable to simulate reality and test the sensitivity of the system before decisions are made by managers. Simulation modeling can lead to optimal solutions that would reduce the system costs significantly while improving the system performance significantly.

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Appendix A: Conceptual Flow of Fresh Express Arena Simulation Model

We discussed the conceptual model in Section 3.2. In this appendix, we provide more details regarding the eight steps in conceptual flow of our simulation model. Figure A.1 indicates the logic details of step 1 and 2. Step 2 shows the logic used by retail stores before placing an order at the DC.

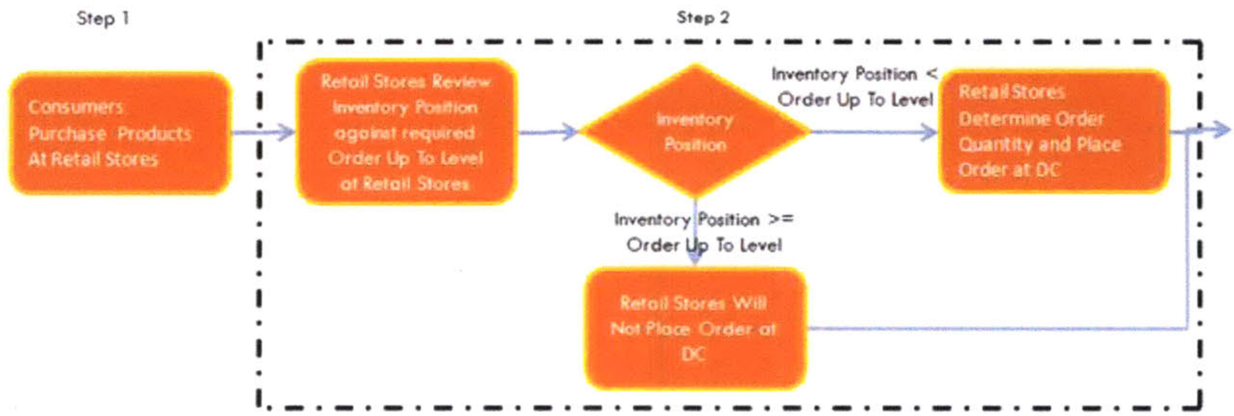


Figure A.1: Conceptual Flow—Step 1 and Step 2

Figure A.2 shows the logic details of steps 3 and 4. In step 3, we use an algorithm that we developed to allocate the available inventory at the DC to each of the retail stores. As mentioned earlier in Section 3.1.4, we assume that the DC treats all the retail stores equally and does not prioritize a particular store over another. The algorithm steps are:

1. If the DC's inventory level is more than the aggregated retail store orders, the DC fulfills each order 100% accordingly.

2. If the DC's inventory level is less than the aggregated retail store orders, the DC checks whether both orders each are more than 50% of the inventory level.

   2.1 If Yes: the DC will split the inventory 50/50 (evenly) and ship out the inventory accordingly to each retail store.

2.2 If No: the DC will fulfill the smaller order 100%, then ship the remaining inventory to fulfill the bigger order.

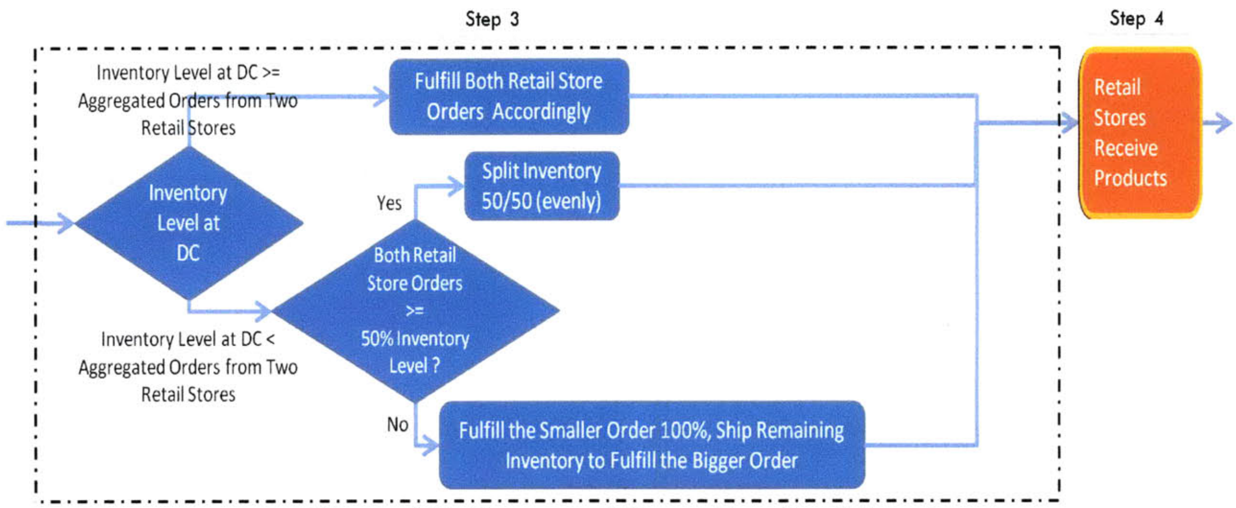


Figure A.2: Conceptual Flow—Step 3 and Step 4

The algorithm can be explained numerically using following scenarios. For example, if available inventory at the DC is 100 units:

Scenario 1: Store A orders 60 units, Store B orders 90 units; the DC will split the inventory equally and ship out 50 units to Store A, 50 units to Store B.

Scenario 2: Store A orders 30 units, Store B orders 90 units; the DC will ship 30 units to Store A and ship the remaining inventory of 70 units to Store B.

Scenario 3: Store A orders 90 units, Store B orders 30 units; the DC will ship 30 units to Store B and ship the remaining inventory of 70 units to Store A.

Scenario 4: Store A orders 40 units, Store B orders 35 units; the DC will ship 40 units to Store A and ship 35 units to Store B.

Figure A.3 shows the logic details involved in step 5. In this step, Chiquita periodically reviews the IP at the DC via the VMI program described in Section 3.1.1 and creates an order to its plant if necessary.

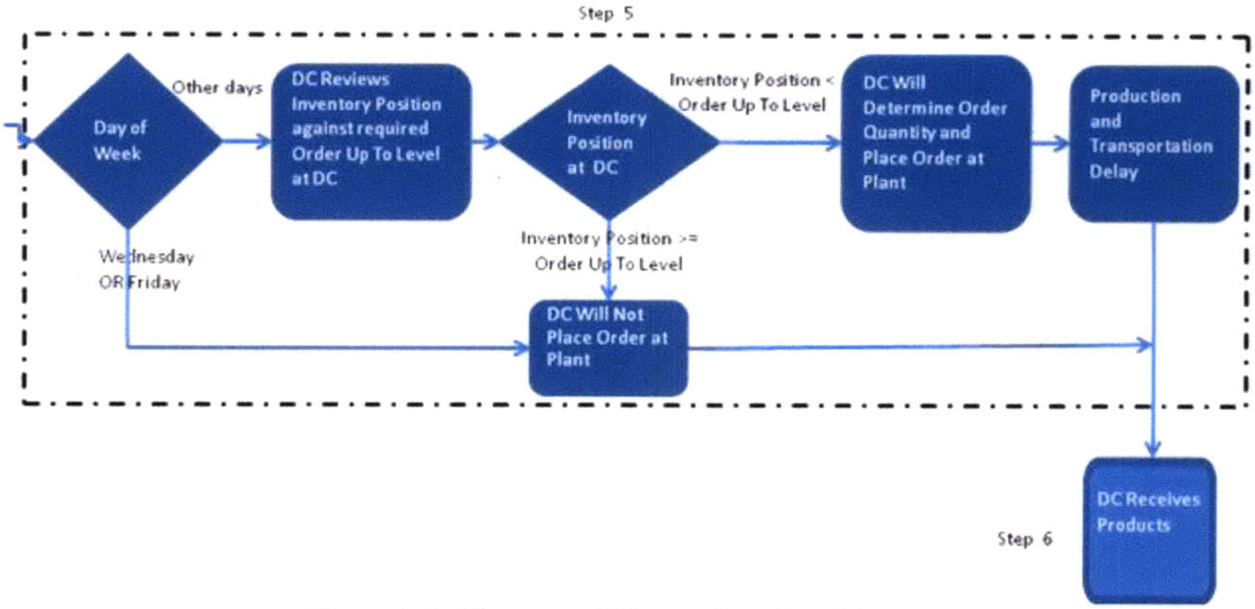


Figure A.3: Conceptual Flow—Step 5 and Step 6

Figure A.4 shows steps 7 and 8; we have discussed their details in the Section 3.2.

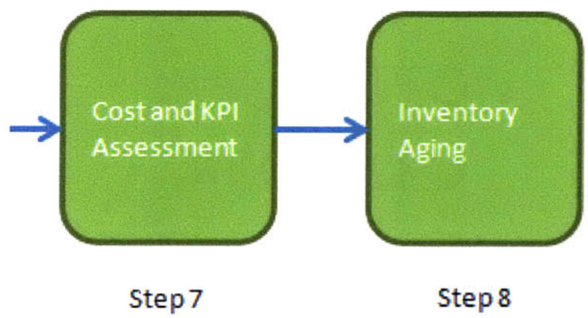


Figure A.4: Conceptual Flow—Step 7 and Step 8

Figures A.5 through A.10 show the Arena simulation model developed using above eight steps.

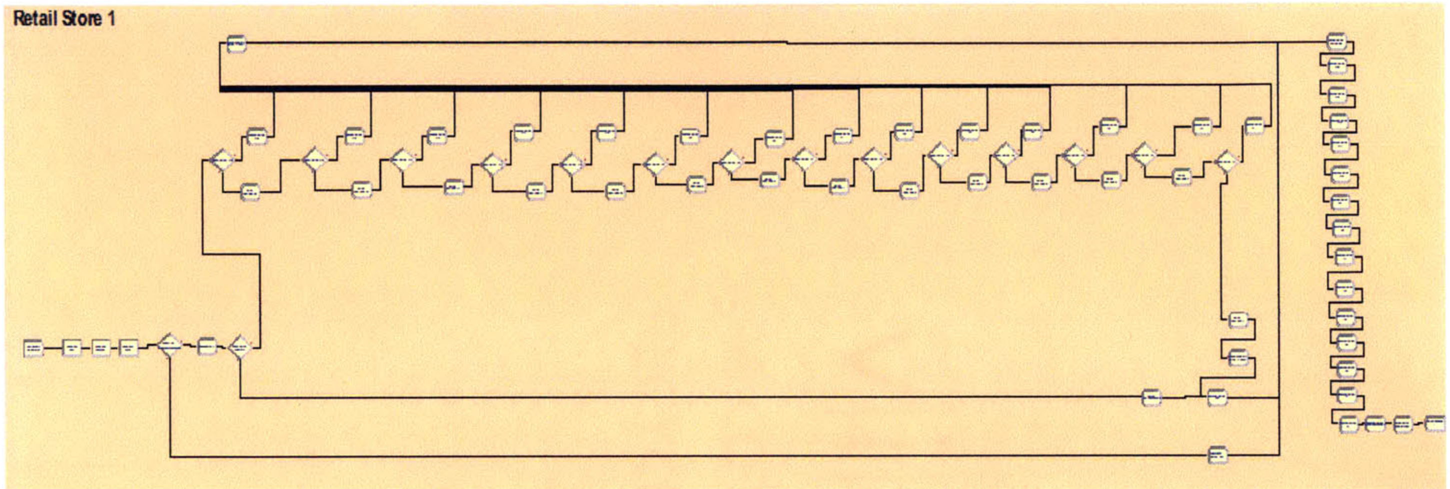


Figure A.5: Retail Store 1 in Arena Simulation Model

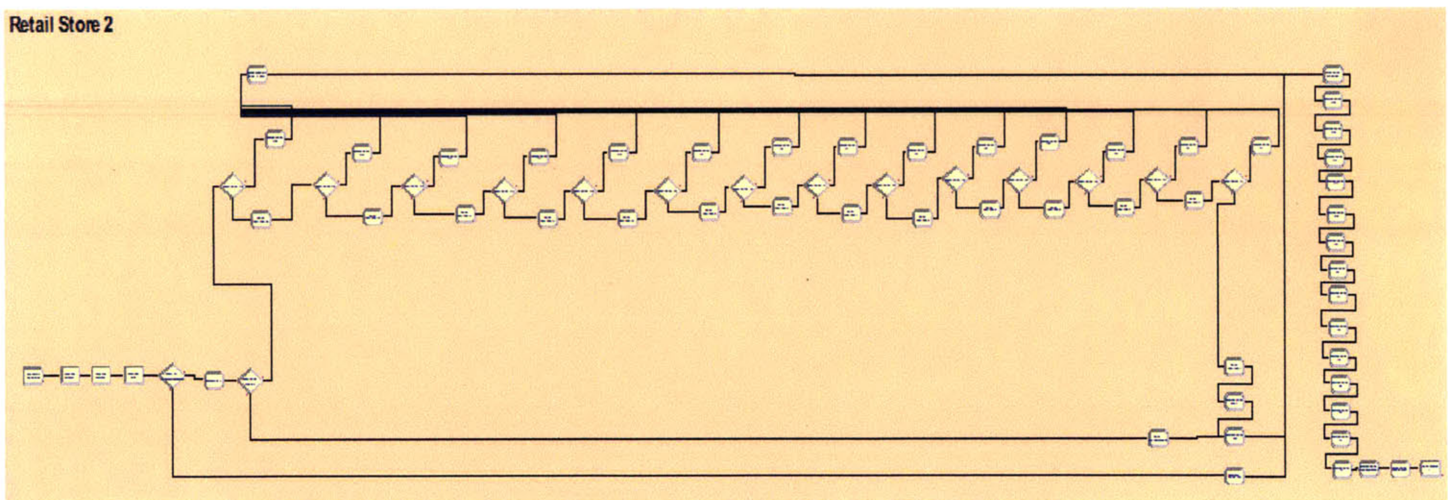


Figure A.6: Retail Store 2 in Arena Simulation Model

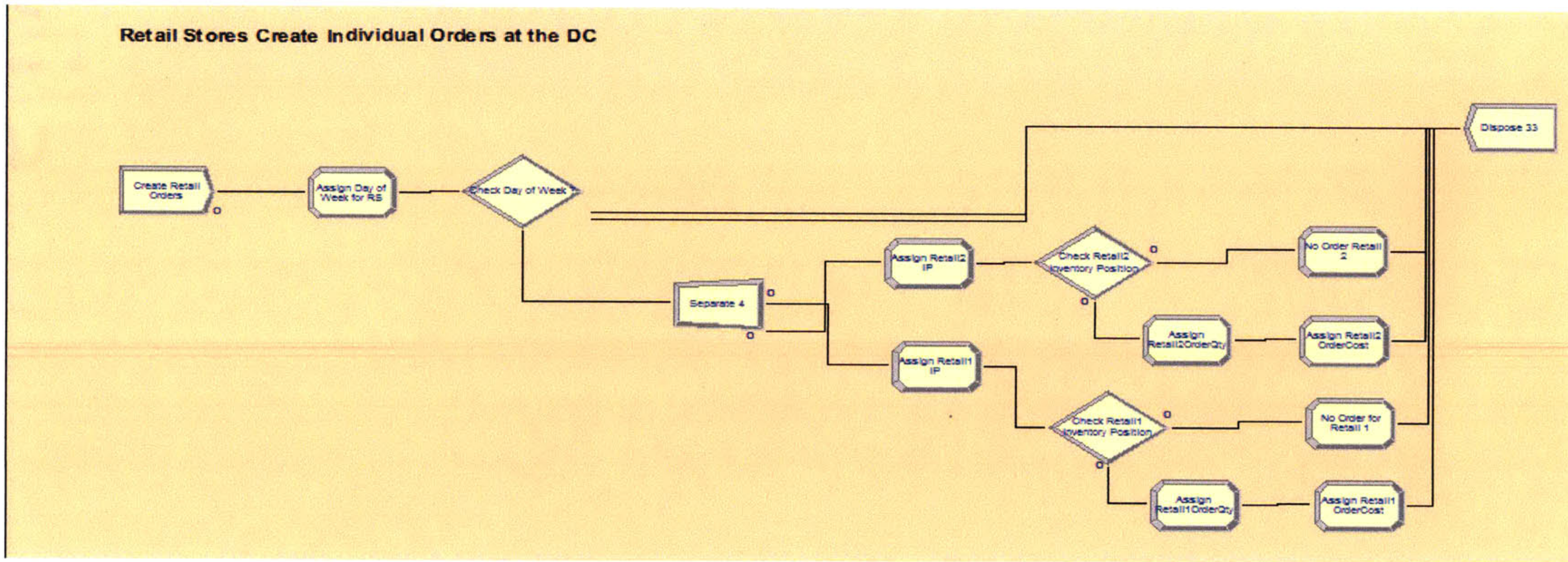


Figure A.7: Order Creation Process by Retail Stores in Arena Simulation Model

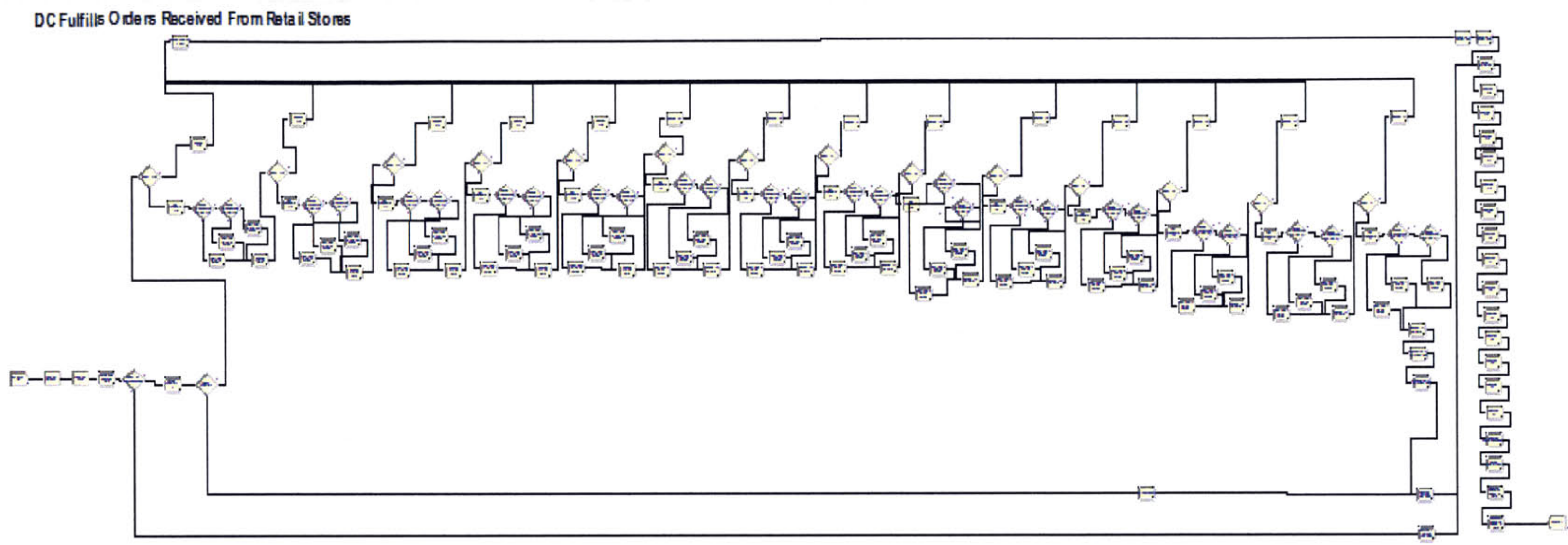


Figure A.8: Customer DC in Arena Simulation Model

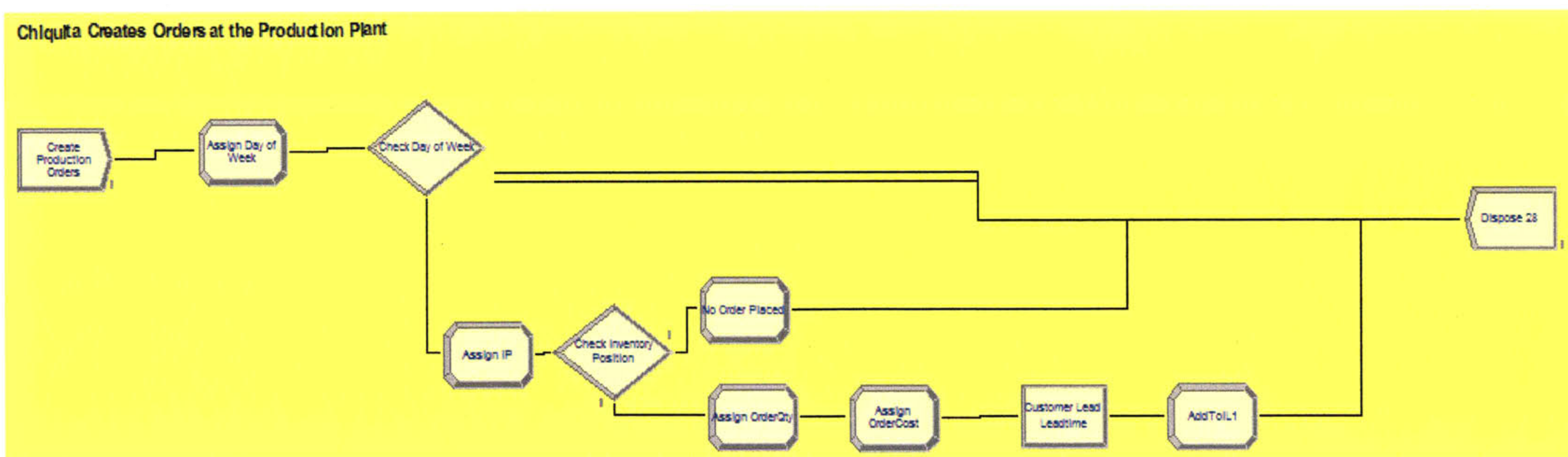


Figure A.9: Order Creation Process by Chiquita at the Plant in Arena Simulation Model

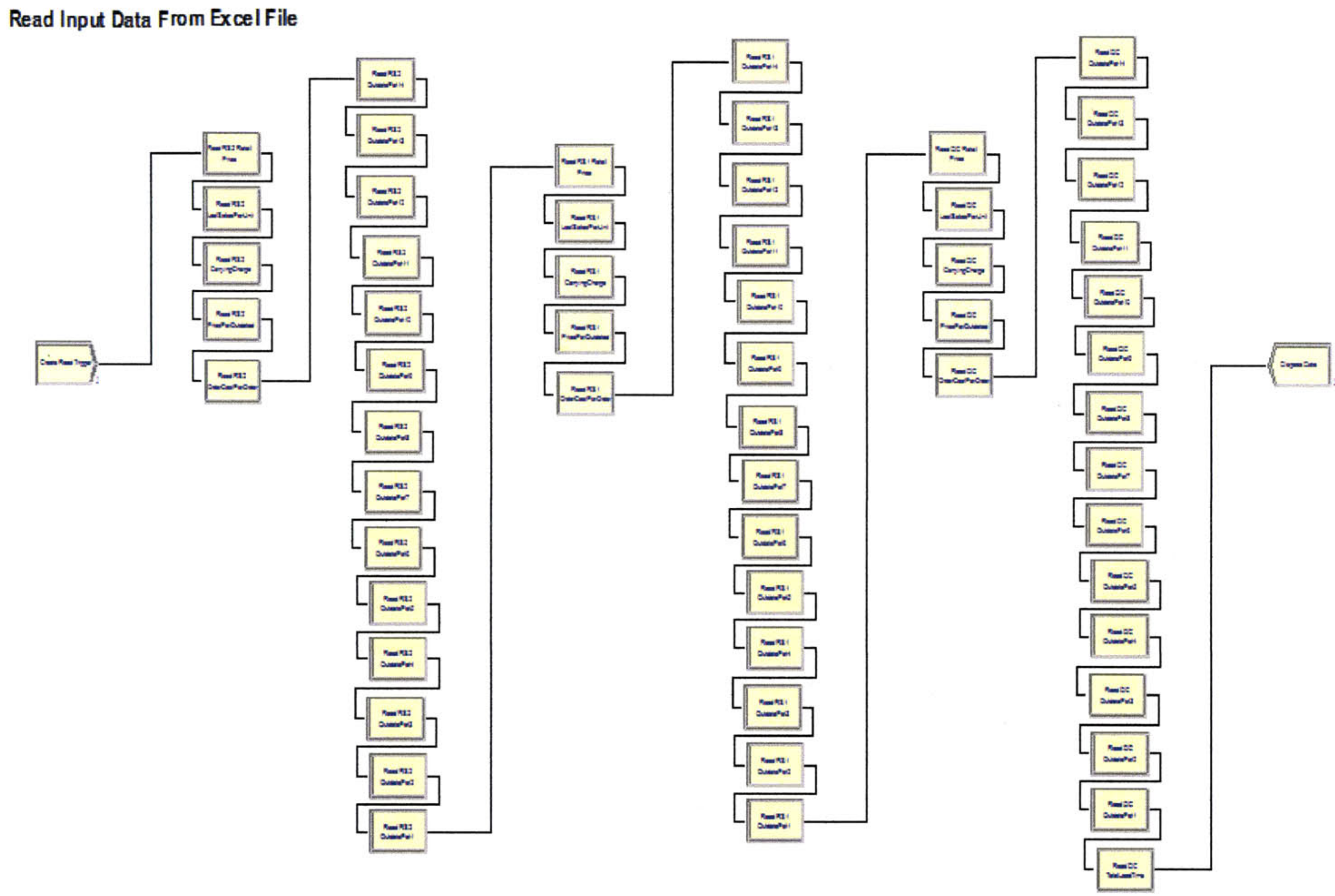


Figure A.10: Reading Input Data from Excel File in Arena Simulation Model

Appendix B: User Guide for Fresh Express Arena Simulation Model

In this appendix, we explain how to use the simulation model that we discussed in our thesis. The simulation model was implemented using Arena software and Microsoft Excel © 2007. We divide the appendix into the following sections.

- B.1 Introduction to the Fresh Express Arena Simulation Model
- B.2 Setting Up the Model
    - B.2.1 Excel Input Parameters for the Supply Chain
    - B.2.2 Replication Parameters for Arena Simulation
- B.3 Running the Model
    - B.3.1 Running the Model in Arena
    - B.3.2 Built-in Reports in Arena
    - B.3.3 User Customized Results in Excel
- B.4 Sensitivity Testing Setup

For additional information on Arena software and the features offered beyond the scope of this appendix, we recommend the user to refer to the manual provided by Rockwell Automation, the manufacturer of Arena software.

B.1 Introduction to the Fresh Express Arena Simulation Model

Arena is a discrete-event systems simulation tool and it was used to program and simulate Chiquita's Fresh Express Supply Chain for the purposes of this thesis. A Microsoft Excel file was used feed the input parameters into this Arena model. In this Excel file, the model user can specify the input parameters specific to each individual echelon of supply chain that we discussed in Chapter 4. The Arena simulation model reads these input parameters before running the simulation. To that end, we have integrated the Excel file with the Arena simulation model.

Additionally, the user needs to setup replication parameters for the Arena simulation model. At the end of simulation runs, Arena provides results for the output variables using Arena's built-in reports. Users can also obtain results for the specific output variables at the required level of granularity, provided a specific output file and the output format are specified to the model by the intended user. The sections below provide more details regarding the process involved.

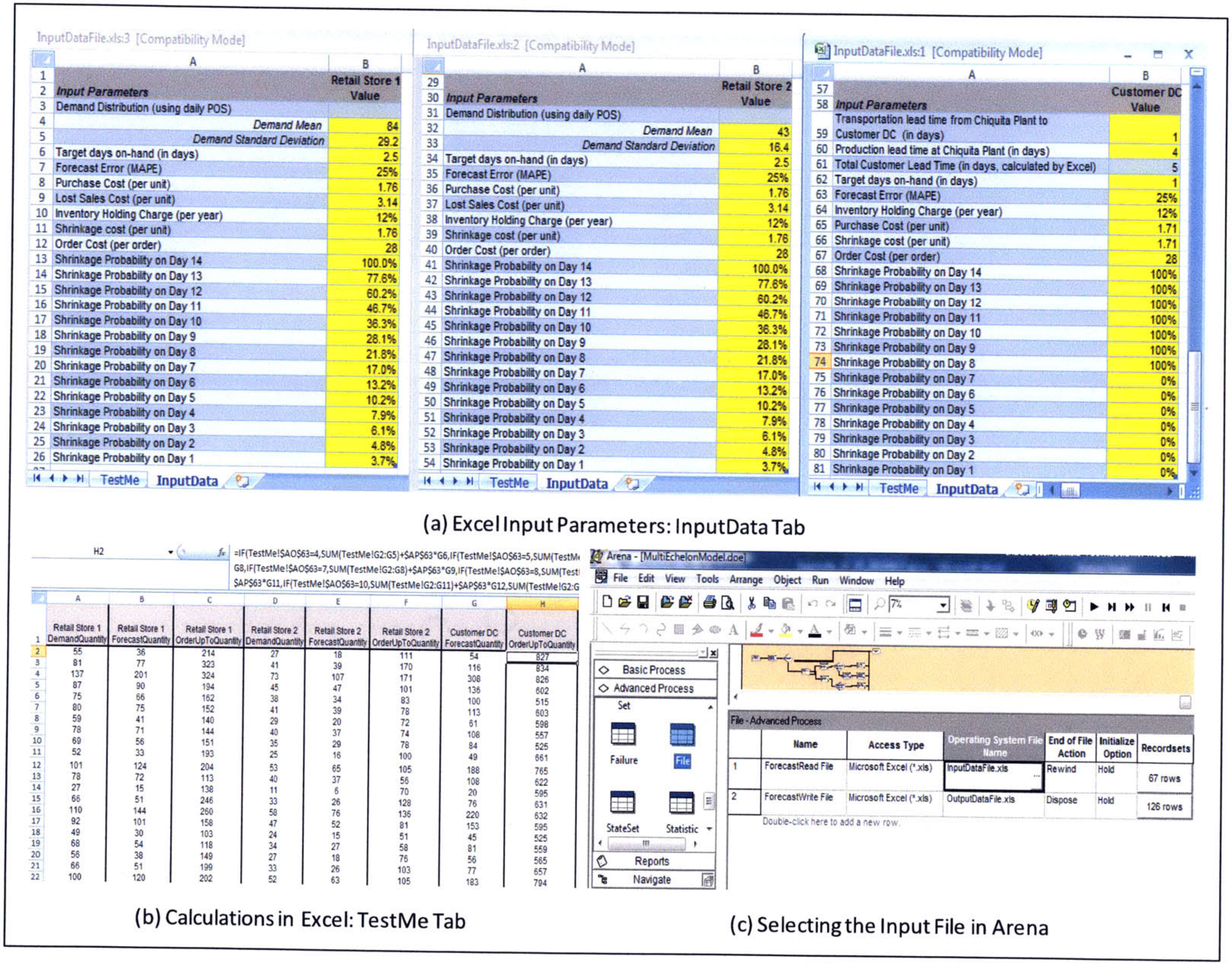
B.2 Setting Up the Model

This section provides details regarding the input parameters to be specified by the model user.

B.2.1 Excel Input Parameters for the Supply Chain

As mentioned in Section B.1, the user needs to specify the input parameters specific to the supply chain in file the *InputDataFile.xls.* Figure B.1 (a) shows the screenshot of this file and the input parameters to be specified by the user. The user needs to specify a valid data value for each of the cells marked in yellow. We have defined a valid range for each of these input data cells. If the user enters any incorrect value (for example, negative values) into these cells, an input error messages twill appear to the user. The user needs to resolve any errors that are prompted before proceeding to the actual Arena simulation.

The user is allowed to enter data only in the *InputData* tab. The *TestMe* tab as shown in Figure B.1 (b) is protected and used for the calculations explained in Section 3.1.5 (Figure 3.1). The Arena simulation model reads the data from this tab. Figure B.1 (c) shows how to select and setup the file *InputDataFile.xls* in Arena.



(a) Excel Input Parameters: InputData Tab

(b) Calculations in Excel: TestMe Tab

(c) Selecting the Input File in Arena

Figure B.1: Preparing the Excel File with Input Parameters

B.2.2 Replication Parameters for Arena Simulation

After preparing the Excel file with input parameters as mentioned Section B.2.1, the user also needs to setup the replication parameters for the simulation model. Figure B.2 shows the screenshot from Arena where the user needs to specify these parameters.

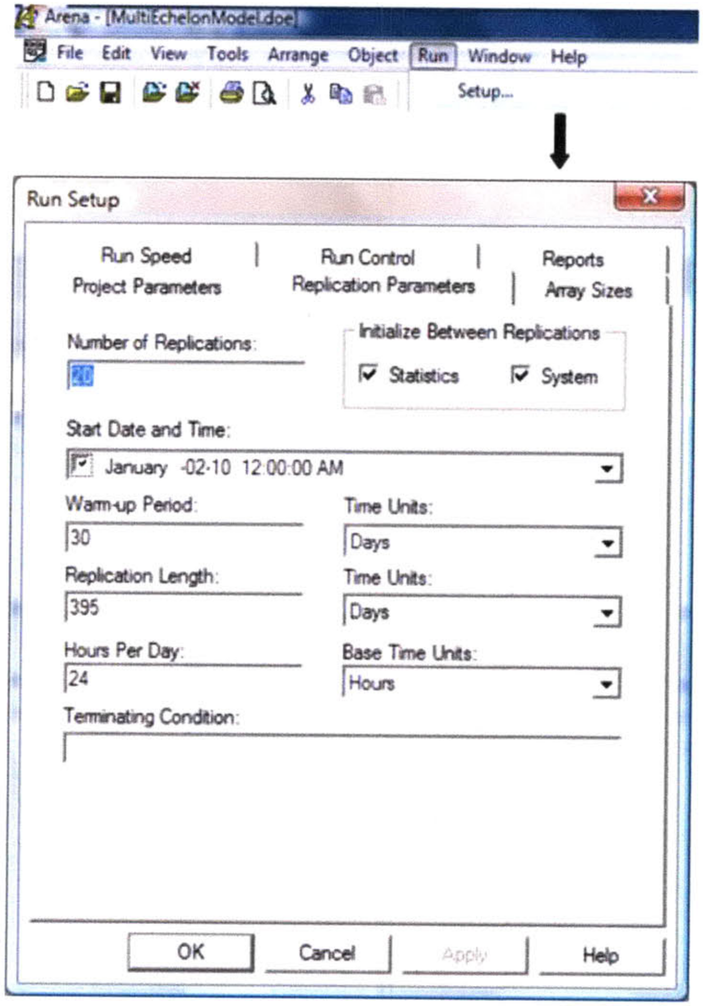


Figure B.2: Setting the Replication Parameters

We explain the key parameters shown in Figure B.2 as below.

I. *Number of Replications:* This indicates the number of independent iterations or replications the simulation model is required to perform before producing final set of results. We recommend 20 replications to capture the variability in the system and produce reliable results. This means that the simulation model will run twenty times with a different set of random data every time and at the end of 20th replication it will produce the results for user-specified output variables.

II. *Start Date and Time:* This indicates the beginning date and time for the simulation run. For example, if we want to conduct the simulation for 365 days in future, the Start Date and Time indicates the very first day on which the simulation begins.

III. *Warm-up Period:* In general, for simulating the situations that do not start without inventory or material in process, the user needs specify warm-up period. For the simulation model discussed in this thesis, we recommend 30 days of warm-up, which we determined through tests. This means that the statistics collected over first 30 days will not be counted towards final performance measures reported at the end of simulation runs. In other words, the simulation model requires 30 days to stabilize the system and start performing close to the average conditions of the system that match with reality.

IV. *Replication Length:* This indicates the duration for which user would like to conduct the simulation. For example, we wanted to collect data from the simulation for 1 year. Given that we had 30 days of warm-up, the replication length was set to 395 days. The user needs to account for the warm-up period while setting the replication length.

B.3 Running the Model

After successfully completing the process in Sections B.1 and B.2, the user can proceed to running the model.

B.3.1 Running the Model in Arena

The user should first check the model for any errors as a routine procedure. If no changes are being made to the model and procedure mentioned above is correctly followed by the user, there should be no errors. Figure B.3 shows how to check the model for errors in Arena. The user should get the message *No errors or warnings in model* as shown below. If there are any errors, the user should review those errors and resolve them before running the simulation model.

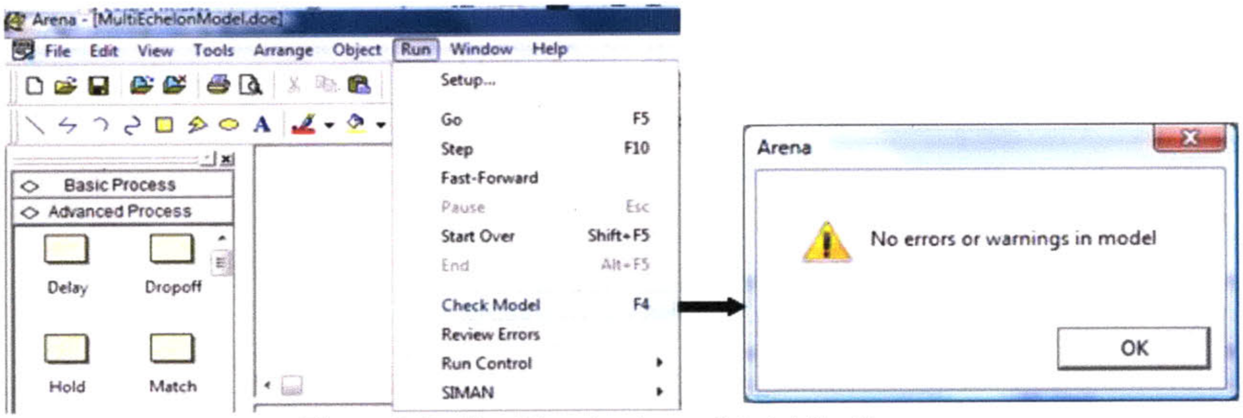


Figure B.3: Checking the Arena Model for Errors

Next, the simulation run can be started by the user just by selecting option *GO* in from the drop-down *Run* menu as shown in Figure B.3. Alternatively, the user can select the arrows as shown in Figure B.4 below to start the simulation run in normal mode or fast-forward mode. Running the model in fast-forward modes saves significant amount of time. If the user wants to view the animation, then simulation speed can be controlled (slowed down) using the bar shown in Figure B.4. Using animation increases the time required to finish the simulation runs.

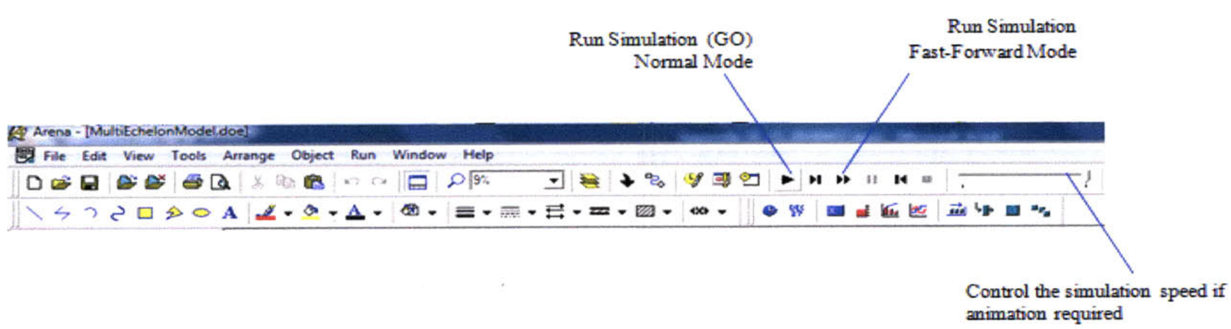


Figure B.4: Running the Arena Model

B.3.2 Built-in Results Reports in Arena

At the end of the simulation run, Arena will generate the results for the output variables specified by the user. The Arena software prompts the message shown in Figure B.5, indicating that results are ready for the user to review. The option to enable or disable the display of results at the end of simulation run can be set by the user under *Reports* as shown in Figure B.2.

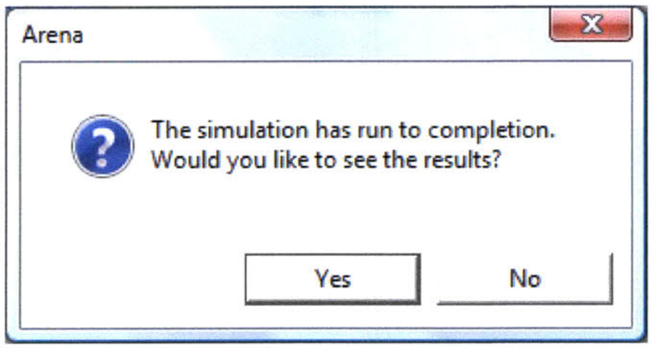


Figure B.5: Result Message Prompt by Arena

In general, the user can specify some statistics to be collected under *Project Parameters* as shown in Figure B.2. Figure B.6 and B.7 indicate how to collect statistics for already-existing variables in the model and the custom variables defined by the user for the purpose of this model. For most of the variables in this model, the statistics collection is turned on by selecting the *Report Statistics* check-box for *Variable* under the *Basic Processes* panel as shown in the Figure B.6. The user can see the complete list of variables in the model and select the statistics for variables that are of interest. Additionally, the user can specify new or custom variables that are of interest under the *Statistics* option which is listed under the *Advanced Process* panel as shown in Figure B.7. We have created four custom variables, which are the total relevant cost for the DC, Retail Store 1, Retail Store 2 and the system.

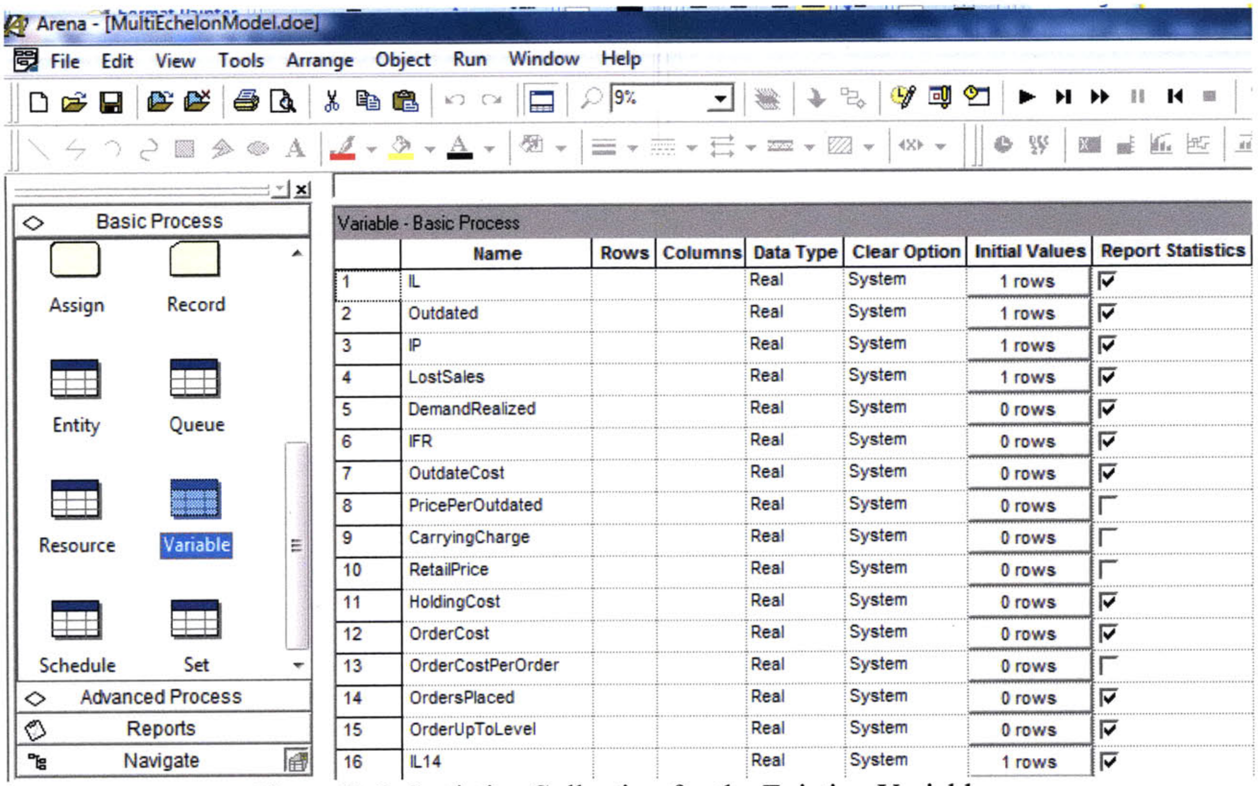


Figure B.6: Statistics Collection for the Existing Variables

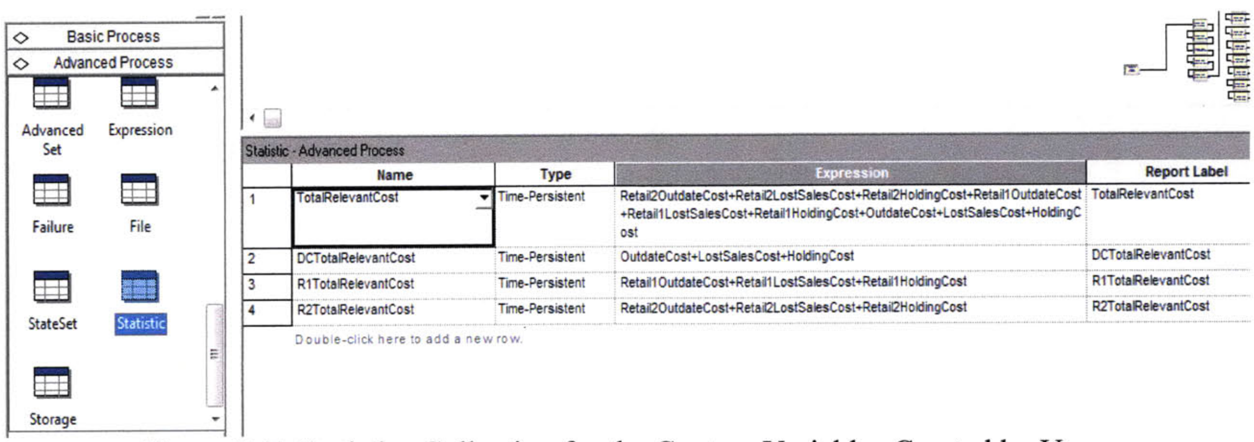


Figure B.7: Statistics Collection for the Custom Variables Created by User

For each of the variables selected for statistics collection, Arena provides six statistics (columns) as described in Section 4.2.4. Figure B.8 shows the screenshot of the available Arena reports to the user. The *Category Overview* provides summary of results over all iterations together where as *Category by Replication* provides the results for each individual iteration. The *Category*

Overview results are more relevant for the purpose of this analysis. There are other reports that may or may not be relevant depending upon the user's specifications.

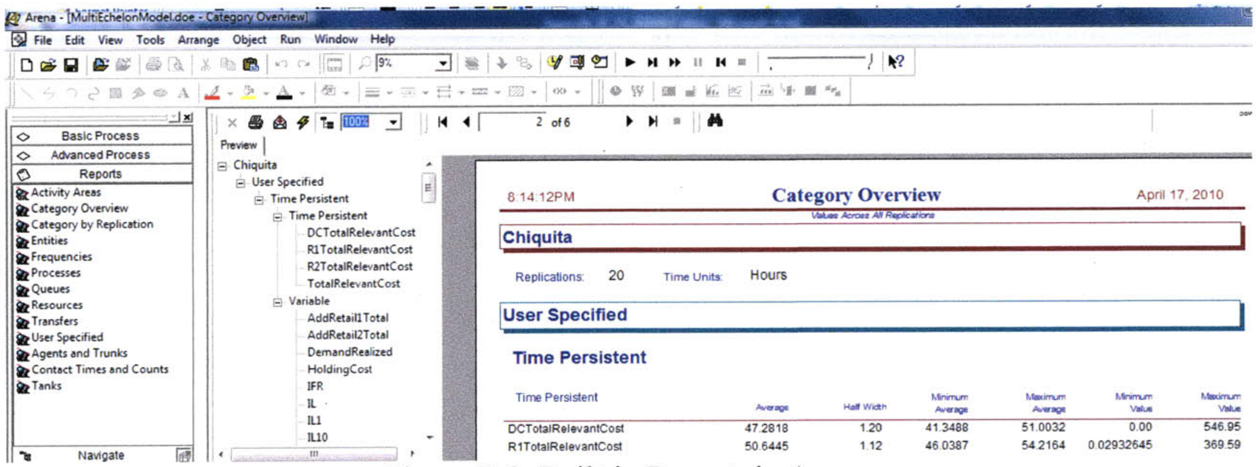


Figure B.8: Built-in Reports in Arena

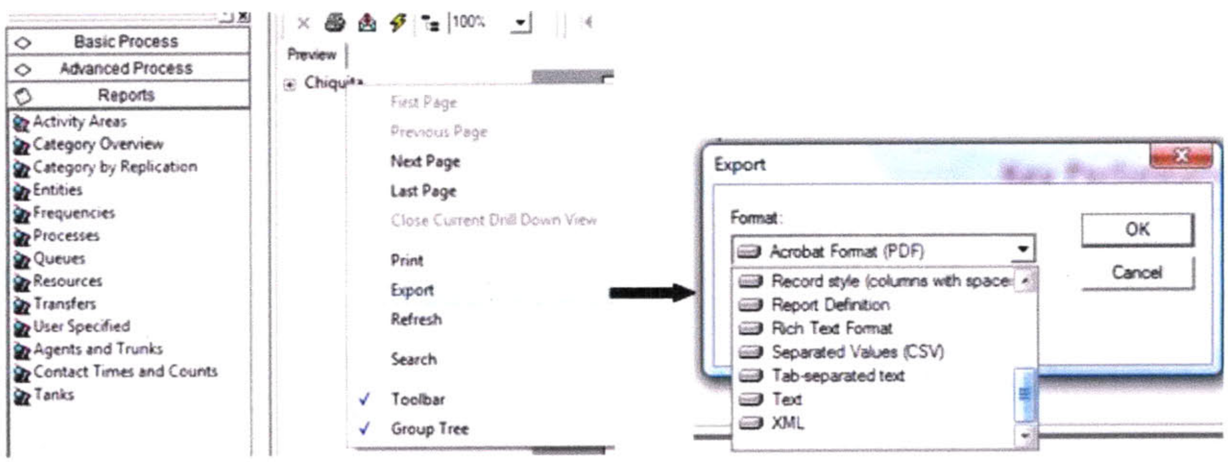


Figure B.9: Exporting the Arena Reports

The user can export these reports into another format by simply right-clicking on the report under *Preview* and then selecting *Export* option as shown in the Figure B.9

B.3.3 User-Customized Results in Excel

The user can develop an additional program in the Arena model for exporting any specific output variables at a different level of detail (daily, monthly, etc.) than the level reported in Arena's built-in reports if needed. We developed a program to export daily results for few output variables as shown in Figure B.10. The default export starts after warm-up period of 30 days, but the user can change it that if needed. For example, if the user is interested in reviewing the IFR at the DC for each individual day simulated in Arena and for all twenty iterations, then the Excel file *OutputDataFile.xls* will contain those results as shown in Figure B.11. The user needs to specify this filename in Arena as shown in Figure B.1 (c). This makes the simulation extremely slow; on our laptop computer, a simulation run takes 1 minute without this additional export versus 120 minutes with export. We do not recommend exporting these types of additional results unless it is extremely necessary for the purpose of analysis. Results reported in Arena's built-in reports are generally sufficient for the purpose of analysis.

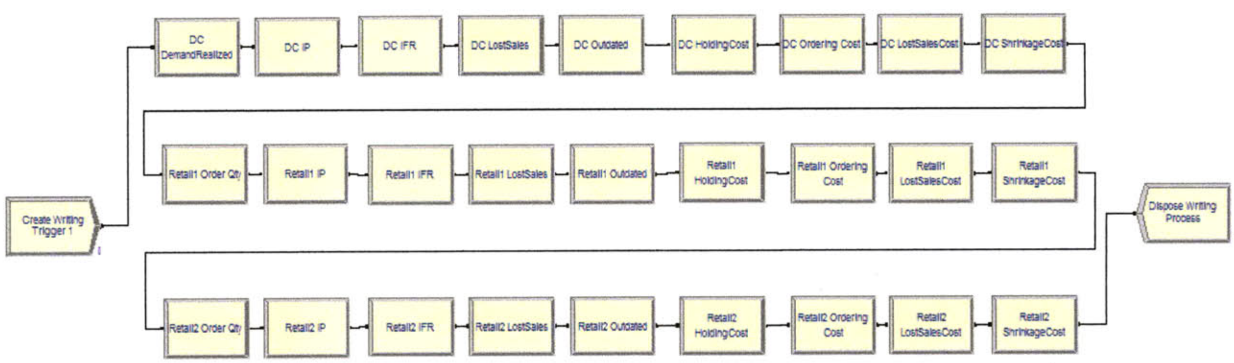


Figure B.10: Additional Export Program

	A	B	E	F	G	H	I	J	K	L	N	O	P	
1	Simulation Iteration	Day	DC ItemFillRate	DC Lost Sales	DC Total Shrinkage	DC Holding Cost	DC Ordering Cost	DC Lost Sales Cost	DC Shrinkage Cost	Retail Store 1 Inventory Position	Retail Store 1 OrderQty	Retail Store 1 ItemFillRate	Retail Store 1 Lost Sales	Ret Total
32	1	31	100	0	0	81	28	0	0	131	169	100	0	
33	1	32	100	0	0	32	28	0	0	156	156	100	0	
34	1	33	100	0	0	32	28	0	0	217	0	100	0	
35	1	34	100	0	0	83	0	0	0	107	132	100	0	
36	1	35	100	0	0	72	0	0	0	145	107	100	0	
37	1	36	100	0	0	101	28	0	0	139	131	100	0	
38	1	37	100	0	0	87	28	0	0	139	43	100	0	
39	1	38	100	0	0	82	28	0	0	120	19	100	0	
40	1	39	100	0	0	23	28	0	0	74	190	100	0	
41	1	40	100	0	0	45	28	0	0	123	210	100	0	
42	1	41	100	0	0	28	28	0	0	209	56	100	0	
43	1	42	100	0	0	6	28	0	0	171	74	100	0	
44	1	43	100	0	0	30	28	0	0	126	169	100	0	
45	1	44	100	0	0	3	28	0	0	197	85	100	0	
46	1	45	100	0	0	52	28	0	0	148	149	100	0	
47	1	46	100	0	0	51	0	0	0	205	3	100	0	
48	1	47	100	0	0	87	0	0	0	99	90	100	0	

Figure B.11: Additional Export File - OutputDataFile.xls

B.4 Sensitivity Testing Setup

We discussed the details of the sensitivity analysis in Chapter 4. If the user wants to conduct sensitivity analyses, appropriate values should be entered in the file *InputDataFile.xls* as shown in Figure B.1 (a). We mentioned the constraints on values for each input parameter in the file *InputDataFile.xls;* the user should keep those constraints in mind while conducting the sensitivity analysis. Then all the steps as mentioned in Appendix B should be followed to obtain and review the results. In Chapter 4, we also discussed interpretation of various statistics provided by Arena.

Appendix C: List of Terms and Abbreviations

Table C.1: Key Abbreviations

Abbreviation	Definition
ABC	ABC Inc., Chiquita's biggest retail customer
DC	Distribution Center
DCHoldingCost	Inventory Holding Cost at the DC
DCIFR	Item Fill Rate at the DC
DCIL	Inventory Level at the DC
DCLostSalesCost	Lost Sales Cost at the DC
DCOutdateCost	Shrinkage Cost at the DC
DCTotalRelevantCost	Total Relevant Cost at the DC
FIFO	First-In-First-Out policy
IFR	Item Fill Rate
IL	Inventory Level
IP	Inventory Position
KPI	Key Performance Indexes
MAPE	Mean Absolute Percentage Error
OUL	Order-Up-to Level
POS	Point of Sale
Retail1HoldingCost	Inventory Holding Cost at the Retail Store 1
Retail1IFR	Item Fill Rate at the Retail Store 1
Retail1IL	Inventory Level at the Retail Store 1
Retail1LostSalesCost	Lost Sales Cost at the Retail Store 1
Retail1OutdateCost	Shrinkage Cost at the Retail Store 1
Retail1TotalRelevantCost	Total Relevant Cost at the Retail Store 1
Retail2HoldingCost	Inventory Holding Cost at the Retail Store 2
Retail2IFR	Item Fill Rate at the Retail Store 2
Retail2IL	Inventory Level at the Retail Store 2
Retail2LostSalesCost	Lost Sales Cost at the Retail Store 2
Retail2OutdateCost	Shrinkage Cost at the Retail Store 2
Retail2TotalRelevantCost	Total Relevant Cost at the Retail Store 2
SystemTotalRelevantCost	Total Relevant Cost for the System
TargetOnHandDays	Target Days On-Hand Inventory Level
VMI	Vendor Managed Inventory

Table C.2: Terms for Figure 4.8, 4.13, and 4.18

Term	Definition
DCIL01	Inventory that is 1 day old in Bin 1 at the DC
DCIL02	Inventory that is 2 days old in Bin 2 at the DC
DCIL03	Inventory that is 3 days old in Bin 3 at the DC
DCIL04	Inventory that is 4 days old in Bin 4 at the DC
DCIL05	Inventory that is 5 days old in Bin 5 at the DC
DCIL06	Inventory that is 6 days old in Bin 6 at the DC
DCIL07	Inventory that is 7 days old in Bin 7 at the DC
DCIL08	Inventory that is 8 days old in Bin 8 at the DC
DCIL09	Inventory that is 9 days old in Bin 9 at the DC
DCIL10	Inventory that is 10 days old in Bin 10 at the DC
DCIL11	Inventory that is 11 days old in Bin 11 at the DC
DCIL12	Inventory that is 12 days old in Bin 12 at the DC
DCIL13	Inventory that is 13 days old in Bin 13 at the DC
DCIL14	Inventory that is 14 days old in Bin 14 at the DC
Retail1IL01	Inventory that is 1 day old in Bin 1 at the Retail Store 1
Retail1IL02	Inventory that is 2 days old in Bin 2 at the Retail Store 1
Retail1IL03	Inventory that is 3 days old in Bin 3 at the Retail Store 1
Retail1IL04	Inventory that is 4 days old in Bin 4 at the Retail Store 1
Retail1IL05	Inventory that is 5 days old in Bin 5 at the Retail Store 1
Retail1IL06	Inventory that is 6 days old in Bin 6 at the Retail Store 1
Retail1IL07	Inventory that is 7 days old in Bin 7 at the Retail Store 1
Retail1IL08	Inventory that is 8 days old in Bin 8 at the Retail Store 1
Retail1IL09	Inventory that is 9 days old in Bin 9 at the Retail Store 1
Retail1IL10	Inventory that is 10 days old in Bin 10 at the Retail Store 1
Retail1IL11	Inventory that is 11 days old in Bin 11 at the Retail Store 1
Retail1IL12	Inventory that is 12 days old in Bin 12 at the Retail Store 1
Retail1IL13	Inventory that is 13 days old in Bin 13 at the Retail Store 1
Retail1IL14	Inventory that is 14 days old in Bin 14 at the Retail Store 1
Retail2IL01	Inventory that is 1 day old in Bin 1 at the Retail Store 2
Retail2IL02	Inventory that is 2 days old in Bin 2 at the Retail Store 2
Retail2IL03	Inventory that is 3 days old in Bin 3 at the Retail Store 2
Retail2IL04	Inventory that is 4 days old in Bin 4 at the Retail Store 2
Retail2IL05	Inventory that is 5 days old in Bin 5 at the Retail Store 2
Retail2IL06	Inventory that is 6 days old in Bin 6 at the Retail Store 2
Retail2IL07	Inventory that is 7 days old in Bin 7 at the Retail Store 2
Retail2IL08	Inventory that is 8 days old in Bin 8 at the Retail Store 2
Retail2IL09	Inventory that is 9 days old in Bin 9 at the Retail Store 2

Table C.2 continued

Term	Definition
Retail2IL10	Inventory that is 10 days old in Bin 10 at the Retail Store 2
Retail2IL11	Inventory that is 11 days old in Bin 11 at the Retail Store 2
Retail2IL12	Inventory that is 12 days old in Bin 12 at the Retail Store 2
Retail2IL13	Inventory that is 13 days old in Bin 13 at the Retail Store 2
Retail2IL14	Inventory that is 14 days old in Bin 14 at the Retail Store 2
DCOutdated01	Shrinkage from Bin 1 at the DC
DCOutdated02	Shrinkage from Bin 2 at the DC
DCOutdated03	Shrinkage from Bin 3 at the DC
DCOutdated04	Shrinkage from Bin 4 at the DC
DCOutdated05	Shrinkage from Bin 5 at the DC
DCOutdated06	Shrinkage from Bin 6 at the DC
DCOutdated07	Shrinkage from Bin 7 at the DC
DCOutdated08	Shrinkage from Bin 8 at the DC
DCOutdated09	Shrinkage from Bin 9 at the DC
DCOutdated10	Shrinkage from Bin 10 at the DC
DCOutdated11	Shrinkage from Bin 11 at the DC
DCOutdated12	Shrinkage from Bin 12 at the DC
DCOutdated13	Shrinkage from Bin 13 at the DC
DCOutdated14	Shrinkage from Bin 14 at the DC
Retail1Outdated01	Shrinkage from Bin 1 at the Retail Store 1
Retail1Outdated02	Shrinkage from Bin 2 at the Retail Store 1
Retail1Outdated03	Shrinkage from Bin 3 at the Retail Store 1
Retail1Outdated04	Shrinkage from Bin 4 at the Retail Store 1
Retail1Outdated05	Shrinkage from Bin 5 at the Retail Store 1
Retail1Outdated06	Shrinkage from Bin 6 at the Retail Store 1
Retail1Outdated07	Shrinkage from Bin 7 at the Retail Store 1
Retail1Outdated08	Shrinkage from Bin 8 at the Retail Store 1
Retail1Outdated09	Shrinkage from Bin 9 at the Retail Store 1
Retail1Outdated10	Shrinkage from Bin 10 at the Retail Store 1
Retail1Outdated11	Shrinkage from Bin 11 at the Retail Store 1
Retail1Outdated12	Shrinkage from Bin 12 at the Retail Store 1
Retail1Outdated13	Shrinkage from Bin 13 at the Retail Store 1
Retail1Outdated14	Shrinkage from Bin 14 at the Retail Store 1
Retail2Outdated01	Shrinkage from Bin 1 at the Retail Store 2
Retail2Outdated02	Shrinkage from Bin 2 at the Retail Store 2
Retail2Outdated03	Shrinkage from Bin 3 at the Retail Store 2
Retail2Outdated04	Shrinkage from Bin 4 at the Retail Store 2

Table C.2 continued

Term	Definition
Retail2Outdated06	Shrinkage from Bin 6 at the Retail Store 2
Retail2Outdated07	Shrinkage from Bin 7 at the Retail Store 2
Retail2Outdated08	Shrinkage from Bin 8 at the Retail Store 2
Retail2Outdated09	Shrinkage from Bin 9 at the Retail Store 2
Retail2Outdated10	Shrinkage from Bin 10 at the Retail Store 2
Retail2Outdated11	Shrinkage from Bin 11 at the Retail Store 2
Retail2Outdated12	Shrinkage from Bin 12 at the Retail Store 2
Retail2Outdated13	Shrinkage from Bin 13 at the Retail Store 2
Retail2Outdated14	Shrinkage from Bin 14 at the Retail Store 2

Appendix D: Additional Results of the Sensitivity Analysis

In Chapter 4, we discussed the results obtained through our simulation model for the base scenario and the optimal policy. We also discussed the results obtained by conducting the sensitivity analysis with respect to the forecast error and the transportation lead time. In this appendix, we provide the results obtained through sensitivity analysis in the form of graphs indicating the impact of forecast error and transportation lead time on the costs at each individual echelon and the system.

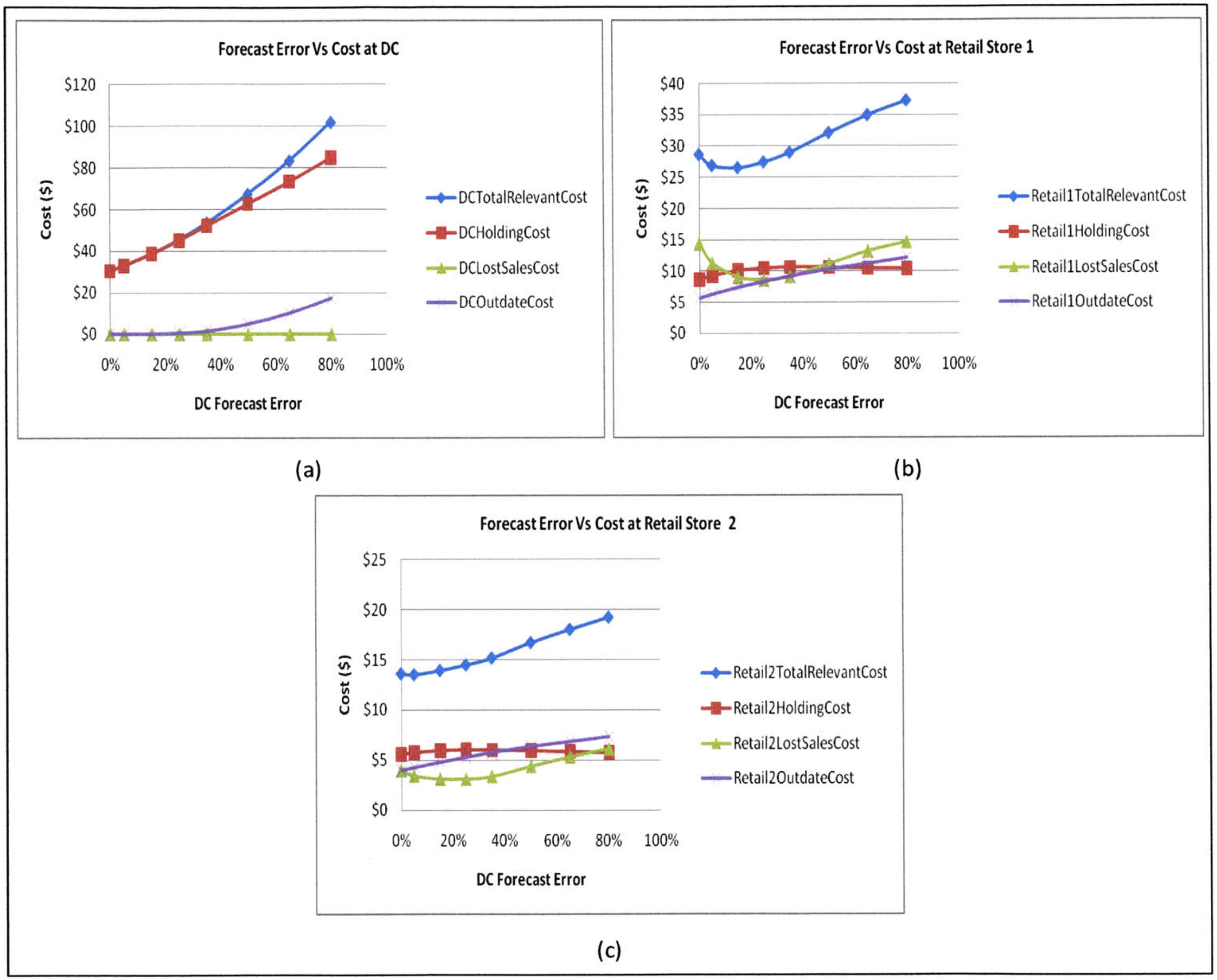


Figure D.1: Impact of DC's Forecast Error on the Cost

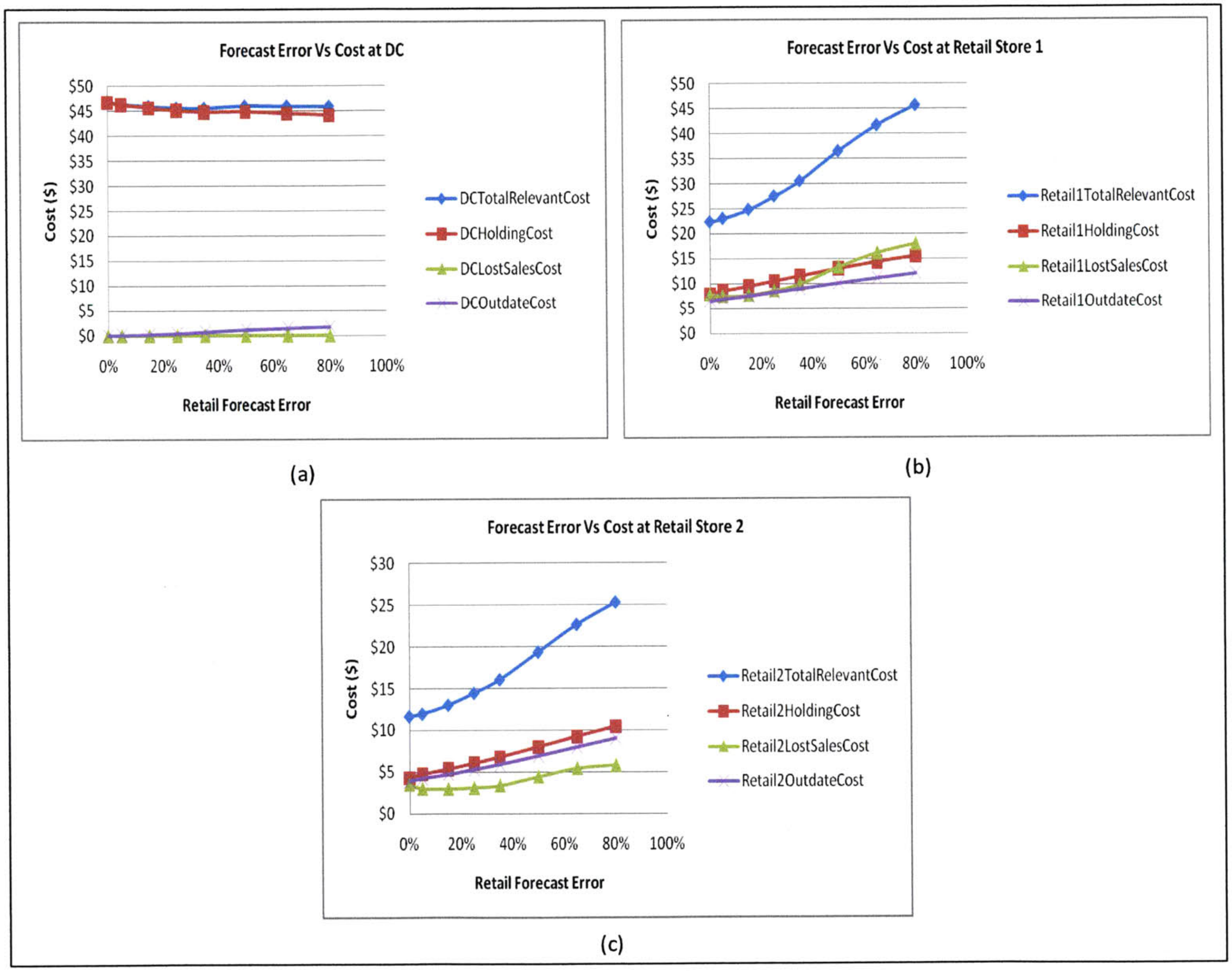


Figure D.2: Impact of Retail Store's Forecast Error on the Cost

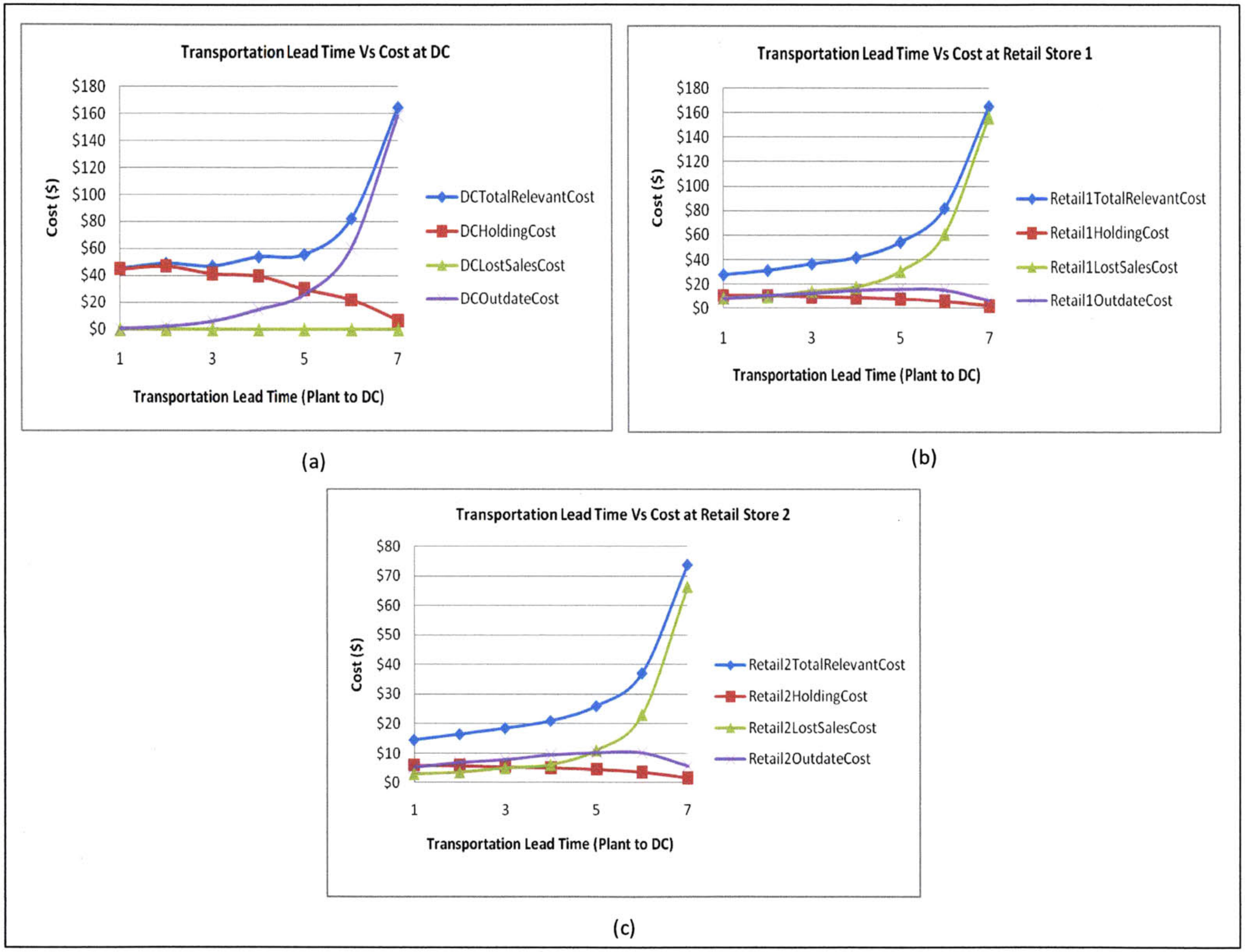


Figure D.3: Impact of Transportation Lead Time on the Cost