

Obsolescence Reduction Through Product Segmentation

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SUBMITTED TO THE PROGRAM IN SUPPLY CHAIN MANAGEMENT
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF ENGINEERING IN LOGISTICS

AT THE

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

JUNE 2016

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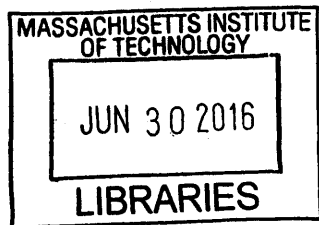
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Submitted to the Program in Supply Chain Management
on May 6, 2016 in Partial Fulfillment of the
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ABSTRACT

The Hershey Company faces a risk of obsolescence across its supply chain as it follows the First In First Out (FIFO) technique at its manufacturing plant distribution center instead of distributing goods based on either the demand at each retailer's end or the useable shelf life of the goods being distributed. The two different stages at which a product can turn obsolete are a) when it reaches expiry and b) during the end of a season or promotion run for a specialty product. The existing picking strategy does not differentiate between orders based on the type of products or the volume served by destination/retailers. This could lead to the risk of obsolescence or return of products in some retailers as the products reach expiry before sales at the retailer's end due to insufficient remaining shelf life. Through this project, we aim at reducing the total obsolescence of a product by proposing a new picking strategy based on the sales volume at each distribution channel and the remaining shelf life of products at the manufacturer's site. The cut-off value or the ratio of volume served by fast moving customer distribution centers to the total volume at which the obsolescence within the supply chain would be minimal was determined for a set of products using an excel simulation model. Hierarchical clustering was performed on all products to form two clusters of distribution centers based on the shipped order quantities and the fractional volume served by both the clusters was determined. The new model was proposed for those product-distribution center combinations with fractional volumes greater than the cut-off as they are most likely to benefit with reduced level of obsoletes.

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ACKNOWLEDGEMENTS

We would like to express our sincere gratitude to our supervisor, Dr. Andre Carrel for the continuous support, motivation, useful comments, remarks and engagement through the learning process of this master thesis.

We would like to thank Mr. Satya Sanivarapu for coordinating this project and for his guidance, timely help and support. We would also like to thank Ms. Jeanne Marie Wildman for her valuable comments on this thesis.

Lastly, we are gratefully indebted to the CTL department for giving us this wonderful opportunity and the SCM faculty for providing extended help and support.

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1 INTRODUCTION

The Hershey Company (THC) is a leading manufacturer of candy, mint and gum in the United States. The Hershey Company has recently undergone a global supply chain transformation and has adopted new practices for developing a flexible supply chain network (as shown in Figure 1-1) targeting a diverse range of consumer and customer needs.

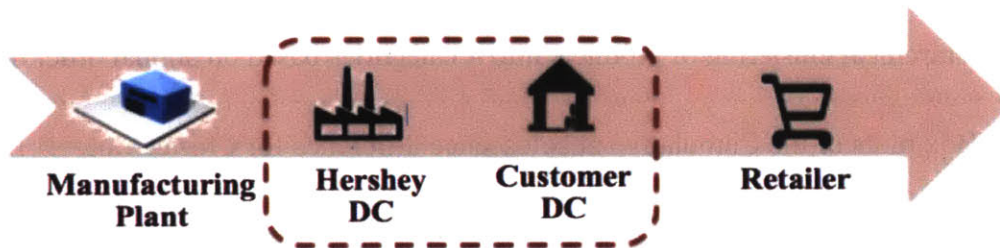


Figure 1-1 A supply chain overview of The Hershey Company

The current picking strategy followed by the Hershey company (FIFO) solely allocates orders based on the date of product manufacturing and does not consider factors such as type of products, shipping volume or characteristics of the destination distribution center/retailer. A particular challenge faced by THC is obsolescence of product in the supply chain, before reaching the customer. The obsolescence could arise either from product perishability (across the supply chain or at the retailers end) or from unsold or returned items after festive seasons or promotional events. As a part of this project, we shall explore the shipping data to manage the SKU velocity or sales volume at distribution centers. The customer distribution centers served by the Hershey company shall be classified based on the volumes of the items shipped as Fast (high volumes of any product) and Slow (lowest volumes). We shall also assess the shortcomings of the current picking strategy, the possibility of an alternate strategy or an appropriate product segmentation (clustering) technique and the conditions under which it shall be beneficial and reduce obsolesces. Our team shall provide recommendations for modifying the existing picking strategy with a dual SKU-DC

cluster picking strategy in order to:

- a) Ship product with minimum remaining shelf life to a fast moving distribution center.
- b) Ensure shipping of fresh products to slow moving customer distribution centers.
- c) Reduce the total obsolescence on the manufacturers and the retailers side and increase their willingness to accept products.

The impact of the proposed strategy on reduction of waste and obsoletes across the supply chain shall be evaluated and compared against the current practice using an Excel simulation model.

2 LITERATURE REVIEW

In this section, we would like to explore the features of perishable goods, the reasons for obsolescence, the possible ways to reduce obsolesces and the pros and cons of existing product segmentation methods. The literature review covers the industrial background and the importance of obsolescence reduction and will help us in designing the analysis model.

As we are focusing on reducing obsolescence by matching the remaining shelf life with retail velocity, we shall review the research and progress in three main categories: shelf-life optimization of perishable goods, obsolesces and obsolescence reduction, and product segmentation methods.

2.1 Shelf-Life Optimization of Perishable Goods

This section covers two important aspects of the consumer products dealt with in this project: perishability and shelf life of the product. Consumer products in the food industry can be classified into three categories: perishable, non-perishable and semi perishable. The items manufactured by The Hershey Company (mainly chocolates) are perishable in nature i.e. they deteriorate after a fixed time period when not stored properly. The supply chain of perishable goods is slightly different from the others, as they require special storage, handling and transportation (Elzakkera , 2014).

The main factors determining the efficiency of a supply chain of perishable goods are the relative velocity or the speed at which a product moves from the shelves of a store, and its shelf life. The shelf life of any product refers to how long a perishable product may be stored under any conditions (dry, refrigerated, with chemicals) before it is rendered unfit for consumption or sale. It is critical to manage the warehousing and distribution centers of fast moving products with a low shelf life efficiently as they dominate the sales in terms of volume (Elzakkera, 2014). However, the supply chain distribution network of such products are often the most neglected as they have low profit margins.

Schotzko (2000) explained in his research the importance of ‘product freshness’ and why retailers demand a certain minimum remaining shelf life for all their products from distributors. Products that do not meet the minimum shelf life requirements at the retailers’ end are either sold at a lower price or returned as obsolesces. Thus, only a part of the shelf life is available in a product’s supply chain, which needs to be optimized by maintaining the right levels of inventory at various nodes of the supply chain. If the Sales and Planning team do not consider the product shelf life, part of the inventory could exceed its shelf life and turn obsolete at the distributor or manufacturer's site itself (Elzakker, 2014). Such a situation not only leads to disposal costs but also to demand non-fulfillment, causing lost sales. Most research in the area of shelf life optimization focuses primarily on adding shelf-life constraints to the Economic Lot Scheduling Problem (ELSP). However, these models would not be applicable to the perishable goods industry, as they assume a constant demand rate throughout the year and exclude the effect of seasonality and promotional offers when computing demand.

Entrup (2005) examined the effect of quality degradation over time and discusses the importance of integrating shelf-life of products in advanced planning in terms of revenue generated by the remaining shelf-life. The shelf-life is modeled by tracking the production day and selling day of each product. He argues that the longer the remaining shelf-life, the more valuable the products at the retailers’ end. Further extrapolating Entrup’s work, Farabani et al. (2011) suggested schemes that would integrate the production and distribution decisions of a perishable food company and compared it with a sequential planning scheme. Farabani (2011) assumed a linear decay on a daily basis for each product in storage. The company would face a linear penalty for quality decay in each of its products. He also added limitations to the maximum shelf-life based on the harvest period and the sales period.

Eksioglu and Jin (2006) proposed a two stage supply chain for perishable products consisting of production facilities and retailers. To reduce obsolesces, they ensured that the inventory at a production plant in a given timeframe would not exceed the quantity sent to the retailers in the next T time periods, where T was the shelf-life of the given product. Another approach suggested by them was to manage the overlapping production batches within a time interval less than the remaining shelf life of the products.

Thus, most techniques listed in literature typically included shelf life directly into the planning phase either by tracking the age of products, by tracking the production and sales dates, or through the product quality. Our recommended approach would also track shelf life for controlling obsolesces in various nodes of THC's supply chain.

2.2 Obsolesces and Obsolescence Reduction

Obsolete inventory refers to the portion of the inventory held at any node of a supply chain that has reached the end of its product life cycle or has not seen any sales or usage within a given time period or the shelf life pre-determined by the industry. Companies that do not have a robust inventory management increase their probability of obsolete inventory level (Rick, 2010).

Inventory is a function of many variables such as demand and demand variability, supply lead time and lead time variability, supply chain design, manufacturing capabilities versus customer purchase characteristics, transportation modes, and desired service levels. The major reason for high levels of inventory at a distribution center is an uncertainty in both supply and demand. In the subsequent sections we discuss the various strategies that have been adopted by companies for obsolescence management.

2.2.1 Inventory Replenishment Method

One of the commonly used methods for reducing obsolescence is to change the inventory replenishment policy. Inventory levels can be accurately controlled by integrating with the Sales &

Operations Planning team or by using automatic replenishment policies when the stock reaches a certain level. (Priti, 2010) Automated replenishment can be done by either using a) Vendor managed Inventory (VMI) or b) Kanban system.

Companies that implement VMI (such as THC) visit the site of their suppliers or customers to and decide the safety stock and inventories levels before placing the orders or signing contracts. Suppliers retain the ownership of inventories until consumed or redirect them to point of use locations. The biggest advantage of implementing a VMI strategy is improved cash flows and reduced risks for the manufacturers. Conversely, Kanban, a Japanese technique, uses a card or visual signals for replenishing inventory by monitoring and triggering signals at lowered inventory levels. It is typically implemented, as a two-bin system wherein signals are sent when one of the bins is empty. The bins are subsequently replenished in optimal quantities. Studies have proved that both of these approaches improve the overall accuracy and turnover ratio, and reduce occurrences of stock-outs (Priti, 2010). Controlling the replenishment cycle time can also be done by accurate assessment of product life cycles. Based on the production schedules the operations planning and sales team determine the right lot sizes and ordering schedules, thus enabling the availability of the right products at the right time.

2.2.2 Warehousing

Warehouse management ensures the centralized management of integral tasks such as tracking inventory levels, maintaining stock locations, and managing obsoletes. The industry wide methods for inventory valuation in a warehouse management system are First in, First Out (FIFO) and Last in, First Out (LIFO).

A FIFO warehouse system refers to an inventory management system in which the first or oldest stock is used first and the stock or inventory that has most recently been produced or received is

only used or shipped out until all inventory in the warehouse or store before it has been used or shipped out.

On the other hand, LIFO is an inventory management system in which assets produced or acquired last are the ones that are used, sold or disposed of first. Companies that manufacture homogenous commodity products such as stone, coal, sand and bricks which are stacked in large piles with oldest batches at the bottom, or do not have enough space in the warehouse for rotation of batches, follow the LIFO method of inventory evaluation. This method is most beneficial for tax savings and in financial evaluation.

FIFO ensures that the oldest stock is used first and a reduction in obsolesces and costs of maintaining obsolete inventory. Companies that manufacture perishable goods, or goods subjected to obsolescence, generally follow the FIFO method of inventory valuation (Katherine, 2015). Such firms believe that FIFO to be a better indicator of ending inventory, and more profitable since the age-wise stock or old inventory is used to value the cost of goods sold.

In this project, we investigate a third strategy of warehouse management for perishable goods, which is a mixture of both LIFO and FIFO. Based on the relative velocity of the goods at each distribution center and their sales pattern at the retailers served, the products with highest shelf life can be distributed to the slow movers and vice versa. The distribution centers catering to lower customer demand or sales would be satisfied by LIFO at the plant warehouse level and those distribution centers with high selling speeds would have inventory replenishment using the FIFO method at the plant warehouse. A minimum required shelf life level for the retailer would be maintained at the main distribution center to ensure that products do not reach expiry at the manufacturer's end. Currently, no company has reported a mixed picking or warehouse management strategy in literature.

2.2.3 Reduction of Replenishment Lead Times

As discussed in the previous sections, companies manage the inventory levels through automatic replenishment and controlling the replenishment cycle time.

Lead-time of any product is a function of three different time periods: the review period, manufacturing time and transportation time (Chuck, 2008). The review period corresponds to the time for processing an order upstream. The manufacturing time refers to the time from which an order is placed until it is ready to be shipped. The transportation time refers to the duration of transportation until received at the next location. Choosing the suitable mode of transport and relieving congestion at docking and unloading play a vital role here. Any reduction of lead time in these 3 stages can lead to a better replenishment cycle (Chuck, 2008). With shorter and less variable lead times, inventory management would be easier leading to lower level of obsolesces.

2.2.4 Revise Order Cycles / Quantities

The smaller and more frequent the order quantities placed by a distribution center to a plant, the lesser the inventory. Chuck (2008) had observed that an impact on the supply chain of companies can be observed merely by changing the production scheduling based on the demand of the products manufactured. For instance, to maintain production capacity, manufacturing plants could possibly increase changeovers or offset losses by managing the schedule of low demand products in smaller intervals.

2.2.5 Improving Forecasting Methods

Reviewing the existing forecasting techniques to juxtapose the production runs and sales pattern can help in managing the inventory and reducing obsolescence (Chuck, 2008). Firstly, companies need to analyze the input data, classify the relevant drivers of demand and later examine the reasons for variation in demand. Secondly, the forecasts must reflect true customer order quantity

and dates. Lastly, collaboration with the marketing and sales team for influencing the pricing and promotional activity of high demand products is essential to make forecasts more accurate.

2.2.6 Centralization of Inventory

By centralizing the order placements to one location, a reduction in order quantities may be possible. This can further increase the order frequency, thus lowering the overall order quantity. The centralized vs. distributed analysis is a major supply chain decision and requires extensive analysis from customers' requirements to suppliers' capabilities.

2.2.7 Reduction of SKU Counts

Product variety diminution or reduction in the number of SKUs produced is another technique that can help in freeing up space at the warehouse and easing production planning. On collaborating with the sales and marketing team, the company can revisit the agreement terms and eliminate some 2-count or x-count packs that do not affect sales.

Other common practices followed for reducing inventory would include: reducing setup time and costs, re-evaluating the cost of holding inventory, understanding warehouse storage procedures, and understanding labor, transportation, and inventory cost trade-offs. (Chuck, 2008) Adopting the aforementioned measures will benefit the retail level by reducing wastage and increasing retailers' willingness to accept more products. Similarly, we hope to improve the picking and storage efficiencies at Hershey's distribution centers.

2.3 Product Segmentation Methods

In this study, we will propose a product segmentation strategy for The Hershey Company which can be implemented using the available picking options in Hershey's distribution centers. This section summarizes the pros and cons of the popular product segmentation methods in literature. Currently there are multiple product segmentation methods for inventory management across industries. The three most popular industry-wide classification methods are: single-criterion ABC

classification, multi-criteria inventory classification, and classification using data mining with unsupervised learning and supervised learning. These methods are compared and selected under different situation, mainly based on trade-off between two criteria: the level of detail in data versus the difficulty level of data collection and method implementation.

2.3.1 Single-Criterion ABC Classification

ABC classification is the traditional and most widely used method in real world implementation. In this method, products are classified into A, B, and C groups based on a single criterion – annual demand value, which is the product of annual demand quantity and average unit price. Based on historical data, items with greatest annual demand value, e.g. the top 20%, are categorized into class A. Items with the annual demand value at, e.g. the bottom half are binned into class C, while the remaining are classified as class B. Products within each class will then be treated differently in terms of storage location, picking strategy, and frequency of demand forecasting (Altay Guvenir & Erel, 1998). Although this method is easy to implement, the level of comprehensiveness in the analysis is limited since only one dimension of data is used. This is the trade-off for the minimal requirement in data and straightforwardness of analyzing process. When there are multiple dimensions of data input need to take care, a multi-criteria inventory classification is utilized.

2.3.2 Multi-Criteria Inventory Classification

While annual demand value is a criterion frequently incurred in product segmentation analysis, some other criteria are usually involved in analysis also, such as replenishment lead time, product availability, level of service (Ramanathan, 2006). When more than one dimension of input data needs to be taken into consideration, multi-criteria inventory classification becomes an option. Currently there are two multi-criteria inventory classification methods being used commonly, the analytic hierarchy process (AHP) measure and data envelope analysis.

AHP is a method using pair-wise comparison to assign weights and grades for each criterion based on expertise's judgment. The common practice of AHP in inventory classification involves the following steps: to assign weight to each identified criterion based on importance, to evaluate each product's performance with respect to every criterion, and to consolidate each product's overall performance into one final score according to the weight for each criterion. Products are then classified based on the final scores (Ishizaka & Labib, 2011).

On the other hand, data envelope analysis is a simple weighted linear optimization, with one variable representing each criterion, and one constraint formulated for each product in the optimization model. Unlike AHP that heavily depends on human judgment in pair-wise comparison, data envelope analysis is a mathematical model purely based on available data without subjective decision making (Ramanathan, 2006).

While both AHP and data envelope analysis are able to produce a more thorough analysis, the heavy requirement of multiple dimensions of data constrains their application. On top of that, the feature of the methods also limits the usage. The pair-wise comparison of AHP implies the subjectivity of the measure. For data envelope analysis, its requirement to use every single entry of available data implies the model is sensitive to inclusion or suppression of an item, and it is time consuming to reformulate the model when changes occur in data. Therefore, the results may highly depend on the set of criteria and data in use.

2.3.3 Classification with Unsupervised / Supervised Learning

In recent years, with the rising attention to big data, data mining using both supervised learning and unsupervised learning has also been applied in product classification. Supervised learning applies artificial intelligence to a big set of training data to understand which factors impact product's inventory picking performance, and how significant is each factor's impact, whereas unsupervised learning requires broader information for the machine learning process, since neither

training data nor pre-classified groups are available (Yu, 2011). Among all product segmentation methods mentioned, data mining has the highest requirement in data and analysis, but the results are relatively objective with minimum human intervention.

3 EXPLORATORY DATA ANALYSIS

In this section, we shall discuss the initial data visualization and analysis performed before developing the base model.

3.1 Initial Data Source

To perform the analysis, The Hershey Company provided the team the following data:

- a) Sales record of various products: This Table consists of a list of various products manufactured and sold in 2014. It contains approximately 3500 records (seasonal and everyday items included) wherein each record lists SKU number, description of the product and its major ingredient, package type, seasonality of the product, and the yearly total revenue of the item in 2014 as shown in Figure 3.1-1.

ITEM	Desc	Packtype	SEASON	CY Doll
34000.5	RSEPBC KINGSZ 2.8OZ 24/6	0002 - KING SIZE	NS - Non-Seasonal	100xxx
34000.3	HSYMILK 6PK DSP 24	0067 - 6PK	NS - Non-Seasonal	99xxx
34000.3	SYRUP CHOC BTL 24OZ 24	0148 - LG BOT 18-26OZ/750ML	NS - Non-Seasonal	98xxx
34000.2	KITKAT REGCT 1.5OZ 36/12	0115 - REG CT	NS - Non-Seasonal	97xxx
34000.4	RSEPBC REGCT 1.5OZ 36/12	0115 - REG CT	NS - Non-Seasonal	96xxx
34000.2	H KITKAT SS 10.78OZ DSP 36	0123 - SNACK SIZE-REG	HAL - Halloween	95xxx
34000.2	HSYMILK REGCT 1.55OZ 36/12	0115 - REG CT	NS - Non-Seasonal	94xxx
34000.2	HSYALM REGCT 1.45OZ 36/12	0115 - REG CT	NS - Non-Seasonal	93xxx
34000.2	CNCRM 1.55OZ REGCT 36/12	0115 - REG CT	CHR - Christmas	92xxx
34000.3	WLM HSYMILK 6PK 9.3OZ 1440	0067 - 6PK	NS - Non-Seasonal	91xxx

Figure 3.1-1 Sales Record of items in 2014

- b) Shipment quantities of products at every Customer DC: This dataset describes the volume of each product shipped out of all customer DCs every month for three years (January 2013

to October 2015). Each record indicates quantities shipped per week and contains the Hershey Item Number, Customer DC, date of shipment etc.

- c) On-hand inventory at customer DC: This dataset consists of the average on hand inventory held at each customer DC on a weekly basis for three years. Each record includes SKU number, customer DC, date of record, and average on-hand inventory.

The SKUs were separated into classes (as defined by the parent company): everyday items and seasonal items. Everyday items refer to those SKUs available in market throughout the year whereas seasonal items refer to the special products designed for and sold during the one of the following four holidays: Valentine's day, Easter, Halloween and Christmas.

3.2 Data Visualization for everyday items

In this section we would like to understand the key characteristics of various everyday items and select the attributes that would be helpful in building the base model. We believe that the number of items sold every year, the number of distribution centers served, the shipped volumes and revenue generated from each product are most critical to our work. We do not display the distribution center ID's or the full SKU codes as a part of IP protection. The products and distribution centers have been given fictitious names and are not consistent with all the graphs represented in the section.

As revenue is of utmost importance to any company, we tried to categorize the various SKUs based on the revenue generated so that we can prioritize our strategies for the top revenue items.

For everyday items, a snapshot of the ABC analysis based on revenue generated is shown in Figure 3.2-1.

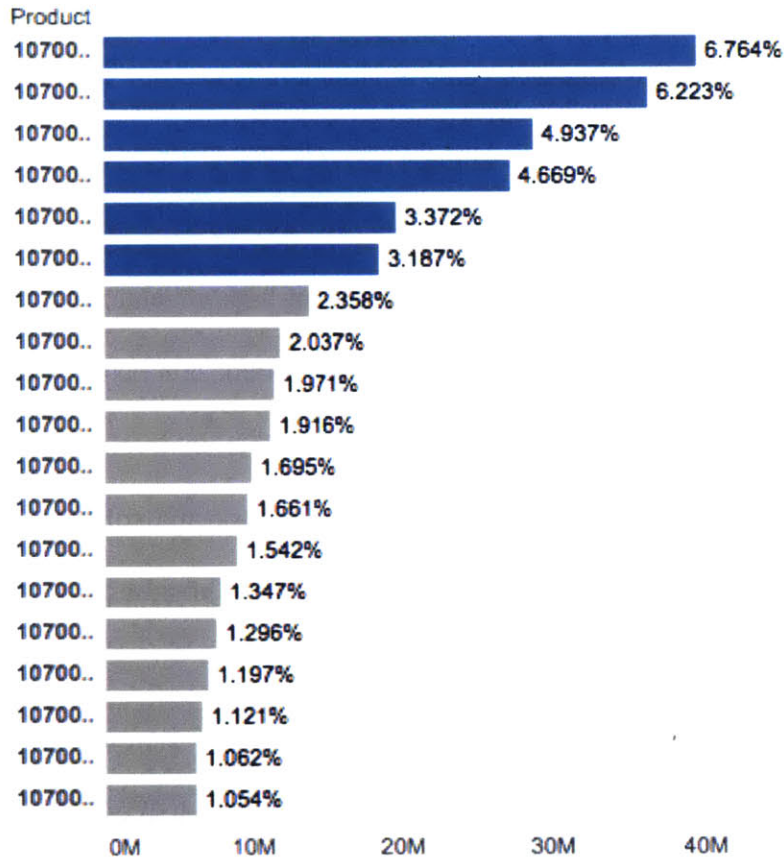


Figure 3.2-1 Revenue based analysis of everyday items

Figure 3.2-1 displays the various items in 2014 along with its fraction of total revenue generated (in %) of various items (product codes not fully disclosed) in 2014. The horizontal axis corresponds to the total revenue generated by the given product in year 2014. The analysis reveals that the top 6 items contribute to 80% of revenue generated. We shall at first develop our models for the top revenue items, and further extend to the rest of the product items

We tried to analyze the number of items sold by each DC every year and if introduction of additional items every year modified the overall shipping volumes or reduced the fraction of existing products. We observed for a random sample of 11 customer DCs the annual distribution pattern of all the products as shown in Figure 3.2-2. Figure 3.2-2 describes the % of volume and the total number of items served by each of the 11 DC's in the years 2013, 2014 and 2015. The

percentage values sums up to 100 % in each column as it represents the fractional volume served by the given DC over the total volume served by all the DCs. The number of distinct items or variety sold in the major DCs remain the same, however each year recorded an increase in the number of product variants shipped out of a DC.

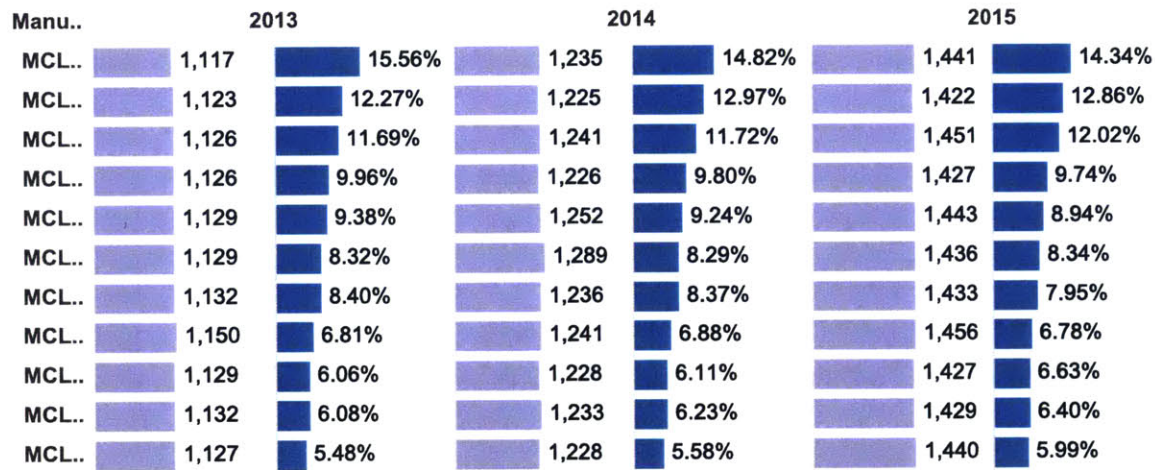


Figure 3.2-2 Yearly shipped volumes (%) and number of items sold for certain DCs

Though the total shipped volume increased yearly, the relative order remains unchanged, and the percentage that is shipped out of any given DC does not vary much. Introduction of new items does not change the behavior of distribution patterns at most DCs. Thus we need not factor in the effect of addition or deletion of SKU's in our simulation model.

We also wanted to check the effect of seasonality on monthly shipping pattern for various DC's as we might have to account for that in our model.

In Figure 3.2-3, the monthly shipment pattern for various DCs (randomly chosen and named) can be observed. The percentages denote fraction of volume shipped every month over the total annual volume shipped out of the given DC.

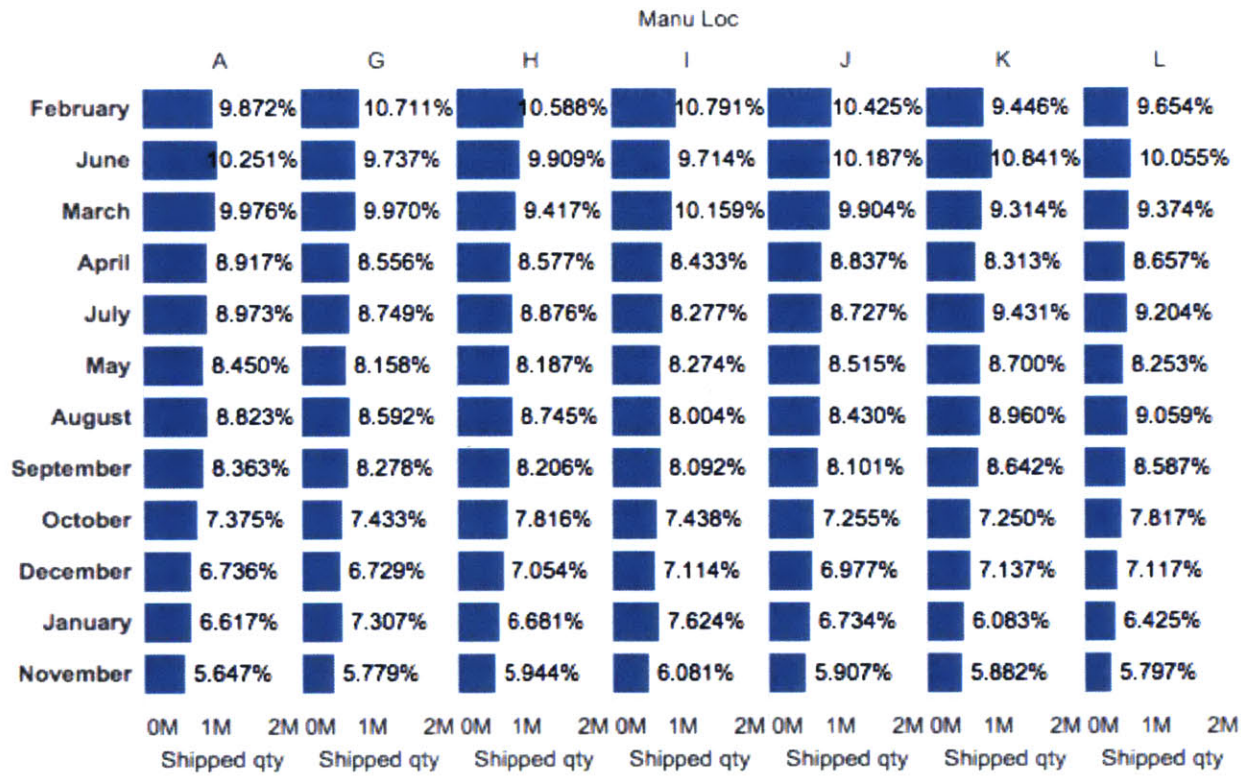


Figure 3.2-3 Monthly shipments out of a set of DC's

It can be noted that for everyday items, the volume that is shipped in any given month (measured as a percentage of the total annual shipped volume of that product) is fairly similar across DCs. Thus, the average monthly quantity (of a given product) can be used as a proxy while developing our simulation model instead of using individual monthly order quantities. The months during which, on average, the most volume was shipped were February, June, and March. This can be attributed to inventory shipping for Valentines Day, Halloween and Easter. It was observed for all the items across all the DC's. Figure 3.2-4 shows the distribution of average monthly quantities of the top 6 products (by volumes) across multiple DC's.

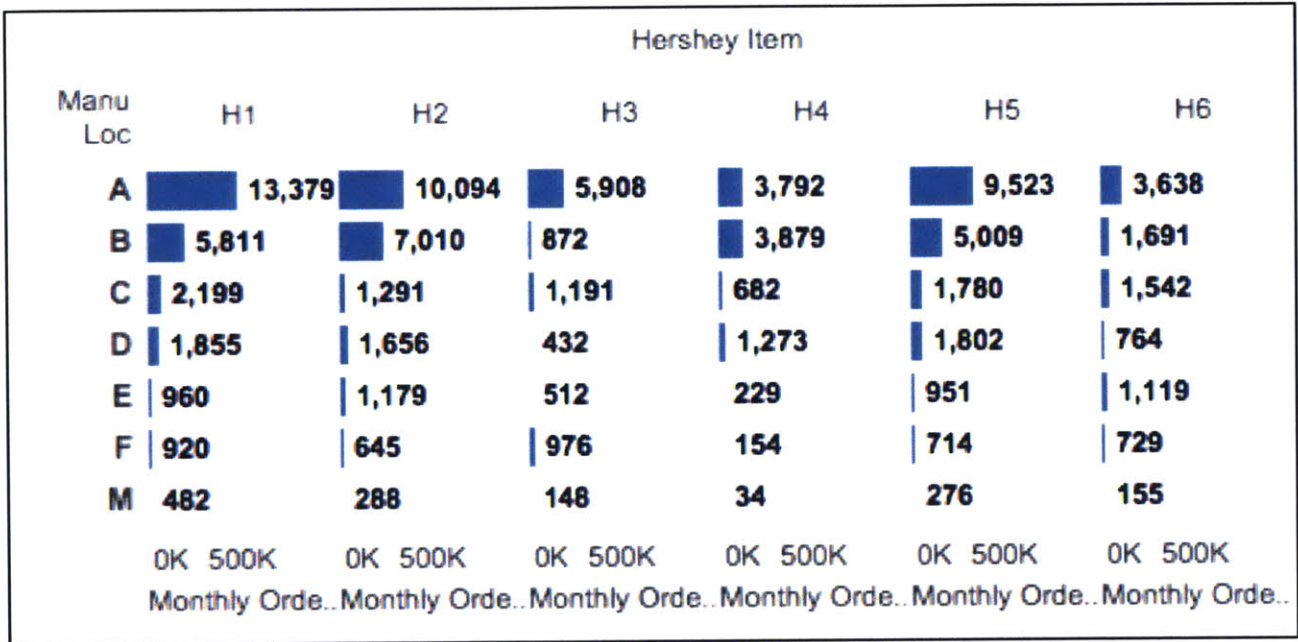


Figure 3.2-4 Average monthly order for a product-DC combination

In Figure 3.2-4, The horizontal axis denotes the monthly order quantities at every DC. We can see that for any given item, the quantity shipped to every DC varies. For some DC's the quantity shipped would be as high as 10000s, and in other cases the average monthly quantity shipped would be as low as 100's. The existing order picking strategy for all these DC's is however similar. Thus, we need to cluster the DC's into different groups based on order quantities as the retail velocity at a DC shipping high volumes of a product may be different from that of a DC shipping low volumes.

Next, we tried to observe if there was any correlation between total volume shipped across all DCs and the revenue generated by a given item. Revenue is not a function of the overall volume shipped alone. There are many other factors such as distribution pattern at the DC, prices charged at the DC, returns or obsolescence at the retailers end, which affect the total revenue generated by a product. Thus while building our model, we do not consider the revenue generated or the costs associated with a given product.

Figure 3.2-6 shows the month-wise inventory held at each distribution center for the top six products. Each column represents one distribution center. For each month, the horizontal axis shows the monthly inventory (units) held for the six items at a given DC. The highest fraction of inventory levels across most DCs was maintained in the months of March and August. Thus the total obsolescence can also vary based on the quantities shipped across different months.

	A	B	C	D	E	F	G
March	173,847	121,197	162,824	237,257	212,303	214,952	215,421
August	196,995	116,068	175,091	228,566	202,864	192,539	193,288
June	169,783	111,278	151,109	212,660	180,275	177,505	170,711
December	171,970	110,151	121,004	190,347	189,637	178,551	150,801
July	150,646	98,359	128,791	181,754	156,705	157,018	147,310
September	146,357	80,769	117,063	156,350	139,417	135,931	151,161
November	121,355	68,460	81,878	133,846	129,907	131,547	125,933
April	94,962	64,254	93,850	140,083	125,951	116,766	117,900
February	86,997	63,643	90,955	136,433	124,455	96,930	88,436
May	82,124	52,825	74,059	103,931	103,595	105,216	95,125
October	95,623	46,595	74,157	114,033	85,336	91,139	98,190
January	72,523	49,532	64,575	119,492	89,639	96,755	75,257

Figure 3.2-5 Monthly inventory for a given set of DCs for the top 6 products

	A	B	C	D	E	F	G
H1	35,627	21,659	27,990	33,086	25,876	26,540	22,795
H2	25,047	16,924	7,690	39,963	28,515	33,895	36,428
H3	22,829	14,605	19,665	30,171	31,064	23,176	18,867
H4	6,820	3,642	16,705	18,313	11,257	11,921	14,959
H5	14,099	10,646	9,491	2,301	10,155	10,675	6,418
H6	6,020	3,795	6,847	8,271	6,798	8,436	6,416
H7	7,139	3,687	6,501	8,290	7,443	6,363	6,300
H8	8,313	4,157	6,088	7,020	5,384	5,425	4,683
H9	5,691	2,909	6,455	6,933	4,523	5,057	5,512
H10	5,516	2,745	4,649	6,176	5,074	4,685	5,522

Figure 3.2-6 Inventory levels held for 10 products at randomly selected DCs

Figure 3.2-7 shows the inventory levels held at various DC's for various products. We can observe that for each Hershey item, inventory held at various DC's differ, similar to the volume shipped out of every distribution center.

3.3 Data Visualization for seasonal items

For seasonal items we observe the order quantities shipped out of DCs every month and if there's any inventory build up in the previous months to predict the production scheduling of such products before a season.

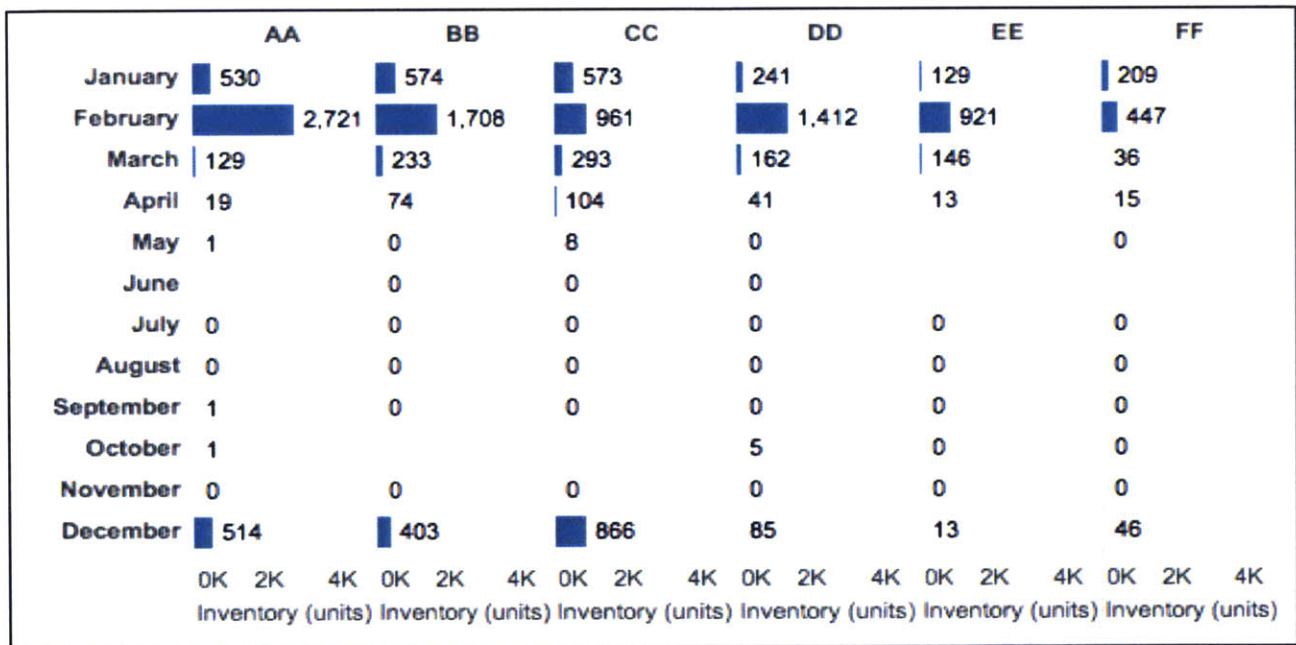


Figure 3.3-1 Monthly shipments out of few DCs for Easter special products

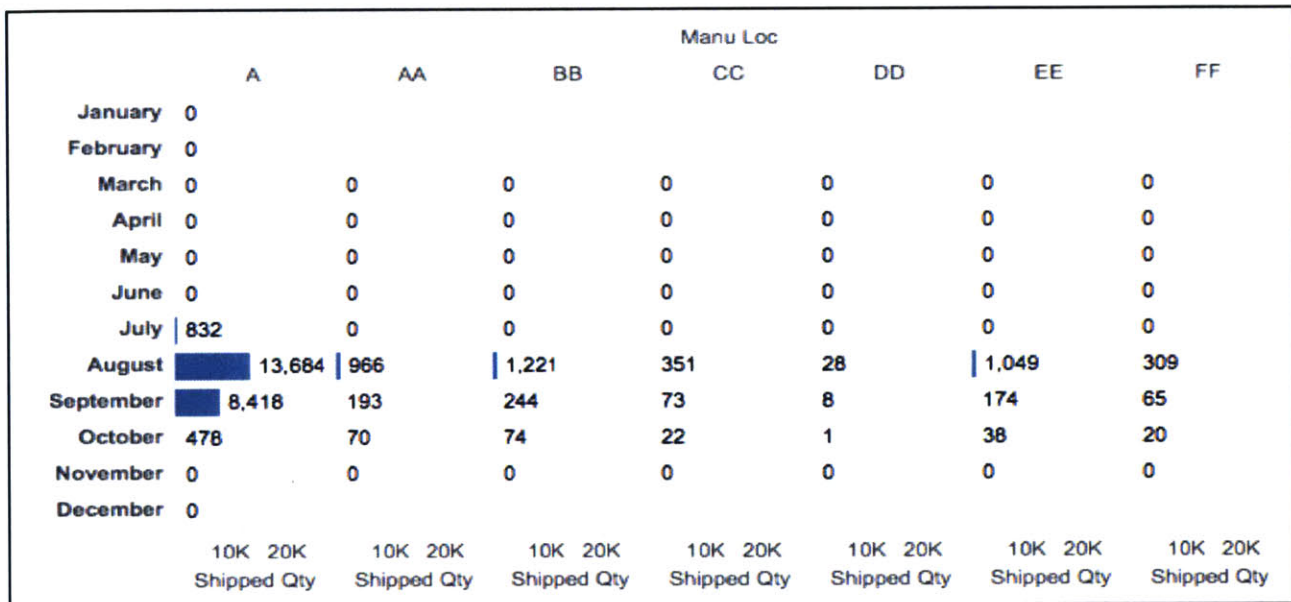


Figure 3.3-2 Monthly shipments out of few DCs for Halloween special products

We can observe the shipping volumes across DCs for two categories of seasonal products (Easter and Halloween) in Figures 3.3-1 and 3.3-2. In the case of Easter, boxes are shipped out only in December, January, February, and March. For Halloween, boxes are typically shipped in August, September and October.

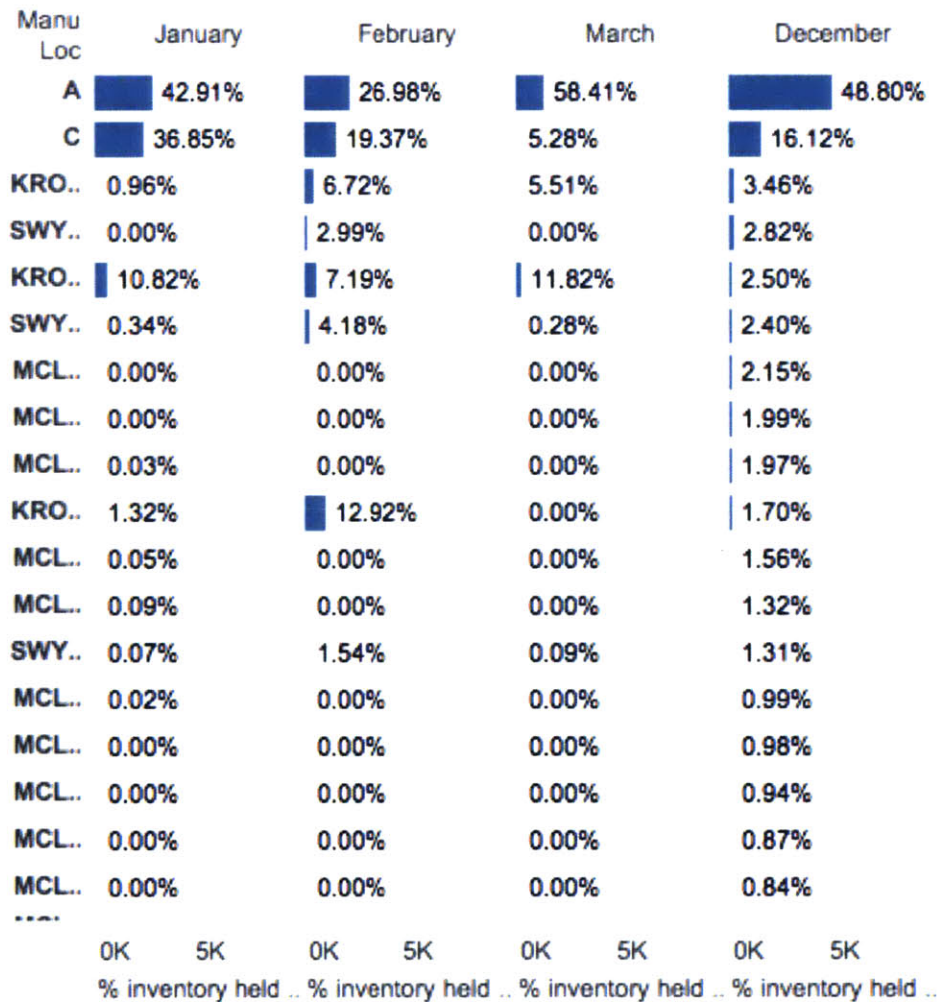


Figure 3.3-3 Inventory held at all DCs during the Easter shipping months

Figure 3.3-3 shows the inventory distribution (in absolute percentages) across all DC's for Easter items in January, February, March and December. The vertical column sums up to 100%. We can clearly see a trend, where 60-70% of the total volume is shipped by a small group of DC's (the fast movers for those seasonal items) and the rest by the remaining DC's. (Figure 3-11). Ideally, the manufacturing plant would run only one production batch for most of these festival demand items.

(as confirmed by the company) When the demand increases from certain DCs or if the DC has a capacity constraint, there could be multiple production runs (not more than 2). Thus, we decided not to extend our model for seasonal items.

4 METHODOLOGY

While reviewing the literature, we identified that product velocity in various retailers is not widely considered a criterion by now. Most existing study only takes care of the overall demand level by using annual demand value, rather than a deeper focus on the demand pattern in different retailers for each product. However, product velocity is one of the key elements determining the possibility of product obsolesces at the Hershey Company.

Through reviewing the literature, the team understands the importance of product segmentation and picking strategy to obsolescence reduction in food industry, and the limitation in current segmentation criteria selection. These information indicates the practical significance to include product velocity into consideration and to examine the feasibility of the “2 Clusters” picking strategy.

In this section, we will explain in detail how the analysis is formulated. This analysis consists of a conceptual model, an Excel simulation model, and a clustering model using unsupervised learning.

4.1 Conceptual Model

In order to better understand the logic behind the new picking method proposed by The Hershey Company, we present a simple conceptual model in this section to visualize the differences between the "2 Clusters" picking strategy and the “FIFO Only” picking strategy. On a conceptual level, this allows us to see if the “2 Clusters" picking strategy can potentially be a better picking strategy in terms of obsolescence quantity and product freshness before moving on to detailed analysis.

The conceptual model demonstrates changes in the inventory level of a fictitious product at the Hershey’s DC, given the monthly production and ordering quantities as input. In this model, we simplify the manufacturing and warehouse management process with the following assumptions:

- All data are captured on a monthly basis;

- There is a constant monthly production rate of N units. These N units will be considered the same batch of inventory and have the same length of remaining shelf life;
- There is a constant monthly ordering quantity of N units;
- Fast-moving and slow-moving clusters are pre-defined;
- Every month the orders from one cluster are aggregated together and will be picked at once;
- Initial inventory is set at N units;
- All parameters in the model are assumed with zero variability.

4.1.1 “FIFO Only” Picking Strategy

Figure 4.1.1-1 illustrates the inventory level with the “FIFO Only” picking strategy at the end of Month 0, 1, and 2 accordingly. Each month’s inventory level and age are specified in the figure for different batches of products. As shown in the legend, white blocks represent the unpicked inventory to remain in the warehouse. This inventory will be carried out to the next month, and become one month older then. The blue blocks represent the inventory picked in this cycle. These units will be shipped out from the warehouse and therefore be removed from inventory. The size of the blocks is an analogy of the size of the inventory. Following the assumptions, at the beginning (end of Month 0), there are N units of inventory at 0 month old. After a month (end of Month 1), the remaining inventory becomes one month older, while another month worth of inventory is newly produced. Based on FIFO, in this month, the oldest block of inventory will be picked. Similar for Month 2 and onwards: the products being picked are always 2 months old, regardless of whether the product will be going to a fast-moving or slow-moving retailer.

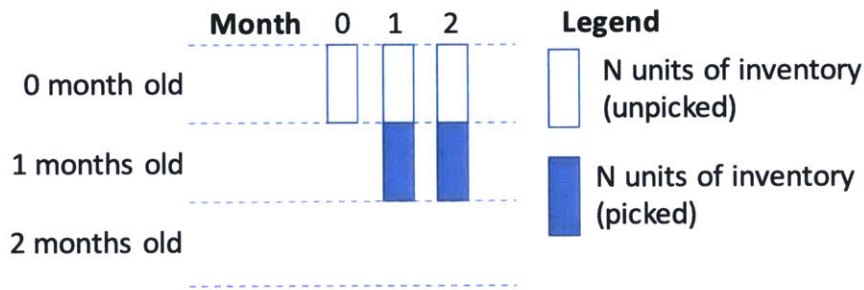


Figure 4.1.1-1 Conceptual Model of the "FIFO Only" Picking Strategy

4.1.2 "2 Clusters" Picking Strategy

With a "2 Clusters" strategy, the same amount of product is produced and picked each month as with the "FIFO Only" strategy. However, depending on the split between the fast-moving and slow-moving retailers, the product for slow-moving retailers will be picked using a LIFO picking strategy whereas the rest will still be picked using FIFO strategy.

We first test a scenario with 50% of the ordering quantity designated for fast-moving retailers and the other 50% designated for slow-moving retailers (Figure 4.1.2-1). At the end of Month 1, $N/2$ units will be picked from the oldest side, so that fast-moving retailers get product at 1 month old. On the other hand, another $N/2$ units will be picked from the freshest side, so that slow-moving retailers will get products that are 0 month old. Remaining inventory will be one month older at the end of Month 2 while another N units of products are produced. The oldest products going to faster-moving retailers become 2 months old, but the products going to slow-moving retailers are the freshest possible. The same situation applies from Month 3 onwards.

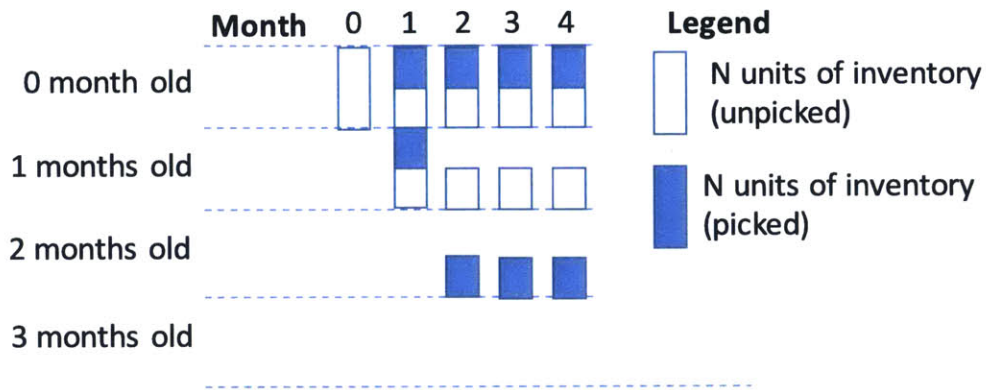


Figure 4.1.2-1 Conceptual Model of the "2 Clusters" Picking Strategy: Half-Half Split

In this scenario, the product shipped to slow-movers using the “2 Clusters” strategy is 1 month fresher than the product shipped to slow-movers using the “FIFO only” strategy. As a trade-off, product shipping to fast-movers will be up to 1 month older than that using the “FIFO only” strategy. If all other aspects remain the same as those in the “FIFO Only” model, slow-movers possess a lower risk of obsolescence in the “2 Clusters” model than that in the “FIFO Only” model, while the risk of obsolescence for fast-movers becomes higher. This trade-off implies that the “2 Clusters” picking strategy may or may not be better depending on whether the gains from slow-movers outweigh the losses from fast-movers. In other words, the “2 Clusters” can be better only if the reduction of obsolescence from slow-movers is more than the increase of obsolescence from fast-movers.

In addition, we also test the “2 Clusters” model with 75% of retailers being classified as fast-movers and 25% classified as slow-movers (Figure 4.1.2-2) and vice versa (Figure 4.1.2-3). The comparisons suggest that when there is higher ratio of slow-movers, fast-movers will sacrifice more by receiving even older products. This again implies that the “2 Clusters” model may only be considered better if the trade-off is worthwhile.

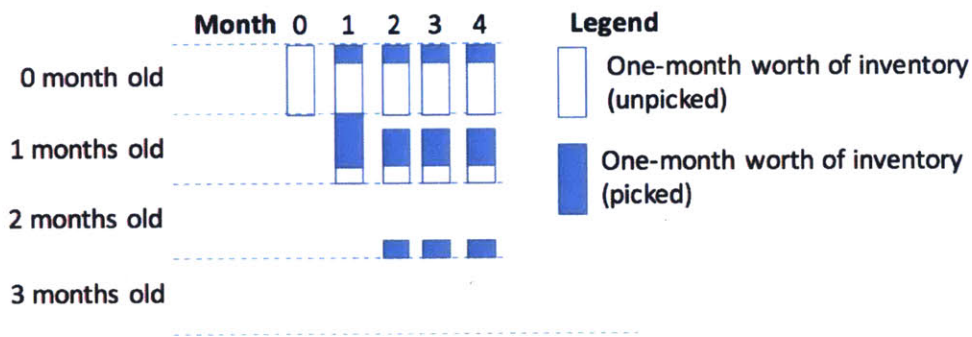


Figure 4.1.2-2 Conceptual Model of "2 Clusters" Picking Strategy: 75% Fast-Movers and 25% Slow-Movers

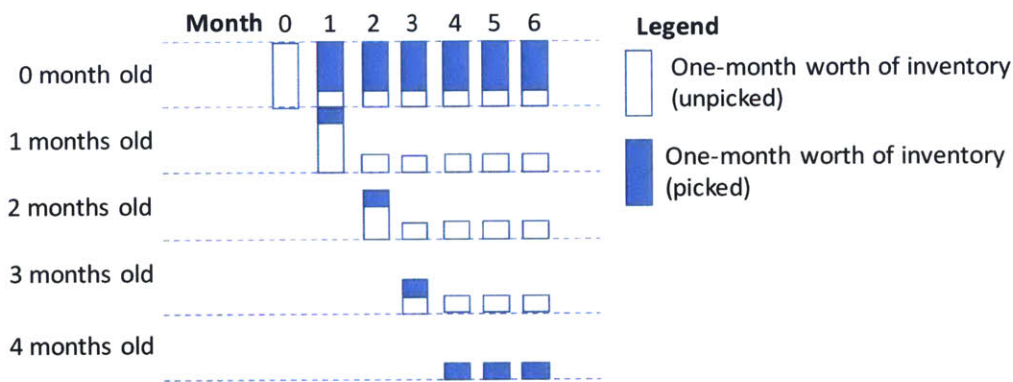


Figure 4.1.2-3 Conceptual Model of "2 Clusters" Picking Strategy: 25% Fast-Movers and 75% Slow-Movers

With these initial results in mind, we built an Excel simulation model to simulate the moves of inventory, picking quantity, and obsolescence at a more granular level to analyze the insights of the two picking strategy. In particular, we relax the assumption of deterministic demand.

4.2 Excel Simulation Model

In the Excel model, we simplify Hershey’s supply chain system and focus on simulating the behavior in the Hershey’s DC and at retailers, aiming to capture the cumulative amount of obsolescence over 5 years (60 months) for one everyday product with both the “FIFO Only” and “2 Clusters” picking strategy. As in the conceptual model, the data in the simulation model are captured on a monthly basis. We first build a base model and set its key parameters to be as close as possible to the actual setting at the Hershey Company’s manufacturing site, bearing in mind the

simplifications of the model. The data used for setting the parameters are for one of Hershey’s top revenue SKUs that is sold all year round, i.e., an everyday item. This section explains the key assumptions and settings for each section in the base model.

4.2.1 Production

At Hershey’s, everyday items are produced in regular batches throughout the year. So here we assume constant production rate at 150,000 units per month. Since shelf life is measured in months, all products produced in a given month are considered the same batch with the same remaining shelf life. At the beginning of the simulation, we assume 150,000 units of inventory are in Hershey’s DC before first month production starts. In the model, we use a production table (Figure 4.2.1-1) to record the monthly production volume of the item, with columns to represent the timing of the 5-year simulation, and rows to represent the remaining shelf life of the batch of inventory at the end of a period. For example, the first cell refers that the end of Month 1 produces 150,000 units. We assume products have 12 months remaining shelf life once produced.

		Year 1											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Production	Shelf Life	1	2	3	4	5	6	7	8	9	10	11	12
	12	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000

Figure 4.2.1-1 Production Table of Excel Simulation

4.2.2 Picking at Hershey’s DC

In the base model, we assume the total ordering quantity each month is a random number uniformly distributed between 120,000 and 170,000 units to simulate the variability of ordering quantity in different months. This gives an average monthly ordering quantity at 145,000 units. This number is set slightly lower than the monthly production rate to represent the slight overproduction in real life in case of product loss during production and transportation.

We also set another input to capture the split between fast-movers and slow-movers, and it is represented as a percentage. For example, when the split is set at 20%, it means 20% of the total

ordering quantity will be going to fast-mover, while the remaining 80% order is for slow-mover. To simplify the simulation, we use aggregated monthly order for each cluster, i.e. one aggregated order for fast-mover and one for slow-mover, rather than to simulate the ordering quantity for each retailer. The ordering quantity for each cluster is calculated by the split of the total ordering quantity.

In “FIFO Only” model, the whole order will be picked from the old side of the inventory without differentiating whether it is for fast-movers or slow-movers. We use a picking table to keep track of the quantity and batch of the picked inventory. One example of the first year picking table is illustrated in Figure 4.2.2-1. Similar layout as in the production table, the columns represent the timing of the 5-year simulation, and rows represent the remaining shelf life of the items picked at the end of a period. For example, the last column indicates that at the end of Month 12, 112,430 units are picked from the oldest products at that moment, the batch with 9 months’ remaining shelf life. But there are still 9,134 units in the order not fulfilled yet. So these 9,134 units will be picked from the previous batch, the batch with 10 months’ remaining shelf life.

		Year 1											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Picking	Shelf Life	1	2	3	4	5	6	7	8	9	10	11	12
	12												
	11	53778	21190	40312									
	10		96222	128810	52216	103492	107957	124695	76675	90595	59134	37570	9134
	9					57472	46508	42043	25305	73325	59405	90866	112430
	8												
	7												
	6												
	5												
	4												
	3												
	2												
	1												
	0												

Figure 4.2.2-1 Picking Table for “FIFO Only” Model of Excel Simulation

The picking table also shows that if one batch of product is so old that it will definitely expire before being sold, the batch will no longer be picked and will be directly counted in obsolescence. In the base model, we assume a combined total time spent across the supply chain is 1.35 months,

including transporting products from Hershey’s DC to customer DC, staying in customer DC, and transporting from customer DC to retailer. We also assume that retailers will only be willing to accept any items with at least 2 months of remaining shelf life. Tracing back these numbers indicates if a product has no more than 3 months’ remaining shelf life in Hershey’s DC, it will be counted as obsolete. This is because even if the product can be shipped out from Hershey immediately, no retailer will accept it since it will be with no more than 2 months’ remaining shelf life by then. To simplify the base model, we assume the time spent in supply chain and the minimum required remaining shelf life at retailers is constant. In the picking table, we use grey to highlight the cutoff for obsolescence. Orders will only be picked from batches above that cutoff. Similarly, “2 Clusters” model also has a picking table to track the quantity and batch of the picked inventory. The order will be picked partially from the old side, using FIFO for fast-movers, and partially from the fresh side, using LIFO for slow-movers, depending on the split. In the example showed in Figure 4.2.2-2, the quantity is split into half FIFO and half LIFO. The last column in the example illustrates that at the end of Month 12, 60,782 units are picked from the latest batch just produced with 12 months’ remaining shelf life for slow-movers. Meanwhile, fast-movers will get 2,237 units with 6 months’ remaining shelf life, and 58,546 units with 7 months remaining shelf life. These are the oldest products remaining in Hershey’s DC but not yet considered obsolescent.

		Year 1											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Picking													
Shelf Life		1	2	3	4	5	6	7	8	9	10	11	12
12		26889	58706	84561	26108	80482	77233	83369	50990	81960	59270	64218	60782
11		26889											
10			58706	20156									
9				64405	26108	3635		7504					
8						76847	77233	65439	50990	16562	6313		
7								10427		65399	52957	64218	58546
6													2237
5													
4													
3													
2													
1													
0													

Figure 4.2.2-2 Picking Table for “2 Clusters” Model of Excel Simulation

In the simulation, we let the total picking volume to be the same for both picking strategies in every round so that to ensure it is a fair comparison.

4.2.3 Inventory at Hershey’s DC

There is another set of tables in the simulation to trace the remaining inventory in Hershey’s DC at the end of each period. Each month 150,000 units with 12 months’ remaining shelf life will be newly added in inventory. Inventory carried over from the previous month will become one month older. Corresponding to the obsolescence captured in the picking table, those obsolescent items will go to a threshold in the inventory table, since they will never be picked.

For example, Figure 4.2.3-1 is the record of first year inventory in the “FIFO Only” model. At the end of Month 12, a total of 11 batches of products are carried over from the end of Month 11 and become one month older. However, the oldest 3 batches of products with no more than 3 months’ remaining shelf life are considered obsolescent. Therefore, picking can only be applied to the batch with 4 months’ remaining shelf life, and the remaining inventory of the batch after picking is 125,183 units. Meanwhile another batch of newly produced products with 12 months’ remaining shelf life is added.

The inventory table for the “2 Clusters” model is formed based on the same logic.

		Year 1											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Inventory													
Shelf Life		1	2	3	4	5	6	7	8	9	10	11	12
12		150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000
11		103825	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000
10			36141	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000
9				27263	108010	150000	150000	150000	150000	150000	150000	150000	150000
8						86851	150000	150000	150000	150000	150000	150000	150000
7							66139	150000	150000	150000	150000	150000	150000
6								58559	150000	150000	150000	150000	150000
5									44982	150000	150000	150000	150000
4										26840	78495	123980	125183
3											26840	78495	123980
2												26840	78495
1													26840
0													
Expired													

Figure 4.2.3-1 Inventory Table for “FIFO Only” Model of Excel Simulation

4.2.4 Obsolescence

This simulation model captures the obsolescence at both Hershey's DC and at retailer end. As explained in previous sections, the obsolescence at Hershey's DC consists of those inventory not in time to be picked. These items will directly be considered obsolescence even though technically they may not be expired yet, because retailers will not accept them for their short remaining shelf life.

To model the obsolescence at retailers' end, we use a simple exponential function to specify the different risk levels of obsolescence for products with different length of remaining shelf life. In the base model, we mark a product with 100% possibility to become obsolescent if the product is at the month of expiry or already expired when reaching retailer. For products with 1 month of remaining shelf life, we assume their risk of becoming obsolescent is half of that for expired product for slow-movers, i.e. 50% possibility to become obsolescent. In other words, for slow-moving retailers, the obsolescence risk of any product with one more month remaining shelf life will go down to half of that for product with one less month remaining shelf life. In this study, we create a term called Obsolescence Ratio to reflect this difference of obsolescence risk level for products with different remaining shelf life. Obsolescence Ratio is defined as

$$\frac{\text{Obsolescence risk for product with } i \text{ months remaining shelf life}}{\text{Obsolescence risk for product with } (i + 1) \text{ months remaining shelf life}} \times 100\%$$

Based on this definition, slow-movers' obsolescence ratio in the base model is assumed at 2. Fast-movers have a shorter turnaround time, so they are likely to sell a higher percentage of products with same remaining shelf life comparing to slow-movers. In this case, we assume for fast-movers, the risk of obsolescence of a product with one more month remaining shelf life will reduce to one-eighth of that for product with one less month remaining shelf life, e.g. products with 1 month remaining shelf life when reaching retailer will have a 12.5% chance to be obsolescent. In another

word, fast-movers' obsolescence ratio in the base model is assumed at 8. The obsolescence quantity at retailer for the "2 Clusters" model can then be calculated from this ratio and the picking quantity from each batch of products. For the "FIFO Only" model, since the order from fast-mover and slow-mover are mixed, we use a weighted average of the risk of obsolescence for both clusters to represent the risk of obsolescence in the "FIFO Only" model. The weight for each cluster again is defined by where the split of the clusters is. Figure 4.2.4-1 lists the risk of obsolescence of different lengths of remaining shelf life for all clusters.

Remaining Shelf When Leaving Hershey (mth)	Remaining Shelf When Reaching Retailer (mth)	Cluster 2 (Slow-Moving)	Cluster 1 (Fast-Moving)	FIFO Only
12	11	0.05%	0.00000001%	0.01%
11	10	0.1%	0.00000009%	0.02%
10	9	0.2%	0.0000007%	0.04%
9	8	0.4%	0.000006%	0.08%
8	7	0.8%	0.00005%	0.2%
7	6	1.6%	0.0004%	0.3%
6	5	3.1%	0.003%	0.6%
5	4	6.3%	0.02%	1.3%
4	3	12.5%	0.2%	2.7%
3	2	25.0%	1.6%	6.3%
2	1	50.0%	12.5%	20.0%
1	0	100.0%	100.0%	100.0%
0	Expired	100.0%	100.0%	100.0%

Figure 4.2.4-1 Risk of Obsolescence at Retailers of Excel Simulation

From these, we will be able to estimate the total amount of obsolescence each month:

$$\frac{\sum_i [(Quantity\ picked\ from\ inventory\ batch\ i) * (Corresponding\ risk\ of\ obsolescence)]}{Total\ quantity\ picked}$$

From these we can estimate the cumulative amount of obsolescence over 5 years. By comparing the number for the "2 Clusters" and the "FIFO Only" model, we shall be able to tell which strategy generates less obsolescence. By altering the split of the two clusters, we may possibly figure out the criteria for products to be suitable to the "2 Clusters" picking strategy.

4.3 Clustering model

As explained in the previous sections (4.1 and 4.2), we propose a change in the picking strategy from FIFO only to a 2-cluster model for a set of SKU-DC combinations. In this section we shall discuss how this clustering can be done for the various items using multivariate clustering techniques.

As observed in section 3.2, we have only one column of relevant data points (volume shipped out of a DC) to form the SKU-DC clusters. Hierarchical clustering can be used for single dimension data as it provides a generic clustering technique regardless of data types, whilst partitioning clustering requires multiple columns of data that are summarized by a set of representative entities, for e.g., centroids in K means clustering.

At first we obtained a data table containing the volume shipped and the number of shipments for the various items across the multiple distribution centers. The order quantity, Q , for each SKU-DC combination was computed as

$$Q = \frac{\textit{Volume of an item } x \textit{ shipped to DC } y}{\textit{No of times item } x \textit{ was shipped to DC } y}$$

The first clustering shall combine similar products based on order quantities Q into the optimal number of clusters as it is difficult to propose DC-SKU combinations for 2096 products. In this case, the no of clusters formed is 4. For each category of products, hierarchical clustering can be performed to categorize the SKU-DC combinations. For our model, we set the number of required clusters to 2. Hierarchical Clustering then iteratively partitions the entire data set by grouping data points (order quantities) into trees of clusters based on the Euclidean distance. Each DC is assigned a cluster number 1 or 2. Since we've only one dimension of data, we presume that the clusters will be similar in terms of velocity. Cluster 1 corresponds to the high volume products and shall be categorized as Fast and Cluster 2 slow.

Lastly, the percentage of volume corresponding to each cluster can be computed, and based on our simulation results we can propose for which products the 2 cluster model will be more beneficial.

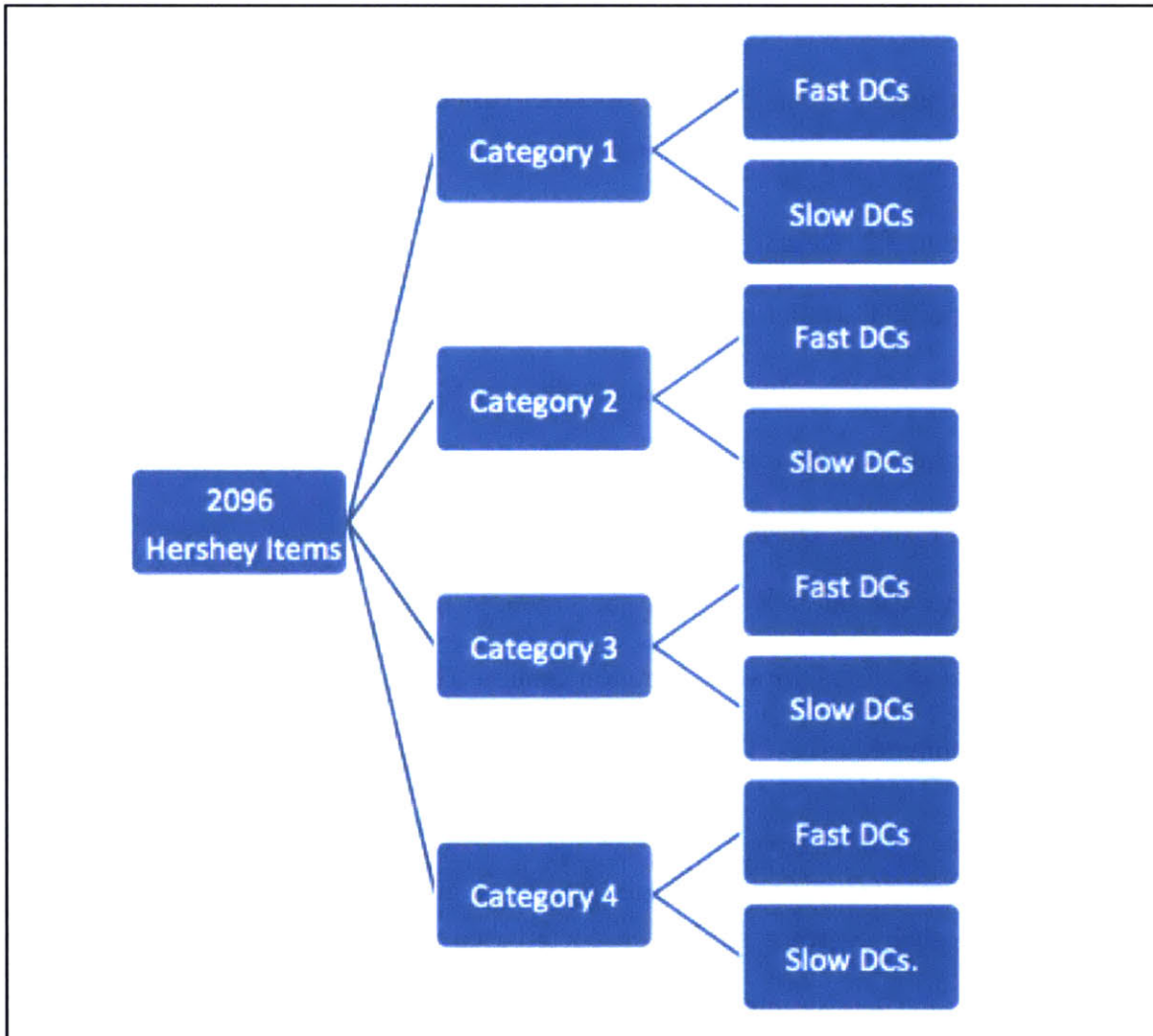


Figure 4.3-1 Outline of the Clustering model for various items

5 DATA ANALYSIS AND RESULTS

5.1 Excel Simulation Model

This section explains our findings using the base model. Throughout the analysis, we realize that even though we extrapolate the simulation to 5 years' duration, the cumulative amount of obsolescence at the end of the simulation varies extensively even with the same set of inputs. This is due to the introduction of random numbers in ordering quantity in the model. In this case, we run the simulation 100 times for each setting, and use the average of the 100 times for a better representative result.

The key finding we identified from the simulation is that the "2 Clusters" picking strategy will only be better when the aggregated ordering quantity from slow-movers is not too high.

In a "2 Cluster" model, since a lower quantity will be picked using FIFO compared to "FIFO Only" model, with constant initial quantity for each batch of inventory, it requires a longer time for each batch of product to be completely picked using FIFO in "2 Clusters" model. This indicates the products picked using FIFO in "2 Clusters" model can be older than that in "FIFO Only" model, and the "2 Clusters" picking may generate more obsolescence in the Hershey's DC. The discrepancy is derived from the split of the clusters.

When there is a small amount ordered by slow-movers, for example 20% of the monthly total ordering quantity, in the "2 Clusters" model, older batches of products are still able to be picked within a reasonable time frame. This is since the majority of the order is still picked using FIFO, but they can still be slightly older than those in "FIFO Only" model. In this case, the additional obsolescence generated in the Hershey's DC with the "2 Clusters" model will be marginal. On the other hand, at retailers' end, since products still have a reasonable length of remaining shelf life, and thanks to the fast selling speed and low risk of obsolescence for fast-movers, the additional obsolescence generated at retailers in the "2 Clusters" model will be a small volume as well. On

the other hand, the small portion of slow-movers can get much fresher products compared to those in “FIFO Only” model. Taking into consideration slow-movers’ large obsolescence ratio, slow-movers are sensitive to product age, i.e. the fresher products shipped to slow-movers can significantly reduce obsolescence there. Obsolescence will be reduced overall using “2 Clusters” picking in this case. Figure 5.1-1 shows the cumulative total obsolescence for both picking strategies when fast-mover make up 80 percent of the customers and slow-mover the remaining twenty percent, resulting from the average of 100 runs of simulation.

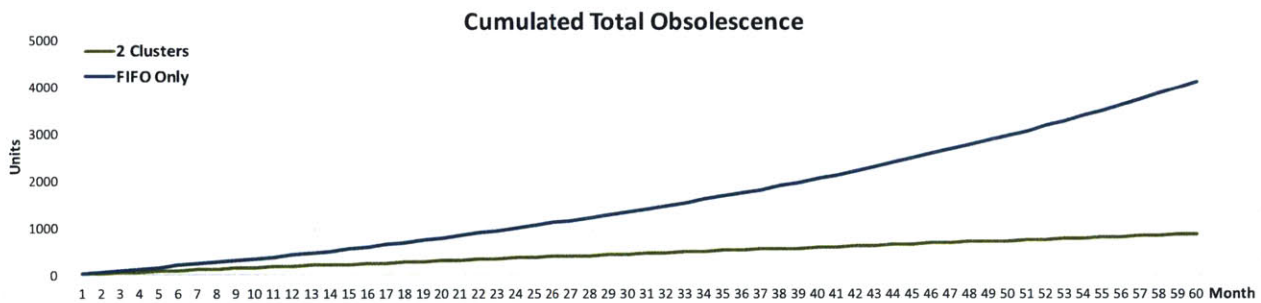


Figure 5.1-1 Cumulative Total Obsolescence: 80% Fast-Movers and 20% Slow-Movers

We use the tables from one simulation run to elaborate on the result. A snapshot of the fifth year picking and inventory status is captured for both the “2 Clusters” model (Figure 5.1-2) and “FIFO Only” model (Figure 5.1-3). We observe that in this run, the oldest product in inventory has 9 months remaining shelf life for both cases, so the obsolescence quantity in the Hershey’s DC is zero for both picking models. For retailers, the old products will only be shipped to fast-movers in the “2 Clusters” model; however, in the “FIFO Only” model, they have a chance to be shipped to slow-movers as all retailers are treated equally. In this case, these old products have less chance to become obsolete in the “2 Clusters” model.

		Year 5											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Picking													
Shelf Life		49	50	51	52	53	54	55	56	57	58	59	60
12		28905	30509	30923	26243	25034	24594	25672	25214	30355	27258	31657	25813
11													
10		19253	21205	23593	7471								
9		96366	100833	100099	97502	100136	86491	70104	47201	43655	27279	29578	8045
8							11883	32586	53653	77765	81751	97048	95208
7													
6													
Inventory													
Shelf Life		49	50	51	52	53	54	55	56	57	58	59	60
12		121095	119491	119077	123757	124966	125406	124328	124786	119645	122742	118343	124187
11		121304	121095	119491	119077	123757	124966	125406	124328	124786	119645	122742	118343
10		100833	100099	97502	112019	119077	123757	124966	125406	124328	124786	119645	122742
9						11883	32586	53653	77765	81751	97048	95208	111600
8													
7													
6													

Figure 5.1-2 Picking and Inventory Table for “2 Clusters” Picking: 80% Fast-Movers and 20% Slow-Movers

		Year 5											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Picking													
Shelf Life		49	50	51	52	53	54	55	56	57	58	59	60
12													
11													
10		106768	109315	113930	95147	70317	43285	21647					
9		37756	43232	40685	36070	54853	79683	106715	126068	149490	135778	144061	123128
8										2285	510	14222	5939
7													
Inventory													
Shelf Life		49	50	51	52	53	54	55	56	57	58	59	60
12		150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000
11		150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000
10		43232	40685	36070	54853	79683	106715	128353	150000	150000	150000	150000	150000
9									2285	510	14222	5939	26872
8													
7													

Figure 5.1-3 Picking and Inventory Table for “FIFO Only” Picking: 80% Fast-Movers and 20% Slow-Movers

Taking Month 60 as an example, in “2 Clusters” model, the probability of obsolescence for products with 12 months remaining shelf life shipped to slow-movers is 0.05%, according to Figure 4.2.4-1 in section 4.2.4, and the probability of obsolescence for product shipped to fast-movers with 9 and 8 months remaining shelf life are 0.000006% and 0.00005%, respectively. Retailers’ obsolescence in “2 Clusters” model in Month 60 can be estimated using a weighted average:

$$25,813 * 0.05\% + 8,045 * 0.000006\% + 95,208 * 0.00005\% = 12.6 \text{ units}$$

Similarly, we can calculate the retailers' obsolescence in "FIFO Only" model in Month 60 are:

$$123,128 * 0.08\% + 5,939 * 0.16\% = 105.5 \text{ units}$$

Just in Month 60, "2 Clusters" model reduces 93 units of retailers' obsolescence, which is 88% of that in "FIFO Only" model. Cumulatively, "2 Clusters" model reduces 79.8% retailers' obsolescence over 5 years, testifying to the practice significance of adopting "2 Clusters" picking strategy under such situation. The cumulative difference of retailers' obsolescence is shown in Figure 5.1-4.

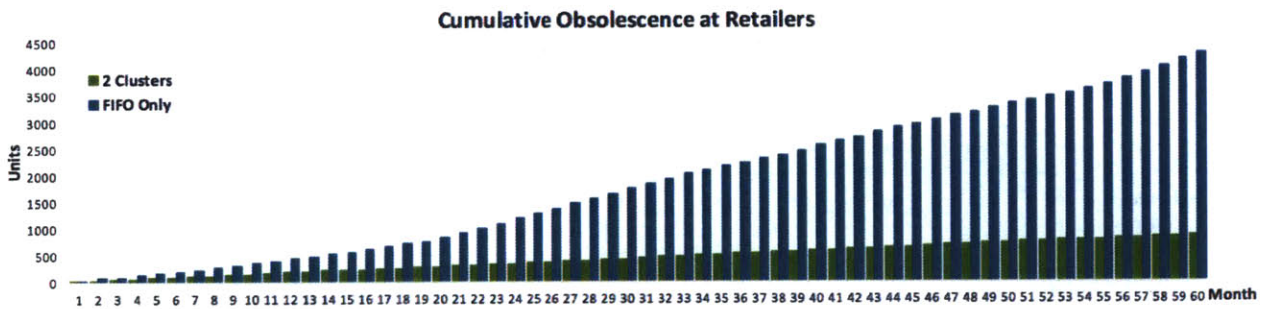


Figure 5.1-4 Cumulative Obsolescence at Retailers: 80% Fast-Movers and 20% Slow-Movers

In contrast, when slow-movers' orders take a big portion of the total ordering quantity, "2 Clusters" picking will actually perform worse than traditional "FIFO Only" picking. Figure 5.1-5 shows the cumulative total obsolescence for each picking strategy when fast-mover and slow-mover split by twenty-eighty, resulting from average of 100 runs of base model.

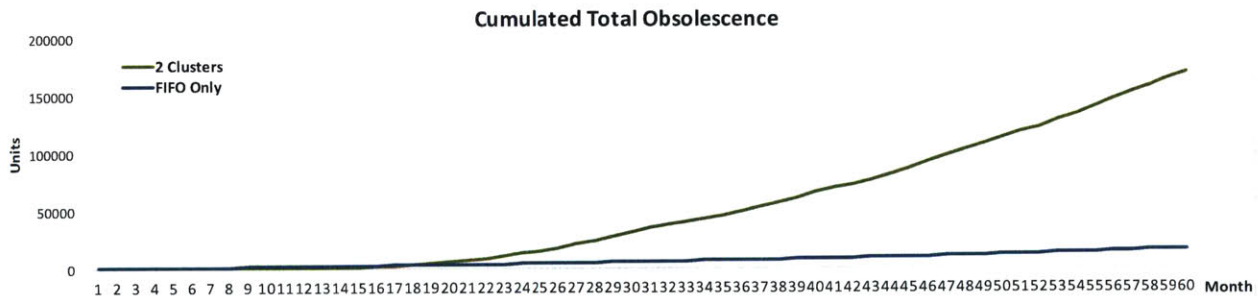


Figure 5.1-5 Cumulative Total Obsolescence: 20% Fast-Movers and 80% Slow-Movers

When a large number, e.g. 80% of the monthly total ordering quantity, is ordered from slow-movers, in the “2 Clusters” model, a majority of the order needs to be served with the fresh products using LIFO, while only a small portion will be picked using FIFO. With constant batch size in inventory, the “2 Clusters” model takes much longer to fully consume the older batches of products. If fast-movers’ order quantity is so small that the old batch is not in time to be fully picked within 9 months, according to base model’s setting, the products will directly become obsolete in Hershey’s DC. This indicates a higher risk for obsolescence in Hershey’s DC. In the meantime, the impact at retailers’ end is not that straightforward. Whereas slow-movers reduced their risk of obsolescence with fresher products, fast-movers may possibly receive older products with the “2 Clusters” picking comparing to that with “FIFO Only” picking, resulting in a higher risk of obsolescence. When slow-movers dominate the order, the incremental obsolescence from Hershey’s DC and fast-moving retailers is so significant that it can hardly be compensated for reduction at slow-moving retailers. “2 Clusters” picking will therefore generate more obsolescence overall.

We use the numbers from one run to demonstrate this impact. Figure 5.1-6 and Figure 5.1-7 show the picking and inventory table in the fifth year for a “2 Clusters” picking and a “FIFO Only” picking strategy, respectively. We can see slow-movers, which receive 80% of the order, on average can have products 4 months fresher in “2 Clusters” picking. This is realized through a trade-off from fast-movers, who get 4 months older products compared to the products they would have under the “FIFO Only” picking.

		Year 5											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Picking													
Shelf Life		49	50	51	52	53	54	55	56	57	58	59	60
12		115314	113658	118806	107831	118268	110232	100830	132302	115190	116203	127648	114828
11													
10													
9													
8													
7													
6													
5						422						718	
4		28829	28415	29702	26958	29145	27558	25207	33075	28798	29051	31194	28707
3													
2													
1													
0													
Inventory													
Shelf Life		49	50	51	52	53	54	55	56	57	58	59	60
12		34686	36342	31194	42169	31732	39768	49170	17698	34810	33797	22352	35172
11		53214	34686	36342	31194	42169	31732	39768	49170	17698	34810	33797	22352
10		25684	53214	34686	36342	31194	42169	31732	39768	49170	17698	34810	33797
9		36730	25684	53214	34686	36342	31194	42169	31732	39768	49170	17698	34810
8		29145	36730	25684	53214	34686	36342	31194	42169	31732	39768	49170	17698
7		46042	29145	36730	25684	53214	34686	36342	31194	42169	31732	39768	49170
6		39812	46042	29145	36730	25684	53214	34686	36342	31194	42169	31732	39768
5		29946	39812	46042	29145	36307	25684	53214	34686	36342	31194	41450	31732
4		8755	1531	10110	19085		8749	477	20139	5888	7291		12743
3			8755	1531	10110	19085		8749	477	20139	5888	7291	
2		17411		8755	1531	10110	19085		8749	477	20139	5888	7291
1		9206	17411		8755	1531	10110	19085		8749	477	20139	5888
0		15271	9206	17411		8755	1531	10110	19085		8749	477	20139
Expired		209447	224718	233923	251335	251335	260090	261621	271731	290816	290816	299565	300042

Figure 5.1-6 Picking and Inventory Table for "2 Clusters" Picking: 20% Fast-Movers and 80% Slow-Movers

		Year 5											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Picking													
Shelf Life		49	50	51	52	53	54	55	56	57	58	59	60
12													
11													
10													
9		44652	36725	35233	20022	17857	5647						
8		99491	105348	113275	114767	129978	132143	126037	147061	141049	136303	145863	139398
7									18316	2939	8951	13697	4137
6													
5													
4													
3													
2													
1													
0													
Inventory													
Shelf Life		49	50	51	52	53	54	55	56	57	58	59	60
12		150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000
11		150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000
10		150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000	150000
9		105348	113275	114767	129978	132143	144353	150000	150000	150000	150000	150000	150000
8								18316	2939	8951	13697	4137	10602
7													
6													
5													
4													
3													
2													
1													
0													
Expired													

Figure 5.1-7 Picking and Inventory Table for "FIFO Only" Picking: 20% Fast-Movers and 80% Slow-Movers

The total impact at retailers' end is still positive. For example, at Month 60, the obsolescence at retailers' end can be calculated as:

“2 Clusters” Picking: $114,828 * 0.05\% + 28,707 * 0.2\% = 112$ units

“FIFO Only” Picking: $139,398 * 0.63\% + 4,137 * 1.25\% = 923$ units

811 units of obsolescence are reduced at retailers' end with the “2 Clusters.” However, at the same time there are an additional 12,743 obsolete units in Hershey's DC since their remaining shelf life reaches the threshold, which leads to a net increase in obsolescence by 11,932 units for “2 Clusters” picking. The cumulative difference of obsolescence at retailers' end and Hershey's DC are shown in Figure 5.1-8 and Figure 5.1-9 respectively. Apparently “FIFO Only” picking works much better in this case.



Figure 5.1-8 Cumulative Obsolescence at Retailers: 20% Fast-Movers and 80% Slow-Movers

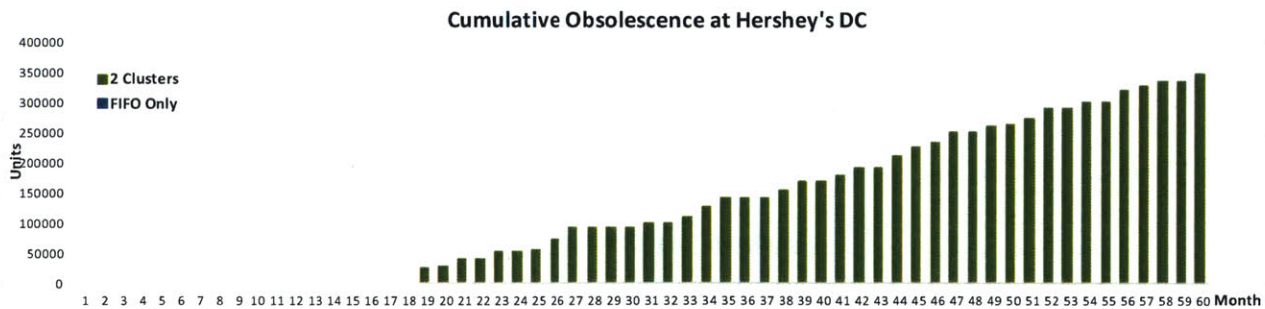


Figure 5.1-9 Cumulative Obsolescence at Hershey's DC: 20% Fast-Movers and 80% Slow-Movers

We further analyze this finding by varying the split of clusters from 10% to 90% (percentage of fast-movers' ordering quantity over total quantity) and trying to identify the conditions better

suiting for each picking strategy. Again we run each setting 100 times and calculate the average total obsolescence.

With the base model setting, we identify that the shift is at 40%, i.e., “2 Clusters” picking has an advantage when at least 40% of the ordering quantity is from fast-movers. Figure 5.1-10 compares the cumulative total obsolescence for the two picking strategies when the cutoff is set at 30%, and Figure 5.1-11 shows cumulative total obsolescence when the cutoff is set at 40%. Both are the average results of 100 simulation runs. We are primarily concerned with the difference between the curves in the middle of the graphs, as the exponential increase of obsolescence with the two-cluster strategy toward the end of the five years is due to the slight overproduction in our model; it can be reduced by adjusting the production schedules accordingly. With 40% orders from fast-movers, the reduction of obsolescence in slow-moving retailers is significant enough while Hershey’s DC is still able to maintain a low obsolescence level. The “2 Clusters” picking strategy is able to help reduce net obsolescence under such conditions.

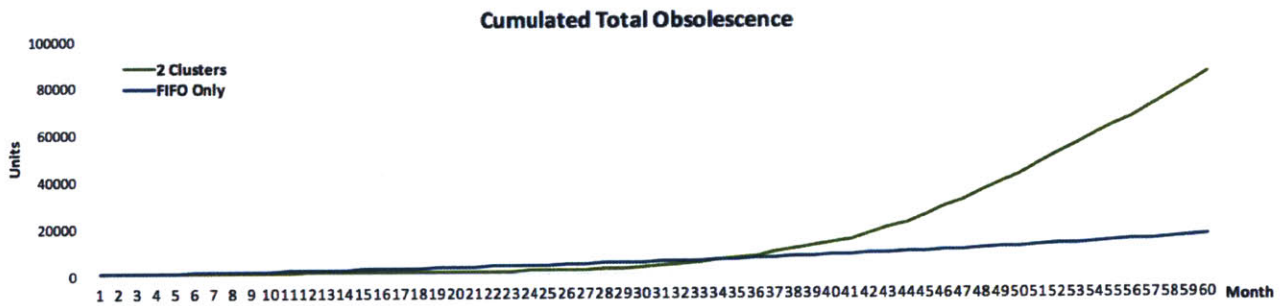


Figure 5.1-10 Cumulative Total Obsolescence: 30% Fast-Movers and 70% Slow-Movers

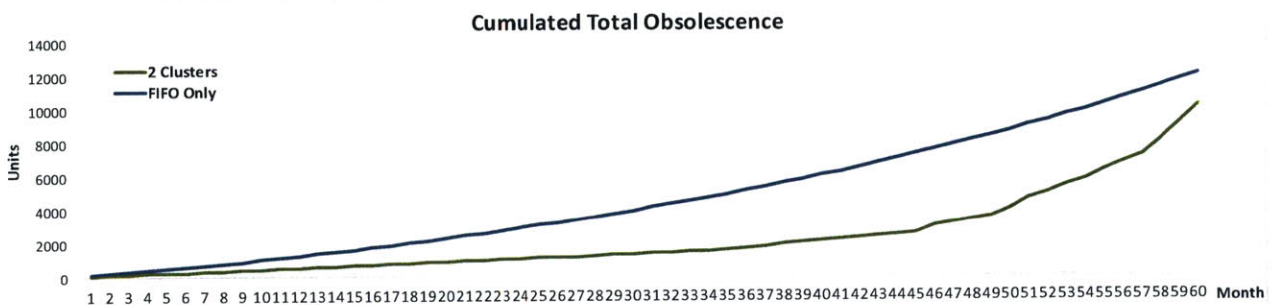


Figure 5.1-11 Cumulative Total Obsolescence: 40% Fast-Movers and 60% Slow-Movers

On the contrary, when fast-movers only account for less than 40% of total orders, there will be fewer orders from fast-mover. In this case, it takes longer to fully consume an old batch of inventory, and the products they receive tend to be older. When too many items of old inventory cannot be picked up in time, the obsolescence in Hershey's DC increases far more than the amount of reduced obsolescence in slow-moving retailers. When such a situation happens, it is better to continue using "FIFO Only" picking.

This cutoff we get from base model relies on the assumption that all inputs are fixed. In the discussion section, we will further analyze the impact of each input on the cutoff by sensitivity analysis. Another finding in this part is that the "2 Clusters" picking strategy has marginal impact on the average freshness of product. Here we use the weighted average remaining shelf life when reaching the retailer every month to represent the average freshness of product. It is calculated by:

$$\frac{\sum_i[(\text{Quantity picked from inventory batch } i) * (\text{Corresponding remaining shelf life})]}{\text{Total quantity picked}}$$

By varying the cluster cutoff from 10% to 90%, we observe that though the freshness of product going to fast-movers and slow-movers individually differs between the two picking strategies, the overall product freshness of a given month is close for both picking strategies, regardless of where the cluster cutoff is. One example is shown in Figure 5.1-12. This chart demonstrates the average freshness of a product for both picking strategies when the cluster cutoff is at 50%. In this simulation run, the average discrepancy of the product freshness (Freshness of "2 Clusters" Picking - Freshness of "FIFO Only" Picking) over the 60-month simulation duration is 0.04 months, with a standard deviation at 0.09 months. Given the scale of 12 months total remaining shelf life, this number is negligible.

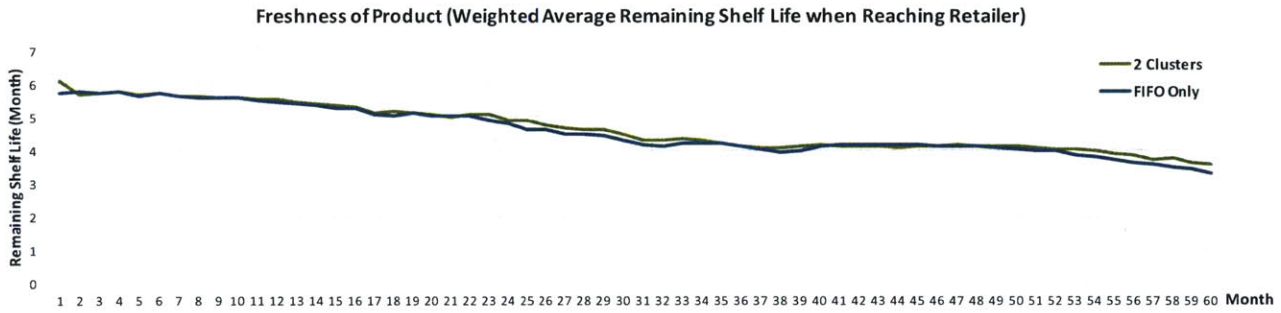


Figure 5.1-12 Freshness of Product: Weighted Average Remaining Shelf Life when Reaching Retailer

5.2 Clustering Model

The simulation model explains how a 2-Cluster model can reduce obsolescence and the impact of changing various parameters such as shelf-life of a product, time in supply chain, production quantity etc. Based on the results for various scenarios, the simulation model can be used to obtain the optimal cluster cut for a given product. However, it is highly time consuming to run the simulation for each product, and to obtain the optimal cluster cut for classifying the destination DCs as slow and fast. Thus, we propose another approach, which is to use a clustering technique to classify the products based on order quantities. Based on this, we recommend the list of products for which the 2-Cluster model would be beneficial.

All the products have been named from H1 to H2096 and DC's from 1 to 373 and the nomenclature is consistent throughout this section. We use a two-stage clustering approach: First, all items were clustered into 4 different categories based only on the total annual order quantities, as shown in Figure 5.2-1.

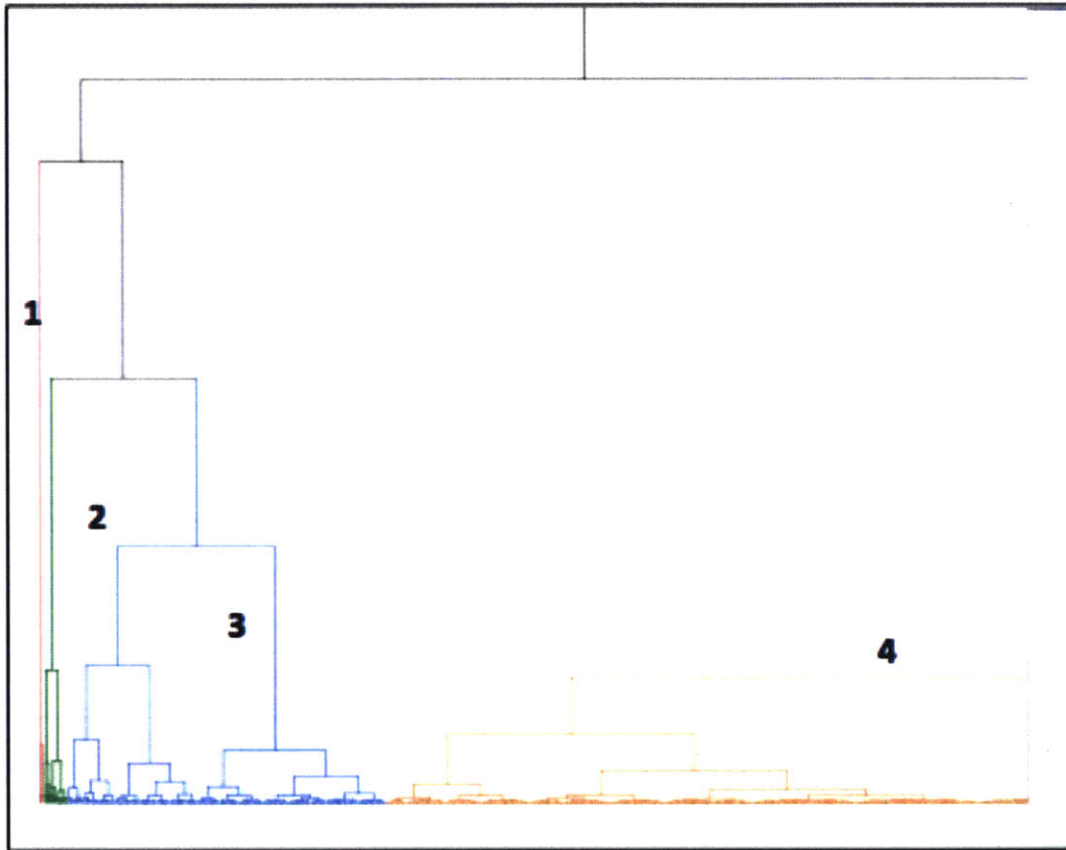


Figure 5.2-1 Hierarchical clustering of products into 4 categories based on annual order quantities

The 4 clusters (referred to hereafter as categories) contained different numbers of products; the details of the categories are shown in Table 5.2-1.

Category	No of Hershey items	Volume of products
1	3	7%
2	18	14%
3	251	21%
4	1824	58%
Total	2096	100%

Table 5.2-1 Category details: Number of products and volume.

For example, from Table 5.2-1, we can see that Category 1 consists of 3 different products: H1, H2 and H3, which comprise 7% of the total volume shipped across all DCs.

Next, we applied clustering a second time, but this time within the categories: All DC's served by one category of product were classified as fast and slow based on the order quantities. Cluster 1 ('fast') implies that the DCs handled high volumes of a given product and cluster 2 ('slow') meant that the DCs handled lower volumes. For instance, if 55 DCs are served with category 1 product, the DCs would be separated into 2 clusters (again through hierarchical clustering) solely based on the shipping volume handled by the DCs. If DC 1 serves 10000 units and DC68 serves 10 units then DC-1 would probably be in Cluster 1 and DC-68 in cluster 2.

The summary statistics for all product-DC clusters are shown in Table 5-2.

Category	1= Fast	2 = Slow	Total no of DCs Served	Volume Served by Fast Movers
1	19	36	55	83%
2	20	30	50	68%
3.1	102	17	119	19%
3.2	19	26	45	70%
4	22	40	45	65%

Table 5.2-2 Summary Statistics for Product-DC Clusters

The individual DC clusters, represented as dendrograms for each category, have been included in the Appendix.

Category 1:

Category 1 consists of 3 products H1, H2 and H3. Category 1 should definitely follow a 2 cluster policy as > 80% of its volume is shipped to fast moving DCs (from Table 5.2-2). In other words, these products are mostly replenished very quickly at majority of the customer DCs as they leave the shelves of the retailers. (Figure 0-2)

Category 2:

Category 2 shows fairly similar clustering as Category 1. Around 68% of the total volume of these 18 products are classified as fast-moving (Figure 0-3), thus Category 2 products would also benefit from the 2 cluster picking model.

Category 3:

Category 3 has further been divided into two sub categories due to the large variability of the number of DC's receiving products in this category. (Figures 0-4 and 0-5) Sub-category 3.1 contains products that are distributed to > 100 DCs (Lesser quantities but to many small-volume DCs) and sub-category 3.2 where the number of DCs served is typically around 50. In this case, we can observe that for products belonging to sub-category 3.1 , the volume served to the fast moving DCs is very low (around 20% of all orders), so the FIFO technique would be not be favorable here. Sub-category 3.2, on the other hand, has 70 % of orders going to fast movers, hence would benefit more from the 2 cluster technique.

Lastly, category 4 products are the very slow moving Hershey items. Most items in this category have very similar order sizes from most DCs. Thus, ideally, they should only be picked with the single cluster policy with all demand for a given period produced in one production run (and thus all having the same remaining shelf life at the Hershey's DC). But if interruptions or other unforeseeable circumstances lead to multiple production runs for these low volume items, with differing remaining shelf lives at the Hershey's DC, the 2-Cluster policy can be implemented (Figure 0-6).

6 DISCUSSION

What happens on running the simulation model n times? Are the results replicated every time for different cut off values? What happens while changing the retailers' obsolescence cut or the lead times at Distribution centers? These are the few questions that are addressed in this section.

6.1 Sensitivity Analysis by Changing the Cluster Cut

First, we conduct a sensitivity analysis for the cut-off value. We alter only the cluster cut-off from 0.1 to 0.9, and for every value, we run our simulation model 100 times under the same set of parameters as our base model (aside from the cluster cut-off). We then compute the Cumulative obsolescence difference, which we define as follows:

Cumulative obsolescence difference for a given year = Cumulative obsolescence in the 2-cluster model at the end of year, n – Cumulative obsolescence in the FIFO model at the end of year, n .

We shall observe what happens to the cumulative obsolescence at the end of a given time period when the % of volume sent to fast movers is lower or exceeds the % of volume sent to slow movers.

6.1.1 Cumulative obsolescence difference over the course of 5 years

A cut-off value of 0.1 implies that the volume shipped to fast movers is 0.1 times the total volume shipped at a given period of time. The rest 90% of orders that are being shipped to the slowest-moving retailers would be picked from the freshest batches of product. The cumulative obsolescence difference when the cluster cut-off value is 0.1 is shown in Figure 6.1.1-1.

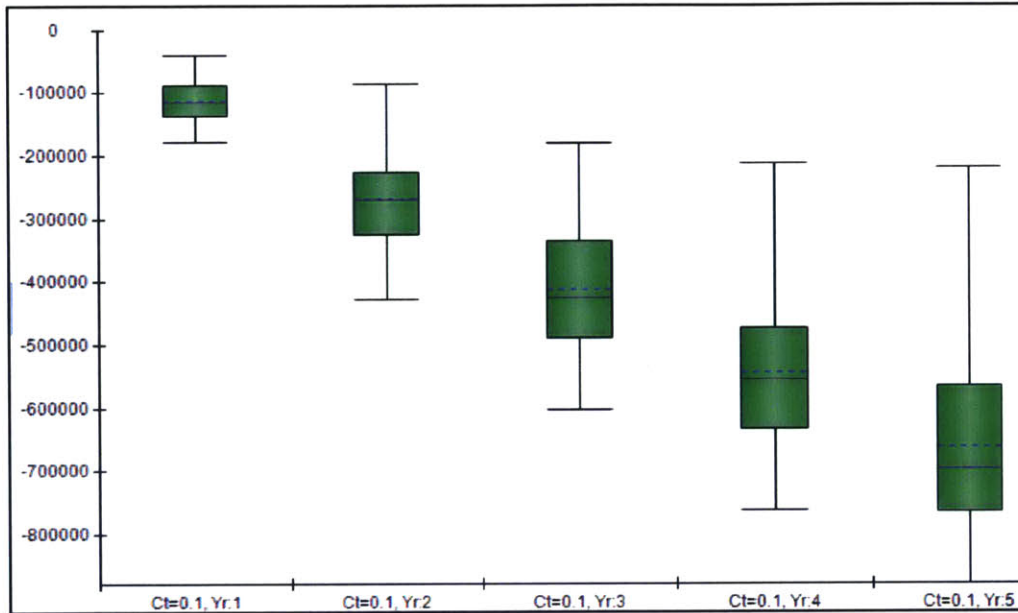


Figure 6.1.1-1 Box plots of the Cumulative obsolescence difference for Cluster Cut = 0.1

In Figure 6.1.1-1, the vertical axis represents the cumulative obsolescence difference and the horizontal shows the time. Box-and-whisker plots are shown for the end of each year from year 1 to year 5. The cumulative obsolescence difference at the end of each year is negative. This implies that the 2-cluster model produces more obsolescence as more volume of product are being shipped to the slow moving DCs. This is logical as slow moving DCs follow LIFO, so the products manufactured first, or with a lower expiry remains at the manufacturing DC and turn obsolete.

We can observe a similar trend when the cluster cut-off is 0.3 (Figure 6.1.1-2) (i.e.) 30 % of the volume is picked as FIFO and the remaining 70% is picked as LIFO as the volume shipped to slow movers is still higher than that shipped to fast movers.

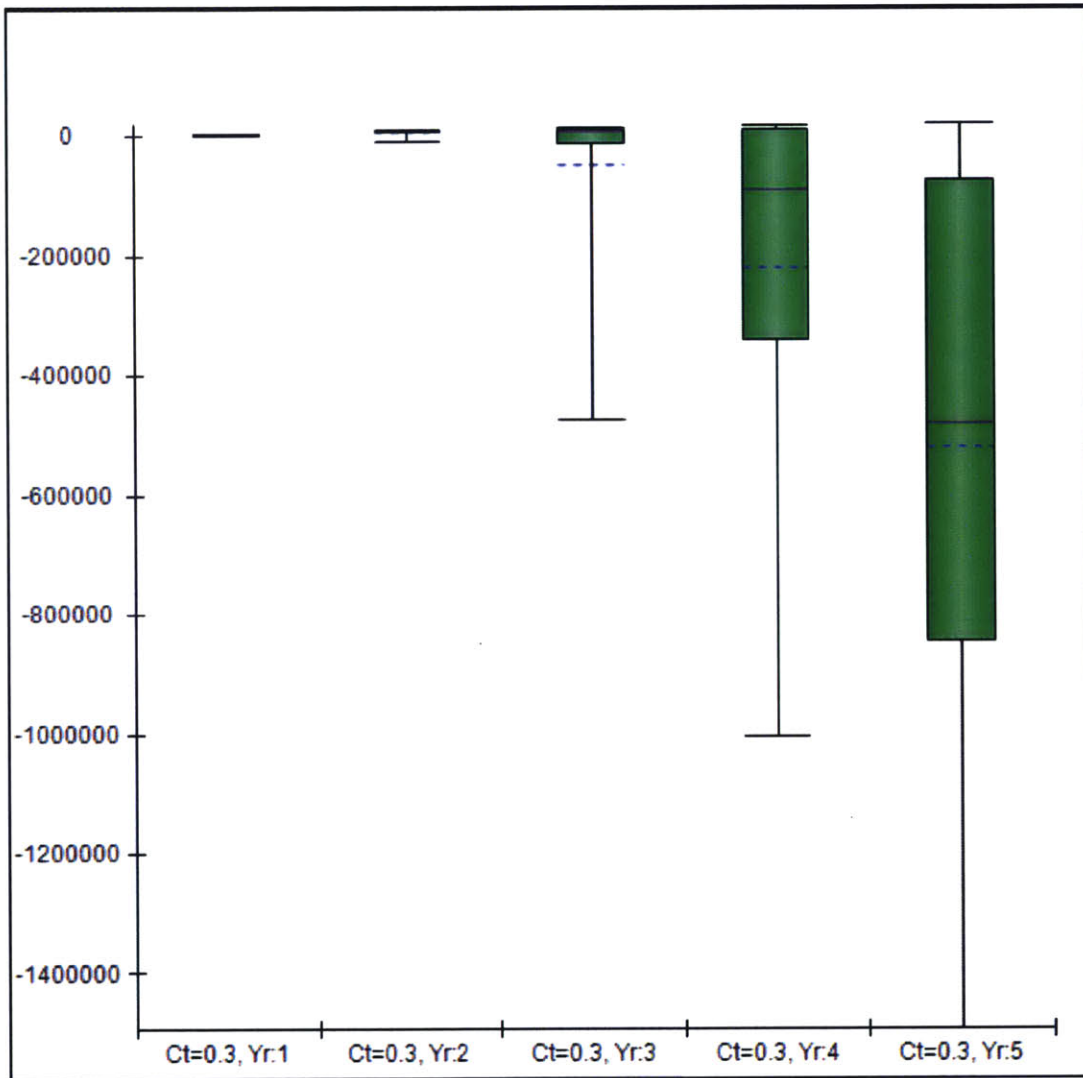


Figure 6.1.1-2 Box plots of the cumulative obsolescence difference for Cluster Cut = 0.3

Figure 6.1.1-3 shows the case where equal volumes of a given product are shipped to fast-moving and slow-moving retailers. We can observe that the cumulative obsolescence difference in most cases is positive. Thus the 2-cluster model proposed by us will be effective in reducing obsolescence. This agrees with the results of our base model.

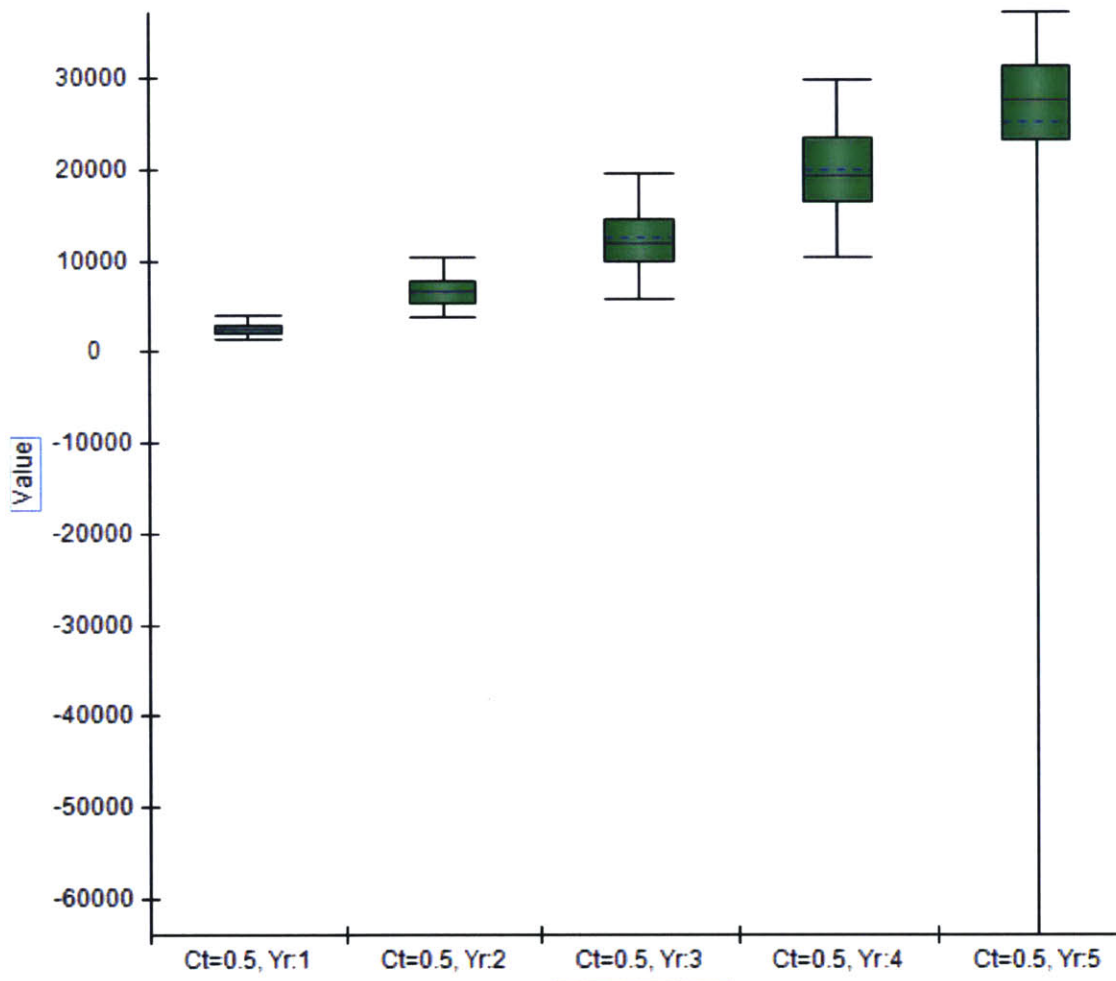


Figure 6.1.1-3 Box plots of the cumulative obsolescence difference for Cluster Cut = 0.5

Increasing the cluster cut-off to 0.7, or having a high ratio of fast movers (Figure 6.1.1-4) reveals that the 2-cluster model would further reduce obsolescence. With each year the cumulative obsolescence difference generated increases probably due to the exponential increase of obsolescence at the retailers end (which shall be explained in the subsequent sections) and increased inventory levels.

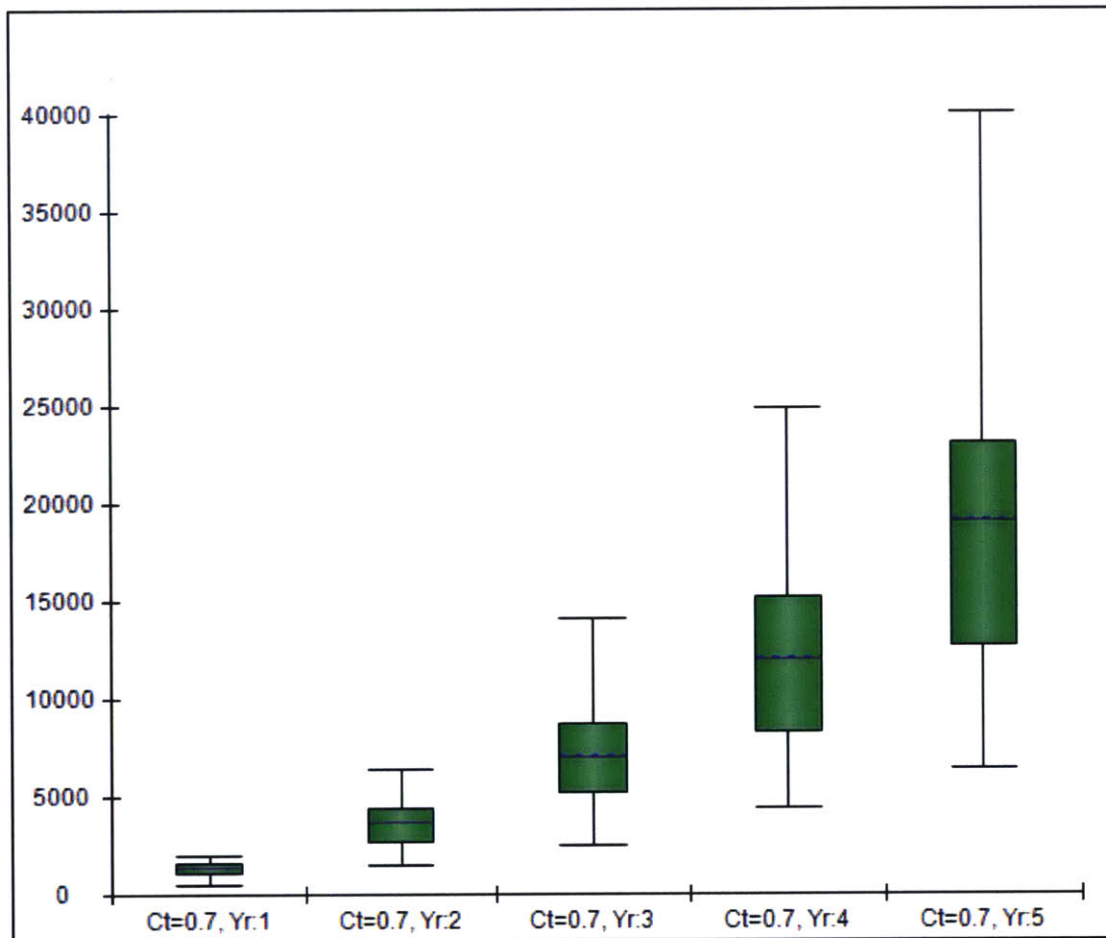


Figure 6.1.1-4 Box plots of the cumulative obsolescence difference for Cluster Cut = 0.7

6.1.2 Cumulative obsolescence difference at the end of 5 years

Figure 6.1.2-1 shows the final state of the system at the end of five years, for varying the cluster cut off from 0.1 to 0.9 in the form of box and whisker plots. The vertical axis corresponds to cumulative obsolescence difference.

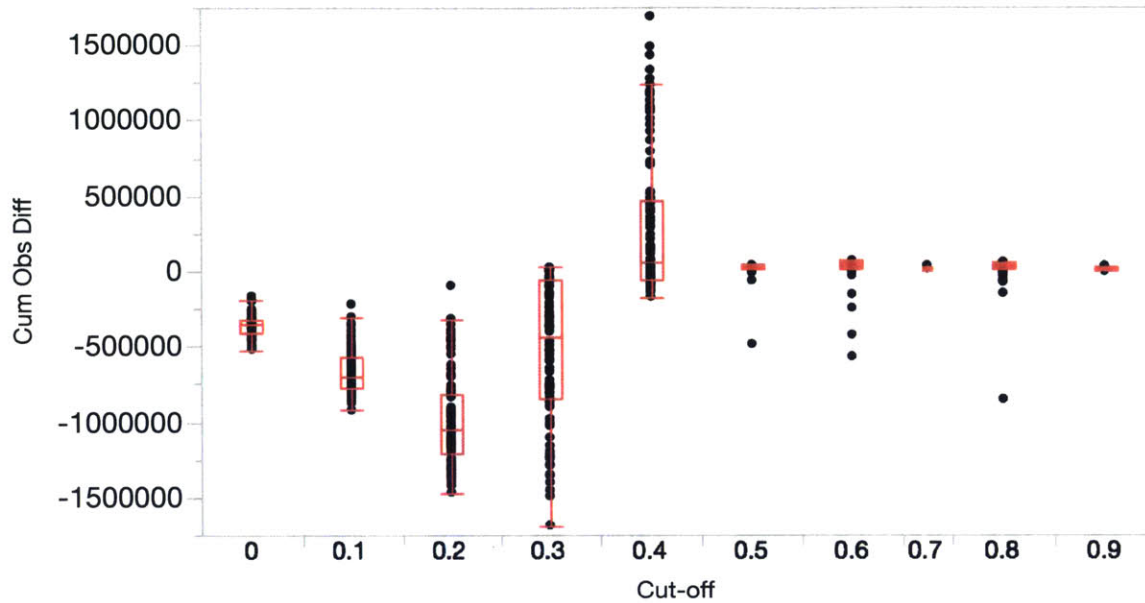


Figure 6.1.2-1 Box plots of Cumulative obsolescence difference (2 Cluster Model - FIFO) for varying cluster cuts

We can see that when the volume shipped to slow moving DC's is higher, the cumulative obsolescence difference is more negative, or the obsolescence is more in the 2-cluster model. Cluster cut at 0 denotes that the picking strategy followed was fully LIFO, or the entire volume was picked only by slow moving distribution centers. The cumulative obsolescence difference between LIFO and FIFO (maintaining other parameters constant) also reveals a higher obsolescence rate. Thus with the current parameter settings, for products having volume distribution to slow movers less than or equal to that of fast movers, a 2 cluster model might not be beneficial.

6.2 Representing orders using a triangular distribution

In our base model, the orders followed a uniform distribution. The order quantities from a sample trial run would follow a distribution similar to that shown in Figure 6.2-1. The total number of orders is 60 (12 months * 5 years) with the order quantities rounded up to the nearest 10000 multiple. The most likely order quantity would be anything between 130000 and 160000 with a

mean around 150000 in case of uniform distribution (as all order quantities have equal probabilities).

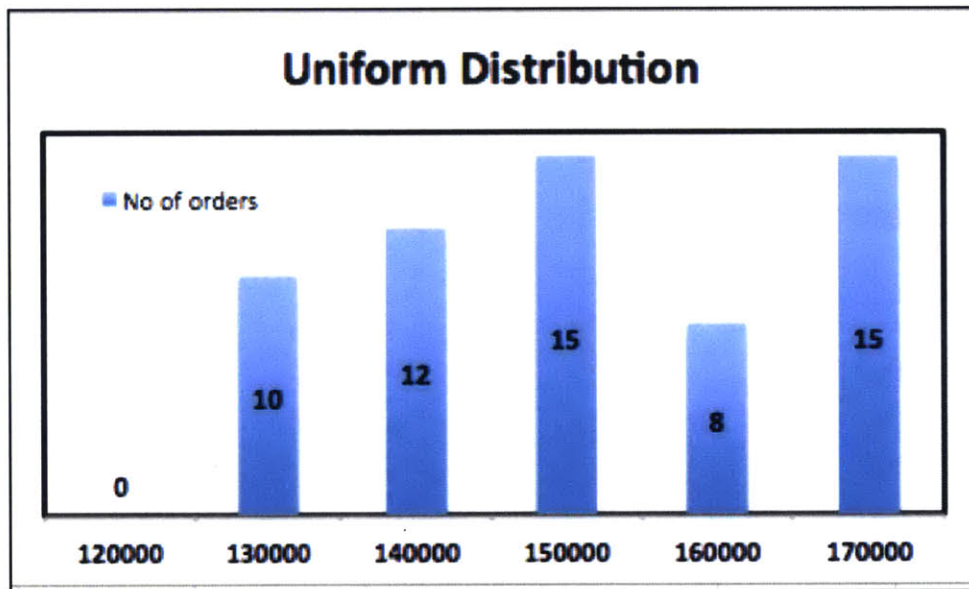


Figure 6.2-1 Histogram of orders following a uniform distribution for a sample trial run

If orders were modeled with a triangular distribution, along with the minimum and maximum specified order quantity, we would introduce a 3rd user input variable called most likely order quantity (c). (see Figure 6.2-2)

An order quantity for a month (x) is randomly generated between the minimum (a) and maximum (b) order quantity and the function is defined as follows.

$$F(x|a, b, c) = \left\{ \begin{array}{l} \frac{2(x-a)}{(b-a) * (c-a)} \text{ for } a \leq x \leq c \\ \frac{2(b-x)}{(b-a) * (b-c)} \text{ for } c < x \leq b \end{array} \right\}$$

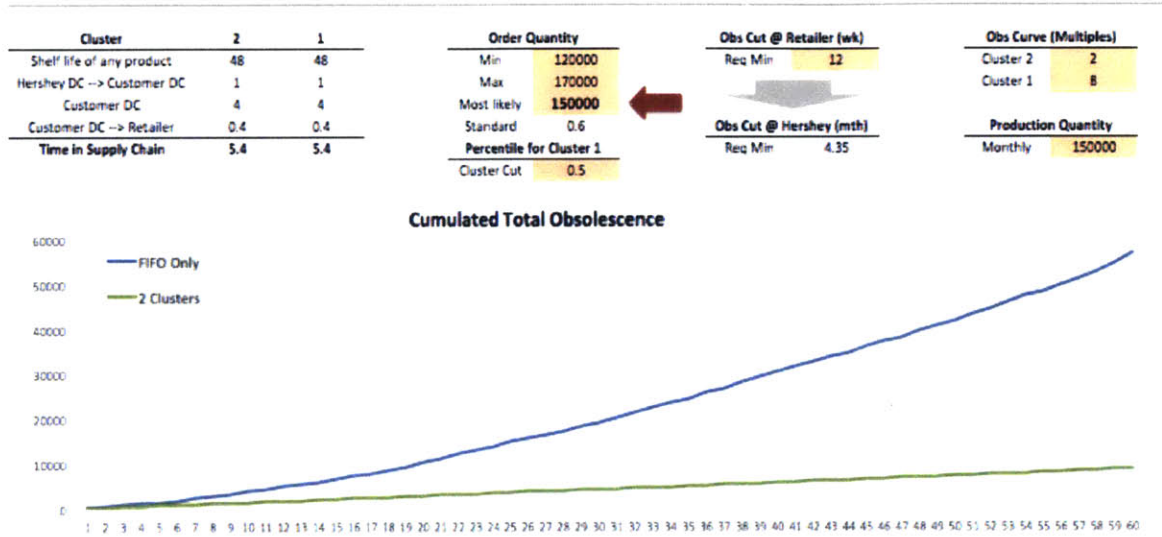


Figure 6.2-2 Screenshot of simulation model with triangular distribution of orders

The order quantities from a sample trial run would follow a distribution similar to that shown in Figure 6.2-3.

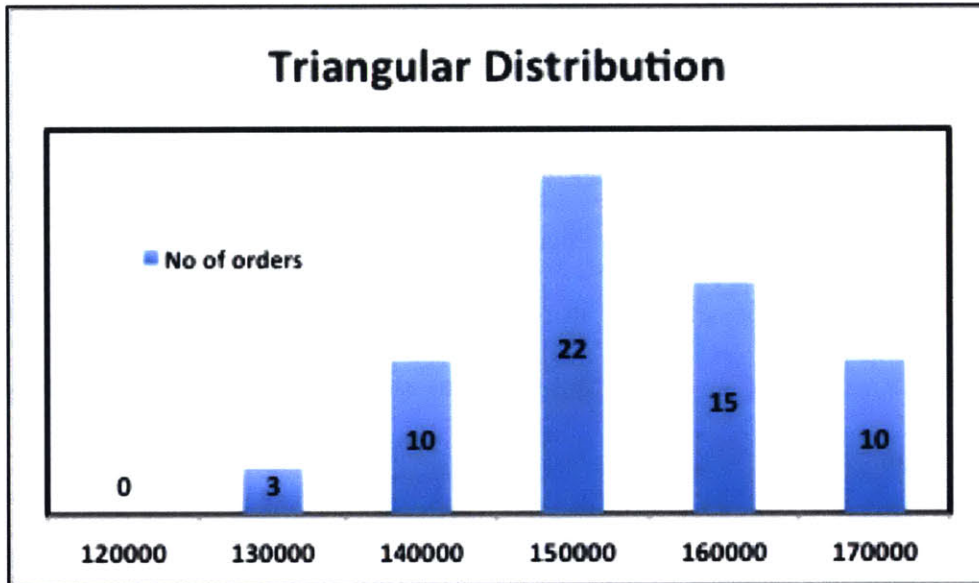


Figure 6.2-3 Histogram of orders following a triangular distribution for a sample trial run

We analyze the cumulative obsolescence difference for three different cluster cuts, namely 0.3, 0.5 and 0.7, and compare the results with the model following a uniform distribution of order quantities in Figure 6.2-4.

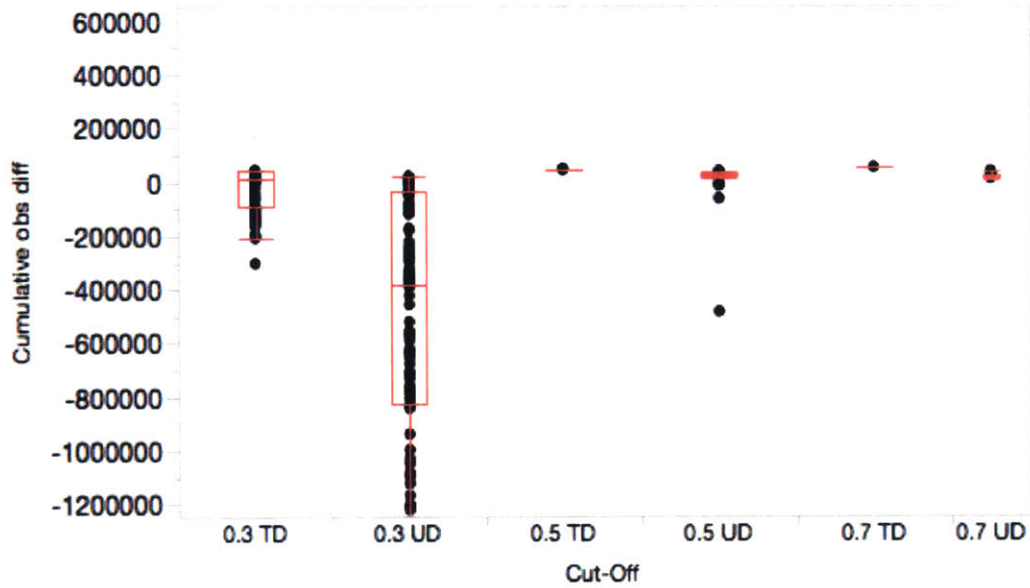


Figure 6.2-4 Box plots of Cumulative obsolescence difference (2 Cluster Model - FIFO) for varying cluster cuts for triangular and uniform distribution

The vertical axis represents the cumulative obsolescence difference in both the models for 100 simulation runs and the horizontal axis represents the cluster cut-off. TD stands for triangular distribution and UD denoted uniform distribution. The box plots reveal that even with order quantities following a triangular pattern, the 2-cluster model might not be effective in reducing obsolescence when the cluster cut-off is less than 0.5.

Thus, the 2-cluster model is more effective in reducing obsolescence when the volume sent to fast movers is equal to or more than the volume sent to slow movers when the orders follow a triangular distribution.

6.3 Impact of Obsolescence Risk at Retailers

In this section, we will explain our further sensitivity analysis by varying the risk of obsolescence at the retailer.

We want to see the impact of the relative ratio of obsolescence risk for fast-movers and slow-movers on total obsolescence quantity. According to Section 4.2.4, we assume the obsolescence ratio for a product is 2 for slow-movers and 8 for fast-movers in the base model. In this analysis,

we only vary fast-mover’s obsolescence ratio while keeping all other parameters same as in base model. Figure 6.3-1 shows the settings for each scenario.

Scenario	Obsolescence Ratio	
	Slow-Mover	Fast-Mover
Base	2	8
1	2	4
2	2	3
3	2	2.8
4	2	2.5
5	2	2

Figure 6.3-1 Obsolescence Ratio

We use 50% cluster cutoff as an example to illustrate the finding. Figure 6.3-2 shows the obsolescence reduction of the “2 Clusters” over the “FIFO Only” picking strategy cumulative over 5 years, with a positive number indicating a positive saving, and vice versa. It is a boxplot of 100 simulation runs for each scenario. According to the figure, we will only be able to safely achieve positive obsolescence reduction in Scenario Base, 1 and 2. In another word, the “2 Clusters” model will only make sense when the obsolescence ratio for fast-mover is no less than 3.

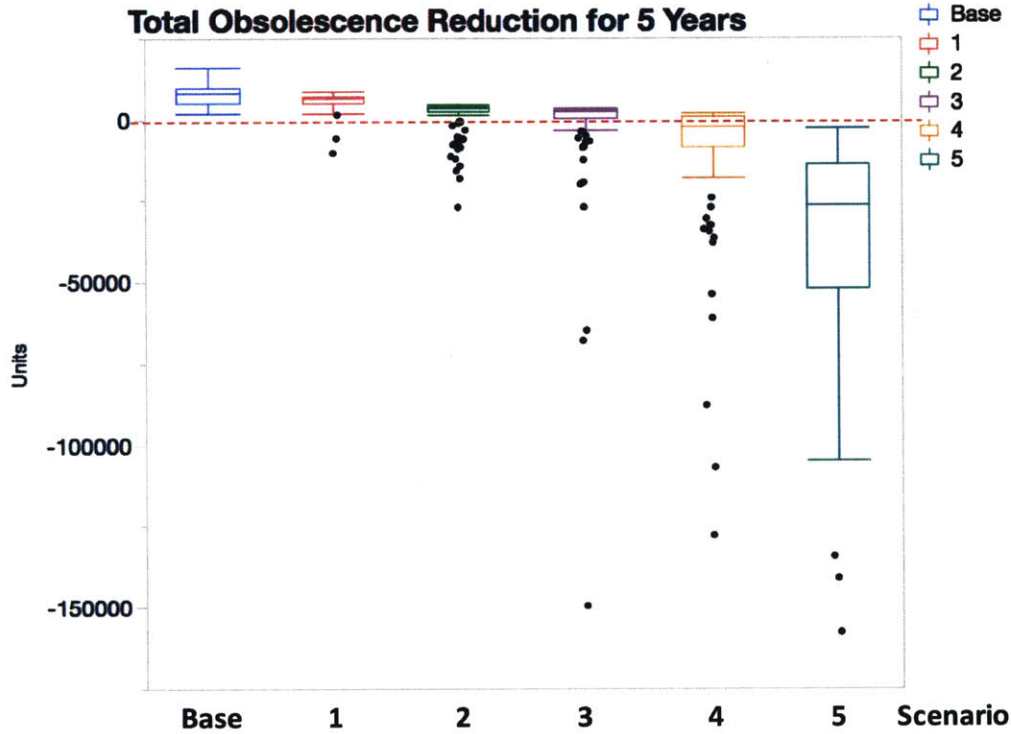


Figure 6.3-2 Total Obsolence Reduction for 5 Years

This is because when the obsolescence ratio of fast-movers becomes smaller and closer to that of slow-movers, the advantage of the “2 Clusters” picking diminishes. As previously explained in section 5.1, the reduction of obsolescence in the “2 Clusters” model is mostly contributed by the reduction of obsolescence in slow-moving retailers. This is because the small obsolescence ratio of slow-mover implies it is sensitive to product age. By providing slow-movers with fresher product, the “2 Clusters” model effectively reduces the obsolescence in slow-moving retailers. By contrast, fast-movers are less sensitive to product age. Given a larger obsolescence ratio, fast-mover’s risk of obsolescence quickly drops below 1%. Take the base model setting as an example: with obsolescence ratio sets at 8, fast-mover’s risk of obsolescence drops below 1% as long as the product has more than 2 months remaining shelf life when reaching the retailer (Figure 4.2.4-1). So even though fast-movers tend to receive older products, the resulting increase in obsolescence at the fast-moving retailers are usually not that significant. However, when the obsolescence ratio

of fast-movers decreases, fast-movers behavior is closer to that of slow-mover. Fast-mover becomes more sensitive to product age, so the obsolescence increase in fast-movers becomes a problem. When the reduction of slow-movers' obsolescence cannot outweigh the increase of obsolescence at the Hershey's DC and fast-movers, the "2 Clusters" model loses its advantage. Another interesting observation here is sometimes the cumulative total obsolescence over time shows an exponential growing trend. One example is shown in Figure 6.3-3, plotting the cumulative total obsolescence for Scenario 3. In this example, the "2 Clusters" model has a clear exponential growing trend especially towards the end of the 5-year horizon.

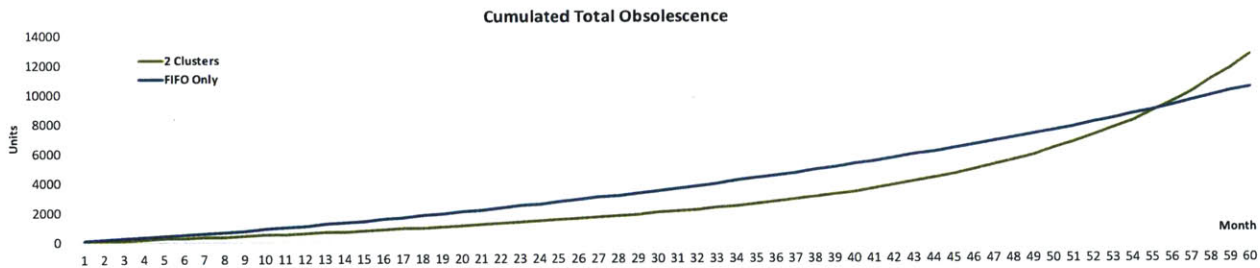


Figure 6.3-3 Cumulative Total Obsolescence for Scenario 3

Such trend is caused by the exponential model of obsolescence risk at retailers. As explained in Section 4.2.2, in the model setting, the monthly average ordering quantity is slightly less than the monthly production quantity. While this tiny over-production ensures us to fulfill all orders, it has a side effect that the inventory in the Hershey's DC will slowly cumulate over time. As an impact, the oldest batch of product in the inventory will become older, and the product picked using FIFO will be older. When this inventory cumulates to a certain stage like a saturation, every month there will be more inventory becomes old enough to obsolete at Hershey's DC, since the inventory is continuously cumulating. Meanwhile larger quantity will need to be picked from older batches, with exponentially higher chance of being obsolescent at retailers. These together result in the exponential growing trend of cumulative total obsolescence. However, such saturation may not make sense in real life because the company should take action to clear stock if they see the

inventory level is too high. In this case, we shall only compare the performance of the two picking strategies before the saturation happens. The saturation can be taken care of if additional information of how the company deals with high inventory level is available.

7 CONCLUSION

Aiming to reduce the obsolescence level throughout supply chain in The Hershey Company, this research was targeted at evaluating the impact of a proposed “2 Clusters” picking strategy on a product’s total obsolescence level. In the “2 Clusters” strategy, orders from high-volume customers (fast-movers) are picked first-in first-out (FIFO), whereas orders from low-volume customers (slow-movers) are picked last-in first-out (LIFO). The proposed strategy was evaluated against the existing “FIFO Only” picking strategy at The Hershey Company. It also proposed viable method to implement the “2 Clusters” picking strategy effectively.

We observed that the “2 Clusters” picking strategy can significantly reduce obsolescence when the aggregated ordering quantity from slow-moving retailers, which would be picked using a LIFO strategy instead of a FIFO strategy, corresponds to a small portion in the total ordering quantity.

Such finding was uncovered by an Excel simulation model. We then used the hierarchical clustering method to cluster products into SKU-DC combinations and delivered a list of SKUs that are most likely to have obsolescence reduction using the “2 Clusters” picking. Moving forward, The Hershey Company can continue to use the simulation model to assess whether the “2 Clusters” picking strategy can benefit a SKU.

The simulation model is sensitive to variables such as the demand pattern, retailer’s obsolescence ratio, etc. While this research simulated the difference between the “2 Clusters” and “FIFO Only” picking strategies, due to the limited reference data available, we used simplifying assumptions in several parts in the model. For example, the risk of obsolescence at the retailers is modeled with an exponential distribution, whose rate parameter is a function of the product age at delivery and retail velocity. A further simplification is the assumption of deterministic time spent by a product between leaving the Hershey distribution center and arriving at the retailer. If relevant data pertaining to factors mentioned above is available, The Hershey Company can have a more

accurate assessment to evaluate whether the “2 Clusters” picking strategy is suitable for any specific SKUs.

Further analysis is recommended to assess the costs and risks associated with implementing the given strategy as well as the impact of the new policy on the financial performance of the company. While reducing cost of obsolescence, this more complicated picking strategy may cause additional operational costs as well as inventory holding costs in the warehouse when compared to the “FIFO only” picking. Furthermore, the potential price markdowns for nearly expired products can also be considered in the model, which would add more complexity but could provide more insights on the cost savings and financial impact of changing the existing picking policy. Such further research can provide The Hershey Company a more thorough understanding of the impact of the “2 Clusters” pick strategy, and therefore help the company make a more confident decision.

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APPENDIX

Dendrogram

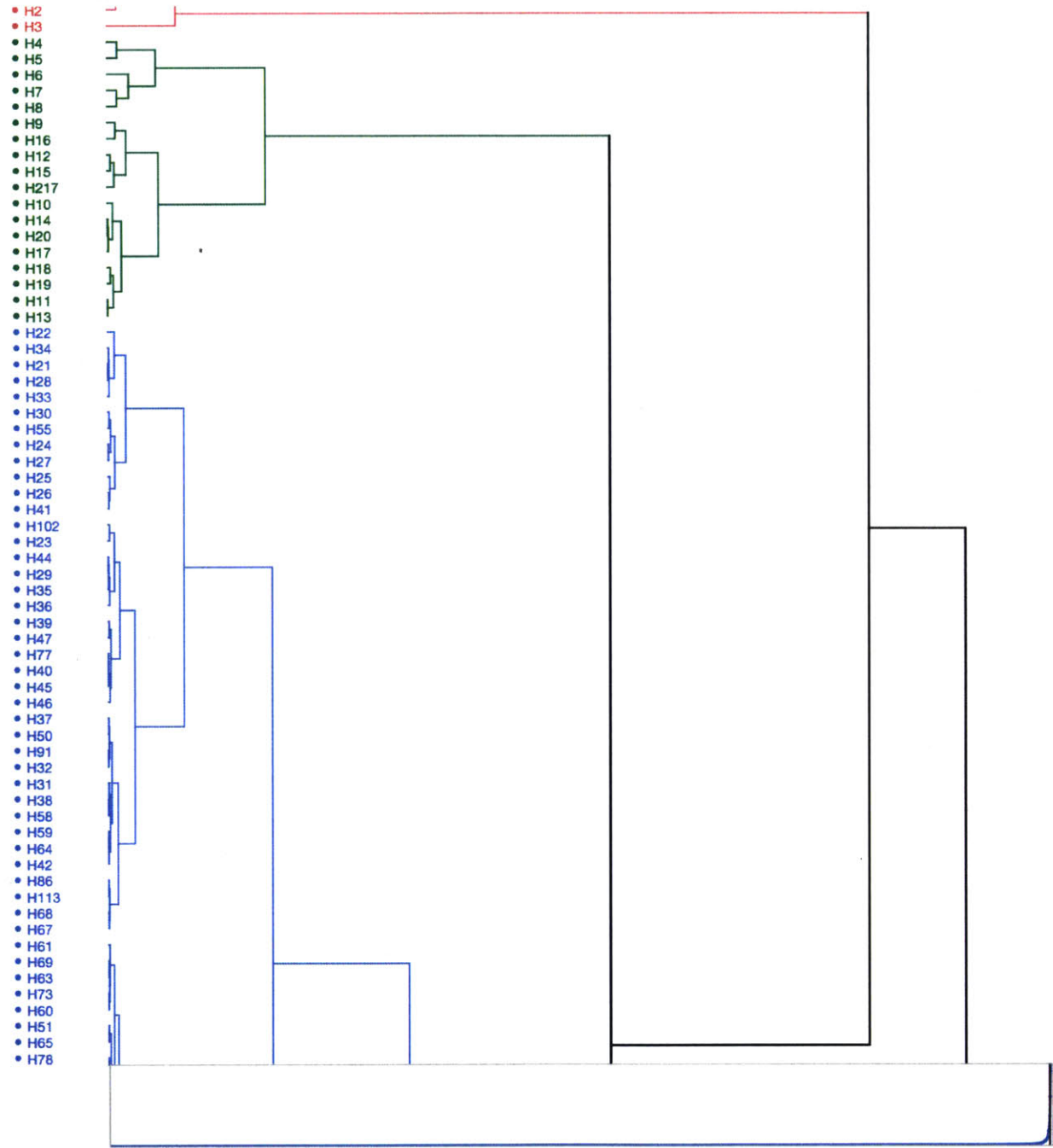


Figure 0-1 Dendrogram for items based on order quantities (Clearer snapshot for section 5.2)

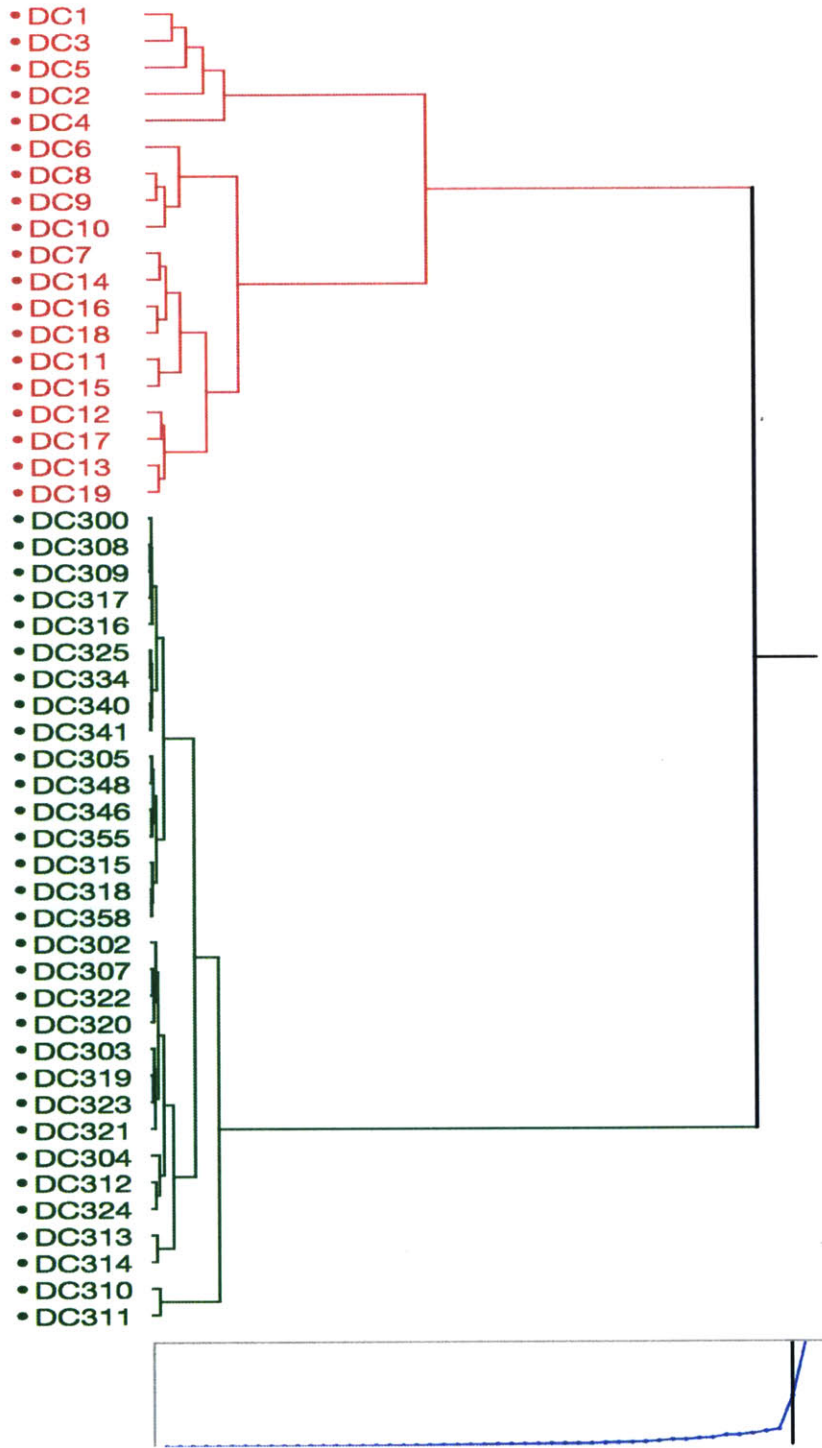


Figure 0-2 Two Cluster DC Model for Category-1 products

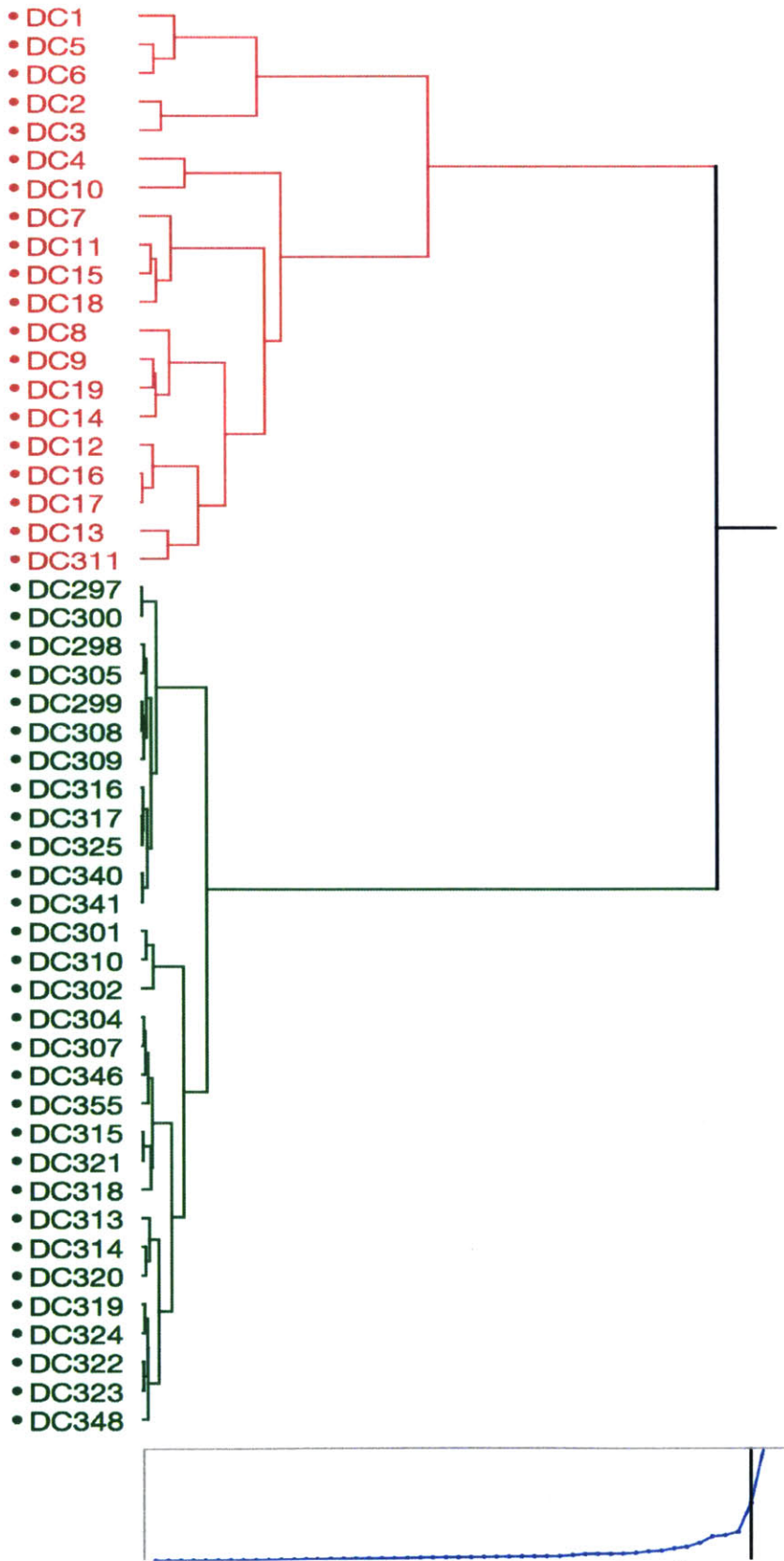


Figure 0-3 Two Cluster DC Model for Category-2 products

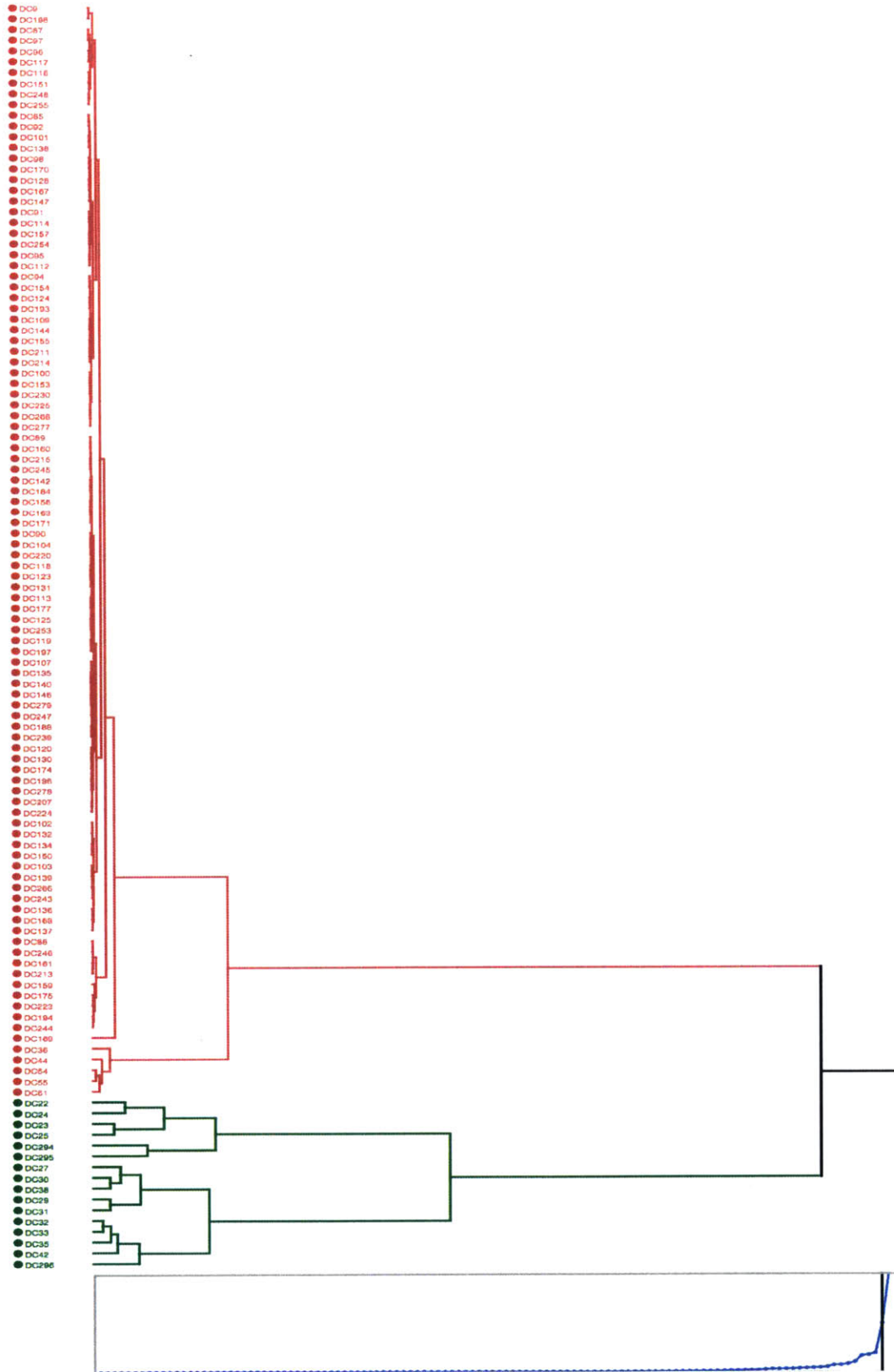


Figure 0-4 Two Cluster DC Model for Category-3.1

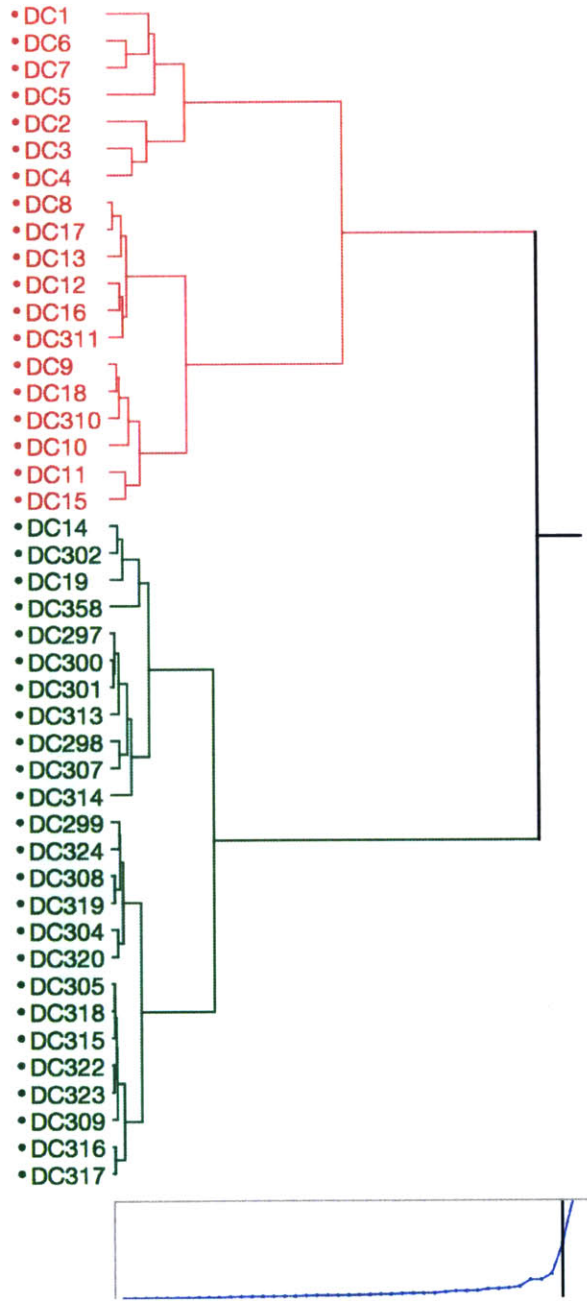


Figure 0-5 Two Cluster DC Model for Category-3.2

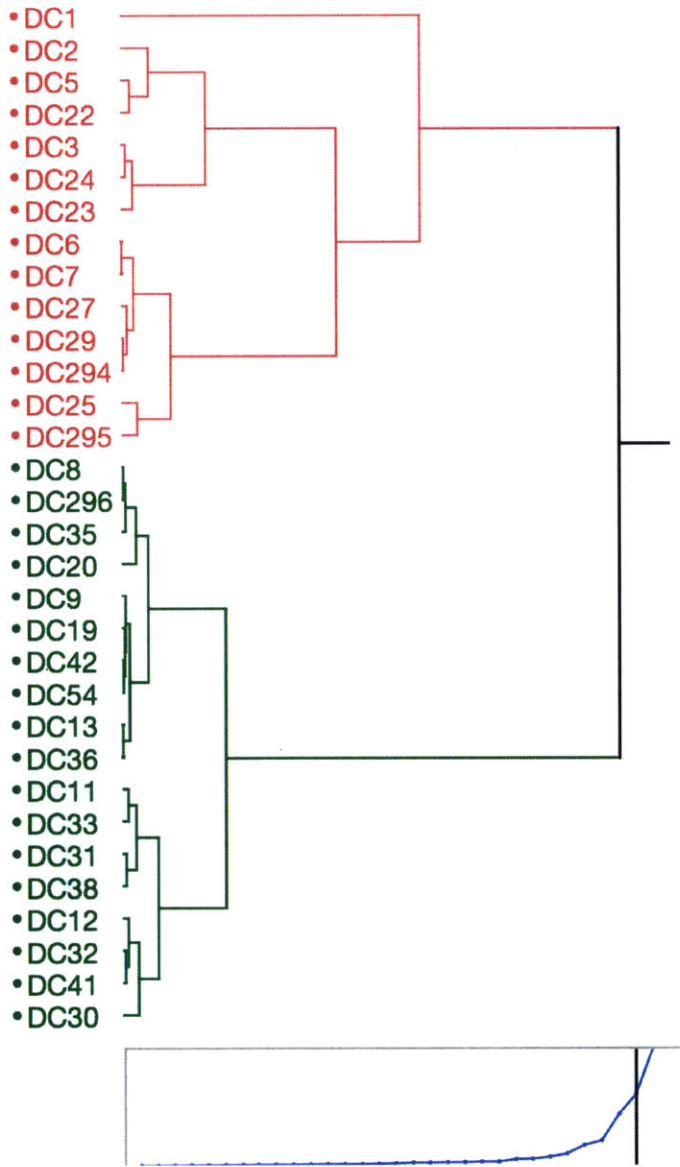


Figure 0-6 Two Cluster DC Model for Category 4