

**STOCK LEVEL OPTIMIZATION AT THE DISTRIBUTION CENTER
THROUGH IMPROVED SUPPLY MANAGEMENT PRACTICES**

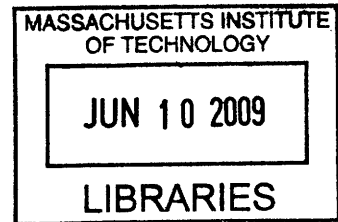
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Submitted to the MIT Sloan School of Management and the Department of Mechanical Engineering
in Partial Fulfillment of the Requirements for the Degrees of

**Master of Business Administration
and
Master of Science in Mechanical Engineering**

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ABSTRACT

This thesis focuses on an inventory and supply management improvement project at Inditex, SA Corporation. Inditex has experienced a higher percentage increase in inventory than in sales over the past few years. As a fast-fashion power house and the largest fashion distributor in the world since August 2008, this trend goes directly against its corporate strategy and competitive advantage. The internship project addresses this trend by focusing on the deterioration in the company's supply management practices. The project developed an optimization model which minimizes total supply chain cost in order to define order points and quantities for a given reference whose demand and variability were also modeled. As a result of these efforts, theoretical inventory turns may be decreased, on average, by 19%.

While these preliminary results are promising, organizational barriers to adoption must also be carefully addressed throughout the project's implementation period. To minimize these risks, a phased implementation approach is recommended which addresses both the technical and organizational hurdles and must be overcome before successful adoption of the tool across the company.

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GLOSSARY

- Supply** : Movements from the Suppliers to the Zara Distribution Centers
Demand : Will be used interchangeably with '**Sales**' and refers to store sales to customers.
Reference : Fashion item completely defined by its Model/Quality/Color (M/Q/C).

1 Industry and Company Overview

1.1 Industry Overview

The fashion retail industry is a highly competitive, cutthroat business. Firms wanting to compete cannot choose one dimension—be it cost, customer satisfaction, innovation, etc—and optimize it for profit. Within fashion retail, a successful firm must win in all these dimensions and all the while have a keen understanding of their customer’s point of view¹.

Historically, this has not always been the case. Up until a few years ago, a company could compete on operational excellence—getting items to the customer faster was, in fact, Zara’s calling card.

What has happened in the industry is that traditional players, such as Gap and H&M, that buy in bulk and source almost exclusively from Asia—the latter sourcing over 60% of its products directly²—have been optimizing their own supply chains to make their model competitive against the ‘fast fashion’ power houses, and these efforts have started to show up on their financials³.

Table 1: Retailer Sales & Inventory Comparative⁴

	07/06		
	Inditex	H&M	Gap
Sales	+15%	+15%	-1%
COGS	+22%	+10%	-12%
Stock/Sales (2007)	0.11	0.33	0.10

¹ (Apparel Specialty Stores, 2004)

² (Dawson & Mukoyama, 2006)

³ (O'Donnell, 2008)

⁴ (H&M Corp., 2007) (Gap, Inc., 2007) (Inditex, S.A., 2007)

At the core of this issue is the notion of ‘time-based competition’, divided into three dimensions: time to market, time to serve, and time to react. Within fashion retailing, the trend up to this point had been of a complex supply chain with thousands of suppliers around the globe. With the success of Zara, Benetton, The Limited, and other time competitors, quick response concepts are being applied to these sectors in an effort to minimize markdowns due to out-of-season or unwanted stock in stores⁵. These efforts have started to bear fruit and gain momentum in other parts of the supply chain, sending shockwaves across an industry that has been hard-hit in the recent economic downturn.

1.2 Company Overview

Inditex is the world’s largest fashion distributor, with eight sales formats: Zara, Pull and Bear, Massimo Dutti, Bershka, Stradivarius, Oysho, Zara Home, and Uterqüe - boasting 4,278 stores in 73 countries⁶.

The Inditex Group is comprised of over one hundred companies associated with the business of textile design, manufacturing and distribution. Thanks to its achievements and the uniqueness of its management model based on innovation and flexibility, Inditex became the largest fashion distribution group in August 2008. Each concept’s commercial activity is carried out through chains of stores managed directly by companies in which Inditex holds all or the majority of the share capital, with the exception of certain countries where, for risk-related reasons, the retail selling activity is performed through franchises.

⁵ (Ferne, 2007)

⁶ (Inditex, S.A.)

The Inditex fashion philosophy—creativity and quality design together with a rapid response to market demands—has resulted in fast international expansion and excellent response to their sales concepts⁷.

Table 2: Inditex Group Key Financials⁸

Fiscal Year⁹	2007	2006	07/06
Turnover	9,435	8,196	+15%
Net Profit [M€]	1,250	1,002	+25%
N° of Stores	3,691	3,131	+560
N° of Countries	68	64	+4
International Sales	62.5%	60.4%	+2.1%
Employees	79,517	69,240	+10,277

The Inditex business model is characterized by the search for flexibility in adapting production to market demand by controlling the supply chain throughout the different stages of design, manufacture and distribution. This enables the Group to focus its own and suppliers' production on changes in market trends during each commercial campaign. At its core, the firm has harnessed communication technologies within the traditional supply chain to redefine the drivers customarily associated with success within the channel¹⁰.

The Group's logistics system is based on constant deliveries from the distribution centers of the various commercial formats to stores throughout each campaign. This system essentially operates through centralized logistics centers for each concept in which inventory is stored and distributed to

⁷ (Inditex, S.A.)

⁸ (Inditex, S.A., 2007)

⁹ Inditex financial year is from 1st February to 31st January of the following year

¹⁰ (Burt, Dawson, & Larke, 2006)

stores worldwide. Constant inventory replenishments also have the side effect of encouraging customers to buy when they visit, rather than delay the purchase since the scarcity climate generated by the firm makes them think the wanted reference may not be there upon return¹¹. As a result, customers make an average of 17 visits to Zara annually, whereas most retailers average three¹².

1.3 Zara Overview

‘Zara is in step with society, dressing the ideas, trends and tastes that society itself has developed. That is the key to its success among people, cultures and generations that, despite their differences, all share a special feeling for fashion.’¹³

Zara—Inditex’s first store concept which accounts for 66.4% of the Group’s sales—is present in 72 countries, with a network of 1,529 stores in prime locations of major cities¹⁴. Its international presence is a testament to the idea that national borders are no impediment to sharing a single fashion culture¹⁵.

Table 3: Key Financials--Zara

Principal indicators	2007	2006	07/06
Net Sales [M€]	6,264	5,534	+13%
EBIT [M€]	1,116	911	+23%
EBIT Margin	18%	16%	

¹¹ (Burt, Dawson, & Larke, 2006)

¹² (Brisebois, 2008)

¹³ (Inditex)

¹⁴ (Inditex, S.A., 2007)

¹⁵ (Inditex)

Stores are replenished twice a week from the central Distribution Centers, located in Spain in regions central to their supply base; one in La Coruña serving warm climates and one in Zaragoza serving colder climates. Zara still sources the vast majority of its references from Europe and has just started increasing its Asian volume.

These two main sourcing categories differ greatly on the supply side decisions they entail. A reference sourced from Europe, a.k.a. ‘proximity’ suppliers usually located in Portugal, Morocco, or Turkey, arrives to the DCs by truck and its lead time may be as short as a few weeks from design to delivery. References sourced from Asia, currently making up around 20% of total volume sourced, are sea freighted to the central DCs where they can then be shipped out to stores around the world—shipping alone takes over six weeks in most cases. These differences in time are key in understanding the differences in Zara’s product mix; high fashion items are mostly sourced from proximity suppliers whereas basic items spanning collections, such as a white T-shirt, will most likely come from Asia. Once the items are at the DCs, the manner through which the references get to the stores is the same regardless of where they are sourced from; references are sorted by store at the DCs and trucked to European stores or air-shipped abroad.

Zara divides the year into two main campaigns: Summer and Winter, each lasting around five months. Each campaign consists of a series of short-term, overlapping collections that are sold for 4-6 weeks and one long-term collection that is sold for the full length of the campaign. A markdown period lasting one month follows each campaign and is responsible for approximately 20% of campaign sales by volume, the lowest markdown rate in the industry¹⁶.

¹⁶ (O’Leary, 2007)

Zara's success has been a by-product of business process re-engineering as the company is considered to have broken, at various points throughout its much acclaimed history, seemingly every established rule in apparel retailing. While most of the industry relies on long-lead time sourcing from Asia, set collections decided on eighteen months prior to the selling season and a fragmented decision chain, Zara takes the opposite position on all these aspects of retail operations. Its core competence is its implementation of rapid *reaction*, JIT principles to the fashion industry¹⁷. The continued sustainability of this time-based competition model is one of the greatest risks facing the Group, especially as potential reaction times are shorted as decisions are made further in advance of the selling season.

Another source of competitive advantage for Zara is its organizational design and the handoffs associated with getting a reference from a supplier to the store. Maintaining an information-oriented culture, stressing relationships within the firm, and stressing the need to manage the supply chain as a single process¹⁸ has allowed the Zara Commercial Dept. to take the rein of all supply management decisions. Shown below in Figure 1 is a diagram representing the supply chain for a typical reference and the decisions associated with each participating function;

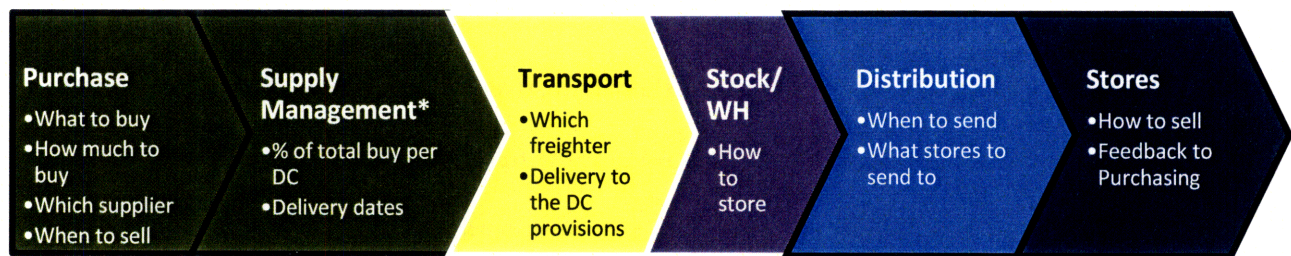


Figure 1: Supply Chain for typical Zara Reference

¹⁷ (Burt, Dawson, & Larke, 2006)

¹⁸ (Schary & Skjott-Larsen, 2001)

The color-code on the figure above represents the corresponding department within the Inditex organization that is responsible for the link in the supply chain, as per:

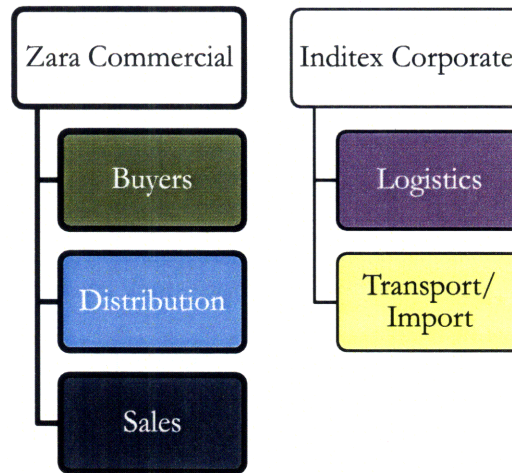


Figure 2: Organization Chart for Departments Involved in the Supply Chain

The project on which this thesis is based on was led by the Logistics organization but affects decisions made at the Supply Management stage of the chain. Operational knowledge resides within the Logistics organization and the project looked to implement a decision tool that puts this knowledge to work for Zara so that the buyers, who are the Supply Management decision-makers and are ultimately responsible for reference availability at the store level, can easily implement operational best practices. These best practices will ensure that availability at the warehouse is not compromised while stock levels are effectively lowered, a key concern for the Logistics organization.

1.4 Chapter Summary

Zara is Inditex's largest and most profitable retail concept, making it greatly responsible for the Group's success and ascent to the #1 fashion distributor position in August, 2008.

Zara's fast-fashion legacy and operational excellence has been a source of competitive advantage for many years, but as the competition becomes better at managing the traditional supply model and Zara starts outsourcing to Asia, revisions to their model are imperative if they hope to remain in the top position.

2 Project Overview

The underlying thesis of this project was that inventory stock levels can be minimized using operations theory and optimization without impacting coverage levels.

2.1 Project Background

Stock levels are a critical operational variable for Inditex Distribution Centers as performance evaluations across the company include this metric as one of two operational variables, the other being stock turnover. Due to the current business model, stock in the warehouses is the result of a series of decisions made mostly from a purely Commercial perspective, a practice that has been key in the success of Inditex as a business but has recently evolved into avoidance of shortages at any cost which translates into increasing stock levels and earlier deliveries to the warehouses.

As Logistic operations grow both in size and complexity, it is becoming increasingly important that those Commercial decisions, namely those that deal with supply management practices, are fine tuned to take fully into account their cost implications and operational impact.

Current practices within the Purchasing organization, i.e. the buyers, is to make these supply management decisions based on a combination of past experience and gut feeling. Some basic Excel models are in place, but they are ad-hoc models each individual buyer develops for a particular

season. No standard process exists for aid in the supply management decision process and no quantitative analysis is done after the season to assess how provisioning was done and compared to sales. Yet another issue is a lack of comprehensive demand forecasting, no system or support tool exists for this step in the buy either, a serious issue as Zara maintains its growth plans over the next few years. The general feeling was that buyers were no longer able to truly understand all the regions that Zara is present in and, as a result, are over-ordering so as to prevent shortages. This over ordering, coupled with no systematic demand forecast allowed stock levels to increase sharply at the DCs.

The Supply Proposal Tool developed by this project addressed work process gaps identified above, namely an operations theory based decision tool to aid in provisioning decisions that uses a demand forecasting model as its input. Standardizing these practices across buyers in the Commercial department allows Zara to monitor how supply management decisions are being made and how they specifically affect the bottom line. The demand forecasts can be used to develop a holistic view of all offerings being sold at the stores throughout the season, and how the collections are planned across different years. The supply management tool itself can systematically tradeoff between holding inventory and incurring in a shortage, thus minimizing the total supply management cost for a given reference and effectively minimize the total stock in the system necessary to realize sales.

In the past year, inventories grew by 22% (see Table 4) in comparison with close competitor's growth of 10%¹⁹. This, together with a sales growth of 13%, means that Inditex is spending 0.16€ in inventory for every 1€ in sales (vs. 0.15€ in Fiscal '06).

¹⁹ (H&M Corp., 2007)

Table 4: Inditex Inventory Data [M Euros]²⁰

	31/01/08	31/01/07
Raw materials and consumables	46,395	38,661
Work in progress	23,826	18,058
Finished goods for sale	936,992	767,184
Total	1,007,213	823,903

The chief concern is therefore not necessarily about an increase in operations expense or particular regard for the Logistics group, the issue is that both these trends reflect something wrong with the flow in the Supply Chain and a decrease in Zara’s ability to react later in the campaign—too many references are blocking the flow. This loss of flexibility and speed goes directly against Inditex’s competitive advantage.

2.2 Problem Statement

Stock levels at the distribution centers are growing faster than sales, increasing stock turnover.

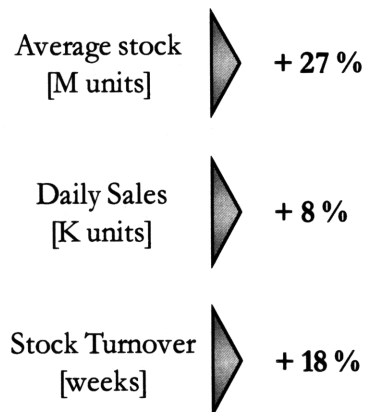


Figure 3: Stock vs. Shipment Historical Comparative (3 yr. CAGR)

²⁰ (Inditex, S.A., 2007)

The reasoning behind this deterioration in stock turnover varies across functions but can be tied back to the increased complexity of distributing to a larger number of stores across many more countries than before. Decision makers, no longer having direct knowledge of demand at each store, are unsystematically adding stock throughout the supply chain to cover uncertainties without accounting for the holistic result.

This trend has been identified by senior management as a source for significant competitive disadvantage and must therefore be addressed. The challenge is to address the increase in stock by implementing a supply management decision tool that follows sound operational theory while minimizing cost and risk to the chain.

2.3 Project Objectives/Goals

The purpose of this internship project was to develop a set of criteria and supporting tools that help align both Commercial and Logistics needs in every decision affecting stock levels in the Distribution Centers. Specific deliverables include:

- A set of practical policies to guide decision making by the Commercial Department on delivery volumes and dates (on the basis of optimal stock level determination)
- A prototype tool that supports full implementation of such policies both by the Commercial Department and the Distribution Centers

2.4 Approach

To address the problem, a Supply Proposal Optimization Model was developed. This model was broken down into four distinct steps:

1. **Demand Forecast:** the forecast was based on historical sales data as well as operations theory to predict demand and its variation. This step was developed as a web-based tool for buyers to use and was therefore carefully designed and iterated based on extensive buyer interviews and feedback.
2. **Initial Store Shipment Forecast:** This is a secondary step to predict the Distribution Department's response to actual sales. The purpose of this step was to identify minimum weekly store stock made up of the appropriate exhibition stock plus the safety stock necessary to account for inefficiencies in distribution.
3. **Optimal Supply Proposal:** This is the integer program (IP) formulation which minimizes total product lifecycle cost. The costs accounted for by the model are the unit holding costs—made up of operational and financial holding cost components ($C_{H:Ops}$ and $C_{H:Fin}$), shortage cost ($C_{shortage}$) and markdown costs ($C_{Markdown}$). The IP trades off the different cost components and returns a supply proposal which defines the delivery quantities and dates for the reference given the total purchase quantity, supplier information and kind of reference being purchased. The formulation takes the form:

$$\min[Total\ Cost = C_{H:Ops} + C_{H:Fin} + C_{Shortage} + C_{Markdown}] \quad (1)$$

4. **Supplier Shipment Proposal:** This proposal is an adjustment to the IP proposal to account for transport time by moving availability at the warehouse dates, which are outputs of the IP formulation, to account for secondary operations prior to shipment and transportation lead time.

2.5 Organization of Thesis

The thesis is divided into four main sections:

- I. Supply Proposal Optimization Model: Chapter 3. This chapter considers Zara's Supply Management problem and the approach taken to resolve it.
- II. Inputs to the Supply Proposal Optimization Model: Chapters 4-6. These chapters present the operational theory and show how each of the inputs to the IP formulation were calculated.
- III. Supply Proposal Tool Results and Analysis: Chapter 7. This chapter presents the preliminary results gathered from the Supply Proposal Prototype Tool and the corresponding sensitivity analysis. It also presents considerations regarding the correct application of the model outputs.
- IV. Recommendations and Next Steps: Chapters 8-9. These chapters look directly at the implementation challenges for both the pilot and future full-scale deployment of the Supply Proposal Optimization results and comment on both new methods to take into account as well as future uses of the results provided by the model.

2.6 Chapter Summary

Inditex's competitive advantage within retail is due in large part to their operations. With mounting stock levels, this advantage is seen to be eroding and pressure has been put on to trim stock as a way to regain flexibility and speed through the supply chain. The way to face this challenge is through overall cost minimization since it goes to the root of the problem and allows operational improvement to be accurately understood across the firm.

3 Supply Proposal Optimization Model

The Supply Proposal has both an IP and an inventory model. The inventory model, however, does not pose any constraints on the IP but rather dictates the cost elements optimized by it.

3.1 Inventory Management Theory

The approach used to define the correct order point and quantity was drawn from classical inventory model theory²¹. In general, the optimization model developed for this thesis minimized total cost by trading off underage and overage costs in the forms described in detail throughout Chapter 6 and can therefore be described as a revised Newsboy model. This approach was chosen to highlight the cost implications of the decision²² and, in the event the proposal is varied because of reasons outside of the theory, the cost differential can be then subsequently assessed. The formulation takes the total aggregate store demand as a single input, since the distribution organization will then allocate inventory to each store according to their sales potential much like a ‘shortage game’ where each store orders more than their desired quantity²³.

A key part of the model is its characterization of a quantity that can be considered a variant of safety stock, the retail exposition stock. After careful consideration, it is understood that within the fashion retail industry a certain amount of minimum stock is necessary at the store to make a sale: ‘Exhibition Stock’. This stock accounts for the references that need to be on display at the store so that customers make a purchase, the method to forecast this quantity is described in Section 3.5.2.

²¹ (Magee, Copacino, & Rosenfield, 1985)

²² (Mo & Harrison, 2005)

²³ (Cachon, 1999)

3.2 Problem Statement

This model defines Y_t : quantity ordered that must arrive at the Distribution Centers on week t .

3.3 Approach

First the dates of interest to the model, important inputs to the Supply Proposal Optimization Model, are defined. Then, using inputs from the auxiliary models described in subsequent chapters, the Supply Proposal IP formulation described below will minimize overall cost by iterating delivery dates, calculating the total cost of each iteration, and choosing the most cost-effective option.

The calculation done for each period of each iteration is as follows:

1. Calculate the maximum and minimum stock levels based on the cumulative values of deliveries and sales.
2. Calculate the forecasted stock using a normal probability distribution curve to account for all potential stock levels (Figure 4, in yellow).
3. Calculate the total cost for each stock level (Figure 4, in blue).
4. Calculate the expected cost for each stock level based on its probability (Figure 4, in red).
5. The sum of all the probable costs is the period cost.

As presented graphically below, the highest cost comes during higher-than-expected sales situations when shortage costs are incurred. As sales decrease toward their expected value or even lower, overall supply chain costs also decrease and then begin to rise as the holding costs start to be significant. It is evident, in the diagram as in the cost discussion on Chapter 6, that for Zara in

particular the shortage cost is much greater than the holding costs and will therefore be the greatest contributor to period cost.

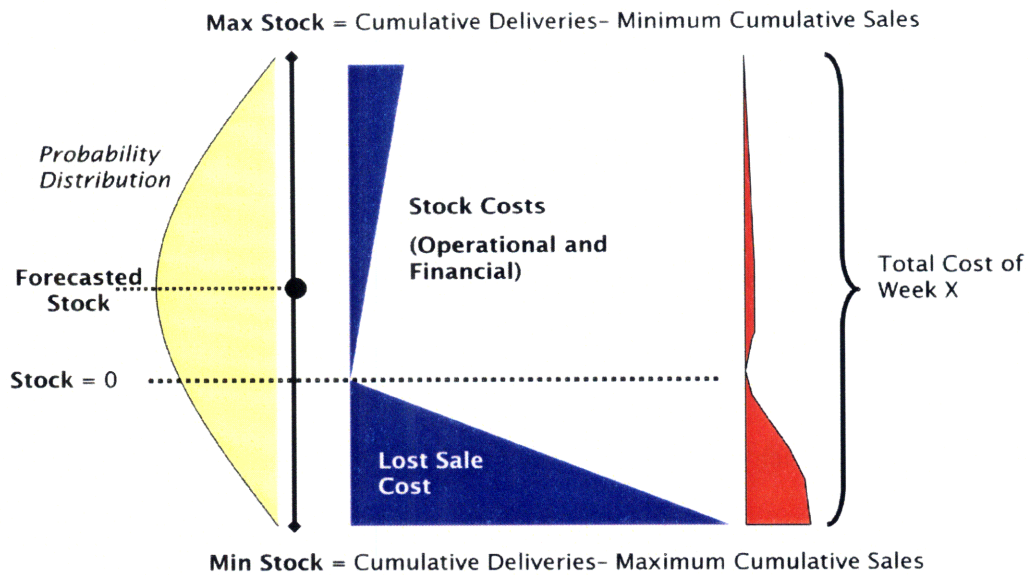


Figure 4: Cost calculation diagram

In the above figure, low sales are associated with maximum stock in the system while high sales are associated with a minimum stock scenario. The red area represents the total cost in a period, defined as expected cost equal to the cost element (in blue) times its probability (in yellow). The IP effectively iterates cost by likelihood so that the cost of any stock position is accounted for by taking into account its associated probability.

3.4 Data Collection

A screenshot of the purchasing tool is shown in Appendix A. Definitions of the relevant variables to be used for the model are described below. Some of the information acquired from the purchasing tool is used for the auxiliary models as well; in this case, these variables will be listed on the appropriate section.

3.4.1 Definition of key dates

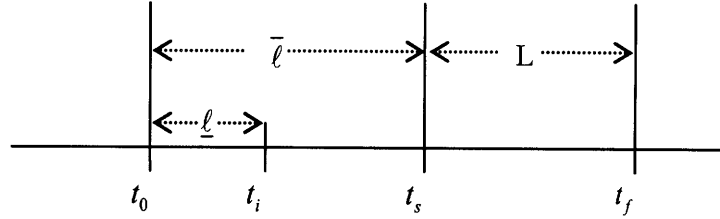


Figure 5: Key dates and their relationship to LT and sales parameters

The figure above shows the relevant dates in a reference's lifetime, where \bar{l} is the maximum supplier lead time, \underline{l} is the minimum supplier lead time, and L is the length of the regular sales period.

1. $t_s = t_0 + \bar{l}$: week of desired first shipment to stores
2. $t_0 = 0$: latest possible week for shipment by supplier without any risk to miss the week of the first shipment (t_s)
3. $t_i = t_0 + \underline{l}$: latest week in which the DC can hold no inventory with no risk to miss t_s
4. $t_f = t_0 + \bar{l} + L$: week in which the regular selling period for the product ends

These time definitions will be maintained throughout the thesis.

3.4.2 IP input data

Input data for the IP consists of:

1. t_s : week of desired first shipment to stores
2. t_f : week in which the regular selling period at the stores ends
3. d_t : expected demand for week t , $t_s \leq t \leq t_f$ (Chapter 5)

4. σ_t : standard deviation of cumulative demand from week t_s to week t (*Chapter 5*)
5. t_0 : latest possible week for arrival without any risk to miss t_s
6. B : unit shortage cost (*Chapter 6*)
7. H : unit holding cost (*Chapter 6*)
8. M : unit markdown cost (cost of leftover inventory) (*Chapter 6*)
9. \underline{q} : minimum supplier shipment quantity
10. \bar{q} : total planned order quantity
11. q_s : planned total quantity of first shipment to stores
12. IS : initial shipment to the stores; occurs at t_s

3.5 Model Description

3.5.1 Decision Variables

- Y_t : quantity ordered that must arrive at the DC on week t
- Z_t : binary indicator $\mathbf{1}_{\{Y_t > 0\}}$
- I_t : Expected net inventory level in the supply chain at the beginning of week t
- I_t^+ : Positive part of I_t , i.e. $I_t^+ = \max(I_t, 0)$
- S_t : Expected number of lost sales/shortages on week t

3.5.2 Analysis and Preprocessing

Before the formulation can be presented, three variables need to be further defined: \underline{q} , q_s , and S_t .

Minimum supplier shipment quantity: \underline{q}

This condition is only relevant for sea freight, since local suppliers have established relationships with Inditex and a minimum shipment quantity by color—the level of specificity carried by the present model—is not a practical constraint since minimum lot size for high-fashion items is irrelevant. In practice, ‘proximity suppliers’ (i.e. non-Asian) will ship any quantity.

For sea freight, minimum quantity is also a tricky supposition since suppliers are most likely shipping large quantities of references to Inditex any given week, since product for all chains is shipped together. After careful consideration, therefore, a minimum shipment quantity of one pallet was agreed on—mostly for operational ease at the DC.

Planned total quantity of first shipment to stores: q_s

The total quantity of the first shipment to stores depends on the demand forecast. As a first approximation, this quantity is calculated according to methods described in Chapter 5 (Equation 40) but the quantity can subsequently be divided into sales coverage and a minimum store stock.

The sales coverage portion is calculated using the traditional coverage formula:

$$\text{Sales Coverage}_t = d_t + z\sigma_t \quad (2)$$

where the choice of z is management's prerogative and represents the preferred level of service. For example, a z equal to 2.33 corresponds to a 98% service level while a z equal to 1.96 defines a 95% service level. These values come directly from the statistics of a Normal Distribution²⁴.

The difference between the calculated coverage stock (X_t) and the initial shipment quantity (IS) is defined as the minimum store stock (E_t). This minimum level accounts for exposition stock necessary to sell the reference at the store as well as for any inefficiency in the distribution. For the optimization model, this minimum stock quantity is taken out of the total available stock in the system, since its intent is to remain at the stores for the duration of the sales period. In practical terms, this adjustment means that a 'shortage' is not necessarily a missed sale but rather a decrease in this effective safety stock.

²⁴ (DelMar & Sheldon, 1988)

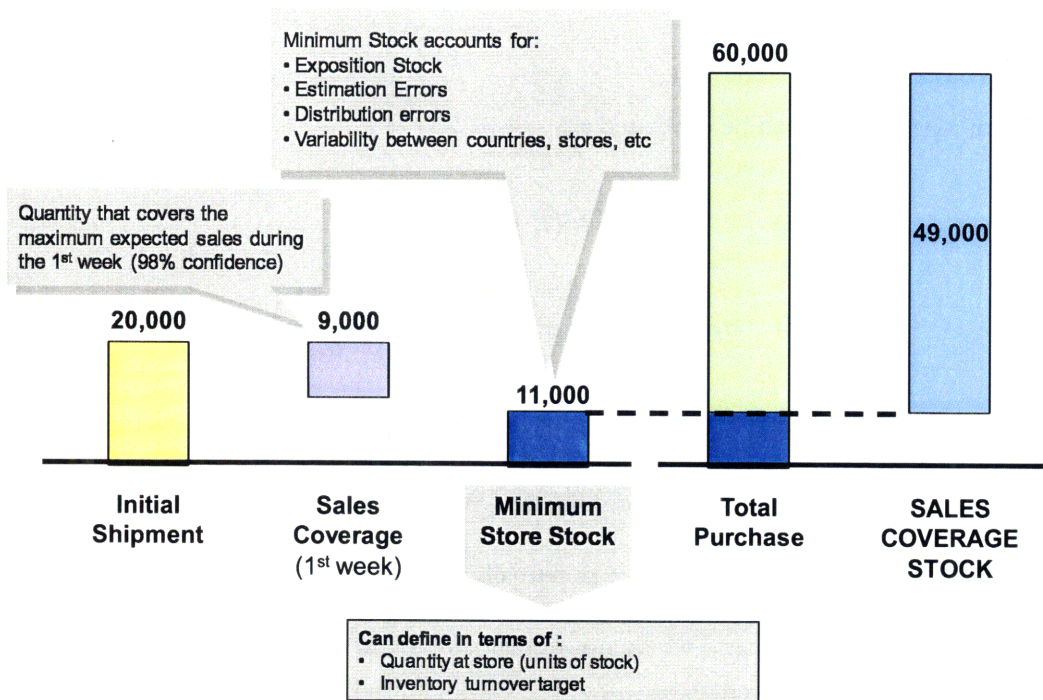


Figure 6: Initial shipment breakdown

The relationship between these two types of available stock is defined as:

$$Y_t = X_t + E_t \quad (3)$$

where X_t is the sales coverage portion of the available stock and E_t is the Exposition stock. Their relationship to the total stock to be allotted is shown above. Note that the exposition stock is an extra stock which is taken out of overall stock as perceived by the IP; this is to say the exposition stock is defined by management and forced to stay at the stores until such a time when there is no other stock available in the system.

Expected Shortages on week t: S_t

Shortages for a given week can be estimated as:

$$\begin{aligned} S_t &= \mathbb{E}[(\mathcal{N}(I_t - d_t, \sigma_t))^-] \\ &= \sigma_t \phi\left(\frac{d_t - I_t}{\sigma_t}\right) + (d_t - I_t) \Phi\left(\frac{d_t - I_t}{\sigma_t}\right) \end{aligned} \quad (4)$$

where ϕ is the standard normal p.d.f. and Φ is the standard normal c.d.f. The above equation defines a convex function that approximates the total number of shortages at time t between lower and upper bounds defined by the inventory potentially present in the system. The lower bound on inventory is defined as the scenario where no supplier shipments have arrived at the DC by week t and the upper bound is the scenario where all inventory has arrived at the DC by week t.

The linear approximation of the shortage calculation expressed by Equation 4 can be expressed as:

$$S_t \geq a_{tn}(d_t - I_t) + b_{tn} \quad (5)$$

where a_{tn} and b_{tn} are input data generated by the approximation algorithm (*see Appendix B*) and represent independent sets of slopes and intercepts, indexed by n, for the approximating function which effectively iterates between the previously defined upper and lower inventory bounds.

3.5.3 IP Formulation

$$\min \left[\begin{array}{l} \text{Total Cost} = C_{H:Ops} + C_{H:Fin} + C_{Shortage} + C_{Markdown} \\ = (H + F) \sum_{t=t_e}^{t_s-1} I_t^+ + B * \sum_{t=t_e}^{t_s} S_t + M * I_{t_s}^+ \end{array} \right] \quad (6)$$

Subject to:

Shortages:
$$S_t \geq a_{tn}(d_t - I_t) + b_{tn} \quad (7)$$

for all $t_0 \leq t \leq t_e$ and $1 \leq n \leq N$

Forecasted Stock: Total stock in the supply chain is equal to the total number of references delivered to the DC minus the cumulative store sales. This number may be positive or negative.

$$I_{t+1} = \sum_{k=t_0}^t Y_k - \sum_{k=t_0}^t d_k \quad (8)$$

Min. Stock: Positive part of the forecasted stock is greater than or equal to zero.

$$I_t^+ \geq 0 \text{ for all } t_0 \leq t \leq t_e + 1 \quad (9)$$

Max. Stock: Positive part of the forecasted stock is greater than or equal to the forecasted stock in the supply chain.

$$I_t^+ \geq I_t \text{ for all } t_0 \leq t \leq t_e + 1 \quad (10)$$

This constraint, coupled with the one above, force the positive part of the forecasted stock to equal either zero or the forecasted stock itself, thus eliminating negative values. Shortages are calculated probabilistically according to Equation 7 above.

Shipment Quantity: Shipment quantity at t must be between the minimum and maximum shipment quantities if there is a shipment at time t . (11)

$$Z_t \underline{q} \leq Y_t \leq Z_t \bar{q} \text{ for all } t_0 \leq t \leq t_e$$

Total Shipments: Total stock distributed to the stores must equal the total order quantity minus the exposition stock, which was taken out and forced into the initial shipment.

$$\sum_{t=t_0}^{t_f} X_t = \bar{q} - \sum_{t=t_0}^{t_f} E_t \quad (12)$$

Initial Shipment: Initial shipment to the stores must be greater than or equal to the initial coverage stock plus the exposition stock.

$$IS \geq X_{t_0} + E_{t_0} \quad (13)$$

4 Supplier Shipment Proposal

Although this is the last step taken by the model, in practice just moving availability dates to a supplier proposal timeline, it is discussed before the other two auxiliary models because it is important to understand risk management practices in general and how the project has dealt with risk considerations.

4.1 Risk Management Theory

The increased level of integration and cooperation along a supply chain leads to new risk categories²⁵. Risk management, developed mainly by the financial services industry, may help in understanding the key risk drivers within the supply chain and enable management to further

²⁵ (Stemmler, 2007)

develop their practical knowledge of overall risk within the firm. With this increased notion of 'holistic risk', the true cost of a firm's risk can be assessed. Logistics, as integrator and director of principal information flow, is inevitably responsible for a high degree of the uncertainty involved.

Risk, as opposed to uncertainty, is measurable. To measure risk in a practical manner, the general idea is to develop a probabilistic model that captures uncertainty at each point in the distribution and use this resulting uncertainty curve to account for the risk involved. This calculation can then be related to expected costs of one option over another. A probabilistic approach to risk, therefore, satisfies the scope of the present undertaking in that it is a simple yet accurate portrayal of supplier shipments—and enough data is available to ensure statistically significant, reliable results.

4.2 Problem Statement

This model defines p'_ℓ : probability that a shipment leaving the supplier's dock on week t will be received ℓ or less weeks later; an input to the IP formulation for Zara's Supply Proposal optimization.

4.3 Approach

This model effectively takes the output of the Supply Proposal—i.e. the week t on which the reference must be available at the DC for shipment to the stores—and pushes it back in time so as to predict when it is the last possible date on which the reference must leave the supplier country's port and still not incur in a shortage. The expected lead time is modeled as a random variable and the normal c.d.f. used to calculate the delivery probability.

4.4 Data Collection

To complete this delivery forecast, two types of data were needed: data supplied by the buyer at the time of forecast using the Supply Proposal Purchasing Web-tool (*See Appendix A*) and historical data gathered from company databases.

The variables supplied by the buyer are:

1. P : Item's country of origin
2. D_s : Earliest date the reference needs to be available at the DC for shipment to the stores
3. L : Expected length of the sales period for the reference being purchased
4. R : Binary indicator which identifies whether the item needs to go through a secondary operation such as pressing, distressing, etc. If this is the case, the availability date is pushed back by two weeks.

Historical data was taken from Inditex's Corporate Import department databases for the past two years (i.e. four campaigns) and filtered through by the same department to maintain both ownership and expert knowledge of transportation and import in the specified data. These lead times reflect total shipment time defined from port of shipment at the supplier end to the Inditex distribution center in Spain.

The necessary historical values are defined by supplier, transportation mode and time of year; the latter consideration to account for the high-season in ocean transport where shipment variability increases with increased activity. The variables are:

1. ℓ_p : average lead time
2. σ_p : standard deviation of the lead time.

3. $\bar{\ell}_p$: max lead time
4. $\underline{\ell}_p$: min lead time

4.5 Model Description

This probabilistic model takes into account the port of shipment of the reference being purchased and returns the probability that the lead time will be such that an item leaving the supplier's port on week t_l will be available at the DC ℓ or less weeks later.

A further adjustment done by this model is in its treatment of secondary operations. The buyer inputs on the purchasing tool whether or not the reference being purchased needs a secondary operation prior to being shipped out. These operations usually take place at Inditex-owned subsidiary plants around the DCs and their lead time is consistent (i.e. not seasonal or particularly dependent on the type of process). Because of these characteristics, the secondary operation lead time may be accurately predicted to be two weeks. Taking all of this into account, if the buyer indicates that a secondary operation is necessary, the model adds two weeks to the lead time estimate on top of the shipment lead time defined by the shipment port.

4.5.1 Probability Calculation

1. $LT = \max(N(\ell_p, \sigma_p), 0)$: random variable representing overall shipment LT
2. $P(LT = \ell) = \int_{\ell-1/2}^{\ell+1/2} \left[\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\ell_p)^2}{2\sigma_p^2}} \right]$: probability that a shipment leaving the supplier on week t arrives on week ℓ

3. $p'_t = P(LT \leq \ell) = \text{normalc.d.f.}(t, \ell_p, \sigma_p) \approx \sum_{t_0}^t p_t$: probability that a shipment leaving the supplier on week t arrives on or before week ℓ

4.6 Model Output

Because of time constraints, this approach was not fully implemented as part of Zara's Supply Proposal tool.

Instead of calculating the probability of delivery, the maximum lead time was assumed and the optimal availability proposal resulting from the IP model was pushed back by this amount. This results in a 100% confidence that the purchased reference will be available at the DC in time for the expected shipment date.

This latter method is still able to account for seasonality within shipment lead times by identifying high-risk (i.e. low capacity) seasons within the year and establishing different values for the input parameters according to the shipment date. A portion of table used for the prototype purchasing tool is shown below (the information has been disguised and is for illustrative purposes only).

Table 5: Shipping Parameters (A)

DC	COUNTRY	TRANSPORT MODE	SEASON	AVE LT	MAX LT	MIN LT	LT ST. DEV.
1	A	AIR	HIGH	1.97	5.00	1.00	1.05
1	A	AIR	NORMAL	1.76	3.00	1.00	0.56
1	A	SEA	HIGH	5.90	9.00	3.00	1.03
1	A	SEA	NORMAL	5.45	8.00	4.00	0.95
2	A	AIR	HIGH	1.70	3.00	1.00	0.53
2	A	AIR	NORMAL	1.70	4.00	1.00	0.67
2	A	SEA	HIGH	5.42	8.00	4.00	1.04
2	A	SEA	NORMAL	5.25	8.00	3.00	1.04

In order to accurately adjust for seasonality, the model starts with the availability date output from the Supply Proposal and converts it to a date (vs. a period) using the stated 'First shipment to stores' date (see Figure 7). It then looks to see whether a secondary operation, done by an Inditex subsidiary and assumed to always last two weeks, is to take place. If this is the case, the binary indicator R will equal 1 and the reference will need to arrive at the DC two weeks earlier so that it is available for shipment to the store at the appropriate time. The model therefore adjusts the availability date to account for the two week secondary operation LT as:

$$Avail.Date = \begin{cases} Date_{Optimization} & R = 0 \\ Date_{Optimization} - 2wks & R = 1 \end{cases} \quad (14)$$

Once the secondary operation correction is complete, the model then adjusts for shipment assuming the reference will ship from the port of origin during the 'Normal' season. If the shipment date calculated falls in the 'High' season, the model then replaces the 'Normal' season LT with that of the 'High' season and returns the predicted latest possible shipment date as per:

$$Ship.Date = \begin{cases} Avail.Date - LT_N & Avail.Date - LT_N \notin High \\ Avail.Date - LT_H & High_{Start} \leq Avail.Date - LT_N \leq High_{End} \end{cases} \quad (15)$$

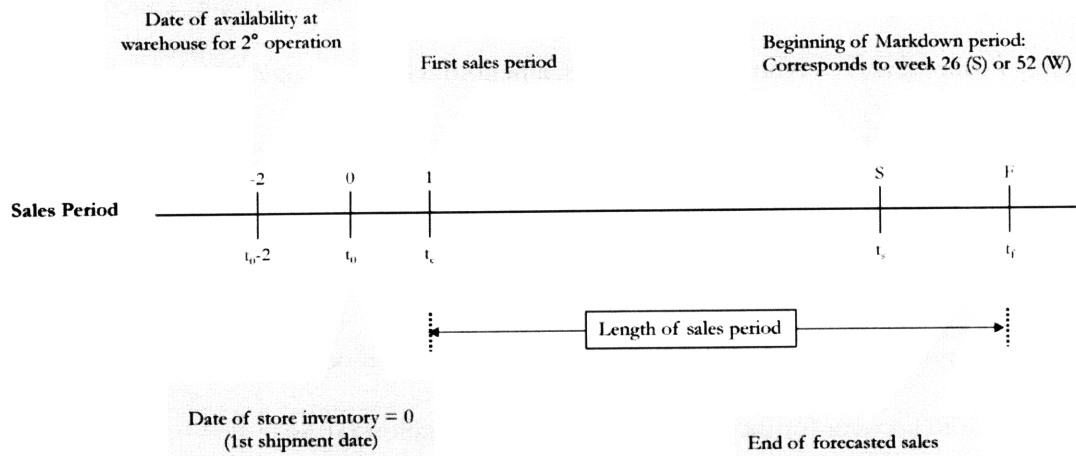


Figure 7: Key date vs. period relationship

4.7 Chapter Summary

Shipment lead times from port of origin to DC were calculated based on historical data spanning multiple seasons. Seasonality is accounted for by allowing for a 'High' and 'Normal' shipping season where the expected LT is adjusted based on forecasted shipping dates.

5 Demand Forecast Model

This demand forecasting model is the backbone of the IP since it defines the variable of most interest and of most inherent uncertainty of the whole model.

5.1 Model Description

The demand forecasting model described in Rosenfield²⁶ will be used to predict the values for the demand parameters α and β , which will define the demand profiles.

²⁶ (Rosenfield)

This methodology isolates the relevant parameters needed to accurately forecast demand. Using statistical significance analysis on the available variables and literature review, it was determined that the two main contributors to demand variability are **time** and **volume**. Time is defined as the duration of the regular sales period for a given reference, i.e. not including the markdown period, and Volume as the total number of units sold of a particular reference during the regular sales period.

It is important to note that the demand forecast is done using data exclusively from the regular sales period and not from the markdown period, since this ensures the sales curve follows a normal lifecycle of fashion retail items.

Interviews with Inditex employees confirmed the assumption that Time and Volume were the key independent variables that can completely predict sales; these are the same dimensions used to segment offerings within their product mix.

Using this information, it was decided that the Alpha-Beta forecasting technique was accurate for the present analysis. Alpha (α) defines the relationship between variability and time, whereas Beta (β) defines the relationship between variability and volume.

5.2 Demand Forecasting Theory

Demand forecasting techniques are a mixture of two distinct processes: prediction of the demand shape and prediction of the demand variability²⁷.

²⁷ (Magee, Copacino, & Rosenfield, 1985)

The demand shape characterization can be the Achilles' heel of the demand distribution forecasting exercise, especially if historical data is available. Although historical data is of value when defining demand shape, i.e. demand density, it is usually necessary to revise it using expert judgment and subsequently update it after early sales have been observed²⁸. For the present case, a normalized aggregate curve was constructed from historical demand data of similar or comparable items to ensure that the correct lifecycle effects were captured. These initial curves were then scaled according to forecasted sales volume and sales period duration. These two parameters characterize both the shape of the demand curve, by scaling it appropriately, and the magnitude of its variability, as explained below.

To define variability, the Alpha-Beta method was chosen. This methodology relates variability to the same parameters used to scale the demand curve, thus making the forecasting process clearer and dependent on a few key variables of interest.

In the formula for the per period variability estimation (see below), these parameters carry an exponential relationship to forecasted length of sales (L) as well as to the sales volume (D).

$$\sigma_p = L^\alpha D^\beta \quad (16)$$

Based on the relationship of demand increments over time and space $\alpha = \beta \cong \frac{1}{2}$, with independent increments. Higher values reflect serial and spatial correlation.

This relationship sometimes raises a common concern with users: that the values for Alpha and Beta are the same across the length of sales and volume of sales spectrum. This is to say, the variability of

²⁸ (Raman, 1999)

a reference that sells 1,000 units and another which sells 100,000 units can be based on the same relationship.

This user mentality is not consistent with the usual Inditex manner of characterizing references, which is in fact dependent on volume and sales period in a way reflected by Equation 16. In order to further understand these concerns, data for one section's full selling season was collected from the Inditex database and plotted in the following figures.

It is generally accepted that low-volume, short-term references (in pink on Figure 8 below) are more variable—and therefore harder to forecast—than high-volume, long-term references (in yellow); an observation reflected by the Alpha-Beta method.

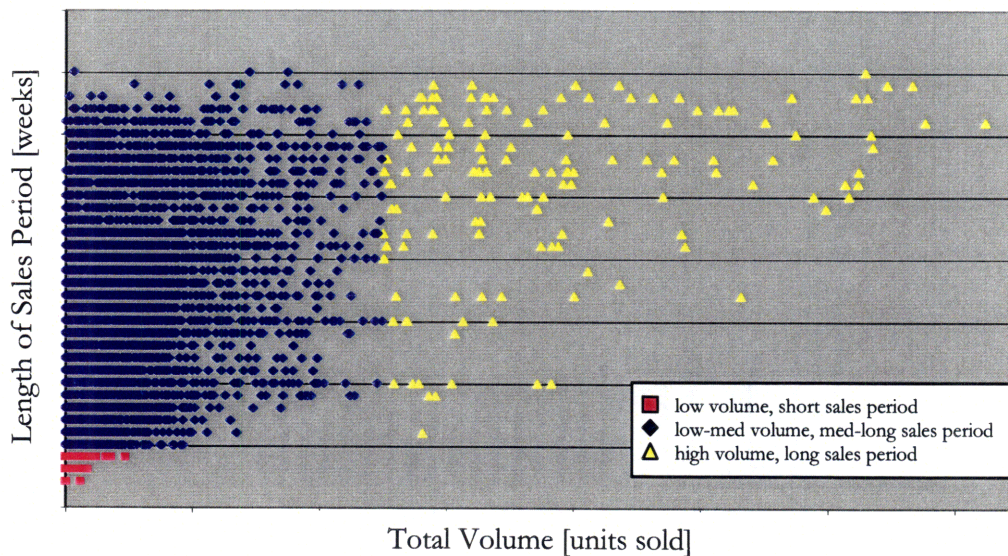


Figure 8: Length of Sales Period vs. Total Volume

Although the theory may seem counterintuitive to some, since the magnitude of the variability is therefore greater for a high-volume and long-term item than that of a low-volume, short-term item; an alternative view of the relationship can help clear up the confusion. This alternative comparison

is the item's coefficient of variability, which is a normalized measure of dispersion within the normal distribution (volatility) and is expressed as the ratio of its variation to total volume as per:

$$Coeff. Var = \frac{\sigma}{V} \quad (17)$$

The coefficient of variation is the correct metric of comparison because it allows the references to be compared using the same context since their calculated variability is dependent on the total volume.

The relationship, therefore, between variability and length of the sales period can be said to be illustrated by the following plot:

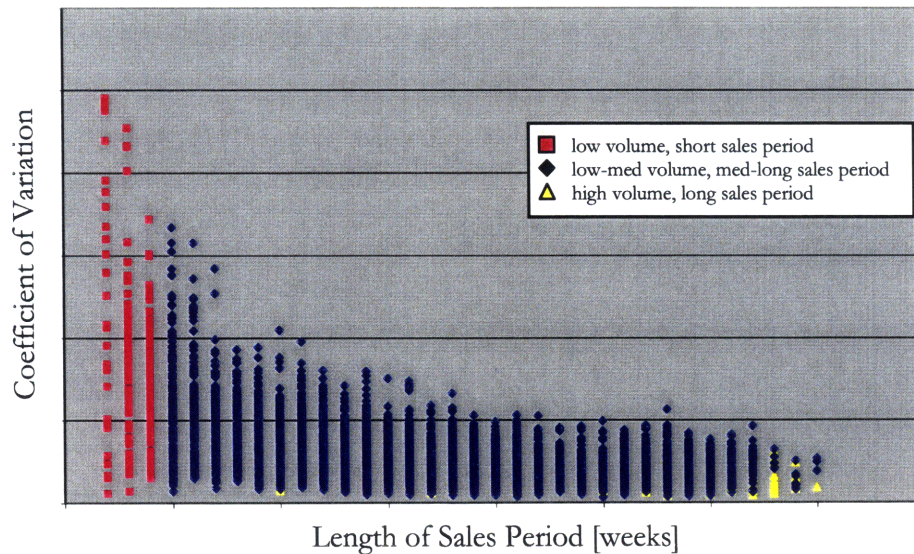


Figure 9: Coefficient of Variation vs. Length of Sales Period

This is the relationship defined by Alpha. It is evident from this plot that short-term items exhibit a higher effective variability than long-term items and that the relationship is one of exponential

decay. Therefore, we expect the values for Alpha to be below 1. This finding is consistent with Inditex's characterization of references, as can be appreciated based on the color coding in Figure 9.

A similar plot can be constructed for the variability-volume relationship, characterized by Beta, for which the statements above also apply:

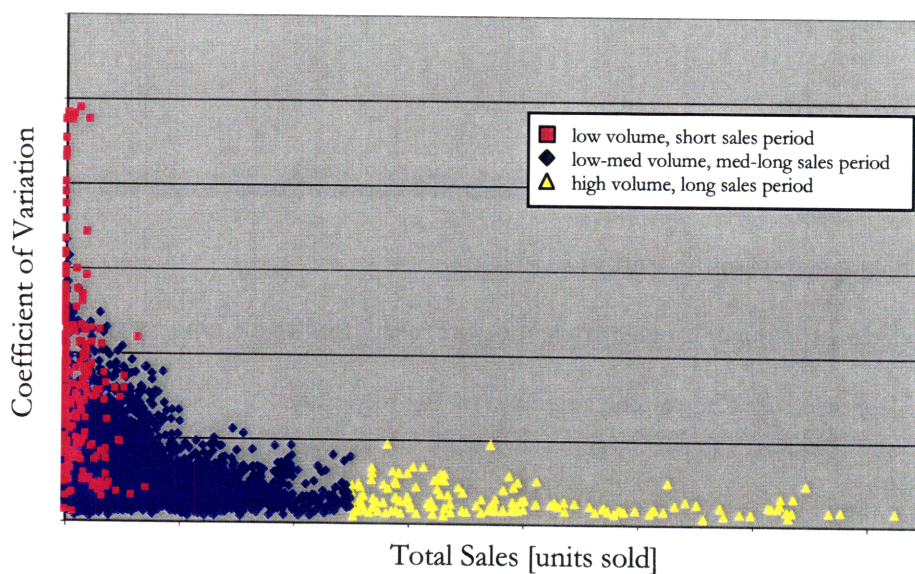


Figure 10: Coefficient of Variation vs. Total Sales

5.3 Problem Statement

This model defines d_t : expected demand (forecast) for week t and σ_t : standard deviation of cumulative demand from week t_s to t ; both of which are inputs to the IP formulation for Zara's ordering problem.

5.4 Approach

Using information supplied by the buyer, a sales forecast was first defined for the reference being purchased. This sales forecast was then turned into a demand forecast for the DCs—which defined the variables of interest for the IP optimization model. Store sales were chosen as the basis for DC demand because the buyers are much more familiar with these trends than they are DC shipments to the stores; and because the distribution department’s data was found to be unreliable.

5.5 Data Collection

There are two main types of data used for the demand forecasting model: data supplied by the buyer and historical data taken from the company database.

The data supplied by the buyer is taken from the purchasing tool at the time when he is about to run the model (*see Appendix A*). The variables defined by the buyer are:

1. S: Section they buy for (Woman, Man, Child)
2. SF: Subfamily of the reference they are purchasing
3. C: Unit supplier cost
4. P: Unit price during regular sales season
5. $M/Q/C_{Si}$: Collection of references from previous campaigns whose demand was similar to the expected demand for the reference being purchased
6. T: Coverage strength for the initial shipment to the stores. This relates to the target weeks of inventory turnover available during the first week of sales according to the following levels:
Strong = 5wks, Medium = 4wks, Weak = 3wks
7. Q: Quantity of total purchase for the campaign

8. L: Expected length of the sales period for the reference being purchased

Historical data is also necessary to run the demand model. In this case, the data is taken from the company database using SQL queries (*See Appendix B*) which also calculate key information necessary for the forecast. A list of historical variables is presented below:

1. p: indexes the period of demand.

By convention, on the date of the first shipment to each store $p = 1$.

2. i: indexes the references shipped during the campaign
3. D_p : total sales (demand) for period p (filtered by section and campaign)
4. σ_p : standard deviation of demand for period p (filtered by section and campaign)
5. D_i : total sales (demand) for $M/Q/C_i$
6. σ_i : standard deviation of demand for $M/Q/C_i$

Table 6: Sales volume structure for all references in a given section

p:	1	2	3	4	D_i	σ_i
$M/Q/C_A$	a	b	c		D_A	σ_A
$M/Q/C_B$	d	e	f	g	D_B	σ_B
$M/Q/C_C$	h	i	j	k	D_C	σ_C
D_p	D_1	D_2	D_3	D_4		
σ_p	σ_1	σ_2	σ_3	σ_4		

$$D_p = \sum_i D_{M/Q/C_{i,p}} \quad (18)$$

$$D_i = \sum_p D_{M/Q/C_{i,p}} \quad (19)$$

5.6 Model Description

Taking the inputs described above, the model begins by defining the demand parameters discussed in the previous theory sections. It then defines an aggregate demand curve and its corresponding demand variability envelope which together make up a cohesive sales forecast.

5.6.1 Demand parameters

Once the data is filtered by section, the formula below is used to predict the standard error of demand:

$$\sigma = KT^\alpha D^\beta \quad (20)$$

where D is the expected demand level and T is the length of the time period being accounted for.

Using data in the form presented on Table 6, a plot of $\ln D_i$ vs. $\ln \sigma_i$ is made and linear regression analysis is performed. The slope of the regression line corresponds to the value of β .

To calculate the value of α , a more involved methodology is needed. As a first approximation, the following approach is taken:

1. Define the interval taken for the samples as an integer $1 \leq I \leq \frac{\max(p)}{2}$ (21)

2. Calculate the total demand for each period iterated according (22)

$$\text{to: } D_I = \sum_{\hat{p}_i}^{\hat{p}+I} D_j \text{ where } \hat{p}_i = (\hat{p} + I)_{i-1}$$

3. Calculate $\sigma_I = \sigma[D_I]$ (23)

4. Plot $\ln(D_I)$ vs. $\ln(\sigma_I)$ and perform a linear regression on the data. (24)

The slope of the regression line obtained above corresponds to the value of α . To define the categories that necessitate different alpha-beta values, the references being plotted are filtered in such a way as to maximize the value of the coefficient of determination (R^2) for both of these regressions.

The linear regressions used to calculate the slope and R^2 values take the general form:

$$\hat{y} = mx + c \quad (25)$$

$$\text{where: } m = \frac{\sum[(x_i - \bar{x})(y_i - \bar{y})]}{\sum(x_i - \bar{x})^2} \quad \text{and} \quad c = \bar{y} - m\bar{x} \quad (26)$$

The quality of the regression is assessed by calculating the coefficient of determination using the form below:

$$R^2 = \left\{ \frac{1}{N} \frac{\sum[(x_i - \bar{x})(y_i - \bar{y})]}{\sigma_x \sigma_y} \right\}^2 \quad (27)$$

$$\text{where: } \sigma_x = \sqrt{\frac{\sum(x_i - \bar{x})^2}{N}} \quad \sigma_y = \sqrt{\frac{\sum(y_i - \bar{y})^2}{N}} \quad (28)$$

A preliminary analysis (*See Appendix C*) on historical demand data for Winter 2007 and Summer 2007 using the above process validates the use of the sections as the filter to define similar demand profiles.

Table 7: Demand parameters for Winter and Summer campaigns using historical demand data over years 2007-2009

CAMPAIGN	SECTION	α	R_α^2	β	R_β^2
Winter	Woman	0.86	0.98	0.91	0.95
Winter	Man	0.61	0.97	0.84	0.93
Winter	Child	0.70	0.95	0.89	0.96
Summer	Woman	0.67	0.88	0.90	0.94
Summer	Man	0.74	0.85	0.85	0.93
Summer	Child	0.70	0.89	0.87	0.94

5.6.2 Demand characteristics: The Sales Curve

The most accessible measure of success for a buyer is sales, so sales are used as a proxy for demand. I say proxy because sales can only be an estimate of demand since past shortages and inefficiencies in distribution decisions affect sales in a way that cannot be readily adjusted for using the present method. It also is unable to account for conditions that are isolated in scope and therefore only known by the buyer. These conditions, however, can be generally understood to be statistically within the variability estimate that accompanies the sales curve, making our predictions relevant.

To estimate the sales curve, the buyer will first input comparable references from previous campaigns into the tool, which then calculates an aggregate demand curve. A normalized demand curve is then abstracted from the aggregate of the demand curves for each similar reference identified.

The curve data, defined as f_p vs. $V(f_p)$, is defined by:

$$\text{Fractional period P: } f_p = \frac{P}{\max(P)} \quad (29)$$

$$\text{Total demand fraction at period P: } V(f_p) = \frac{\sum_{i=1}^n D_{M/Q/C_{S_i},P}}{\sum_{P=1}^{\max(P)} \sum_{i=1}^n D_{M/Q/C_{S_i},P}} \quad (30)$$

It is important to note that the total demand at period P is summed over period P *per store*. This is to say, if Store 1 begins selling the reference on week 34 of the year and Store 2 begins selling on week 36, Store 1's P = 1 is defined as week 34 but Store 2's P = 1 is defined as week 36.

This correction is done to maintain the normal sales pattern across the product lifecycle by getting rid of any variation due to country sale lags, i.e. high sales when the product is first introduced and decay as both the novelty and the inventory decrease.

5.6.3 Demand characteristics: The Sales Forecast

After defining the sales curve of the reference being purchased, a sales forecast is constructed as follows;

1. Take total sales to be equal to the planned purchase quantity:

$$E[D_{Total}] = Q \quad (31)$$

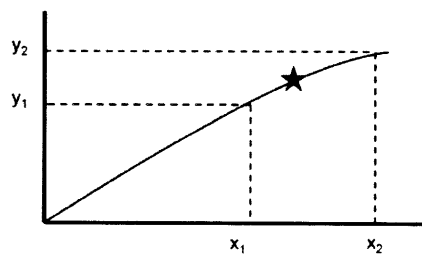
2. Forecast of the mean daily sales:

$$\bar{D}_t = E[D_{Total}] * \{V(f_t) - V(f_{t-1})\} \quad (32)$$

Where $V(f_t)$ characterizes the demand curve used (as described by Equations 12 & 13) which in turn depends on fractional t , defined as:

$$f_t = \begin{cases} 0 & t < t_s \\ \frac{t - t_s}{t_f - t_s} & t_f > t \geq t_s \end{cases} \quad (33)$$

If $f_t \notin \{f_p\}$, then it is the case that no value exists for $V(f_t)$. In this case, $V(f_t)$ is extrapolated using the two values (x_1, y_1) and (x_2, y_2) :



$$V(f_t) = \frac{y_2 - y_1}{x_2 - x_1} * f_t + \left(y_1 - \frac{y_2 - y_1}{x_2 - x_1} * x_1 \right) \quad (34)$$

3. Standard deviation of the daily sales:

$$\sigma_D(t) = t^\alpha \bar{D}_t^\beta \quad (35)$$

From the sales curve, a number of parameters are extracted which serve as forecast assumption checks and some that will serve to measure the forecast against general company performance targets. They are as follows:

BUYER ASSUMPTION CHECKS:

Sales rate for the first 4 weeks of the sales period: $SR = \sum_{p=1}^4 V_{AveStore}$ (36)

Total Sales for each $M/Q/C_{Si}$: $D_{Si} = \sum_P V_{P,Si}$ (37)

Length of sales period for each $M/Q/C_{Si}$: $L_{Si} = \max(p_{Si})$ (38)

COMPANY METRICS:

Average Turnover: $\bar{R} = \frac{\sum R_{M/Q/C_{Si}}}{(M/Q/C_{Si})_{Total}}$ (39)

Quantity of initial shipment to stores: $IS = \begin{cases} T * D_1 & T * D_1 < Q \\ Q & T * D_1 \geq Q \end{cases}$ (40)

5.7 Inputs to the Supply Proposal

- Expected demand (forecast) for week t : d_t is defined as:

$d_t = E[D(t)]$ (41)

- Standard deviation of cumulative demand from week t_s to t ; σ_t is defined by:

$$\sigma_t = \sigma_{V_{cum}}(t) = t^\alpha D_{cum}^\beta \quad (42)$$

where $D_{cum}(t)$ is the cumulative sales from week t_s to t defined as:

$$V_{cum}(t) = \sum_{t_0}^t V_t \quad (43)$$

For a given reference, therefore, this method provides not only a period-by-period forecast of demand but also gives the variability evolution throughout the lifecycle, which shows the upper and lower bounds according to the confidence interval chosen:

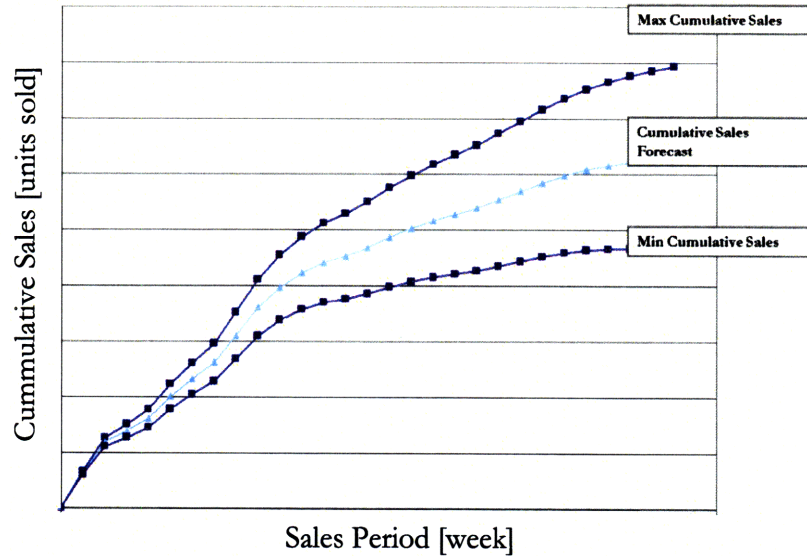


Figure 11: Cumulative Sales Forecast

These upper and lower bounds define, in practical terms, a probabilistic model of demand. This type of formulation is useful in demand forecasting both for its technical propriety but also because it allows the unobservable heterogeneity of preference among a population of consumers to be

represented. It also allows the model to display the effects of all potentially relevant variables even when the gathered information is incomplete. This being fashion retail, probabilistic choice can be thus associated with consumers whose behavior is inherently unpredictable²⁹.

5.8 Forecast Analysis

In gauging the demand forecast accuracy, significant effort was spent ensuring that variability was correctly accounted for. The shape of the demand curve, however, was assumed to be generally correct based on the buyer's experience and his ability to choose correct references for comparison. Based on sample reference/comparison pairs given by the buyer's for the past two campaigns, it is safe to assume that the overall shape of demand is consistent with historical data. A sample comparative, for illustrative purposes, is shown in Figure 12.

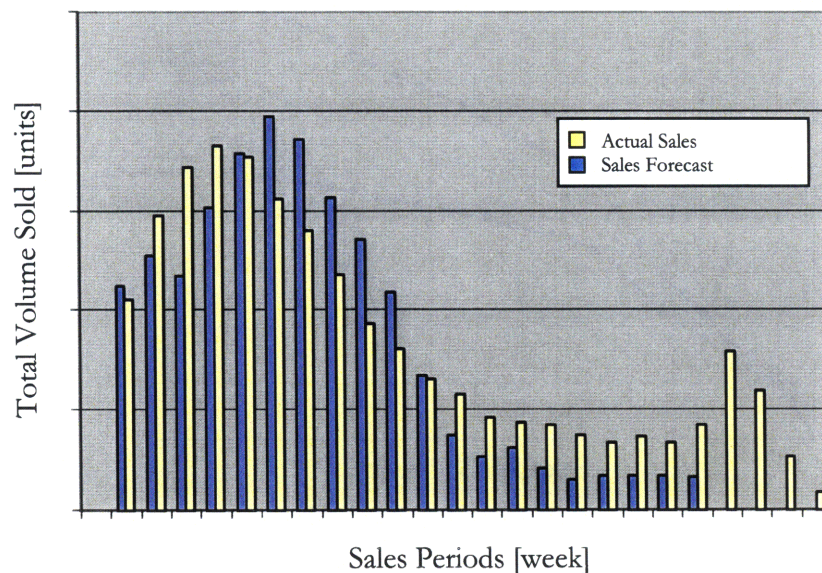


Figure 12: Sales Forecast vs. Real Sales

²⁹ (Mahajan & van Ryzin, 1999)

Forecasting into the future based on historic data or experience, however, can be a risky endeavor. It is important to maintain perspective on this issue and allow the user to manipulate the shape of the curve until it resembles his prediction as much as possible. No work was done to fine-tune demand shape, since from the beginning of the project it was understood that sales volume forecasting is the buyer's responsibility. The critical variable extracted for the IP was the cumulative demand volatility, to aid in risk management within supply management decision making.

The final relationship to consider is that of the values of Alpha and Beta to the predicted variability. A sensitivity analysis was conducted by varying the values of Alpha and Beta concurrently between 0.5 and 1. The effect of this on the coefficient of variation is shown below for a sample reference;

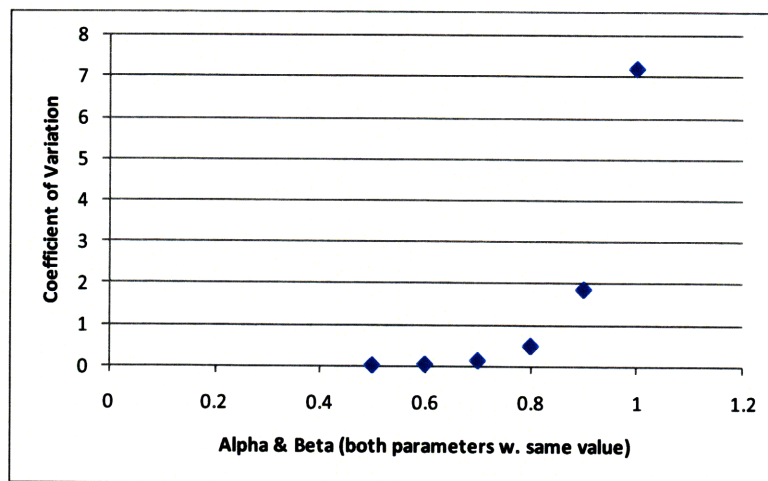


Figure 13: Variability vs. Alpha & Beta (Sensitivity)

As the values of both Alpha and Beta are varied by 10%, the coefficient of variation varies, on average, by 74%--a byproduct of the exponential relationship that both parameters have to the variability. In order to understand if the demand parameters have equal weight on this relationship, the value of Beta was held constant at 0.5 and Alpha varied between 0.5 and 1 to get the isolated effect of Alpha.

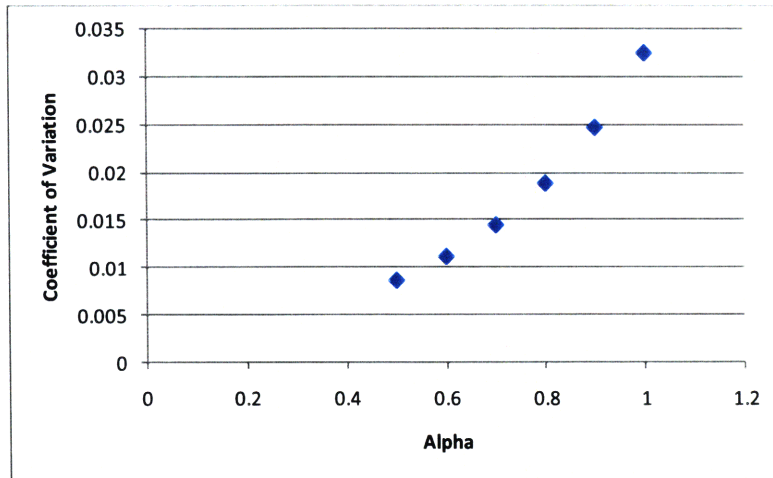


Figure 14: Variability vs. Alpha (Beta=0.5)

This relationship shows how, as Alpha alone is varied by 10%, the coefficient of variation increases by 23%; much shallower an increase than on the compounded case. It is also worth noting that the magnitude of the increase is much lower than the one seen in the compounded analysis when both parameters are varied. This effect is constant throughout the sample.

This approach was then repeated for Beta. The plot showing the isolated effect of Beta on the coefficient of variation for a sample reference is shown below;

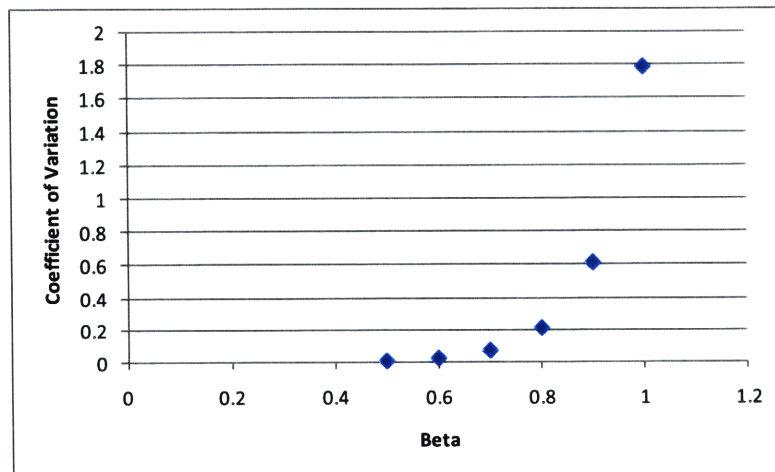


Figure 15: Variability vs. Beta (Alpha=0.5)

This second plot shows how a 10% increase in Beta, when isolated from variation in Alpha, leads to a 65% increase in the coefficient of variation. The magnitude of the increase is also much greater than the magnitude of the increase when Alpha alone is varied. These differences in both percent increase and magnitude lead to the conclusion that Beta is the dominant parameter for the demand variability estimate, an expected result since the magnitude of demand is much larger than the magnitude of the sales period. Both parameters, however, display an exponential relationship to variability so it is important to maintain both in control since a small error could lead to a faulty forecast.

5.9 Chapter Summary

Demand can be accurately estimated from similar references for a new reference being purchased. Although the demand curve may be fairly similar in shape, the key to an accurate forecast is the correct characterization of demand variability. This latter estimation is done using historical data not only from similar references, as identified by the buyer, but by all references that are statistically similar to the one being purchased.

It was found that variability can be fully described by a reference's forecasted volume and length of sales period and characterized by the parameters Alpha and Beta, which depend on the reference's Campaign (Summer vs. Winter) and Section (Woman, Man, Child).

6 Cost Estimation

6.1 Problem Statement

This model defines the costs taken as inputs to the IP optimization, defined as:

B : unit shortage cost (lost sale cost), $f(PVP, cost)$

H : unit holding cost, $f(\text{financial}, \text{operational})$

\bar{H} : unit cost of leftover inventory, $f(\text{PVP}, \text{markdown})$

6.2 Approach

In order to accurately predict the marginal cost of each day of inventory, the costs were divided into three major categories of cost: Holding Cost, Lost Sale cost and Markdown cost. The sum of these costs gives the unit cost of inventory per day, which is then optimized by the Supply Proposal Optimization Model.

6.3 Holding Cost

The unit holding cost is defined as the cost incurred by Inditex for having stock at its DCs. This cost is estimated as the sum of two distinct categories of stock cost: financial cost, meaning the cost of the investment in sitting inventory and the credit risk associated with it³⁰, and operational cost, meaning the cost of housing the inventory at the DC itself. These are described in greater detail in the following sections.

6.3.1 Financial Holding Cost

The Financial cost is the cost of investing in sitting inventory instead of alternative investment opportunities. The logistics impact on the capital element of ROI is determined by the financing options for the inventory³¹ and this ratio is therefore chosen as the closest proxy of financial opportunity cost. For the present model, it has been estimated as the ROI missed if the money had been held in a bank savings account since, under current economic conditions, this is the safer and

³⁰ (Stemmler L. , 2002)

³¹ (Stemmler L. , 2002)

most predictable option available. It is assumed that the bank yearly interest return is 5%, therefore the Financial Holding Cost is calculated as 5% over the reference's cost.

6.3.2 Operational Holding Cost

Operational cost is comprised of two true costs: the cost to Zara for renting its warehouses from its parent company, Inditex, and the cost of the equipment needed to store the inventory until such a time as it is sent to the stores. This cost is defined per storage method: flat folded (F) or hung stock (H) per DC.

To calculate operational cost, it is only necessary to account for the space and equipment needed to house the stock between the time it is placed in its position at the DC and the time it is picked to be sent to the stores. The cost of unloading, sorting, picking, packing and shipping the stock is ignored since each item sent must go through all these stages regardless of the amount of time it spends at the DC.

The weekly rental cost for the storage area per unit stored is calculated as follows:

1. Calculate the cost per square meter of warehouse space for each storage method
2. Calculate the number of items that can be stored in a square meter as a function of storage method and DC.

3. Divide the former quantity by the latter to get cost in $\frac{\text{€}}{\text{unit/week}}$.

The weekly equipment cost is then calculated as the amortized cost of the equipment necessary to house the stock during the period it is inside the DC storage areas. This cost does not take into

account equipment whose amortization period has already passed, that is, equipment purchased over 10 years ago. The weekly equipment cost for the store area per unit stored is therefore calculated as:

1. Calculate the total weekly amortization cost of the storage equipment for each storage method.
2. Divide this cost by the number of items that can be stored in a square meter as a function of storage method and DC to get cost in the same units as above.

6.4 Lost Sale (Shortage) Cost

The unit shortage cost is defined as the missed sale cost incurred because there was a shortage of stock at the DC. This hard link between a missing reference at the producer end of the supply chain and a stock out at the retail end is consistent with empirical evidence in this field. For a branded fashion item, the stock-out of goods at the points of sale explains almost two-thirds of sales lost by producers, while it is worth only half of those lost by the retail end³².

From a practical perspective, a shortage is quantified as the unit markup for the item being purchased since a missed sale implies that the item was never purchased from the supplier and therefore a profit opportunity was lost.

6.5 Markdown Cost

The unit cost of leftover inventory is defined as the loss of margin directly resulting from an item going from its season price to its sales period price. This cost is charged once—on the day of the start of the discount period for the campaign and applied to all units still on the supply chain for the given reference.

³² (Perona, 2002)

The markdown cost is calculated directly from the sales period price and the markdown percentage corresponding to the buyer purchasing the reference as:

$$\begin{aligned} \text{Markdown Cost} &= P_{\text{sales}} - P_{\text{markdown}} \\ &= P_{\text{sales}} * \%_{\text{Markdown}} \end{aligned} \tag{44}$$

An important input to the markdown cost model is the date of the start of the sales period, whose estimation, taking as its starting point the transportation model parameters described in Section 3.4.1, is described below.

The transportation model was used to define key dates needed by the IP model; the buyer inputs the date of the first shipment to stores, t_s , and this date becomes the link between the model ‘periods’ and the calendar weeks it is calculating over.

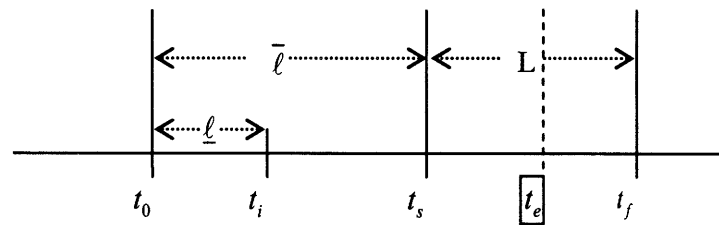


Figure 16: Key dates and their relationship to LT and sales parameters

Using historical data, the week where the sales period begins for a given campaign is estimated and converted to its corresponding period, t_e , within the model, calculated based on its relation to t_s .

The effect of country-specific dates for the start of the sales period is mitigated by the country-specific standard error. This is to say: the total aggregate standard error, in Table 8 below, is within the same range as the standard error by country.

Table 8: Historical mean and standard deviation of sales period start date by campaign

Campaign	Mean [week #]	Sigma
Summer	26	0.57
Winter	53	1.06

As a first approximation the model will take the average week number, as in week 26 corresponds to the 26th week in the year, as the start of the sales period and not differentiate between countries.

6.6 Sensitivity Analysis

In order to get a sense of the magnitude of each of the costs and which would eventually be the dominant lever, several tests were performed using historical sales data.

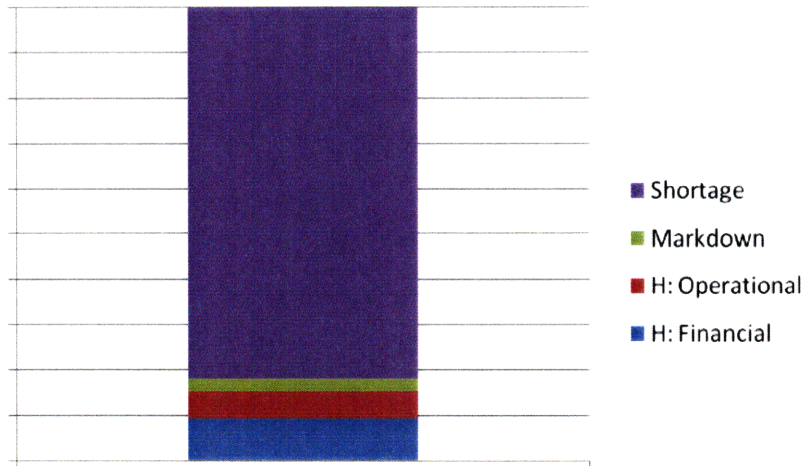


Figure 17: Cost magnitude comparison

It is important to note that the values in Figure 17 have been eliminated and the relative magnitudes presented in the figure are for illustration purposes only. What can be readily appreciated is the fact that shortage cost is the dominant cost, which is completely in line with the purchasing department's

disposition to over-order so as to minimize this cost. One of the previously stated assumptions which led to the project—that buyers were overestimating demand for fear of lost sales—is likely seeing as they account for the greatest portion of profit opportunity.

6.7 Chapter Summary

There are three cost categories that need to be taken into account when addressing period unit cost within retail operations:

- Holding cost, comprised of an operational and a financial element and defined as the opportunity cost for the firm;
- Shortage cost, defined as the lost profit opportunity due to insufficient or inefficiently distributed stock; and
- Markdown cost, reflecting the lost margin on a reference when the price goes from regular sales price to discounted price.

Within Inditex, the shortage cost is the greatest contributor to overall cost and is therefore the main lever behind any improvement effort.

7 Supply Proposal IP Results

The previous chapters have discussed the models that define the necessary inputs to the Supply Proposal IP described in Chapter 3. The following discussion presents the model results and corresponding analysis.

7.1 Model Output

The optimization returns a shipment arrival plan, which was verified against historical data on sales and real arrival at the warehouse information.

Taking true sales and supplier shipment data from the Inditex databases, stock histograms were constructed for specific references reflecting both historical performance and the theoretical performance which would have occurred had the optimization been adopted.

In practice this meant taking real sales data for the specified reference and, coupling it with the real arrival to the DC data, constructing a stock histogram that showed the total stock in the system during each week of the sales period. For this histogram, stock was defined as per Equation 8, making d_k equal to real sales and Y_k equal to real arrivals to the warehouse. Once these weekly stock levels were calculated, average stock turnover was calculated for each reference. This metric refers to the total stock in the system, meaning the total number of items that have been delivered to Zara by outside distributors and have not yet been sold at the stores. Stock turnover therefore includes stock at the distribution centers, stock in secondary operations, in-transit stock, and store stock.

The average, real stock turnover is calculated as the ratio of average weekly stock to average weekly sales as per;

$$\overline{Stock\ Turnover}_{real} = \frac{\overline{Stock}_{real}}{\overline{Sales}_{real}} = \frac{Ave[\sum_{k=t_0}^t Y_{k,real} - \sum_{k=t_0}^t d_{k,real}]}{Ave[d_{k,real}]} \quad (45)$$

The real stock turnover was then compared to the theoretical stock turnover that would have resulted had the Supply Proposal been in place. This theoretical stock turnover was calculated in the

same manner as defined in Equation 45, but the deliveries to the DC (defined by Y_k) taken to be the ones supplied by the IP, i.e.:

$$\overline{Stock\ Turnover}_{IP} = \frac{\overline{Stock}_{IP}}{\overline{Sales}_{real}} = \frac{Ave[\sum_{k=t_0}^t Y_{k,IP} - \sum_{k=t_0}^t d_{k,real}]}{Ave[d_{k,real}]} \quad (46)$$

Stock Turnover was the chosen metric given its wide use throughout Inditex and because it reflects the resulting decision variables proposed by the IP. Stock turnover ‘targets’ are set across Zara for each *type* or *kind* of reference and these categories are defined in much the same manner as described in Section 5.2 during the demand forecast pre-processing. These targets are not in fact hard numbers but ranges of where turnovers should lie between; therefore it is not surprising that an IP that universally minimizes stock turnover to a certain point was not developed for the present thesis. The correct approach is one of overall optimization based on the ability to realize sales, i.e. of getting the correct stock level-to-sales ratio, and not one that simply sets the ratio to a low level since some references warrant higher ratios.

The present cost approach minimizes total supply chain cost by effectively minimizing shortages—the occurrence reflecting the highest per-unit cost. The effect of this is reflected on the stock turnover metric since the decision variable, delivery to the DC, is the defining factor in the calculation.

An initial trial was done with ten references belonging to one section for the Summer 2008 campaign. For each reference, a stock histogram was constructed as described above and the decision variables compared to the real purchasing practices. Figure 18 below illustrates the type of analysis done during this initial trial, the data has been disguised.

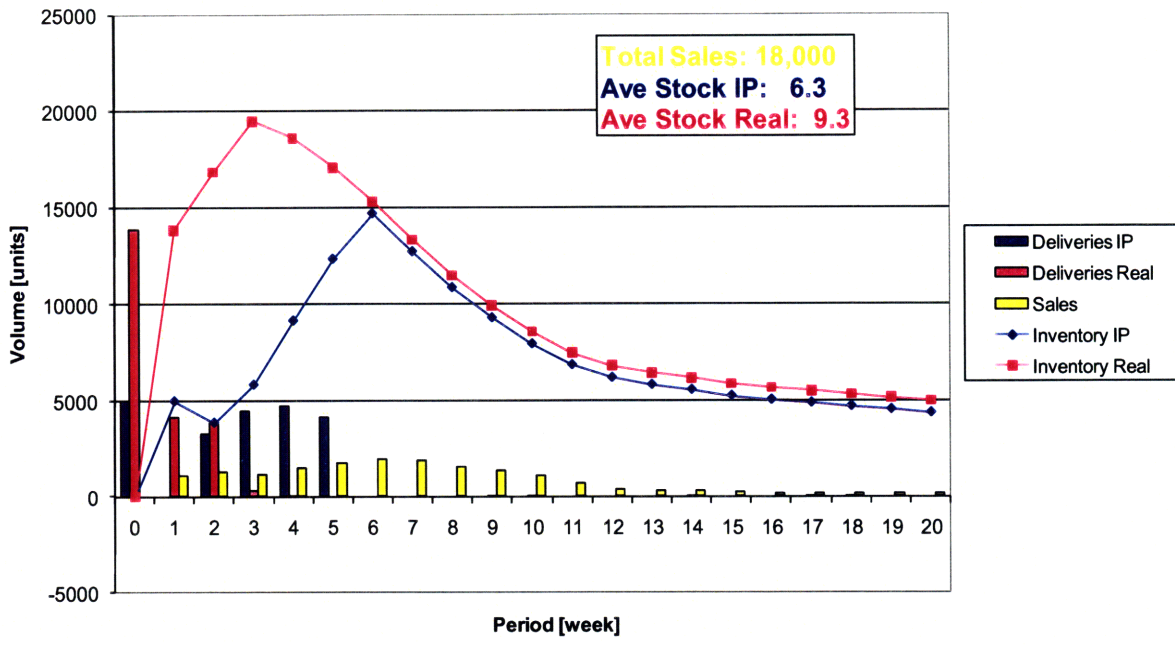


Figure 18: IP Output Histogram

The resulting proposal, shown by the blue bars in the figure above, shows a common trend when compared to the real purchasing practices, shown in pink. The IP breaks up the total purchased quantity into smaller, more frequent shipments to the DCs. This allows the stock levels to follow the sales trends more closely and aids in supply management by effectively delaying the peak stock period while also decreasing the magnitude of the stock peak.

In some cases, as illustrated by Figure 19 below, the real provisioning done matches the IP results. It is important to note that weekly shipments are highly unlikely and, in practice, the Supply Proposal will be consolidated into fewer deliveries while maintaining the general effect of the optimization. As shown in the figure below, shipments will still be spaced out throughout the life of the reference and

stock levels will follow the overall sales trend. These supply management decisions are an excellent illustration of a true implementation of the IP.

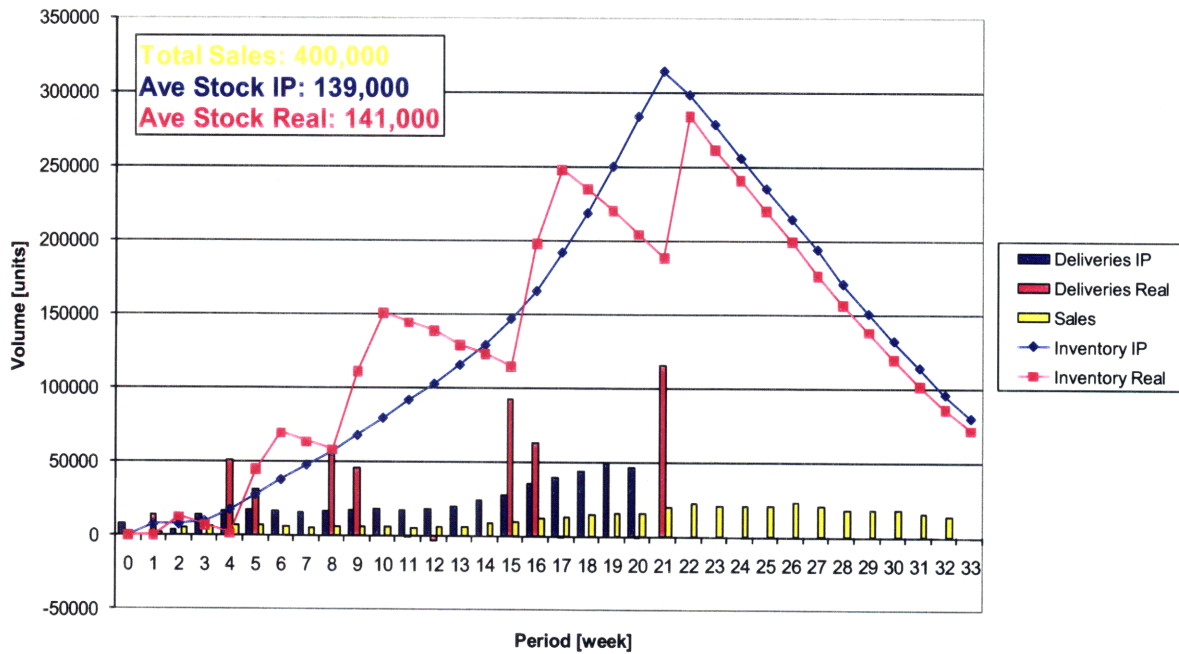


Figure 19: IP Optimization Histogram-Good Provisioning Example

Taking data from histograms like the ones shown in Figure 18 and 19, the stock turnover change was calculated. These percent differences in stock turnover between the current method and the IP recommended supply management plan are calculated according to Equation 47 and shown in The above formula, taking the difference between two stock turnover calculations based on the same sales data, also represents the percent difference in the average stock for each reference. Simple arithmetic shows this since, the denominator for all terms being sales, the numerator for stock turnover (average stock) is the only remaining term.

Table 9 below.

$$'Proposal\ vs.\ Real' = \frac{StockTurnover_{IP} - StockTurnover_{real}}{StockTurnover_{IP}} \quad (47)$$

The above formula, taking the difference between two stock turnover calculations based on the same sales data, also represents the percent difference in the average stock for each reference. Simple arithmetic shows this since, the denominator for all terms being sales, the numerator for stock turnover (average stock) is the only remaining term.

Table 9: Initial Trial Stock Turnover Comparison

Reference ID	Proposal vs. Real
1	+12%
2	-40%
3	-2%
4	-17%
5	-17%
6	-29%
7	+6%
8	-24%
9	-18%
10	-51%

An important thing to note about the initial trial numbers above, which consistently repeated itself across all trials, is that the optimization does not automatically decrease the stock turnover; i.e. does not necessarily decrease the available stock in the supply chain. In some cases, such as references 1

and 7 above, the current supply management practices allowed the stock level to get below that which would have optimized the overall operations. What the IP does, then, is optimize the delivery dates of the purchased stock so that the greatest number of sales can be realized.

The numbers in Table 10 below show the aggregate effect of all the trials made; the actual figures have been disguised.

Table 10: Stock turnover--Optimization vs. Historic Performance

Stock Turnover	Current	Proposal	Proposal vs. Real
Ave. weeks	9.7	7.9	-19%

7.2 Sensitivity Analysis

Sensitivity analysis is a useful tool since it is, in general, a method to determine the degree to which factors in a problem affect the result³³. This exercise is important since it ultimately helps identify those factors that exert the greatest leverage to the overall cost of Zara's supply management decisions.

Looking at the overall per period cost trends as a percentage of total cost using a sample trial, shown below, it is evident that the cost percentages change as the product goes through its lifecycle. The model is minimizing shortages at the beginning of the sales period, where such shortages may impact sales much more so than later on in the period as the reference is no longer 'new' or as fashion-forward as during introduction. This mathematical byproduct of the formulation is in line

³³ (Magee, Copacino, & Rosenfield, 1985)

with the decision criteria within retail and therefore an accurate representation of the buyer's preferences.

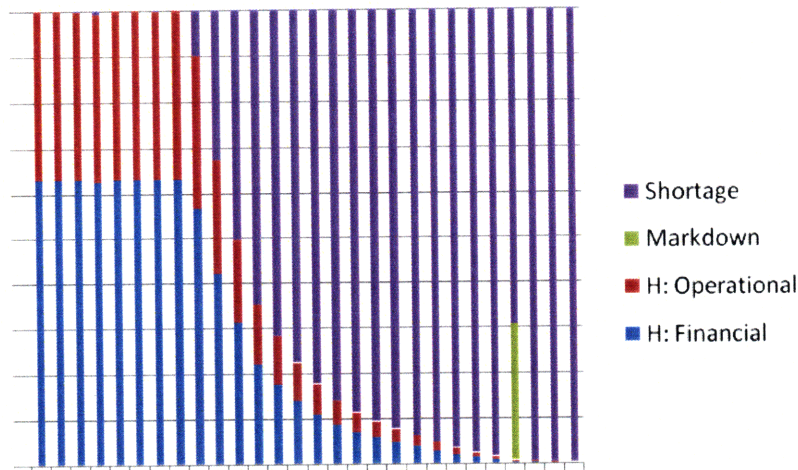


Figure 20: Cost categories as a % of total period cost

It is also relevant to note the magnitude difference between the costs of holding one unit of inventory when compared to the cost of a lost sale, showing that the margins (or lost profit) are much greater than the cost of idle inventory (see Figure 17). This relationship is further enhanced if the value of customer satisfaction and the effect of shortages on customer loyalty were to be taken into account. Because of this consideration, the driving cost at each period is the shortage cost and, unless other costs are increased by a factor of over a hundred, the model will always choose to hold an extra unit of inventory over a lost sale.

Acknowledgement of this dynamic explains the model behavior in the latter periods, but it is also interesting to note the interactions in the early periods where cumulative variability is still under control and shortages are therefore easily controlled. In these cases, the demand model parameters drive the cost components since the shortage calculation depends on the expected volatility of

demand. A 1% increase in Alpha, for example, results, on average, in a 2.5% increase in cumulative demand volatility whereas a 1% increase in Beta results, on average, in an 8.0% increase in cumulative demand volatility. The implication of these numbers is that a poor demand forecast, or incorrect volatility estimation, can underestimate potential shortages and lead to a useless supply management plan.

7.3 Chapter Summary

The Supply Proposal Optimization Model focuses on overall cost optimization to decide when references should be delivered to the DC and in what quantities. It is making the tradeoff between holding stock and incurring a shortage while taking into account all available supply within the Inditex chain, i.e. from the DC to the stores. The markdown cost is dependent of the amount of inventory left in the chain once the markdown season begins and is therefore only charged once.

The model penalizes a loss of profit (shortage) much more than an additional day of holding, but even so it still breaks up shipments to minimize holding costs once the shortage risk has been hedged.

8 Implementation

8.1 Recommendations for Implementation

The Supply Proposal Optimization Model should be implemented in three phases to allow buy-in through experiential success. By undertaking implementation using a phased approach, feedback can be quickly addressed and momentum ensured. The present plan focuses on moving the tool from

early feasibility to proven concept; work needs to be done to design support systems and incentives to deploy the tool to the organization.

These phases for proof of concept are:

8.1.1 Phase 1: Historical Stress Test

The Model should stress tested against Zara's most demanding buyers across a variety of dimensions within the largest section, i.e. Woman ('SRA'). A stress test is understood to be a variation of sensitivity analysis, where each identified 'critical factor' is varied until the formulation breaks down³⁴. Understanding the limits of the present formulation is just as important as understanding its results.

This stress test should first be completed against historical data from key buyers, identified based on

- volume,
- duration of sales period,
- % of Asian vs. proximity suppliers, and
- reference's margin.

These four dimensions will give a complete sample of references when extremes at both ends of the spectrum are considered.

The stress tests should be run in the same manner as the trials that were done for the present study; that is, buyers should identify similar items to the chosen reference and a demand forecast should be

³⁴ (Poirier, 2004)

completed. This demand forecast is then fed to the Optimization Model and a Supply Proposal is established. The Supply Proposal is then plotted against real demand and the resulting inventory levels and expected shortages are modeled to estimate the total cost of the Model's Supply Proposal vs. the cost of the true supply plan.

During this period, the accuracy of the demand forecast should also be considered and any changes to the variability parameters should be done after careful consideration of the change's impact.

8.1.2 Phase 2: Pilot Test I—Key buyers

A pilot should be undertaken for the next purchasing season, with the tool allowed to make supply decisions. The purpose of this pilot will be to gain user experience information and buy-in from individual buyers who are willing to participate in the test.

This pilot should again focus on key buyer groups, but representative items should be identified within each buyer group and tracked for the duration of the campaign. Key metrics (stock turnover and shortages) should be calculated for the chosen references and compared against references within the same category that were purchased under the traditional method.

The results from this pilot will not be evident until the end of the purchased campaign, but close monitoring of key metrics will give an indication of tool decision performance. Feedback from users regarding tool design and UI should be channeled appropriately in preparation for Phase 3, as the number of user will be significantly higher and functionality essential.

8.1.3 Phase 3: Pilot Test II—Full collection

The purpose of this third phase is to control the Supply Proposal tool's rollout. A buyer group, chosen from the groups that have already taken part in Phases 1 and 2, should be identified and all individual buyers within this group should use the tool to purchase their collections.

This will allow new users to experience the tool and can serve as the first official deployment, while making sure that the users get the necessary support that such a change entails. The same metrics should be kept as in Phase 2 and compared against historical data from the previous season.

8.2 Requirements for Implementation

In order for the Supply Proposal tool to be successfully implemented, resources must be available for its management and troubleshooting, and users must be willing to adopt its recommendations.

8.2.1 Technical Requirements

The technical design of the tool itself has been documented, but the code should be translated into a more common language (such as Java) to make its troubleshooting accessible to a greater number of people. The web UI should be finalized so that the necessary functionality is consistently available to users.

The data which feeds the tool comes from two distinct sources:

- Commercial databases and
- Import databases.

The data from the commercial databases, although readily available, is currently processed prior to use so that key parameters are easily filtered. A long-term solution is to have these data tables automatically refresh at predetermined intervals so that information is always current and time is not wasted putting the tables together.

Data from the Import databases is not accessible, so the Import department will provide maintenance to the tables used for the optimization model. This was agreed to because the necessary reports are made up of data that is currently being tracked; in the future, consideration must be given to the sustainability of this arrangement.

The other category of technical issues may arise due to expertise of the people maintaining the tool. As such, training should be specified for both users and anyone wanting to adapt or change the code.

8.3 Barriers to Implementation

Implementation of the Supply Proposal tool will not be an easy task. The sheer scope of the project is a daunting task for stakeholders, implementers, and users. The key lies in understanding the issues beyond the technical that may detract from continued advancement. To shed light on these potential barriers, a three lens analysis was performed and is presented below.

8.3.1 Three lens analysis

8.3.1.1 STRATEGIC LENS:

The Supply Proposal tool was developed within the Logistics department, who is not the end user of the tool. The Logistics department within Inditex has historically been responsible for ensuring that all decisions taken by the Commercial Dept. regarding the supply chain are followed through.

A major issue with past projects has been implementation and follow up, especially within Inditex: a company that needs change in order to be successful. The hectic pace offers little support for systems integration and the Supply Proposal tool, since it deals directly with how work is done, is quite risky for it needs to work in order for anyone to agree to use it. For this reason, four people were identified who will be responsible for maintaining the tool and ensuring that it is implemented. One person is from Logistics, the other from Commercial Management, the third from Distribution and the last from IT.

8.3.1.2 CULTURAL LENS

Inditex is a company that needs change in order to be successful, and as such an idea or recommendation thought innovative and with a decent opportunity at success will be given a shot.

At its core, the Supply Proposal tool is about change within the organization ultimately responsible for Inditex's success. General practice inside the group is that the buyers make the supply management decisions and the transport and logistics departments are responsible for making sure those decisions are executed.

Currently the buyers depend on recalled experience and gut to make these supply management decisions, even though interviews show that they are sometimes unable to accurately recall how a particular reference performed in the past. This, coupled with the fact that they currently lack a structured way to look up relevant comparable references means that a lot of the ‘tribal knowledge’ is no longer sufficient to succeed. This is blatantly true when looking at the buyer performance metrics which used to be sales and percent of purchase that was marked down at the stores at the end of the regular sales period. Recently an operational metric, stock turnover, has been added to their performance review and this project is poised to address deterioration in this particular metric before the buyers start any bad habits. What is particularly promising about this shift is that stock turnover is already the key metric for the Logistics and Distribution organizations, thus making it a likely candidate for cross-functional alignment.

The people within this organization view the project with some distrust as it is not a tool to help them make key decisions but rather a tool focused on the secondary decisions that mitigate error in the key decisions. The tool is being framed as a support tool vs. a final decision tool so that the end users are comfortable with it, a strategy that has been successfully deployed in other retail channels across the UK³⁵. What is a challenge is the idea of uncertainty—the system will track the tool’s proposal and the changes made by the user, if the tool proposed a better decision will the user be penalized? If the user improved on the tool’s proposal, why should the tool then be trusted to make decisions? The users are therefore wary of the tool in general, mostly because they are afraid of leaving measurable evidence of their performance when such measures are, strictly speaking, mostly dependent on chance.

³⁵ (Perry, 2008)

For management, the greatest challenge is to make sure that tool does not enter the rumor mill as a 'solution to the bad decisions being made by the users', since this will only lead to animosity between the groups involved and ensure greater push-back from the users themselves.

8.3.1.3 POLITICAL LENS

The project is being championed by management who exert a lot of influence throughout their organizations and, as such, the project will be eventually implemented in some way. In the greater scope of things, the project is compatible with the interests of all stakeholders since the metrics by which everyone is measured against are addressed by the tool. However, in the day to day work process, the Supply Proposal tool will be more challenging to implement because of the change necessary for its success.

Although nobody has yet vocalized or disputed the necessity and relevance of this project, specific measures must be taken to ensure that any concerns are shared with the key decision makers and with the project team. Informal conversations and continued efforts are imperative to maintain momentum since, as the market environment changes, the alerts that precipitated this project have been subsiding but the core problem still resides within the company.

8.4 Chapter Summary

Full implementation and adoption of the Supply Proposal tool within Inditex is still a stretch goal. Before the tool is completely accepted by the stakeholders involved, a phased introduction to both test out the technical limitations and address the organizational concerns is recommended. By understanding the full scope of the barriers to implementation and developing a plan to address

them as they turn up, confidence in the tool and its relevance will grow and adoption will come with less obstacles.

9 Conclusions

9.1 Summary

Zara is Inditex's largest and most profitable retail concept, but as the competition begins to close the gaps in strategy, revisions to their model are imperative if they hope to remain in the top position. With operations at the core of Zara's competitive advantage, mounting stock levels represent a negative trend that is viewed as a symptom of lost flexibility and agility since it clogs up the chain and prevents new items from being delivered JIT.

In order to regain control of the operations and leverage the 'rapid response' strategy across the new global setting, this project addressed supply management decision-making as a key lever to optimize. The decision tool was designed in four pieces: supplier shipment forecast/ risk mitigation assessment; demand forecast; cost estimation; and an optimization IP that minimized total cost.

Shipment lead times and variability were taken from historical data and the maximum times used to ensure the least risk. The demand forecast was constructed in two parts: demand shape, from similar references, and demand volatility, calculated using the Alpha-Beta method.

For the cost minimization model, three categories of cost were taken into account: holding cost, both financial and operational; shortage cost; and markdown cost. By balancing these three costs per period and minimizing the total inventory cost throughout the reference's complete selling period the IP model returns an optimal supply management schedule; identifying dates and quantities for

delivery to the Zara DC's. For Zara in particular, the shortage cost is the greatest contributor to overall cost and is therefore the main lever behind any improvement effort.

The project made a lot of headway in addressing the technical requirements for implementation but much work needs to be done to prepare the organization for such a step change in decision making. By introducing the tool using a phased approach, much can be gained in terms of adapting the tool to the specific needs of the users and also in terms of securing buy-in for the tool's proposals.

9.2 Recommended Next Steps

This project delved into the problem of minimizing total supply chain costs by addressing inventory management decisions. Further development into this overall theme can be pursued under the added layer of 'consumer choice'. Research on this topic is motivated by the recognition that consumers are frequently willing to buy a different color or size within a product category if their preferred variant is either not offered or offered but not in stock. This is to say, consumers are often willing to substitute rather than go home empty handed³⁶. The implications of this research area for the present problem are evident—it is an additional consideration where assortment and inventory decisions at the *collection* level need to be rationalized on a cost-value basis. This is a crucial consideration since it implies that greater choice at the store leads to more volatile demand as items become substitutes for each other which in turn drives up inventory costs.

The present tool may help to a degree in pursuing such a holistic view to inventory management.

The demand forecast, in aggregate, will and should serve as the basis of such an analysis where fine-

³⁶ (Mahajan & van Ryzin, 1999)

tuning of the shortage costs becomes increasingly relevant. For the present model, shortage costs drive inventory allocation to minimize risk but the consumer choice model redefines a shortage. A true shortage is not due to one reference being out of stock but rather when one reference plus all of its reasonable substitutes are out of stock. This is especially true of Zara in particular since, because of lack of advertising, a full collection's offering is not readily known by the shopper.

9.3 Final Comments

As the retail fashion industry moves to greater focus in time-competition, Zara's competitive advantage at risk of erosion. By optimizing supply management decision making using sound operations theory, inefficiencies in the system may be addressed without compromising the expert assessment of demand within the Group.

Shortages being the main concern of management, it is evident that improved inventory allocation based on quantitative cost analysis can lead to both lower stock levels throughout the supply chain and decreased risk of shortages at the stores. This shift to do 'more with less' will prevent incorrect references from ever reaching the pipeline, thereby allowing Zara greater flexibility in product distribution and positioning to ensure that customers around the world find exactly what they are looking for at their local store.

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Appendix A: Supply Management Proposal Tool Prototype

Item definition

Campaña Centro compra Coste Comprador
 Sección Subfamilia PVP Paquetería Confección
 Modelo/Calidad / Descripción del artículo siendo comprado ¿Reoperación? Sí No

Sales forecast based on similar items

Comparables Añadir comparable

12008 6463 / 521 - 350 (BLANCO)
 Descripción del artículo comparable xxxxxxxxxxxxxxxxx

Foto

Venta 1ª 4 semanas 200.000
 Venta total 1.100.000
 % Entrada en Saldo 20%

12008 5263 / 321 - 350 (BLANCO)
 Descripción del artículo comparable

Ver distribución de ventas

Distribución ventas comparables

Sales forecast scaled for item being purchased

Color Añadir color

1º Envío

Fuerte
 Medio
 Bajo

1ª Sem en tienda

Nº Sem de Venta

V inicial	V Total
C1 <input type="text"/>	<input type="text"/>
C2 <input type="text"/>	<input type="text"/>
C3 <input type="text"/>	<input type="text"/>

V 1ª 4 sem Compra

Venta prevista Ver previsión ventas

Generar plan de entradas

Figure A- 1: Zara Web-based Purchasing Tool Prototype

Appendix B: IP Formulation and Shortage Calculation Note

I adapt here the analysis from Foreman et al. (2008). Under a conservative assumption that demand is incurred at the very beginning of every week and supplier deliveries are received at the very end, the approximate expected shortages during any given week t can be written as

$$\begin{aligned} S_t &= \mathbb{E}[(N(I_t - d_t, \sigma_t))^-] \\ &= \sigma_t \phi\left(\frac{d_t - I_t}{\sigma_t}\right) + (d_t - I_t) \Phi\left(\frac{d_t - I_t}{\sigma_t}\right), \end{aligned} \quad (1)$$

where ϕ and Φ are the standard normal p.d.f. and c.d.f., respectively. In order to enable the implementation of the convex function (1) in a linear optimization model, we now develop a linear approximation consisting of the upper envelope of N of its tangents. A lower bound I_t^{LB} for I_t that is independent of the decision variables is given by

$$I_t^{LB} = - \sum_{k=t_0}^t d_k,$$

and corresponds to the case where no supplier shipment has been received by time t . Likewise, an upper bound I_t^{UB} for I_t that is independent of the decision variables is given by

$$I_t^{UB} = \bar{q} - \sum_{k=t_0}^t d_k,$$

and corresponds to the case where the total planned order quantity has been received by week t .

Next, for every week t one can calculate iteratively a discrete set of N sampling points $\mathcal{P}_t \subset [I_t^{LB}, I_t^{UB}]$ indexed by n , and the slopes a_{tn} and intercepts b_{tn} of the corresponding tangents to the r.h.s. of (1), using numerical implementations of ϕ and Φ along with the maximum error rule algorithm:

- The algorithm initiates with $\mathcal{P}_t = \{I_t^{LB}, I_t^{UB}\}$;
- In each iteration, tangents are constructed for each new point in \mathcal{P}_t , and the x-axis values of the intersection of tangents corresponding to adjacent points in \mathcal{P}_t are added as new points;
- The algorithm terminates when the maximum difference between the y-axis values of these intersections and the corresponding function values reaches a specified upper bound.

This algorithm generates the input data (a_{tn}, b_{tn}) for $t_s \leq t \leq t_e$ and $1 \leq n \leq N$. The linear approximation of (1) is then obtained as

$$S_t \geq a_{tn}(d_t - I_t) + b_{tn} \text{ for all } (t, n),$$

which implements the upper envelope described above since S_t has a positive coefficient as part of an objective function to be minimized

Appendix C: Alpha-Beta Plots

Plots showing sample Beta and Alpha values using real sales data from Summer 2007 and Winter 2007 campaigns.

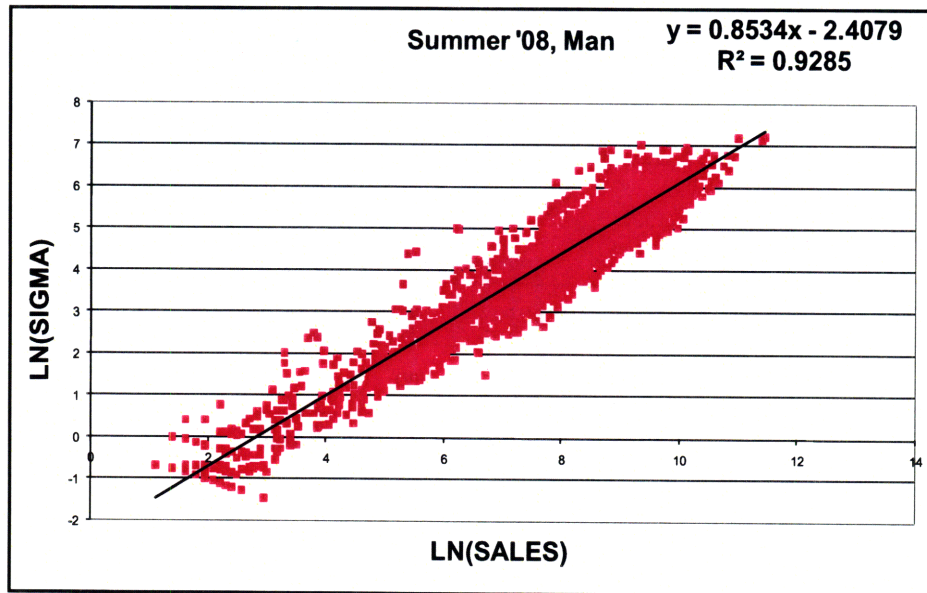


Figure A- 2: Beta plot for Man

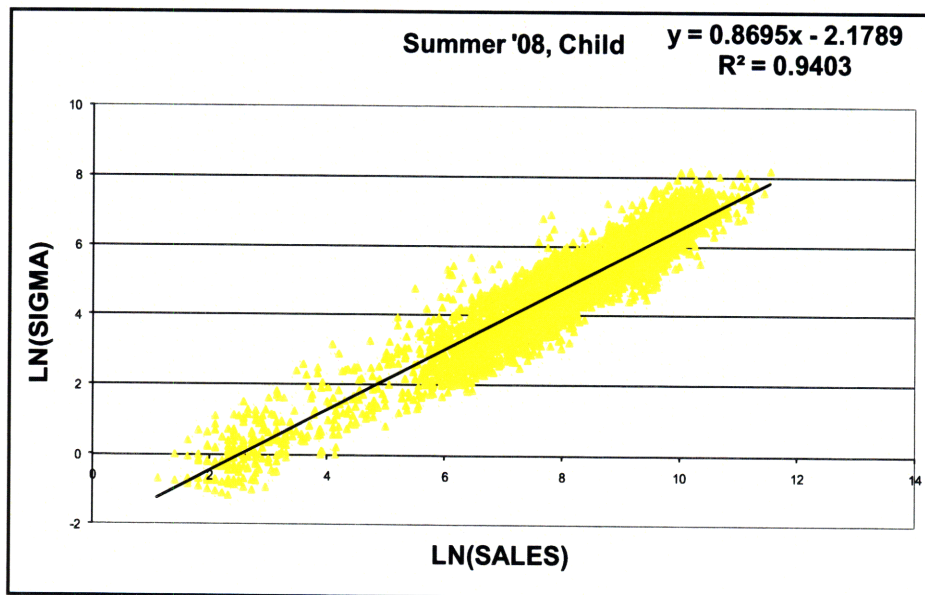


Figure A- 3: Beta plot for Child

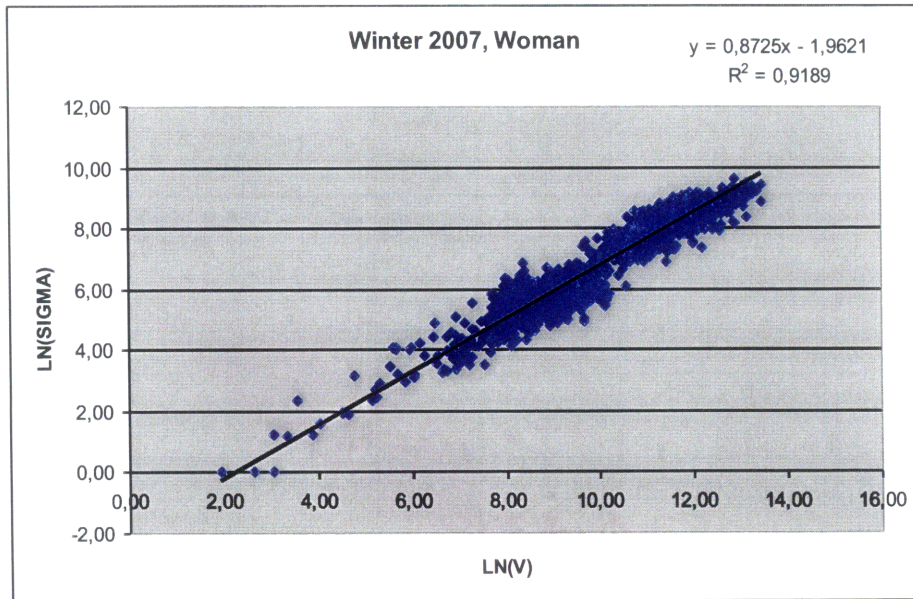


Figure A- 4: Beta plot for Woman

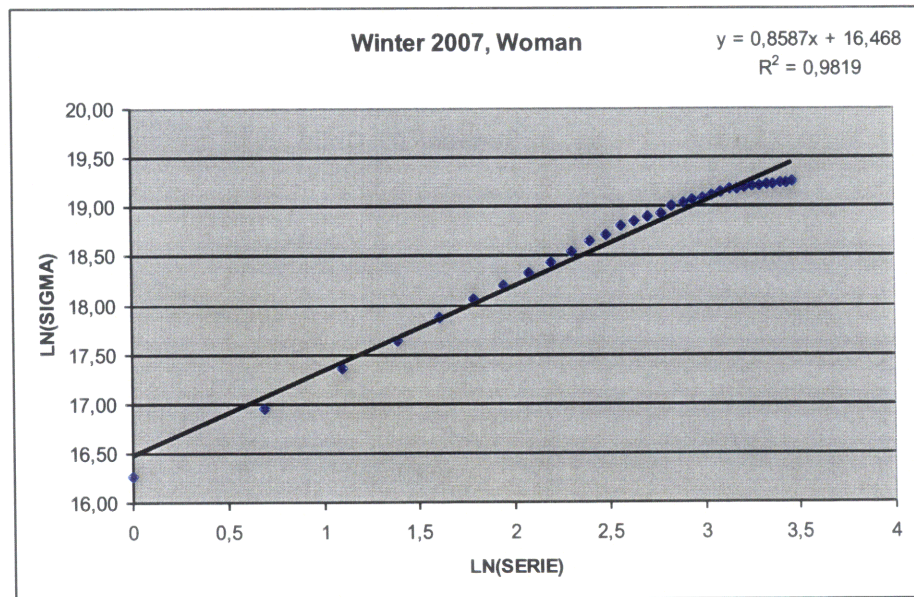


Figure A- 5: Alpha plot for Woman

Appendix D: AMPL IP Formulation Script

```
# PROPUESTA DE APROVISIONAMIENTO
#####
# Variables #
#####

var CANT_ENTRADA_P {p in P_0..P_FIN} integer >= 0;
var CANT_ENTRADA {p in P_0..P_FIN} =
    CANT_ENTRADA_P[p] + STOCK_EXPOSICION[p];
var Z {p in P_0..P_FIN} binary;
var INV {p in P_0..P_FIN+1};
var INV_POS {p in P_0..P_FIN+1};
var ROTURA {p in P_0..P_SALDO} >= 0;
var COSTE_VENTAPERDIDA_TOTAL =
    COSTE_VENTAPERDIDA * sum {T in SEM} ROTURA[T];
var COSTE_INV_TOTAL = COSTE_INV * sum {p in P_0..P_FIN} INV_POS[p];
var COSTE_ENTRADASALDO_TOTAL =
    COSTE_ENTRADA_SALDO * INV_POS[P_SALDO];

#####
# Modelo #
#####

minimize COSTE_TOTAL:
    COSTE_VENTAPERDIDA_TOTAL + COSTE_INV_TOTAL +
    COSTE_ENTRADASALDO_TOTAL;

subject to
VENTA_PERDIDA {T in SEM, R in 1..4}:

    ROTURA[T] >= PENDIENTE_ROTURA[T,R] * (VENTA_PREVISTA[T] - INV[T]) +
```

CONSTANTE_ROTURA[T,R];

STOCKTOTAL_PREVISTO {p in P_0..P_FIN}:

$$\text{INV}[p+1] = (\text{sum}\{m \text{ in } P_0..P_ACTUAL[p]\} \text{CANT_ENTRADA}[m]) - (\text{sum}\{m \text{ in } P_0..P_ACTUAL[p]\} \text{VENTA_PREVISTA}[m]) ;$$

INVENTARIOTOT_POSMIN {p in P_0..P_FIN+1}:

$$\text{INV_POS}[p] \geq 0;$$

INVENTARIOTOT_POSMAX {p in P_0..P_FIN+1}:

$$\text{INV_POS}[p] \geq \text{INV}[p];$$

CANTIDAD_ENTRADA_MIN {p in P_0..P_FIN}:

$$\text{CANT_ENTRADA_P}[p] \geq Z[p] * \text{MIN_CANT}[PAISEMBAQ];$$

CANTIDAD_ENTRADA_MAX {p in P_0..P_FIN}:

$$\text{CANT_ENTRADA_P}[p] \leq Z[p] * \text{VENTAPROM_TOTAL} ;$$

CANTIDAD_ENTREGADA:

$$\text{sum}\{p \text{ in } P_0..P_SALDO-1\} \text{CANT_ENTRADA_P}[p] = \text{VENTAPROM_TOTAL} - \text{sum}\{p \text{ in } P_0..P_SALDO-1\} \text{STOCK_EXPOSICION}[p] ;$$

CANTIDAD_STOCK_INICIAL:

$$\text{CANT_ENTRADA_P}[P_0] + \text{STOCK_EXPOSICION}[P_0] \geq \text{CANT_PRIMENV} ;$$

Appendix E: SQL Queries

```
-- MAESTRO DE CATEGORIAS
drop table mit3.Categorias;
create table mit3.Categorias(Categoria integer, Nombre varchar(10));
alter table mit3.Categorias add primary key(Categoria);

-- select * from mit3.Categorias

insert into mit3.Categorias (Categoria, Nombre) values (1, 'Basico');
insert into mit3.Categorias (Categoria, Nombre) values (2, 'Moda');
insert into mit3.Categorias (Categoria, Nombre) values (3, 'Fantasia');

-- HISTORICO DE VENTAS
drop table mit3.HistoricoFacturacion;
create table mit3.HistoricoFacturacion(AnoCamp integer, Campana char(1), Seccion integer,
Comprador integer, Categoria integer,
        NumTiendas integer, Modelo integer, Calidad integer, Color integer, Periodo integer,
Ano integer,
        Semana integer, Facturado integer, VentaSaldo integer, Agrupacion integer);
alter table mit3.HistoricoFacturacion add primary key(AnoCamp,Campana,Seccion,
Modelo,Calidad,Color,ano, Semana);

-- select * from mit3.HistoricoFacturacion order by ano, campana, seccion, modelo, calidad, color,
periodo;
-- select * from mit3.dvtasmi07
insert into mit3.HistoricoFacturacion
select 2008 as AnoCamp, 'V' as Campana, d.Seccion, d.Comprador, 0 as Categoria,
count(distinct(d.tienda)), d.modelo, d.calidad,
        d.color, -99 as Periodo, d.Ano, d.Semana,
        (select sum(v.unidades) from mit3.dvtasmv08 v where v.seccion=d.seccion and
v.comprador=d.comprador and v.modelo=d.modelo
```

```
and v.calidad=d.calidad and v.color=d.color and v.ano=d.ano and v.semana=d.semana and
v.temporada='T')Facturado,
```

```
(select sum(v.unidades) from mit3.dvtasmv08 v where v.seccion=d.seccion and
v.comprador=d.comprador and v.modelo=d.modelo
```

```
and v.calidad=d.calidad and v.color=d.color and v.ano=d.ano and v.semana=d.semana and
v.temporada='S')VentaSaldo,
```

```
0 as Agrupacion
```

```
from mit3.dvtasmv08 d where d.seccion is not null
```

```
group by d.seccion, d.comprador, d.modelo, d.calidad, d.color, d.ano, d.semana;
```

```
insert into mit3.HistoricoFacturacion
```

```
select 2007 as AnoCamp, 'I' as Campana, d.Seccion, d.Comprador, 0 as Categoria,
count(distinct(d.tienda)), d.modelo, d.calidad,
```

```
d.color, -99 as Periodo, d.Ano, d.Semana,
```

```
(select sum(v.unidades) from mit3.dvtasmi07 v where v.seccion=d.seccion and
v.comprador=d.comprador and v.modelo=d.modelo
```

```
and v.calidad=d.calidad and v.color=d.color and v.ano=d.ano and v.semana=d.semana and
v.temporada='T')Facturado,
```

```
(select sum(v.unidades) from mit3.dvtasmi07 v where v.seccion=d.seccion and
v.comprador=d.comprador and v.modelo=d.modelo
```

```
and v.calidad=d.calidad and v.color=d.color and v.ano=d.ano and v.semana=d.semana and
v.temporada='S')VentaSaldo,
```

```
0 as Agrupacion
```

```
from mit3.dvtasmi07 d where d.seccion is not null
```

```
group by d.seccion, d.comprador, d.modelo, d.calidad, d.color, d.ano, d.semana;
```

```
insert into mit3.HistoricoFacturacion
```

```
select 2008 as AnoCamp, 'I' as Campana, d.Seccion, d.Comprador, 0 as Categoria,
count(distinct(d.tienda)), d.modelo, d.calidad,
```

```
d.color, -99 as Periodo, d.Ano, d.Semana,
```

```
(select sum(v.unidades) from mit3.dvtasmi08 v where v.seccion=d.seccion and
v.comprador=d.comprador and v.modelo=d.modelo
```

```
and v.calidad=d.calidad and v.color=d.color and v.ano=d.ano and v.semana=d.semana and
v.temporada='T')Facturado,
```

```

(select sum(v.unidades) from mit3.dvtasmi08 v where v.seccion=d.seccion and
v.comprador=d.comprador and v.modelo=d.modelo
and v.calidad=d.calidad and v.color=d.color and v.ano=d.ano and v.semana=d.semana and
v.temporada='S')VentaSaldo,
0 as Agrupacion
from mit3.dvtasmi08 d where d.seccion is not null
group by d.seccion, d.comprador, d.modelo, d.calidad, d.color, d.ano, d.semana;

```

```

insert into mit3.HistoricoFacturacion

```

```

select 2007 as AnoCamp, 'V' as Campana, d.Seccion, d.Comprador, 0 as Categoria,
count(distinct(d.tienda)), d.modelo, d.calidad,
d.color, -99 as Periodo, d.Ano, d.Semana,
(select sum(v.unidades) from mit3.dvtasmv07 v where v.seccion=d.seccion and
v.comprador=d.comprador and v.modelo=d.modelo
and v.calidad=d.calidad and v.color=d.color and v.ano=d.ano and v.semana=d.semana and
v.temporada='T')Facturado,
(select sum(v.unidades) from mit3.dvtasmv07 v where v.seccion=d.seccion and
v.comprador=d.comprador and v.modelo=d.modelo
and v.calidad=d.calidad and v.color=d.color and v.ano=d.ano and v.semana=d.semana and
v.temporada='S')VentaSaldo,
0 as Agrupacion
from mit3.dvtasmv07 d where d.seccion is not null
group by d.seccion, d.comprador, d.modelo, d.calidad, d.color, d.ano, d.semana;

```

```

call mit3.SP_PERIODOS_POR_SEMANA();

```

```

-- CARACTERISTICAS DE VENTA

```

```

drop table mit3.CaracteristicasVenta;
create table mit3.CaracteristicasVenta(Ano integer, Campana char(1), Seccion integer, Comprador
integer, Categoria integer,
Modelo integer, Calidad integer, Color integer, TotalPeriodos numeric(10,0),
TotalVenta numeric (10,0),

```

```

        PromedioVenta numeric(10,2), DesviacionEstandarVenta numeric(10,2),
LNTotalVenta numeric(10,5),
        LNPromedioVenta numeric (10,4), LNDesviacionEstandarVenta numeric (10,4));
alter table mit3.CaracteristicasVenta add primary key(Ano, Campana, Seccion, Comprador, Modelo,
Calidad, Color);

```

```
-- select * from mit3.CaracteristicasVenta order by ano, campana, seccion;
```

```
insert into mit3.CaracteristicasVenta
```

```
select hf.anocamp, hf.campana, hf.seccion, hf.comprador, 0 as Categoria, hf.modelo, hf.calidad,
hf.color,
```

```
    count(Periodo) as TotalPeriodos, sum(Facturado) as TotalVenta,
```

```
    avg(cast(Facturado as numeric(10,2))) as PromedioVenta,
```

```
    stddev(cast(Facturado as numeric(10,2))) as DesviacionEstandarVenta, 0.00 as LNTotalVenta,
```

```
    0.00 as LNPromedioVenta, -99 as LNDesviacionEstandarVenta
```

```
    from mit3.HistoricoFacturacion hf where Facturado is not null and ventasaldo is null and
Facturado>0 and color<>0
```

```
group by hf.anocamp, hf.campana, hf.seccion, hf.comprador, hf.categoria, hf.modelo, hf.calidad,
hf.color
```

```
order by hf.anocamp, hf.campana, hf.comprador, hf.seccion, hf.modelo, hf.calidad, hf.color;
```

```
--CATEGORÍAS
```

```
update mit3.CaracteristicasVenta set Categoria= 1 where Modelo <> 0 ;
```

```
update mit3.CaracteristicasVenta set Categoria= 1 where Calidad <> 0 ;
```

```
update mit3.CaracteristicasVenta set Categoria= 1 where Color <> 0 ;
```

```
update mit3.CaracteristicasVenta set Categoria= 1 where TotalVenta > 0 ;
```

```
update mit3.CaracteristicasVenta set Categoria= 1 where PromedioVenta > 0 ;
```

```
update mit3.CaracteristicasVenta set Categoria= 1 where DesviacionEstandarVenta > 0;
```

```
/*
```

```
PARA VARIAS CATEGORIAS
```


** hasta este punto todos los registros 'basura' tienen categoria = 0 y los 'buenos' tienen categoria=1.
Lo que quieres hacer es diferenciar entre los registros 'buenos'.

ASUMIR QUE LA CATEGORIA SE DIVIDE POR LA CANTIDAD TOTAL DE VENTA > 50.000

```
update mit3.CaracteristicasVenta set Categoria=2 where TotalVenta >= 50000;
```

**ahora todos los 'buenos' > 50.000 categoria=2 y <50.000 categoria=1

ASUMIR QUE LA CATEGORIA SE DIVIDE POR LA CANTIDAD TOTAL DE VENTA (>50.000) Y PERIODOS (>5)

```
update mit3.CaracteristicasVenta set Categoria=2 where TotalVenta >= 50000 and TotalPeriodos>5;
```

```
update mit3.CaracteristicasVenta set Categoria=3 where TotalVenta >= 50000 and TotalPeriodos<=5;
```

*/

```
update mit3.CaracteristicasVenta set LNTotalVenta = ln(TotalVenta) where categoria=1 ;
```

```
update mit3.CaracteristicasVenta set LNPromedioVenta = ln(PromedioVenta) where categoria=1 ;
```

```
update mit3.CaracteristicasVenta set LNDesviacionEstandarVenta = ln(DesviacionEstandarVenta) where DesviacionEstandarVenta>0;
```

-- AÑADE CATEGORIA AL HISTORICO DE FACTURACION

```
update mit3.HistoricoFacturacion hf set Categoria =
```

```
(select distinct cv.Categoria from mit3.CaracteristicasVenta cv where cv.ano=hf.anocamp and cv.campana=hf.campana and
```

```
cv.seccion=hf.seccion and cv.modelo=hf.modelo and cv.calidad=hf.calidad and cv.color=hf.color);
```

```
update mit3.HistoricoFacturacion set Categoria = 0 where categoria is null;
```

```
update mit3.HistoricoFacturacion set Categoria = 0 where Facturado is null;
```

```
update mit3.HistoricoFacturacion set Categoria = 0 where VentaSaldo is not null;
```

--***CÁLCULO DE ALFA**

-- CARACTERISTICAS DE PERIODOS

drop table mit3.CaracteristicaPeriodo;

create table mit3.CaracteristicaPeriodo(campana char(1), seccion integer, categoria integer, serie integer,

agrupacion integer, TotalFacturado integer);

alter table mit3.CaracteristicaPeriodo add primary key(campana, seccion, categoria, serie, agrupacion);

-- select * from mit3.CaracteristicaPeriodo order by campana, seccion, categoria, Serie;

call MIT3.SP_SERIES;

drop table mit3.CaracteristicasPeriodo;

create table mit3.CaracteristicasPeriodo(campana char(1), seccion integer, categoria integer,

serie integer, LNserie numeric (10,2), DesvEstVenta numeric (15,2),

LNDesviacionEstandarVenta numeric (10,4));

alter table mit3.CaracteristicasPeriodo add primary key(campana, seccion, categoria, serie);

-- select * from mit3.CaracteristicasPeriodo

insert into mit3.CaracteristicasPeriodo

select campana, seccion, categoria, serie, ln(serie), stddev(totalfacturado) as DesvEstVenta, 0.00 as LNDesviacionEstandarVenta

from mit3.CaracteristicaPeriodo where totalfacturado is not null and categoria <> 0 and campana='V' and serie < 36

-- límite en la serie corresponde a max(periodo)/2 por Campaña/Sección

group by campana, seccion, serie, categoria

order by campana, seccion, serie, categoria ;

```

insert into mit3.CaracteristicasPeriodo
select campana, seccion, categoria, serie, ln(serie), stddev(totalfacturado) as DesvEstVenta, 0.00 as
LNDesviacionEstandarVenta
    from mit3.CaracteristicaPeriodo where totalfacturado is not null and categoria <> 0 and
campana='T' and serie < 35
group by campana, seccion, serie, categoria
order by campana, seccion, serie, categoria ;

```

```

update mit3.CaracteristicasPeriodo set LNDesviacionEstandarVenta = ln(desvestventa) where
desvestventa <>0 ;

```

```

--select campana, max(periodo) from mit3.historicofacturacion
--group by campana

```

```

-- CONSTANTES DE REGRESIONES PARA ALPHA Y BETA

```

```

drop table mit3.RegresionConstantes;
create table mit3.RegresionConstantes(Campana char(1), seccion integer, categoria integer,
PROM_LNSerie numeric (6,4),
    PROM_LNDesvEstVenta numeric (6,4), PROM_LNTotVenta numeric (6,4),
PROM_LNDesvEstTotVenta numeric (6,4));
alter table mit3.RegresionConstantes add primary key(Campana, seccion, categoria);

-- select * from mit3.RegresionConstantes

```

```

insert into mit3.RegresionConstantes
select campana, seccion, categoria, avg(LNSerie) as PROM_LNSerie,
avg(LNDesviacionEstandarVenta) as
    PROM_LNDesvEstVenta, 0.00 as PROM_LNPromTotVenta, 0.00 as
PROM_LNDesvEstTotVenta
    from mit3.CaracteristicasPeriodo
group by campana, seccion, categoria ;

```

```

update mit3.RegresionConstantes rc set PROM_LNTotVenta = (select avg(LNTotalVenta)
    from mit3.CaracteristicasVenta cv
where cv.campana=rc.campana and cv.seccion=rc.seccion and cv.categoria=rc.categoria and
cv.desviacionestandarventa <>0) ;

```

```

update mit3.RegresionConstantes rc set PROM_LNDesvEstTotVenta = (select
avg(LNDesviacionEstandarVenta)
    from mit3.CaracteristicasVenta cv
where cv.campana=rc.campana and cv.seccion=rc.seccion and cv.categoria=rc.categoria and
cv.desviacionestandarventa <>0) ;

```

--REGRESION PARA CARACTERISTICAS DE CATEGORIA: ALPHA

```
drop table mit3.RegresionAlpha;
```

```
create table mit3.RegresionAlpha(Campana char(1), seccion integer, categoria integer, LNSerie
numeric (10,4),
```

```
    LNDesviacionEstandarVenta numeric (10,4), PROM_LNSerie numeric (6,4),
    PROM_LNDesvEstVenta
```

```
    numeric (6,4),ErrorSerie numeric (6,4),ErrorDesvEstVenta numeric
(15,10),MultErrorInter numeric (6,4));
```

```
alter table mit3.RegresionAlpha add primary key(Campana, seccion, categoria, LNSerie,
LNDesviacionEstandarVenta);
```

```
--select * from mit3.RegresionAlpha
```

```
insert into mit3.RegresionAlpha
```

```
select cp.campana, cp.seccion, cp.categoria, LNSerie, LNDesviacionEstandarVenta,
PROM_LNSerie,
```

```
    PROM_LNDesvEstVenta, 0.00 as ErrorSerie, 0.00 as ErrorDesvEstVenta, 0.00 as
MultErrorInter
```

```
    from mit3.RegresionConstantes rc inner join mit3.CaracteristicasPeriodo cp
```

```
    on rc.campana=cp.campana and rc.seccion=cp.seccion and rc.categoria=cp.categoria
```

```
group by cp.campana, cp.seccion, cp.categoria, LNSerie, LNDesviacionEstandarVenta,
PROM_LNSerie,
```

```

PROM_LNDesvEstVenta;

update mit3.RegresionAlpha set ErrorSerie = (LNSerie - PROM_LNSerie)*(LNSerie -
PROM_LNSerie);

update mit3.RegresionAlpha set ErrorDesvEstVenta = (LNDesviacionEstandarVenta -
PROM_LNDesvEstVenta)*
    (LNDesviacionEstandarVenta - PROM_LNDesvEstVenta);

update mit3.RegresionAlpha set MultErrorInter = (LNSerie -
PROM_LNSerie)*(LNDesviacionEstandarVenta -
    PROM_LNDesvEstVenta);

--PARAMETROS PARA CARACTERISTICAS DE CATEGORIA: ALPHA
drop table mit3.CaracteristicasAlpha;
create table mit3.CaracteristicasAlpha(Campana char(1), seccion integer, categoria integer,
CuentaAgrup integer,
    SUMA_ErrorSerie numeric (10,5), SUMA_ErrorDesvEstVenta_A numeric (10,5),
    SUMA_MultErrorInter numeric (10,5), SIGMA_Serie numeric (10,5),
    SIGMA_DesvEstVenta_A numeric (10,5),
    CoeffDeterminacion numeric (5,3));
alter table mit3.CaracteristicasAlpha add primary key(Campana, seccion, categoria);

-- select * from mit3.CaracteristicasAlpha

insert into mit3.CaracteristicasAlpha
select campana, seccion, categoria, count(LNSerie) as CuentaAgrup, sum(ErrorSerie) as
SUMA_ErrorSerie,
    sum(ErrorDesvEstVenta) as SUMA_ErrorDesvEstVenta_A, sum(MultErrorInter) as
SUMA_MultErrorInter,
    0.00 as SIGMA_Serie, 0.00 as SIGMA_DesvEstVenta_A, 0.00 as CoeffDeterminacion
from mit3.RegresionAlpha
group by campana, seccion, categoria
order by campana, seccion, categoria ;

```

```

update mit3.CaracteristicasAlpha set SIGMA_Serie = sqrt(SUMA_ErrorSerie/ CuentaAgrup);
update mit3.CaracteristicasAlpha set SIGMA_DesvEstVenta_A =
sqrt(SUMA_ErrorDesvEstVenta_A / CuentaAgrup);
update mit3.CaracteristicasAlpha set CoeffDeterminacion = (SUMA_MultErrorInter /
(SIGMA_Serie*SIGMA_DesvEstVenta_A*
CuentaAgrup)) where SUMA_ErrorDesvEstVenta_A >0 ;

```

--REGRESION PARA CARACTERISTICAS DE CATEGORIA: BETA

```
drop table mit3.RegresionBeta;
```

```
create table mit3.RegresionBeta(Ano integer, Campana char(1), seccion integer, categoria integer,
Modelo integer,
```

```

    Calidad integer, Color integer, LNTotalVenta numeric (10,4),
    LNDesviacionEstandarVenta numeric (10,4),

```

```

    PROM_LNTotVenta numeric (6,4), PROM_LNDesvEstTotVenta numeric (6,4),
    ErrorTotVent numeric (6,4),

```

```

    ErrorDesvEstVent numeric (10,4), MultErrorVent numeric (10,4));

```

```
alter table mit3.RegresionBeta add primary key(Ano, Campana, Seccion, Categoria, Modelo, Calidad,
Color);
```

```
--select * from mit3.RegresionBeta
```

```
insert into mit3.RegresionBeta
```

```
select cv.ano, cv.campana, cv.seccion, cv.categoria, cv.modelo, cv.calidad, cv.color, LNTotalVenta,
```

```

    LNDesviacionEstandarVenta, PROM_LNTotVenta, PROM_LNDesvEstTotVenta, 0.00 as
    ErrorTotVent,
```

```

    0.00 as ErrorDesvVent, 0.00 as MultErrorVent
```

```
from mit3.RegresionConstantes rc inner join mit3.CaracteristicasVenta cv
```

```

on rc.campana=cv.campana and rc.seccion=cv.seccion and rc.categoria=cv.categoria where
cv.desviacionestandarventa <> 0

```

```

group by cv.ano, cv.campana, cv.seccion, cv.categoria, cv.modelo, cv.calidad, cv.color,
LNTotalVenta,
```

```

    LNDesviacionEstandarVenta, PROM_LNTotVenta, PROM_LNDesvEstTotVenta;

```

```

update mit3.RegresionBeta set ErrorTotVent = (LNTotalVenta -
PROM_LNNTotVenta)*(LNTotalVenta - PROM_LNNTotVenta);

update mit3.RegresionBeta set ErrorDesvEstVent = (LNDesviacionEstandarVenta -
PROM_LNDesvEstTotVenta)*
    (LNDesviacionEstandarVenta - PROM_LNDesvEstTotVenta);

update mit3.RegresionBeta set MultErrorVent = (LNTotalVenta -
PROM_LNNTotVenta)*(LNDesviacionEstandarVenta -
    PROM_LNDesvEstTotVenta);

-- PARAMETROS PARA CARACTERISTICAS DE CATEGORIA: BETA

drop table mit3.CaracteristicasBeta;
create table mit3.CaracteristicasBeta(Campana char(1), seccion integer, categoria integer,
    CuentaMCC integer,
        SUMA_ErrorTotVenta numeric (10,5), SUMA_ErrorDesvEstVenta_B numeric (15,5),
        SUMA_MultErrorVenta numeric (10,5), SIGMA_TotVenta numeric (10,5),
        SIGMA_DesvEstVenta_B numeric (10,5),
        CoeffDeterminacion numeric (5,3));
alter table mit3.CaracteristicasBeta add primary key(Campana, Seccion, Categoria);

--select * from mit3.CaracteristicasBeta order by campana, seccion

insert into mit3.CaracteristicasBeta
select campana, seccion, categoria, count(modelo) as CuentaMCC, sum(ErrorTotVent) as
SUMA_ErrorTotVenta,
    sum(ErrorDesvEstVent) as SUMA_ErrorDesvEstVenta_B, sum(MultErrorVent) as
SUMA_MultErrorVenta,
    0.00 as SIGMA_TotVenta, 0.00 as SIGMA_DesvEstVenta_B, 0.00 as CoeffDeterminacion
from mit3.RegresionBeta
group by campana, seccion, categoria;

update mit3.CaracteristicasBeta set SIGMA_TotVenta = sqrt(SUMA_ErrorTotVenta/
CuentaMCC);

```

```

update mit3.CaracteristicasBeta set SIGMA_DesvEstVenta_B =
sqrt(SUMA_ErrorDesvEstVenta_B / CuentaMCC);
update mit3.CaracteristicasBeta set CoeffDeterminacion =
(SUMA_MultErrorVenta/(SIGMA_TotVenta*SIGMA_DesvEstVenta_B*
CuentaMCC)) where SUMA_ErrorDesvEstVenta_B >0 ;

/* ### DATOS PARA EL MODELO ## */

drop table mit3.CaracteristicasVarianza;
create table mit3.CaracteristicasVarianza(Campana char(1), Seccion integer, Categoria integer,
Alpha numeric (10,5), ConstanteRegresion_Alpha numeric (10,4),
CoeffDeterminacionSQ_Alpha numeric (5,3),
Beta numeric (10,5), ConstanteRegresion_Beta numeric (10,4), CoeffDeterminacionSQ_Beta
numeric (5,3));
alter table mit3.CaracteristicasVarianza add primary key(Campana, Seccion, Categoria);

-- select * from mit3.CaracteristicasVarianza

insert into mit3.CaracteristicasVarianza
select campana, seccion, categoria, 0.00 as Alpha, 0.00 as ConstanteRegresion_Alpha, 0.00 as
CoeffDeterminacionSQ_Alpha,
0.00 as Beta, 0.00 as ConstanteRegresion_Beta, 0.00 as CoeffDeterminacionSQ_Beta
from mit3.CaracteristicasAlpha
group by campana, seccion, categoria
order by campana, seccion, categoria;

update mit3.CaracteristicasVarianza cc set Alpha =
(select SUMA_MultErrorInter from mit3.CaracteristicasAlpha ca where ca.campana=cc.campana
and ca.seccion=cc.seccion and ca.categoria=cc.categoria) /
(select SUMA_ErrorSerie from mit3.CaracteristicasAlpha ca where SUMA_ErrorSerie > 0 and
ca.campana=cc.campana and ca.seccion=cc.seccion and ca.categoria=cc.categoria);

update mit3.CaracteristicasVarianza cc set ConstanteRegresion_Alpha =

```



```

(select PROM_LNDesvEstVenta from mit3.RegresionConstantes rc
  where rc.campana=cc.campana and rc.seccion=cc.seccion and rc.categoria=cc.categoria) -
(Alpha *
(select PROM_LNSerie from mit3.RegresionConstantes rc
  where rc.campana=cc.campana and rc.seccion=cc.seccion and rc.categoria=cc.categoria));

```

```

update mit3.CaracteristicasVarianza cc set CoeffDeterminacionSQ_Alpha =
  (select CoeffDeterminacion from mit3.CaracteristicasAlpha ca
    where ca.campana=cc.campana and ca.seccion=cc.seccion and ca.categoria=cc.categoria) *
  (select CoeffDeterminacion from mit3.CaracteristicasAlpha ca
    where ca.campana=cc.campana and ca.seccion=cc.seccion and ca.categoria=cc.categoria);

```

```

update mit3.CaracteristicasVarianza cc set Beta =
  (select SUMA_MultErrorVenta from mit3.CaracteristicasBeta cb
    where cb.campana=cc.campana and cb.seccion=cc.seccion and cb.categoria=cc.categoria) /
  (select SUMA_ErrorTotVenta from mit3.CaracteristicasBeta cb where SUMA_ErrorTotVenta >
0
  and cb.campana=cc.campana and cb.seccion=cc.seccion and cb.categoria=cc.categoria);

```

```

update mit3.CaracteristicasVarianza cc set ConstanteRegresion_Beta =
  (select PROM_LNDesvEstTotVenta from mit3.RegresionConstantes rc
    where rc.campana=cc.campana and rc.seccion=cc.seccion and rc.categoria=cc.categoria) -
(Beta *
  (select PROM_LNTotVenta from mit3.RegresionConstantes rc
    where rc.campana=cc.campana and rc.seccion=cc.seccion and rc.categoria=cc.categoria));

```

```

update mit3.CaracteristicasVarianza cc set CoeffDeterminacionSQ_Beta =
  (select CoeffDeterminacion from mit3.CaracteristicasBeta cb
    where cb.campana=cc.campana and cb.seccion=cc.seccion and cb.categoria=cc.categoria) *
  (select CoeffDeterminacion from mit3.CaracteristicasBeta cb
    where cb.campana=cc.campana and cb.seccion=cc.seccion and cb.categoria=cc.categoria);

```

--CONSTANTES PARA ESTIMAR LA VENTA PERDIDA (DE VISUAL BASIC)

drop table mit3.ConstanteVentaPerdida;

create table mit3.ConstanteVentaPerdida(Semana int, Periodo int, ValorA numeric(15,4), ValorB numeric(15,4));

-- select * from mit3.ConstanteVentaPerdida

alter table mit3.ConstanteVentaPerdida add primary key (Semana, Periodo);

-- ** CONSULTA PARA VALIDAR SIMULACIONES **

select 2008 as Ano, edcamp, edsecc, edmode, edcali, edcodc,
week(cast(concat(concat(edanoe,concat('-',concat(edmese,'-'))),
eddiae) as date)) as semana,
sum(edun01+edun02+edun03+edun04+edun05+edun06+edun07+edun08+edun09+edun10+edu
n11) as entrada

from hcv2008.dentprov

-- escoge la tabla de entradas a consultar y filtra por modelo/calidad/color usando el 'where'
command:

where edmode= 754

and edcali= 28

--and edcodc=

group by edcamp,edsecc,edmode,edcali,edcodc, week(cast(concat(concat(edanoe,concat('-',concat(edmese,'-'))),eddiae) as date))

order by edcamp,edsecc,edmode,edcali,edcodc, semana;

/* ENTRADAS VS. FACTURACION VS. VENTA

drop table mit3.ComparativoMovimientos

create table mit3.ComparativoMovimientos(Ano integer, Campana char(1), Seccion integer,
Comprador integer, Modelo integer,

Calidad integer, Color integer, TotalCompra integer, TotalFacturado integer,
TotalVenta integer);

```
alter table mit3.ComparativoMovimientos add primary key (Ano, Campana, Seccion, Comprador, Modelo, Calidad, Color);
```

```
-- select * from mit3.ComparativoMovimientos
```

```
insert into mit3.ComparativoMovimientos
```

```
select 2007 as Ano, 'I' as Campana, rasecc, racomp1, ramode, racali, racolo, (select
```

```
sum(edun01+edun02+edun03+edun04+edun05+edun06+edun07+edun08+edun09+edun10+edun11) from hci2007.dentprov where edsecc=rasecc
```

```
and edmode=ramode and edcali=racali and edcodc=racolo ) as TotalCompra,
```

```
sum(rafacu) as TotalFacturado, sum(ravenu) as TotalVental
```

```
from ici2007.sz_artre0
```

```
where ratien < 7000 and rats ='I'
```

```
group by rasecc, racomp1, ramode,racali,racolo
```

```
order by rasecc, racomp1, ramode, racali, racolo;
```

```
insert into mit3.ComparativoMovimientos
```

```
select 2007 as Ano, 'I' as Campana, rasecc, racomp1, ramode, racali, racolo, (select
```

```
sum(edun01+edun02+edun03+edun04+edun05+edun06+edun07+edun08+edun09+edun10+edun11) from hci2007.dentprov where edsecc=rasecc
```

```
and edmode=ramode and edcali=racali and edcodc=racolo ) as TotalCompra,
```

```
sum(rafacu) as TotalFacturado, sum(ravenu) as TotalVental
```

```
from ici2007.sz_artre0
```

```
where ratien < 7000 and rats ='I'
```

```
group by rasecc, racomp1, ramode,racali,racolo
```

```
order by rasecc, racomp1, ramode, racali, racolo;
```

```
-- FECHAS DE ENTRADA EN SALDO
```

```

drop table mit3.SaldoporPais;

create table mit3.SaldoporPais(AnoCamp integer, Campana char(1), Pais integer, AnoSaldo integer,
SemanaSaldo integer);

alter table mit3.SaldoporPais add primary key(AnoCamp, Campana, Pais);

-- select * from mit3.SaldoporPais

insert into mit3.SaldoporPais
select distinct afanoc, afcamp, afpais, afanis, week(cast(concat(concat(afanis,concat('-
',concat(afmeis,'-'))),
        afdiis) as date)) as semanasaldo
        from comun.afcampa where afanoc >= 2006 and afmarc='Z' and afanis <> 9999
group by afanoc, afcamp, afpais, afanis, afmeis, afdiis
order by afanoc, afcamp, afanis, semanasaldo;

-- HISTORIAL DE ENTRADAS

drop table mit3.Entrada;

create table mit3.Entrada(ano integer, campana char(1), seccion integer, pedido integer, modelo
integer, calidad integer,
        color integer,semana integer, numentrada integer, entrada integer);

alter table mit3.Entrada add primary
key(ano,campana,seccion,pedido,modelo,calidad,color,semana,numentrada, entrada);

-- select * from mit3.Entrada

insert into mit3.Entrada
select distinct 2007 as Ano, edcamp, edsecc, edmode, edcali, edcodc,
week(cast(concat(concat(edanoe,concat('-',concat(edmese,'-'))),
        eddiae) as date)) as semana,
sum(edun01+edun02+edun03+edun04+edun05+edun06+edun07+edun08+edun09+edun10+edu
n11) as entrada
        from hci2007.dentprov
group by edcamp,edsecc,edmode,edcali,edcodc,edanoe,edmese,eddiae

```

order by edcamp,edsecc,edmode,edcali,edcodc,semana;

*/

/* ##### PROCEDIMIENTOS ##### */

/* PARA EXPORTAR A EXCEL

```
@export on;
@export set BinaryFormat="Size"
CsvColumnDelimiter=";"
CsvIncludeColumnHeader="true"
CsvIncludeSQLCommand="false"
CsvRemoveNewlines="false"
CsvRowCommentIdentifier=""
CsvRowDelimiter="\r\n"
DateFormat="yyyy-MM-dd"
DecimalNumberFormat="Unformatted"
Destination="File"
Encoding="IBM00858"
ExcelIncludeColumnHeader="true"
ExcelIncludeSQLCommand="false"
ExcelIntroText=""
ExcelTextOnly="false"
ExcelTitle="DbVisualizer export output"
Filename="C:\DATOS_CONSTVP.csv"
Format="CSV"
HtmlIncludeSQLCommand="false"
HtmlIntroText=""
HtmlTitle="DbVisualizer export output"
```

```
NumberFormat="Unformatted"
QuoteTextData="ANSI"
ShowNullAs="(null)"
SqlIncludeCreateDDL="false"
SqlIncludeSqlCommand="false"
SqlRowCommentIdentifier="--"
SqlSeparator=";"
TimeFormat="HH:mm:ss"
TimeStampFormat="Unformatted"
XmlIncludeSqlCommand="false"
XmlIntroText=""
XmlStyle="DbVisualizer";

select * from mit3.constanteventaperdida;
*/
```

```
/*
```

```
-- Generar SQL
-- Versión: V5R4M0 060210
-- Generado en: 18/09/08 16:18:18
-- Base de datos relacional: S44C0600
-- Opción de estándares: DB2 UDB iSeries
```

```
SET PATH "QSYS","QSYS2","MIT3" ;
```

```
CREATE PROCEDURE MIT3.SP_PERIODOS_POR_SEMANA ()
LANGUAGE SQL
SPECIFIC MIT3.SP_PERIODOS_POR_SEMANA
```

```
NOT DETERMINISTIC
MODIFIES SQL DATA
CALLED ON NULL INPUT
SET OPTION ALWBLK = *ALLREAD ,
ALWCPYDTA = *OPTIMIZE ,
COMMIT = *NONE ,
DECRESULT = (31, 31, 00) ,
DFTRDBCOL = *NONE ,
DYNDFTCOL = *NO ,
DYNUSRPRF = *USER ,
SRTSEQ = *HEX
BEGIN
```

```
DECLARE V_SECCION INTEGER ;
```

```
DECLARE V_SEMANA INTEGER ;
```

```
DECLARE V_MODELO INTEGER ;
```

```
DECLARE V_CALIDAD INTEGER ;
```

```
DECLARE V_COLOR INTEGER ;
```

```
DECLARE V_PERIODO INTEGER ;
```

```
DECLARE V_SECCION_OLD INTEGER DEFAULT - 1 ;
```

```
DECLARE V_MODELO_OLD INTEGER DEFAULT - 1 ;
```

DECLARE V_CALIDAD_OLD INTEGER DEFAULT - 1 ;

DECLARE V_COLOR_OLD INTEGER DEFAULT - 1 ;

DECLARE V_PERIODO_OLD INTEGER DEFAULT - 99 ;

DECLARE ENDTABLE INT DEFAULT 0 ;

DECLARE CURSOR_PRUEBA CURSOR FOR

SELECT SECCION , MODELO , CALIDAD , COLOR, SEMANA , PERIODO

FROM MIT3 . HISTORICOFACTURACION

ORDER BY SECCION , MODELO , CALIDAD , COLOR , ANO, SEMANA

FOR UPDATE OF PERIODO ;

DECLARE CONTINUE HANDLER FOR NOT FOUND

SET ENDTABLE = 1 ;

DECLARE EXIT HANDLER FOR SQLEXCEPTION

SET ENDTABLE = 0 ;

OPEN CURSOR_PRUEBA ;

FETCH CURSOR_PRUEBA


```
        INTO V_SECCION , V_MODELO , V_CALIDAD , V_COLOR , V_SEMANA ,  
V_PERIODO ;
```

```
WHILE ENDTABLE = 0 DO
```

```
IF (
```

```
V_SECCION_OLD <> V_SECCION OR
```

```
V_MODELO_OLD <> V_MODELO OR
```

```
V_CALIDAD_OLD <> V_CALIDAD OR
```

```
V_COLOR_OLD <> V_COLOR
```

```
) THEN
```

```
    SET V_PERIODO_OLD = 1 ;
```

```
END IF ;
```

```
IF ( V_PERIODO = - 99 ) THEN
```

```
    UPDATE MIT3 . HISTORICOFACTURACION
```

```
    SET PERIODO = V_PERIODO_OLD
```

```
    WHERE CURRENT OF CURSOR_PRUEBA ;
```

```

SET V_PERIODO_OLD = V_PERIODO_OLD + 1 ;

END IF ;

SET V_SECCION_OLD = V_SECCION ;

SET V_MODELO_OLD = V_MODELO ;

SET V_CALIDAD_OLD = V_CALIDAD ;

SET V_COLOR_OLD = V_COLOR ;

FETCH CURSOR_PRUEBA

    INTO V_SECCION , V_MODELO , V_CALIDAD , V_COLOR , V_SEMANA ,
V_PERIODO ;

END WHILE ;

CLOSE CURSOR_PRUEBA ;

END ;

-- Generar SQL
-- Versión: V5R4M0 060210
-- Generado en: 18/09/08 16:18:18
-- Base de datos relacional: S44C0600
-- Opción de estándares: DB2 UDB iSeries

```

```

SET PATH "QSYS","QSYS2","MIT3" ;

CREATE PROCEDURE MIT3.SP_SERIES ( )
  LANGUAGE SQL
  SPECIFIC MIT3.SP_SERIES
  NOT DETERMINISTIC
  MODIFIES SQL DATA
  CALLED ON NULL INPUT
  SET OPTION ALWBLK = *ALLREAD ,
  ALWCPYDTA = *OPTIMIZE ,
  COMMIT = *NONE ,
  DECRESULT = (31, 31, 00) ,
  DFTRDBCOL = *NONE ,
  DYNDFTCOL = *NO ,
  DYNUSRPRF = *USER ,
  SRTSEQ = *HEX
  BEGIN

  DECLARE V_CAMPANA CHAR(1) ;

  DECLARE V_SECCION INTEGER ;

  DECLARE V_CATEGORIA INTEGER ;

  DECLARE V_PERIODO INTEGER ;

  DECLARE V_SERIE INTEGER;

  DECLARE V_MAX_SERIES INTEGER;

  DECLARE V_COUNTER INTEGER;

```

```

DECLARE V_COUNTER2 INTEGER;
DECLARE V_COUNTER_AGRUPACIONES INTEGER;

DECLARE CURSOR_PRUEBA CURSOR FOR

SELECT ceiling(max(PERIODO) / 2)
as MAX_SERIES

FROM MIT3 . HISTORICOFACTURACION
;
DECLARE GLOBAL TEMPORARY TABLE SESSION.TMP_AGRUPACIONES ( periodo
INTEGER) ON COMMIT PRESERVE ROWS;

OPEN CURSOR_PRUEBA ;

FETCH CURSOR_PRUEBA

INTO V_MAX_SERIES ;

SET V_COUNTER = 1;
WHILE V_COUNTER <= V_MAX_SERIES
DO
    SET V_COUNTER2 = 1;
    SET V_COUNTER_AGRUPACIONES = 1;
    WHILE V_COUNTER2 <= V_MAX_SERIES * 2
    DO
        INSERT INTO SESSION.TMP_AGRUPACIONES VALUES (V_COUNTER2);
        IF MOD(V_COUNTER2, V_COUNTER) = 0 then

UPDATE MIT3 . HISTORICOFACTURACION SET AGRUPACION =
V_COUNTER_AGRUPACIONES

```

```

        where periodo in (select periodo from
SESSION.TMP_AGRUPACIONES);
DELETE FROM SESSION.TMP_AGRUPACIONES;
insert into mit3.CaracteristicaPeriodo (campana, seccion, categoria, serie, agrupacion,
TotalFacturado)
select campana, seccion, categoria, V_COUNTER as serie, V_COUNTER_AGRUPACIONES
as agrupacion,
sum(facturado)
from mit3.HistoricoFacturacion
where agrupacion = V_COUNTER_AGRUPACIONES
group by campana, seccion, categoria
order by campana, seccion, categoria;
SET V_COUNTER_AGRUPACIONES = V_COUNTER_AGRUPACIONES +1;
END IF;
SET V_COUNTER2 = V_COUNTER2 +1;
END WHILE;
SET V_COUNTER = V_COUNTER +1;
END WHILE;

select campana, seccion, categoria, sum(facturado)

from mit3.HistoricoFacturacion
group by campana, seccion, categoria
order by campana, seccion, categoria

CLOSE CURSOR_PRUEBA ;

END ;
*/

```