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Supply Chain Management in the Fashion Retail Industry: a multi-method approach for the optimisation of performances

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Cinderella is the proof that a new pair of shoes can change your life

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se sono arrivata a questo traguardo è anche merito vostro!!!

Abstract

Fashion and Apparel Supply Chains work in a very fast-changing environment always demanding better quality, higher availability of products, broader assortments and shorter delivery times. Then, an efficient Supply Chain Management can make the difference between success or failure in the market. In this context, this thesis analyses the characteristics of this particular industry at different levels. Starting from the analysis of the whole Supply Chain, aimed at identifying the most critical areas and processes, this work proposes a reference framework for the definition and subsequent optimisation of the physical and informative flows. The model also includes all the cost and revenue items connected to the processes which are characteristic of a Fashion Supply Chain working with a wide network of direct-operated or franchising mono-brand stores. In recent years, the traditional model, only based on a brick & mortar business, has been overcome due to the wide spread of e-commerce. This evolution forced companies to adopt a new integrated strategy, called Omni-Channel Retailing, in order to meet customers requests and offer a wider product selection. With these perspectives, the framework has been revised and extended in order to represent no longer only the physical network but also the mobile purchasing paths and allow us to evaluate how this new integrated strategy may impact on the performances of a traditional Supply Chain. From all these analysis it emerged that the most critical process for a company operating in this sector, is the Replenishment process, i.e. the definition of the delivery times and quantities from the central warehouse to the whole network of stores and clients. An heuristic optimisation method, called the Bees Algorithm, was adopted to solve this problem and, together with the reference framework, represents a useful Decision Support System for fashion companies in the definition of the purchasing quantities and operations plans well ahead of the sales season.

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Introduction

"Do you think your industry is tough? Imagine customer preferences that can shift literally overnight, product lifecycles measured in weeks, and the value of your product plummeting if you miss the latest trend. Welcome to the world of fast fashion" [Sull and Turconi, 2008]

The previous statement perfectly summarises the main challenges that managers operating in this field have to face every day. The Fashion and Apparel Industry is, in fact, one of the key pillars of the global economy, but it also represents one of the most flexible and unpredictable Industries, given the high volatility of demand and fast changes in customer tastes and trends. Until the late 1980s, traditional fashion and apparel retailers used demand forecasting for the definition of their operations plans long before the actual time of product consumption, i.e. the sales season. In the last decades, though, this sector experienced a real revolution due to the introduction of the "Fast Fashion" model and to the widespread of e-commerce retail sales. The term "Fast Fashion" describes the retail strategy of adapting merchandise assortments to current and emerging trends as quickly and effectively as possible. Even if this concept is now mostly associated with large retailers as Zara and H&M, one of the first brands adopting this strategy well before the term was coined, was the Italian Benetton. This company gave birth to an innovative organisation of the production process which directly followed market demand, allowing them to promptly satisfy customer request, with

an immediate response even to sudden increases in demand, thank to a flexible, coordinated and integrated production. Fast fashion retailers have, in fact, replaced the traditional push model – in which the strategy is based on the prediction of upcoming trends by designers – with an opportunity pull approach, in which retailers respond to customer demand trying to get the right product in the market within just a few weeks, versus an industry average of six months [Hansson, 2011].
Besides this deep change in the management model, the whole Retail business - not only the Fashion and Apparel one - is now facing a new tremendous challenge: surviving in a model that includes the Internet [Shoenbachler and Gordon, 2002]. As online purchasing is continuing to grow, the future of pure brick-and-mortar retailers is called into question. Despite physical stores still remain at the heart of the customer relationship, in fact, online and mobile sales appear to rule [Brown et al., 2013]. Then, in the last decade, the major retailing company are converging towards the "Omni-Channel" strategy, i.e. a synchronized operating model in which all company's channels - traditional stores and mobile channels - are aligned, allowing companies to meet customers' requirements and to be more competitive. In other words, connected customers can shop for and purchase the same items across many different channels: in a physical store, on their home or laptop computers, on their connected mobile devices. This allows them to shop online for virtually anything, virtually everywhere [Solutions, 2012].
In this complex and dynamic context, the present thesis has the main aim of proposing a tool to support companies of this sector in the decision making process of definition of the operations plans long before the beginning of the sales season. The research work is organised as follows. Chapter 1 gives an overview of the main challenges of a typical demand-driven Supply Chain in the Fashion Retail Industry, focusing on the characteristics of products and market, and introducing the Fast Fashion and Quick Response Models. In Chapter 2, after the definition of the process flow, from the design of the clothing item to its introduction in the market, a detailed Risk Analysis allowed us to identify the most critical areas and processes, and the main

target that managers try to perceive. In particular, it emerged that main aim of fashion business is the correct *Time Management*, intended as the ability of being responsive to market fluctuation. To perceive this goal, the *Replenishment* was identified as the most crucial process when managing an extended network of direct-operated or franchising mono-brand stores. The problem of allocating inventory from a central warehouse to several locations satisfying separate demand streams is, in fact, principally aimed at dynamically optimizing stores assortment, trying to ensure high product availability and to minimize overstock or out of stock events.

Those two problems are separately faced. The *Time Management* is analysed in Chapters 3, 4 and 5 by proposing a framework for the optimisation of performances for the traditional pure brick-and-mortar case, and then for the Omnichannel strategy. In particular, Chapter 3 describes the conceptual framework, in Chapter 4 the simulation model is defined and the results are analysed, while Chapter 5 evaluates the impact that the adoption of this new integrated strategy may have on a traditional Supply Chain. In the end, in Chapter 6, a heuristic optimisation algorithm, called the Bees algorithm, is adopted to solve the *Replenishment* problem.

Chapter 1

Fashion and Apparel Industry: Supply Chain Characteristics and Challenges

Contents

1.1 Introduction

Fashion can be seen as the point where the material product, in the form of clothes, meets the immaterial aspect of what looks good at a given point in time. In other words, there is the physical part of the product, that is a garment, which is enriched by symbolic and immaterial value resulting in fashion. One of the main issue is its volatile nature: to be defined "fashion" it must change [Aagerup, 2011]. This peculiarity makes the Fashion and Apparel industry a very dynamic sector, subject to constant and quick changes thus making time a crucial variable within competition. In addition, volatile markets and unpredictable demand are leading to the adoption of specific Supply Chain models which try to manage the complexity in this sector. In this complex context, the main challenge is gaining value through supply chain management, allowing to respond quickly, efficiently and with flexibility to demand fluctuations [Battista and Schiraldi, 2013]. This obviously requires [Masson et al., 2007]:

- *market sensitivity*, which guarantees connection to the customer and capacity to capture trends as they emerge;
- *integration with all the other Supply Chain actors* sharing real-time demand data;
- *process alignment*, both within the company and externally with upstream and downstream partners.

This Chapter, then, describes the main characteristics and challenges of this particular industry analysing customers, products segmentation and Supply Chain models and drivers.

1.2 Complexity of the fashion world

The Fashion and Apparel Industry represents a particular example of the manufacturing Industry and shows several characteristics that make it difficult to manage its productive and logistic process using traditional methods. In particular, three main issues were identified for this sector [Christopher et al., 2004]:

- *Short Product Life Cycles*: the product is designed to capture the mood of the moment, then, compared to other markets, fashion sales trend has a rapid growth, a peak of popularity and immediately a stage of decline or even rejection of the product by the market (Figure 1.1).

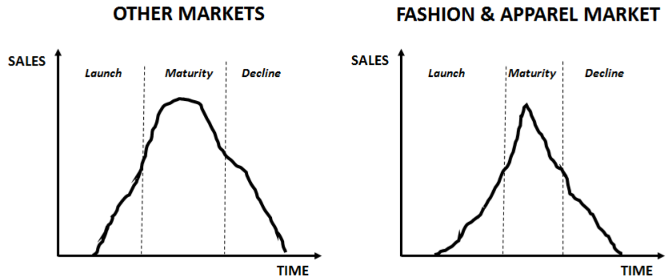


Figure 1.1: Product lifecycle in the fashion industry compared to other markets [Bandinelli et al., 2011]

Since products have a limited time in the market from their introduction to decline, retailers have to be more efficient in the replenishment process [Barnes, 2009].

- *Unpredictable and Volatile Demand*, since it is driven by extremely unstable phenomena, such as weather, movies, sports, etc. Consumer demand could, in fact, completely change in a short time range because an increasing star leads a new fashion trend [Wang et al., 2012b], then nobody can ever tell if a fashion item will be successful on the market;

- *Impulsive Purchasing Behaviour*: given the fickle nature of fashion shoppers and the impulsiveness that surrounds their purchase behaviour, retailers have to arrange layouts and displays items in an appropriate way in order to manipulate purchasing decisions [Newman and Foxall, 2003]. These considerations point out the need to ensure high availability, not only in terms of product range but also in terms of sizes and colours.

Other characteristics highlighted by several studies in this sector are:

- *Extremely Wide Product Variety* [Vaagen and Wallace, 2008]: it comes to thousands of Stock Keeping Units (SKUs) considering variety of sizes and colours, then production lines have to manage highly variable small batches [De Carlo et al., 2013];

- *Demand-Driven Supply Chains* [Walters, 2006]: in recent years, consumer expectation has increased asking for speed, variety and style at low prices;

- *Long and Complex Supply Chains*, which often include suppliers located in several different Countries [Bruce et al., 2007]. In fact, offshore transfer of the labor intensive stages of the supply chain to low-cost countries, has been one of the favourite options of companies in the industrialised countries to offset some of the risks in the volatile world of fashion [Fernie and Azuma, 2004]. This contributes to highly increase lead time even reducing labor cost;

- *Long time-to-market*, there is almost a year lapse from the definition of the clothing item to the delivery to the stores. Table 1.1 shows an example of a Gantt chart for the production and supply process in the winter season and highlights that the development of the collection starts in October while the first sales in the stores are recorded in the following September. It means that wholesalers and stores define their orders before the previous season is over and therefore the level of unsold stocks is not known yet [Forza and Vinelli, 2000] thus contributing to enlarge demand uncertainty [Tiaojun and Jiao, 2011];

- *New Product Development (NPD) Process is long and not always successful.* This activity usually begins two years before production [Bandinelli et al., 2013] and not all items that come out from this process are introduced into the market. The process is difficult to standardise and control thus generating costs of development and prototyping that cannot be recovered by sales. In fact, pattern book only represents the collection idea but items which are not successful during presentation will not be produced.

From all these considerations, it becomes clear that non-value added phases represent an important part of the production process, making logistic costs significantly impact on the total cost of products. If this cannot be a critical issue for companies working in the luxury market, given the

Table 1.1: Example of a Gantt Chart for the Production and Supply Process in the Fall/Winter Season

Steps/Months	**10**	**11**	**12**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**1**	**2**	**3**
Development of collection	■	■	■	■	■													
Presentation			■	■	■													
Sales to wholesalers			■	■	■	■	■											
Raw material purchasing					■	■	■	■	■	■	■							
Production					■	■	■	■	■	■	■							
Deliveries to stores									■	■	■	■						
Selling Season												■	■	■	■	■	■	■

very high contribution margins that they can achieve, for large mass productions, instead, these costs may critically affect on profits, defining company's economic success or failure.

1.3 Market segmentation

Given its great size, the Clothing Retail Industry can be internally divided into several segments according to different variables. One of the most commonly used criteria for differentiating market and customers is the price. According to this, we can distinguish [Bandinelli et al., 2014]:

- *Haute Couture*: are luxurious clothing items, tailored for each customer and made of fine craftsmanship garments. Customers buy haute couture for the emotional value of having an exclusive designer's name [Kim and Mauborgne, 1998];

- *Pret-à-porter* (ready to wear): it represents the transition from handicraft tailoring to industrialization and includes prestigious brands and their core collections;

- *Diffusion*: it is defined by a high qualitative level and a medium stylistic content. Through the development of these lines, luxury brands created the so-called "massclusivity" phenomenon [Zegheanu, 2013], which is a category of mass market consumers who feel they are purchasing something special for a price slightly higher than the high street;

- *Bridge*: while maintaining some stylistic content, products of this segment have prices affordable to most people;
- *Mass Market*: it targets a wide range of consumers and is constantly growing. It is defined by non exclusive items with low prices and low stylistic content.

From a consumer perspective, in addition to gender and age, we can distinguish the following segments [Richards and Sturman, 1977, Corporation, 2010, Jackson and Shaw, 2009] :

- *Conservative*: shoppers who prefer a more traditional look, buying products that will wear well and last in terms of style and durability;
- *Fashion Forward*: consumers who are looking for the newest trends and styles;
- *Comfort Seekers*: costumers who seek value and comfort rather than fashion;
- *Brand-Conscious*: consumers who are very likely to wear current-vogue branded merchandise;
- *Price oriented*: costumers who look for low cost clothing items regardless of the brand and the fashion content.

It is clear that companies have to clearly choose their target market, in terms of customers and products, to consequently define the best business strategy.

1.4 Demand Driven Supply Chains

A traditional Supply Chain in the Fashion Industry (Fig. 1.2) involves [Coraggia, 2009]:

- *Fibres suppliers*: they represent the first ring of the chain. The fibre is the smallest component of fabrics and gives them color and weight;

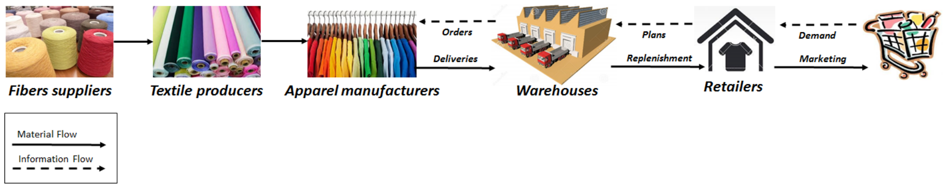


Figure 1.2: A traditional Supply Chain in the Fashion Industry

- *Textile producers*: they prepare different types of raw materials for further processing in order to obtain yarns, fabrics and textiles;

- *Apparel manufacturers*: they perform activities as cutting and sewing in order to tailor the final clothing items;

- *Warehouses*: they have the main purpose of receiving final products from suppliers, often located in far away countries, and distribute them to stores and clients according to their specific orders;

- *Retailers*: they represent the final ring of the supply chain and sell clothing items to final customers trying to satisfy their demand.

Given the characteristics of market and products, these value chains cannot simply follow a static traditional model. According to Fisher [1997], in fact, products can be divided into two main categories: either primarily functional or primarily innovative. While functional products, such as grocery, normally do not change quickly over time and have a stable and predictable demand, innovative products, like fashion apparel, are characterized by newness, greater variety [Vaagen and Wallace, 2008] and customisation [De Felice et al., 2012] which needs low production volumes [De Carlo et al., 2013] and flexibility and makes demand unpredictable [Wang et al., 2012b]. In addition, their life cycle is short [Barnes, 2009], because as imitators erode the competition advantage that innovative products enjoy, companies are forced to introduce a steady stream of newer innovations. With these peculiarities, Fashion & Apparel products require a fundamentally different Supply Chain than do stable, functional products. While an efficient Supply Chain strategy with focus on cost minimization should be used for functional products, a responsive/demand driven strategy with focus on products availability, matching the marketplace with customer demands, could best fit innovative products [Lam and Postle, 2006]. A demand driven Supply Chain involves transforming the traditional chain configuration into an integrated multitier supply network, eliminating information latency. This may reduce operating costs and improve profitability and customer service [Gupta et al., 2015] thank to a real-time information sharing on demand and inventory levels. Through a demand driven approach, that enables companies to react quickly and effectively when unexpected changes arises [Budd et al., 2012], it is possible to:

- improve fill rates and reduce out of stocks thus increasing revenues and recoverable sales;
- reduce inventory levels as demand uncertainty is reduced by the reduction in information latency;
- reduce supply disruptions thank to real-time visibility to the complete demand/supply situation.

In this context, both Lean and Agile models must be introduced in order to improve supply chain management performances. These two models, whose characteristics are summarised in Table 1.2, allow managing the request for speed and efficiency whilst responding with flexibility to demand fluctuations [Battista and Schiraldi, 2013]. With the term "Lean" we mean a supply chain able to meet strict requirements in terms of delivery times, order completeness and accuracy [Bruce et al., 2007], working on forecasts and inventory-focused information exchange. On the other hand, an "Agile" Supply Chain is able to thrive in an environment of rapid and unpredictable changes and to respond to actual changes in demand [Christopher et al., 2004]. An hybrid strategy, then, may take one of several approaches [Digest, 2006]:

- Using make-to-stock/lean strategies for high volume, stable demand products, and make-to-order/agile for everything else;
- Have flexible production capacity to meet surges in demand or unexpected requirements;

Table 1.2: Comparison between Lean and Agile Supply Chain models [Bhatia, 2014]

	Lean	***Agile***
Products	Functional	Innovative
Demand	Predictable	Volatile
Product life cycle	Long	Short
Product Variety	Low	High
Customer drivers	Cost	Assortment
Forecast approach	Calculative	Consultative

- Use of postponement strategies, where "platform" products are made to forecast, and then final assembly and configuration done upon final customer.

1.5 The growth of Quick Response and Fast Fashion

To respond to all the issues illustrated in the previous paragraphs, since the 1980s various management techniques, specific for the fashion and clothing industry have arisen. The increasing demand for fashion products instead of basic/classic ones, the increasing number of mid-season collections in order to expand product offer and the introduction of techniques that allow the reduction of lead Time [Fairhurst and Bhardwaj, 2010], such as *Quick Response* (QR) and *Fast Fashion* (FF), deeply changed this sector.
These new management models clearly differ from the traditional one which is based on planned manufacturing (Figure 1.3). It lies in producing according to orders received during the presentation of collection ("Orders in Hand"), before the sales season. This traditional management model involves a single collection for the whole season and it is still widely employed by luxury brands because the high stylistic and material content of the clothing items requires to produce almost exclusively based on consolidated orders.

Quick Response and Fast Fashion instead, try to respond much more quickly to market needs by planning production on the effective demand

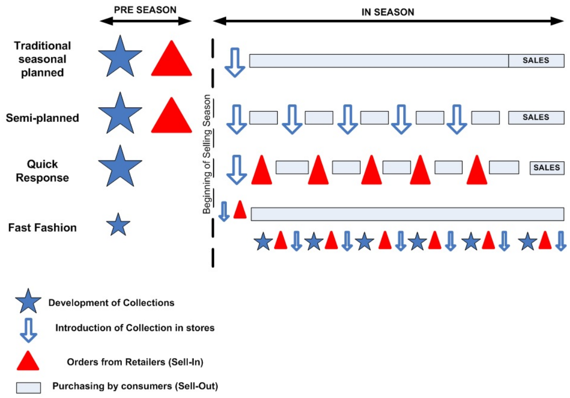


Figure 1.3: Quick Response and Fast Fashion compared to the traditional management approach [HermesLab, 2009]

recorded in stores.

Quick Response was firstly introduced in the US in the 1980s to speed up the response time across the supply chain from a customer choosing a fashion item to its replenishment in the stores [Fernie, 1994]. Its total application involves on-line electronic communication of sales data from retailers to merchandise vendors and the prompt supply of goods needed to return the inventory to previously defined levels [Fiorito et al., 1995]. This method provides several competitive advantages for all supply chain's actors [Birtwistle et al., 2006]. From retailer's point of view, Quick Response systems, through collaborative partnership with the suppliers, allow the reduction of inventories, buying mistakes and lead time thus lowering costs and improving profitability [Birtwistle et al., 2007]. Quick Response is not only used in the Fashion & Apparel sector but, since it is particularly suitable to market with high volatile demand, long replenishment lead time and short life cycle products, it is crucially important also in industries such as consumer electronics and toys [Sethi and Tsan-Ming, 2010].

The development of Fast Fashion in the 1990s and its wide use, lead to overcoming the concept of "season" through the continuous increase of number of annual collections to be presented to customers and delivered to the Point of Sales (POS). This is possible only thank to a rapid reaction to market impulses, very short product life cycles, continuous assortment renewal, fast

inventory turnover in the stores as well as affordable processes and attractive design [Scozzese, 2012]. In other words Fast Fashion systems combine short production and distribution lead times with highly fashionable products [Cachon and Swinney, 2009].
Other models that try to combine the classical planned manufacturing with Fast Fashion systems are called "semi-planned". In the most common case, this process involves two biannual collections integrated with "fast" production and several replenishments during the selling season with the purpose of increasing customer satisfaction [Giancola, 1999].
It is clear that organizational solutions of the supply chain are not restricted to those previously described, but there are a multitude of hybrid solutions used in current practice which try to achieve economic efficiency. In fact typically, neither Fast Fashion or planned manufacturing applies to the whole product range in stores; nearly 80% of goods may be core and basic lines managed in the traditional manner, with fast fashion accounting for up to 20% with high fashionable items or "capsule collections".

1.6 Conclusions

Effective management to achieve competitive advantages includes the ability to manage a complex network as a whole. In the particular context of the fashion industry, the operational strategy consists of ordering, well in advance, a large number of different references, each having a relatively short life cycle of only a few weeks. However, on the contrary, a fashion supply chain must respond quickly to market changes in order to meet customers requests and increase profitability. These opposing requirements, force the management to face several decision making problems in order to find the best definition and mix of all the variables, such as the definition of the Seasonal Budget, the selection of the items composing the collection, the choice of the quantities to be purchased etc., with the aim of maximising profits and customer satisfaction. In this context, next chapter will analyse into detail the whole traditional fashion supply chain focusing on the identification of the main possible risk factors. This study will allow us to identify critical areas that will be better analysed following.

Chapter 2

Supply Chain Risk Assessment: Understanding main targets and critical areas

Contents

2.1 Introduction

According to the United States Fashion Industry Association [Sheng, 2014], the second top ranked fashion industry challenge is "managing supply chain risks" immediately after "increasing production or sourcing costs".
The increasing trend towards globalization and outsourcing is, in fact, leading many industrial sectors to entrust relevant parts of their business to suppliers often located in developing countries. This phenomenon is causing loss of control and of full visibility of the supply chains, thus increasing risks connected to any possible changes or disruptions.
In the highly dynamic context of the Fashion and Apparel Industry, the proper assessment and management of the supply chain risks can be crucial for its efficiency. For example, due to the adoption of traditional long-term demand forecasts, any change or fluctuation may lead to over-stock – producing excessive quantities that quickly become obsolete or out of fashion – or stock-out – undersizing actual sales volume resulting in an image damage and lost sales. Another possible risk is given by the off-shoring trend which, from one side, ensures a substantial cost advantage but from the other, contributes to lengthen geographical distances and lead-time. This leads to the extension of replenishment times and consequently to the difficulty of quickly respond to any delay along the chain or change in market demand.
Despite fashion retail is receiving increasing researcher's attention, in particular concerning supply chain management [Ngai et al., 2014, Iannone et al., 2015, Brun et al., 2008], literature does not show relevant studies related to risk assessment and management. Only few works have been proposed in last few years:

- Venkatesh et al. [2015] use the Interpretative Structural Modelling (ISM) to establish the interdependencies between the risks associated to the apparel retail supply chains in India;

- Shen et al. [2014] and Chiu and Choi [2013] only focus on the financial aspect of risk management;

- Khan [2013], through a case study, explores how design is used as a strategic tool for managing risks in fashion retail;

- Xiaofen and Wei [2012] identify four main risk areas related to external environment, customer and suppliers cooperation and to the enterprise itself;

- Liljander et al. [2009] relate product quality to functional and financial risks which cause a reduction in store brand value;

- Aghekyan-Simonian et al. [2012] analyse the perceived risks connected to online purchases which are mainly related to brand image and online store image;

- Chen and Xiao [2015] evaluate how the entity of the disruption risk influence outsourcing strategies.

Other research works, then, analyse risks connected to outsourcing [Hon Kam et al., 2011], risks related to social and environmental aspects [Freise and Seuring, 2015] or risks that a company may encounter when implementing green initiatives [Wang et al., 2012b].
It is clear that none of them proposes a detailed and structured analysis of the main risk factors connected to each supply chain process. Then, based on these considerations, this chapter wants to fulfil this gap and try to identify the main risk factors connected to each process and to each objective of a typical Fashion supply chain, by defining a complete and general map. Then, thank to a deep analysis of both current practice and literature, and through the use of the Analytic Network Process (ANP) approach, a priority list is defined. In this list the most crucial area on which to focus the attention for further analysis are identified.

2.2 Risk sources

The term "risk" refers to the possible occurrence of a negative event, i.e. an adverse deviation from a foreseen situation [Borghesi and Timidei, 1998]. It is clear, then, that risk sources do not exclusively reside in the effects of external events, such as legal restrictions or natural disasters, but also in the impact of internal changes of strategies, business models and interaction with the actors of the supply network [Tang, 2006].
To assess a company's risk profile, it is useful to highlight the main risk sources within the supply chain. They can be grouped into five categories, as shown in Figure 2.1 [Mason-Jones and Towill, 1998, Christopher and Peck, 2004]:

1. *Risk external to the main company and internal to the Supply Chain*
   a) *Supply Risk*: includes those elements disturbing material and information flow between main company and upstream enterprises [Zsidin, 2003]. It depends on the structure of the supply network since risks increase if the company is dependent from few key suppliers, if it works in a global sourcing perspective, etc.;
   b) *Demand Risk*: includes any possible interference to the material and information flow between central company and the market, across all the other enterprises between them [Svensson, 2002]. Typical risks are connected to the volatility of demand or bullwhip effect.
2. *Risk internal to the main company and to the Supply Chain*
   a) *Process Risk*: the term "process" refers to the sequence of managerial and value added activities internal to the company. These processes are directly dependent on company's assets and on reliability of transports and communications. The risk is then connected to the interruption of these processes;
   b) *Control Risk*: control systems are the set of procedures that rule the processes and the relationships with other network's actors.

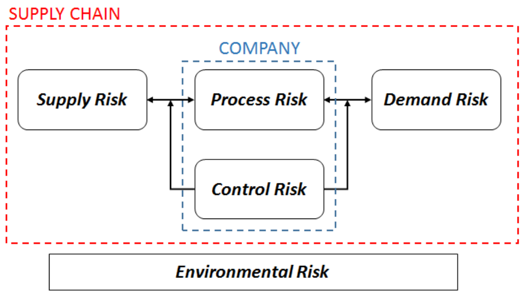


Figure 2.1: Risk sources in the Supply Chain

This risk is internal to the company and related to procurement, production or inventory policies.

3. *Risk external to the Supply Chain*

   a) *Environmental Risk*: is related to external factors which result from economic, socio-political, technological or natural events.

It is important for managers to understand that the risk profile is directly influenced by strategic decisions. Therefore, rather than catalogue every possible risk, the first step of a proper risk management is the analysis of internal processes in order to isolate most critical and relevant weakness factors. After that, it is possible to monitor external environment in order to detect warning signs and, consequently, develop mitigation plans or alternative strategies. Main purpose is to strengthen the "resilience" of the operational structure, which is the ability to quickly recover after an adverse event which disturbs or interrupts the normal activity of the supply chain.

2.3 Research Methodology

Main purpose of this chapter is to assess and prioritize the main risk factors related to each working phase of a fashion company, in order to the identify the most critical area that will be better analysed later in this thesis.
Operational risk is defined as "the risk of loss resulting from inadequate

or failed internal processes, people and systems or from external events" [on Banking Supervision, 2004]. Then, in this context, the Analytic Network Process (ANP) approach [Saaty and Vargas, 2006] was adopted as a tool for risk prioritization based on experts' decision. The ANP represents a generalization of the Analytic Hierarchy Process (AHP) [Saaty, 2001]. Many decision problems, in fact, can not be hierarchically structured because they involve interactions and interdependencies of several elements at different levels. The applied method, through a network-decision structure and not a simple hierarchy, can handle complex problems providing an easy and accurate way to analyse tangible and intangible factors. This part of the research work was conducted in cooperation with a team of experts composed by 12 managers from 6 different companies operating in the Italian Fashion and Apparel Industry. In particular, the team of experts involves: 3 CEOs, 3 purchasing managers, 3 marketing and sales managers, 1 product development managers, 2 planning and scheduling managers. In addition, the study is supported by a deep literature analysis involving more than 60 papers from the most important journals dealing with the topics of supply chain risk management, retailing and operations management in the Fashion and Apparel Industry (e.g. *Int. J. of Production Economics, J. of Retailing and Consumer Service, European J. of Operational Research, Int. J. of Logistics Management*, etc.).
The process flow of the adopted methodology is shown in Figure 2.2.

In order to better understand the context and the problem, first step of the work was the *Process Analysis* (ref. section 2.3.1) also including material and informative flows typical of a fashion retail supply chain.
The second step, where the ANP approach starts, is represented by the *Main targets identifications* (ref. section 2.3.2), for the selection of the focus and of the overall objectives of the entire supply chain.
Thank to the results coming from these first two steps, we were able to break this complex system into its constituent parts and to perform the *Risk factors identification* step (ref. section 2.3.3). More than 90 risk factors were identified and classified according to both targets and processes. Given the high number and according to ANP approach, all the risk factors

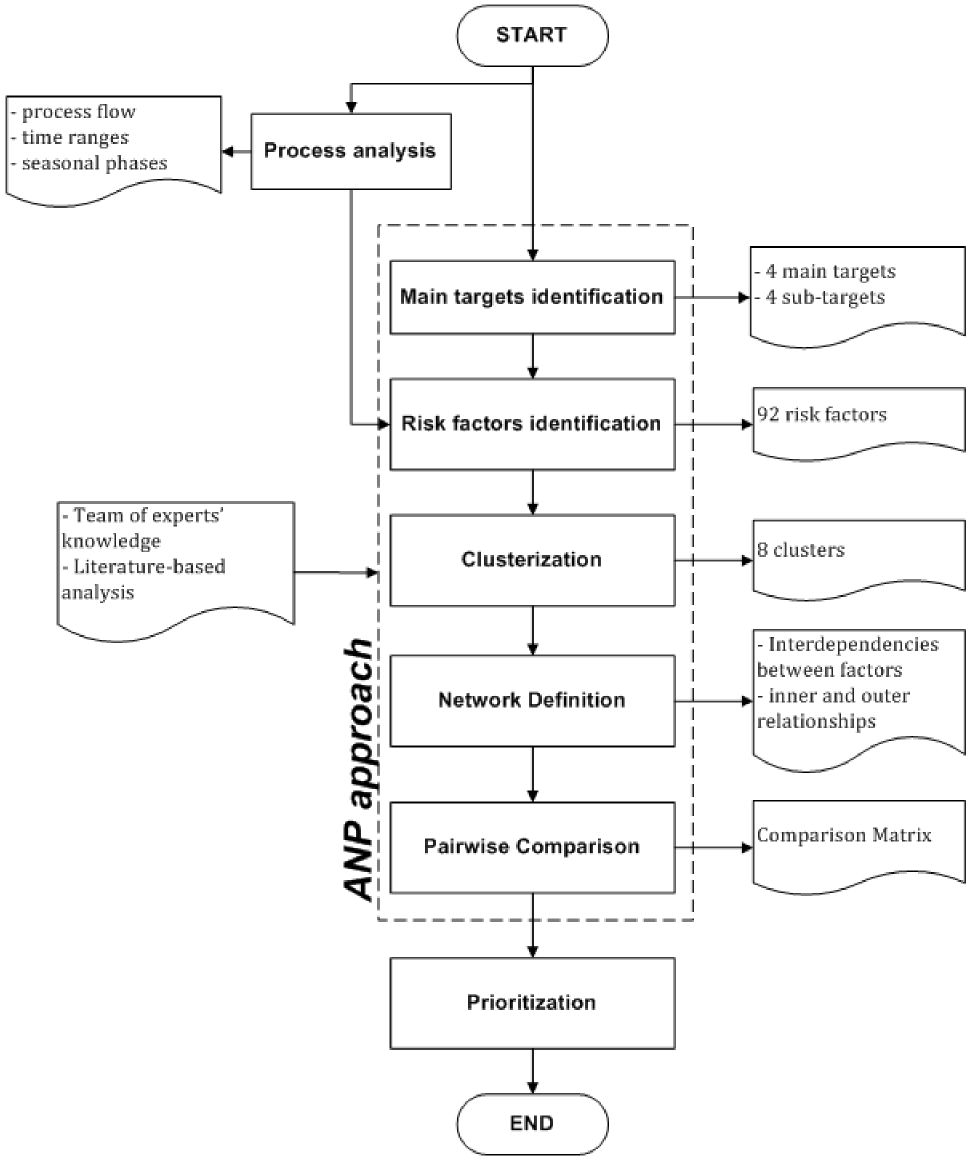


Figure 2.2: Process flow representing the research methodology

were grouped into clusters (*Clusterization* - ref. section 2.3.4) according to similarity criteria. Then, in the *Network Definition* step (ref. section 2.3.5) interdependencies between factors are defined: they include inner (within the same cluster) and outer (among different clusters) relationships. While a hierarchy is a linear to down structure, a network instead develops in all directions and may show cycle between different clusters and loops within the same cluster. In the end, all the clusters and all the connected risk factors are compared (*Pairwise Comparison* - ref. section 2.3.6) thank to a questionnaire survey based on experts' decisions in order to determine relative priorities among elements.
Final goal of the ANP approach is then reached with the *Prioritization* (ref. section 2.3.7) of the list of potential risk factors based on their relative importance in the organisation.

2.3.1 Process Analysis

First step of the approach was the definition of all the processes, material and informative flows typical of the fashion industry. In this particular study, we are referring to companies that operate with an extended network of retailers composed by:

- *wholesalers*: they are supply chain actors that directly buy products from the main company during the sales campaign and then sell them to multi-brand stores. They represent an intermediate ring between producers and market;

- *franchising stores*: they are mono-brand stores not directly managed by the company. They are allowed to use company's brand and distribute its products by directly buying them. It means that all the risks connected to under- or over-stocks are borne by the store itself;

- *direct-operated stores*: they are stores directly managed by the main company. It means that all the decisions, and consequently relates risks, on purchasing and distribution are centralized;

- *factory outlet stores*: in these direct-operated stores, the company sells previous season's unsold stocks at significantly discounted prices. They allow to absorb the risk of over-stocks.

All the main processes performed in a typical Fashion Retail Supply Chain are listed and described in detail in Table 2.1. The table also reports the indicative time range during which each of these processes is performed for the two traditional selling seasons: Fall Winter (F/W) and Spring/Summer (S/S). This timetable is graphically represented in the Gantt chart in Figure 2.3.
The processes are then divided into:

1. *Pre-Season* phase: as the name implies, this phase involves all the activities performed before the beginning of the real sales season, starting from the creation of the collection from the Styling Office and ending with the deliveries of the finished product to clients and stores;

2. *In-Season* phase: it starts with the first sales recorded in the stores and involves all the sales season, including discounts period until the shipment of unsold goods to the central warehouse;

3. *Post-Season* phase: it involves all the activities necessary for the correct management of the unsold items and their delivery to factory outlet stores.

Table 2.1: Main processes in a Fashion Retail Supply Chain

	Time Range		**Process**	**Description**
	F/W	**S/S**		
PRE-SEASON	Sept to Dec	Mar to Jun	*Market trend Forecasting*	In this step, several professional profiles are involved: fashion designers, style consultants, cool-hunters, fashion bloggers and reporters. Their main task is to analyse and forecast market trends for the following season according to main fabrics fairs, emerging street style and movie or pop star trend.
	Oct to Jan	Apr to Jul	*Creation of Seasonal collection*	It is a highly time-consuming activity and provides as output a wide variety of clothing items, but not all of them will be then produced [Bandinelli et al., 2013]. It is a process that can be hardly rationalised from a management perspective since the company needs to offer a wide variety to customers during the sales campaign.
	Jan to Mar	Jul to Sept	*Definition of main assortment*	It is the stage of selection of the items that mainly express the mood of the seasonal collection. They will be surely recommended to the wholesalers and shown in the most representative stores. This selection is responsibility of the Commercial Department and Styling Office.

Table 2.1: Main processes in a Fashion Retail Supply Chain

	Time Range		**Process**	**Description**
	F/W	**S/S**		
	Feb to Apr	Aug to Oct	*Collection presentation and beginning of sales campaign*	The collection is presented in the most important sector fairs (Milano Fashion Week, Première Vision in Paris, etc.) and after that, the sales campaign can start. In this period, the company can record orders from wholesalers. All the clients undergo a financial assessment and then their orders can be approved after the solvency check. Most of these orders may be affected by some changes even after conclusion of this campaign.
	Mar to Jun	Sep to Dec	*Production orders launch*	This phase is almost contemporary to the previous one. Orders already forwarded to production for which there is an insolvency problem, are hold as "suspended orders". They will be not delivered to the client but will be made available for other clients' orders even during the selling season.
	Apr to Jun	Oct to Dec	*Materials procurement and dispatch to production plants*	In this study we suppose that supply of fabrics and accessories is directly borne by the main company. It may happen that this process is, instead, performed by suppliers according to customer's specifications. In this phase, material may not pass through the central warehouse but may be directly delivered from fabric's suppliers to producers.
	Jun to Aug	Dec to Feb	*Finished products receiving*	When receiving finished products in the central warehouse or logistic center, two main checks are performed: (i) *quantity check*: delivery notes must match with actually received items; (ii) *quality check*: through a random check warehouse staff is able to identify possible defects on an entire batch of items. Specific defects on a single item, such as a missing button, can only be found in stores, thus increasing the possibility of returned goods. In addition, since loading/unloading processes are not automated in most cases, during this phase warehouse manpower can be overloaded, thus leading to a lengthening in material handling operations and possible delays in deliveries to customers.
	Jul to Sep	Jan to Mar	*Deliveries to customers and stores*	The personalized kits of items to send to stores and clients are prepared by warehouse staff or, in some cases, by producers themselves. From one side, it results in a leaner material handling process, but on the other, it leads to not optimised transports, since some packages are half-empty.
IN-SEASON	Sep to Feb	Mar to Aug	*Sales to final customers*	It is the actual sales season. During this period no other production orders are launched. In order to meet actual demand, company can ship to stores on-hand inventories, such as those items stuck in the warehouse due to the "suspended orders". In addition, movements of clothing items from one store to another are also allowed.
POST-SEASON	Feb to May	Aug to Nov	*Returns of unsold stock from stores and clients*	At the end of the sales season, the central warehouse receives unsold stocks both from stores and wholesalers according to specific commercial agreements. This step is similar to the *"Finished products receiving"* one since both quality and quantity check must be performed and the same overloading problems may arise.
	May to Jul	Nov to Jan	*Outlet assortment preparation*	Returned items must be refurbished and priced with outlet discounts. In some cases, in order to offer a wider assortment and attract customers, the company launches a specific production of items destined to outlet stores, using left-over fabrics and simple manufacturing.
	Jul to Sep	Jan to Mar	*Deliveries to outlet stores*	This step is similar to the *"Deliveries to customers and stores"* one even if quantities to handle are significantly lower.

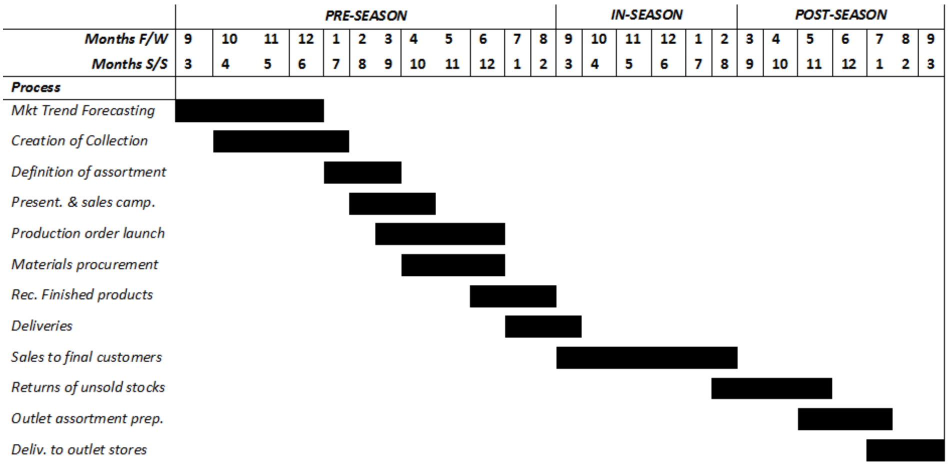


Figure 2.3: Example of a Gantt Chart for the main processes in the Fashion Retail Industry

2.3.2 Identification of Main Targets

Main critical issue of the fashion industry lies in the ability to promptly capture customers tastes and transfer them into successful products. This implies trying to meet customer requests of a large market share offering a wide variety of products. At the same time, it is necessary to reduce time-to-market and whole logistics costs in order to avoid a strong price markdown at the end of the selling season due to rapid changes in trends. Based on these considerations, we identified 4 main targets, 2 of which have 2 sub-targets, as following reported:

1. *Market driven orientation*
   The primary purpose of a supply chain is to satisfy customer's demand. According to it, the whole fashion supply chain is driven by real and current market needs [Walters, 2006], releasing from the total dependence from demand forecasts. The attainment of this target depends from two sub-targets:

   a) *Market sensitivity improvement*: it is intended as the ability to recognise market needs, thank to reliable demand forecasts, and to quickly respond to demand changes;

b) *Brand attractiveness*: it is defined as the intrinsic capacity of a brand to attract market interest. In our context, the company experiences this attractiveness through stores and clients network using their ability of attracting customers.

2. *Cost reduction*

   While the previous target mainly focuses on supply chain effectiveness, the cost and waste minimization refers to the efficiency of supply chain activities. The target of profit maximization from a production/logistics perspective results, in fact, in cost reduction of all the activities along the value chain. This is strictly connected to:

   a) *Time to Market*: refers to the correct time management and possible reduction of all supply chain processes. Any delay , in fact, may cause a late launch of the seasonal collection or late deliveries to stores and wholesalers, and the consequent loss of market share;

   b) *Material and informative flow management*: focuses not only to quantities and types of items in transit along the chain but also to correct data management and exchange between actors.

3. *Brand internationalization and market expansion*

   It refers to the entry in new foreign market and subsequent expansion, and involves decisions regarding marketing strategy and retail format, product, and service mix appropriate to a foreign country [Picot-Coupey et al., 2014]. The expansion process is pursued in already consolidated markets as well, trying to control a wider market share.

4. *Environmental sustainability*

   Fashion and apparel companies recognized as big source of pollutants, and the growing number of environmental conscious consumers are raising the attention on environmental sustainability and corporate social responsibility aspects. This is leading companies to use recycled fabrics and to adopt new programs for monitoring environmental impact of production and distribution.

The choice for the above mentioned targets has been confirmed by literature, as shown in Table 2.2, which reports the references for each of the selected supply chain targets.

Table 2.2: Literature confirmation for the selected supply chain targets

Target		**Reference**
Market driven orientation	Market Sensitivity Improvement	Cillo and Verona [2008] Carniene and Vienazindiene [2014]
	Brand attractiveness	Heuer and Brettel [2015] Tajuddin et al. [2014]
Cost reduction	Time to Market	De Toni and Meneghetti [2000] Heckmann et al. [2015]
	Material and Informative Flow Management	Marufuzzaman and Deif [2010] Tang and S.N. [2011]
Brand internationalization and market expansion		Guercini and Runfola [2010] Caniato et al. [2014]
Environmental sustainability		Li et al. [2014] Caniato et al. [2012] Yonggjian et al. [2014]

2.3.3 Identification of Risk Factors

The core step for the definition of the most critical areas is the identification of the risk factors for all the supply chain processes. They are characterized in reference to each company's target previously introduced and described in detail as follows. This analysis was conducted in cooperation with a team of experts, as already reported in section 2.3, and is supported by a deep literature study. In the following sections, the risk factors identified by the experts are listed and, when detected, the literature reference is reported.

2.3.3.1 Market driven orientation risk factors

The ability to catch customer's tastes is expressed by a reliable demand forecasting process and by a reactive approach to sudden changes in demand during the selling season. Given the need to draft forecasts well ahead of the sales season and given the uniqueness of the fashion products whose success depends on cultural and emotional aspects, elements that may lead to errors and risks are several and mainly related to the Pre-Season phase.

These are:

- *long-term horizon* for the analysis and forecasting process [Forza and Vinelli, 2000], which makes it difficult to predict consumers behaviour;

- *inefficient item classification*: since it is difficult to achieve high forecasting accuracy for single items, it is necessary to group them into product categories [Thomassey and Hapiette, 2007] (for example "clothing" or accessories") in order to better reflect consumers purchasing behaviour;

- *unstable demand*: purchases are impulsive [Park et al., 2012], driven by emotionality and subjectivity leading to high volatility and unpredictability of demand;

- *market heterogeneity*, i.e. high consumer segmentation [Brito et al., 2015] for each sales market, for example based on socio-demographic aspects;

- *different purchase behaviour in each area*: given the breadth of the international market, cultural differences between different Countries, or even different areas in the same Country [Iannone et al., 2013], may result in a different perception of the brand value;

- *competitive initiatives*, such as more frequent collection launches or marketing campaigns;

- *lack of historical data for fashion items*, [Thomassey, 2010] which are new products introduced in the seasonal collection. For these items we cannot draft forecasts according to real historical data since they are not available;

- *Absence of in-store marketing analysis*, such as consumers interviews, in order to test customer satisfaction and their potential intention to come back into the store [Soderlund et al., 2014];

- *No comparison with fabric suppliers* to share information on trends for the new season;

- *Many actors between company and market*: an extended network of wholesalers and distributors makes it more difficult to have quick and reliable feedbacks on final users' purchasing behaviour;

- *Bullwhip effect*, due to poor market visibility, lack of feedback and information sharing between supply chain actors and uncertainties [Miragliotta, 2006]. This leads to high inventory levels to cover demand variability;

- *"on-off" purchases* , referring to a situation of total absence of logistics-productive integration or cooperation with suppliers, neither in demand forecasting nor in collection design;

- *Different contractual terms for returns from wholesalers*, which complicates the definition of product assortment to send to outlet stores.

A company reactive to changes in real demand must rely on a flexible suppliers network and must be constantly updated on actual sales status, allowing to promptly identify any possible deviations. These concepts are outlined in the following risk factors:

- *lack of information from wholesalers* on actual sales status for each item;

- *few different suppliers*: a broader suppliers network may allow to respond quicker to an order by selecting the appropriate supplier;

- *exclusive use of "up-front" buying*, i.e. purchasing and reception of the total product quantity before the beginning of the sales season, by exclusively basing orders on forecasts;

- *No use of real demand as replenishment driver*: retailers do not usually record invisible demand [Bensoussan et al., 2015] and this does not allow to replenish stores with actually requested products;

- *No sold/foreseen deviation analysis*, which does not allow to adjust orders and replenishments plans according to actual demand;

- *Replenishments solely based on stocks*: this implies that no other orders are launched during the seales season but the company responds to any possible change in market demand with on-hand inventories, which may represent "orders suspended" or returned goods.

From *Brand Attractiveness* perspective, instead, the proper management of the stores network may determine the success of the commercial campaign and define the reputation perceived by clients. Then, crucial factors are:

- *Many new product launches failed*, i.e. products designed by the Styling Office that do not meet customers taste;

- *Excessive focus on continuative items*, implying lack of attention in product innovation [Cillo et al., 2010, Unay and Zehir, 2012] and in following trends. This may lead to always offer similar items over time;

- *Customization in international markets*, given the important cultural diversity between Countries, characteristics and practices of each Country must be taken into account [Caniato et al., 2014];

- *Design of only two collections a year*, without infra-seasonal "flash" collection that may allow to differentiate offer and enlarge product variety [Mehrjoo and Pasek, 2014];

- *Poor diversification of sales channels*, intended as different kinds of stores, location or purchasing paths (e.g. e-commerce, buy online-pick up in store, buy in store-home delivery, etc.) [Lanzilotto et al., 2015];

- *Wholesaler's reputation inconsistent with brand image* and unable to attract customers from the target market;

- *Deviation between offered and expected product quality*, which may lead to customer dissatisfaction;

- *Limited On-Shelf Availability*, caused by under-estimation of demand, may lead customers to hopefully purchase another product in the same category [Tan and Karabati, 2013] or may lead to a lost sale ;

- *In-store shopping experience*, which provides customer with more leisure, interaction with product information and automatic item collocation [Choi et al., 2015] in addition to other additional services that enhance the shopping experience (eg. restaurant and play areas);

- *Lack of "key" sizes in stores*: the absence of the size requested by the customer leads to a dissatisfaction even greater that the total absence of the item itself. Generally demand trend for sizes follows a Gaussian curve centred on a particular size which varies according to the customer target and the reference market;

- *Low service level*, due to delivery lots with missing items or sizes, caused for example by production defects;

- *Limited assortment in outlet stores*, in terms of inventory depth and variety breadth, and the mix between basic and fashion merchandise [Rajaram, 2001]. This assortment is strictly connected to returns quantity at the end of the season.

2.3.3.2 Cost reduction risk factors

The Cost Reduction objective can be outlined into two different sub-targets. From a *Time* perspective, the reduction for the processes of collection development, transports, orders management and material handling, allows to enter the market with the right product at the right time. This factor is crucial in the fashion industry due to the very short product life cycle. Then, factors that may cause a long time to market are:

- *Inefficient interaction styling office/marketing office*: the styling office must translate market information into the new collection;

- *Inefficient interaction styling office/suppliers*, that can simplify the process of fabrics selection and guarantee higher product quality;

- *Delays in closing sales campaign* and *increase in distributors orders*, may cause delays in production orders launch and lead to errors in dimensioning orders themselves;

- *Forecasting error for some items*, providing wrong guidelines to the styling office;

- *Process misalignment between actors*, meaning the difficulty of defining "no border" connections between supply chain actors, avoiding delays and over-stocks;
- *Production and delivery of the whole purchase lot before the selling season* and *Production of more items by a single supplier*, which may lead to overload and delivery delays;
- *Poor "virtual integration"* between Supply Chain actors without the use of Internet-based technologies and information sharing systems [Bhimani and Ncube, 2006];
- *Orders launch close to the selling season*, implying that any possible delay from this stage on will cause delays in deliveries to stores;
- *Long production lead time, Delivery delays* of raw materials and *Sole use of foreign suppliers* [Macchion et al., 2015], are all factors that may involve an extension in throughput time thus exposing companies to possible disruptions in material flows;
- *Wrong delivery scheduling*, which may lead either to overload the warehouse or to out-of-stock for deliveries to stores;
- *Use of low cost transports* mainly for international transports;
- *Inefficient item division in warehouse, Limited storage/material handling capacity* and *No automated warehouse*, that may create a bottleneck for product flow causing longer delivery times;
- *Short delivery times for foreign clients*, which usually require advanced deliveries unlike the national market;
- *Urgent deliveries* and *Frequent replenishments*, in order to adapt products availability according to actual demand;
- *Long lead time between returns and resending to customers*: it is related to defective goods and not to unsold goods. In this case, there is the risk of late resending of refurbished items with a possible rejection by the customer;

- *Returns procedures not shared with multi-brand customers*, which may complicate and delay the management of unsold stocks which require the following activities: receiving, inspection, storage, internal transports and eventual refurbishment [De Brito and de Koster, 2003];

- *No Electronic Data Interchange (EDI) system*, which makes it difficult to share information in real time with all supply chain actors [Angeles et al., 2001].

At the same time, an efficient *Flow Management* implies an appropriate material movement along the supply chain, duly supported by a continuous information sharing among all actors. Critical factors in this context are:

- *No accurate quality control in laboratories/suppliers*, which may also lead to *Excessive defective percentage* often verifiable only in stores, causing returns from clients;

- *Limited flexibility* [Tang and Tomlin, 2008] and production capacity of suppliers that do not allow quickly changes in production orders;

- *No optimization due to strong differentiation of orders* in terms of sizes and colours;

- *No control on production progress status* able to guarantee the respect of the delivery schedule;

- *Poor raw material quality* resulting in an appropriate value for money and a consequent customer dissatisfaction;

- *Need to optimize lots delivered by different suppliers*: these lots may be already divided into customers orders, thus leading to not optimized transports for almost empty packages;

- *Overload for receiving entire production lot*: it is typical of traditional companies that are based on "planned" manufacturing. They do not distribute supplies during the selling season, but they receive whole production lots before it;

- *High safety stock due to unreliable demand forecast* [Wang et al., 2012a], which may lead to high holding costs and forced price markdowns;

- *Errors in clients assortment*, leading to unnecessary transport and material handling operations for returns management;

- *Forced markdowns due to late deliveries or due to over-stock*: it is due to short product life cycle. The reduction of the selling price is not related to marketing strategies, then represents a cost for the company;

- *Misalignment between virtual and physical inventory*, due to errors or delays in material handling operations;

- *Lost sales due to stock out*, for any sudden unpredictable change in trend and/or in weather conditions [Bertrand et al., 2015];

- *Items exchange between stores* in order to meet customers request. These additional and possibly unnecessary movements must be always guaranteed in any case;

- *Overload at the end of the season*, for the reception of unsold goods. It is similar to the Pre-Season overload due to the reception of production lots;

- *Difficult returns identification without a detailed archive* and *Deviations between delivery notes and actual deliveries*, that lead to errors in exactly identifying items and delays in warehouse operations;

- *Returns of entire lots for high defective percentage*, that requires additional refurbishment, material handling and transport operations.

2.3.3.3 Brand internationalization and market expansion risk factors

Market expansion is ensured by continuous product and process innovation which allows to meet requests of different customer targets and increase service level. In addition, an international expansion plan allows to access to new markets and increase brand prestige. In this perspective, possible critical issues are:

- *Unstable political/economic conditions in target markets*: excessive macroeconomic variability impacts on purchasing possibilities;

- *Inappropriate selection of stores location*, which may be inconsistent with brand image or not appropriately chosen in order to attract the largest number of people from the chosen market. The best choice must also evaluate market saturation and competitive pressure [Merino and Ramirez-Nafarrate, 2015];

- *High number of international competitors* and *Poor diversification from competitor's products*, represent an obstacle in brand strengthening and recognition;

- *Wrong selection of international distributors*, whose task is to develop the market and to seek new customers;

- *Inability to expand clientèle* in already controlled markets due to inappropriate trend forecast;

- *No sharing procedure for sales plans by main company*, in order to allow supplier to adapt and adjust processes according to retailers needs;

- *Weak infrastructures in new markets* and *Inadequate logistic system for international expansion*, hampering transports and all other logistics operations due to inefficient facilities;

- *Poor brand recognition abroad*, that can represents a stop in purchases.

2.3.3.4 Environmental sustainability risk factors

In recent years, there is growing attention by consumers on *Environmental Sustainability* in all its aspects, from production to transports and recycling. Then, many company are launching their sustainable initiatives, such as Levi's with its entire Spring/Summer 2013 collection in recycled PET or

H&M with its use of sustainable materials, reduction of transport emissions and of electricity use. With this purpose, main risk factors are:

- *Lack of attention to "green" consumers*: they are a market segment that considers environmental impact as significant choice factor [Braga Junior et al., 2015] especially for raw materials and manufacturing techniques used;

- *No use of organic fabrics, recyclable materials or local resources (eco-design)*: they should be introduced in the collection development already in the conceptual phase and are necessary to create a sustainable closed loop supply chain [Payne, 2015, Clancy et al., 2015];

- *Limited use of excess fabrics* with the purpose of reducing waste;

- *No IT support to production (eg. to cutting)*, that may help in reducing wastes compared to manual operations;

- *Long distances between raw materials and finished products producers*, leading to increasing transport emissions;

- *No assessment/control on suppliers environmental policies*: in order to be effective, all plans and policies must be shared with all suppliers and logistics operators;

- *Excessive production waste*, due to production errors or to non-optimal use of raw materials;

- *No packaging recovery/recycling*: packaging is the major part of waste and the most difficult to recycle, the re-use must be encouraged [da Cruz et al., 2014].

All the above-mentioned risk factors are related to a process, as indicated in Tables 2.3 and 2.4 for the Pre-Season phase and in Table 2.5 for the In- and Post-Season.

Table 2.3: Risk map for the Pre-Season phase (part 1)

Target	MARKET DRIVEN ORIENTATION		COST REDUCTION		BRAND INTERN. & MKT EXP.	ENVIRONMENTAL SUSTAINABILTY
Process	**Improvement in Market Sensitivity**	**Brand Attractiv.**	**Time to Market**	**Mat. & Inf. Flow Mng**		
Market trend Forecasting	Long-term horizon Inefficient item classification Unstable demand Market heterogeneity Different purchase behaviour in each area Competitive initiatives Lack of historical data for fashion items Absence of in-store marketing analysis No comparison with fabric suppliers				Unstable political/economic conditions in target markets Inappropriate selection of stores location High number of international competitors	Lack of attention to "green" consumers
Creation of Seasonal collection		Many new product launches failed Excessive focus on continuative items Customisation in international markets Design of only two collections a year	Inefficient interaction Styling O./Marketing O. Inefficient interaction Styling O./Suppliers		Poor diversification from competitor's products	No use of organic fabrics, recyclable materials or local resources (eco-design)
Assort.	Many actors between company and market	Poor diversification of sales channels				
pres. & sales camp.	Lack of information from wholesalers	Wholesaler's reputation inconsistent with brand image	Delays in closing sales campaign Increase in distributors orders		Wrong selection of international distributors Inability to expand clientele	
Production orders launch	Bullwhip effect Few different suppliers "On-Off" purchases		Forecasting error for some items		No sharing procedure for sales plans by main company	

Table 2.4: Risk map for the Pre-Season phase (part 2)

Target	MARKET DRIVEN ORIENTATION		COST REDUCTION		BRAND INTERN. & MKT EXP.	ENVIRONMENTAL SUSTAINABILTY
Process	Improvement in Market Sensitivity	Brand Attractiv.	Time to Market	Mat. & Inf. Flow Mng		
Mat. procur. & dispatch to prod. plants		Deviation between offered and expected product quality	Process misalignment between actors Production of more items by a single supplier Production & delivery of whole lot before the sell. seas. Poor "virtual integration" Orders launch close to the selling season Long production lead time Delivery delays Sole use of foreign suppliers	No accurate quality control in laboratories/suppliers Limited flexibility No optimisation due to order differentiation Limited production capacity Excessive defective percentage No control on production progress status		Limited use of excess fabrics No IT support to production Long distances between raw materials & finished products producers No assess./control on supp. environ. policies Excessive production waste
Finished products receiving	Exclusive use of "up-front buying"		Wrong delivery scheduling Inefficient item division in warehouse Use of low cost transports	Poor raw materials quality Need to optimise lots of different suppliers Overload for receiving entire production lot High safety stocks due to unreliable demand forecast		No packaging recovery/recycling
Deliv. to customers and stores	No use of real demand as replenish. driver No sold/foreseen deviation analysis Replenishments solely based on stocks	Limited On-Shelf Availability Lack of "key" sizes in stores Low service level	Limited stor./mat. hand. capacity - No automated wareh. Short delivery times for foreign clients Urgent deliveries Frequent replenishments	Errors in clients assortment Forced markdowns due to late deliveries Misalignment between virtual and physical inventory	Weak infrastructures in new markets Inadequate logistic system for international expansion	

Table 2.5: Risk map for the In-Season and Post-Season phase

<table>
<tr><th rowspan="2">Target</th><th colspan="2">MKT DRIVEN ORIENTATION</th><th colspan="2">COST REDUCTION</th><th rowspan="2">BRAND INTERN. & MKT EXP.</th><th rowspan="2">ENVIR. SUST.</th></tr>
<tr><th>Improv. in Market Sensitivity</th><th>Brand Attractiv.</th><th>Time to Market</th><th>Mat. & Inf. Flow Mng</th></tr>
<tr><td>Process</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="3">Sales to final cust.</td><td rowspan="3"></td><td rowspan="3">In-store shopping experience</td><td rowspan="3">No Electronic Data Interc. (EDI) system</td><td>Lost sales due to stock-out</td><td rowspan="3">Poor brand recognition abroad</td><td rowspan="3"></td></tr>
<tr><td>Forced mark down due to over-stock</td></tr>
<tr><td>Items exchange between stores</td></tr>
<tr><td rowspan="4">Returns of unsold stock from stores and clients</td><td rowspan="4">Different contractual terms for returns from wholesalers</td><td rowspan="4"></td><td rowspan="2">Long lead time between returns and resending to customers</td><td>Overload at the end of the seas.</td><td rowspan="4"></td><td rowspan="4"></td></tr>
<tr><td>Difficult returns identif. without a detailed archive</td></tr>
<tr><td rowspan="2">Returns procedures not shared with multibrand customers</td><td>Deviations between deliv. notes and actual deliv.</td></tr>
<tr><td>Returns of entire lots for high defective percentage</td></tr>
<tr><td>Outlet assort. & deliv.</td><td></td><td>Limited assortment in outlet stores</td><td></td><td></td><td></td><td></td></tr>
</table>

It is clear that the most critical issues concern all the processes performed before the selling season, since traditional companies define their collection, forecasting and orders well before the introduction of the products into the market; 85% of the risk factors, in fact, are related to the Pre-Season phase. Then any possible error or deviation in this stage will be reflected and amplified during the actual selling season.

2.3.4 Clusterization

Following the ANP approach, all the previously mentioned risk factors have been grouped into homogeneous clusters (ref. Tables 2.6 and 2.7), that are:

1. *Competitive environment*, that includes external risks not directly controllable by main company. In particular it is referred to risks related to the target market and to competitors;

2. *Relationship between supply chain actors*, that concerns policies and strategies with which all actors interacts;

3. *Offer*: this cluster is specifically related to offered products and services;
4. *Informative flow*, involving all factors connected to communication, informative systems and data exchange;
5. *Process and timing control*, focused on management and optimisation of processes;
6. *Distribution*, involving transports and material handling activities;
7. *Knowledge of customers/end-users*, looking at the ability to appropriately capture trends and market needs;
8. *Quality and quantity control*, focusing on the production processes.

2.3.5 Network Definition

The overall structure of the network, which shows relationships between criteria and clusters is shown in Figure 2.4. All these connections, represented by the arrows, have been identified though a cause-effect analysis. Each risk factor represents a node and is related to the others with a "parents-children" connection. When a node is linked to other nodes in its own cluster, the arrows become loops on that cluster representing an inner dependence.
The detailed connections between the risk factors of the different clusters are graphically shown in Figure 2.5 and reported in the correlation matrix (ref. Appendix A), where numbers 1 or 0 respectively indicate whether there is a connection between the two elements or not.

2.3.6 Pairwise Comparison

This step is necessary to establish the relative importance of two elements in reference to their "parent" node. This pairwise comparison answers to the question: "Given a target and two elements of a cluster, influencing a third element of the same or another cluster, which of the two elements is

Table 2.6: Clustering (part 1)

	1 - Competitive Environment	**2 - Relationship between SC actors**	**3 - Offer**	**4 - Informative flow**
.1	Long-term horizon	No caparison with fabric suppliers	Customisation in international markets	Lack of information from wholesalers
.2	Unstable demand	Many actors between company and market	Design of only two collections a year	Inefficient interaction Styling Office/Marketing Office
.3	Competitive initiatives	Bullwhip effect	Limited assortment in outlet stores	Poor "virtual integration"
.4	High number of intern. competitors	Few different suppliers	Excessive focus on continuative items	No EDI system
.5	Unstable political/economic conditions	"On-Off" purchases	Poor diversification from competitor's products	Deviation between delivery notes and actual deliveries
.6	Weak infrastructures in new markets	Exclusive use of "up-front buying"	Replenishments solely based on stocks	No IT support to production
.7	Inadequate logistic system for international expansion	Different contractual terms for returns from wholesalers	Inefficient item classification	Difficult returns identification
.8	Poor brand recognition abroad	Wholesaler reputation inconsistent with brand image	No (eco-design)	Misalignment between virtual and physical inventory
.9	Different purchase behaviour in each area	Inefficient interaction Styling Office/Suppliers	Limited use of excess fabrics	
.10		Delays in closing sales campaign	Many new product launches failed	
.11		Increase in distributors orders		
.12		Process misalignment between actors		
.13		Production of more items by one supplier		
.14		Production & delivery of whole lot before the sales season		
.15		Orders launch close to the sales season		
.16		No sharing procedure for sales plans		
.17		Returns procedure not shared with multi-brand customers		
.18		Sole use of foreign suppliers		
.19		Wrong selection of international distributors		

Table 2.7: Clustering (part 2)

	5 - Process and timing control	**6 - Distribution**	**7 - Knowledge of customers**	**8 - Quality and quantity control**
.1	Low service level	Poor diversification of sales channels	Market heterogeneity	Deviation between offered and expected production quality
.2	Lack of "key" sizes in stores	Use of low cost transports	Lack of historical data for fashion items	Limited On-Shelf Availability
.3	Long production lead time	Short delivery times for foreign clients	Absence of in-store marketing analysis	No accurate quality control in laboratories/suppliers
.4	Delivery delays	Urgent deliveries	No use of real demand as replenishment driver	Poor raw materials quality
.5	Inefficient item division in warehouse	Frequent replenishments	Lack of attention to "green" consumers	Excessive defective percentage
.6	Long lead time between returns and resending	Forced markdowns due to late deliveries	In-store shopping experience	High safety stocks due to unreliable demand forecast
.7	Limited production capacity	Need to optimise lots of different suppliers	Forecasting error for some items	Overload for receiving entire production lot
.8	Limited flexibility	Items exchange between stores	Inability to expand clientèle	Lost sales due to stock-out
.9	No optimisation due to order differentiation	Long distance between raw materials & finished products producers	Inappropriate selection of stores location	Forced mark down due to over-stock
.10	No control on prod. progress status	Wrong delivery scheduling	No sold/foreseen deviation analysis	Overload at the end of the season
.11	Errors in clients assortment	Limited storage capacity-No automated warehouse		Returns of entire lots for high defective percentage
.12	No control on supplier environmental policies			Excessive production waste
.13	No packaging recovery/recycling			

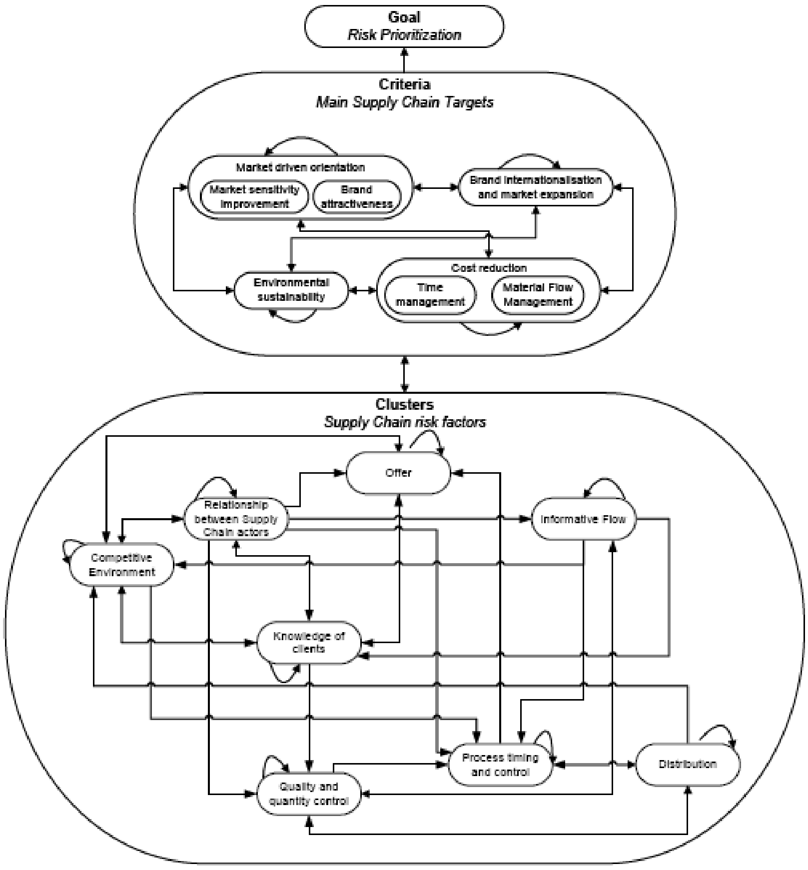


Figure 2.4: Network structure for the risk prioritization

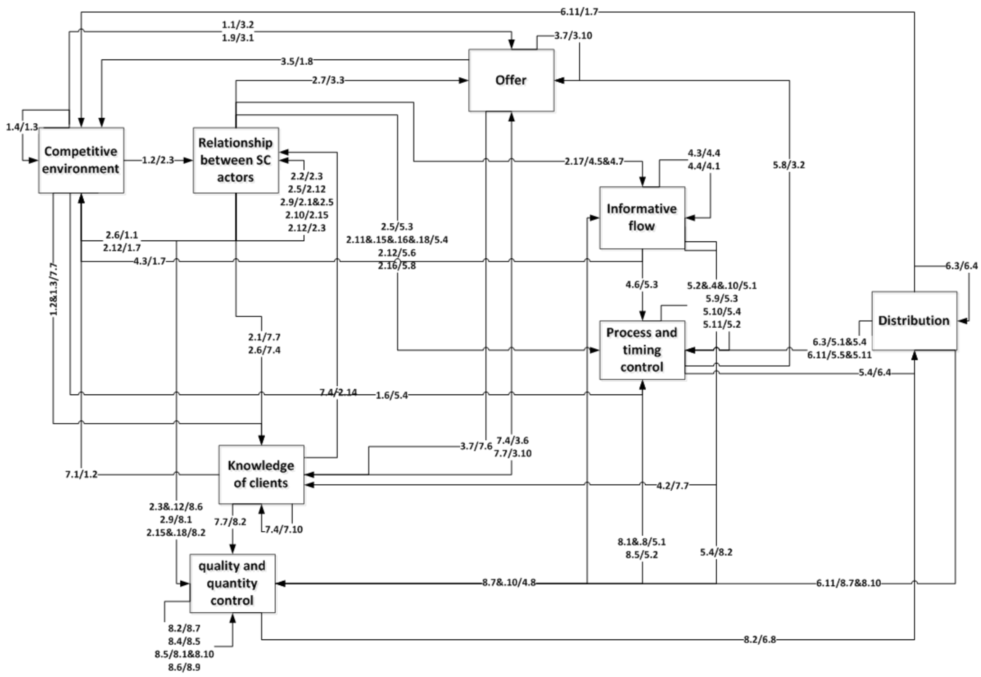


Figure 2.5: Detailed connections between risk factors

Table 2.8: Saaty's fundamental scale

Numerical Scale	Verbal Scale
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values

more important referred to the target and how much?". Then, each couple of children nodes will be pairwise compared with respect to their parent. This relative importance is expressed by a numerical judgements taken from a numerical scale of 9 points, called "fundamental scale of Saaty" [Wind and Saaty, 1980], in which the value 1 means that the two children nodes influence in the same way the parent node, while the value 9 means that one of the two children nodes completely influences the parent node (Table 2.8).

In this thesis, the pairwise comparison is performed through the submission of a questionnaire survey, composed by 238 questions, to:

- the team of experts involved in the whole analysis (ref. section 2.3);
- other 5 experts from 3 Italian Fashion companies: 1 CEO, 2 logistics and distribution managers, 2 purchasing managers.

From this survey the comparison matrices originate. One comparison matrix (A) is originated for each cluster and contains expert's judgements a_{ij} based on the Saaty's scale.

$$\mathcal{A} = \begin{pmatrix} 1 & a_{12} & ... & a_{1n} \\ a_{21} & 1 & ... & a_{2n} \\ ... & & & ... \\ a_{n1} & a_{n2} & ... & 1 \end{pmatrix}$$

with $i, j = 1, ..., n$ (number of elements in each cluster). Each element in the matrix represents the geometric average of the expert's judgements.

For those matrices it is then necessary to check the consistency of judgements through the Consistency Ratio (CR):

$$CR = \frac{CI}{RI} \tag{2.1}$$

where CI is the Consistency Index defined as:

$$CR = \frac{\lambda_{max} - n}{n - 1} \tag{2.2}$$

with λ_{max}, the maximum eigenvalue of matrix A, and RI (Random Index) an experimental value depending on n.
If CR is greater than 0.1, the deviation from the perfect consistency condition is deemed unacceptable, then expert's opinions must be changed. If CR is lower than 0.1, the consistency can be accepted [Saaty, 2009].

2.3.7 Prioritization

The eigenvector associated to the dominant eigenvalue (λ_{max}) for each matrix, expresses the relative priority of the elements.
The results obtained from the ANP approach for our analysis are reported as follows:

- Table 2.9 shows the targets ordered according to their priority, i.e. for decreasing weights. As expected, the *Cost Reduction* perspective (i. e. *"Time to Market"* and *"Material Flow Mng"*) is considered the most crucial for the business immediately followed by *Market Driven Orientation* (i. e. *"Improvement in Market Sensitivity"* and *"Brand Attractiveness"*) which is an important aspect especially for demand-driven supply chains, as fashion industry's ones. *Environmental sustainability* instead, although is receiving increasing attention from researchers is still considered the less important by the interviewed managers. Nevertheless, this aspect is becoming essential for attracting the always increasing "green" market share and the launch of the "Higg Index" by the Sustainable Apparel Coalition in 2012 [SAC, 2012] provided a useful tool to fashion companies for evaluating their social and environmental sustainability and contributed to

Table 2.9: Prioritization of the targets according to their weights

Priority	***Target***	***Weight***
1	Time to Market	0,4447
2	Mat. and Inf. Flow Management	0,3137
3	Improvement in Market Sensitivity	0,1672
4	Brand Attractiveness	0,0628
5	Brand Intern. & Market Expansion	0,0087
6	Environmental Sustainability	0,0029

make them aware of this issue;

- Table 2.10 shows the complete list of risk factors and the corresponding calculated weights;

- Figure 2.6, Table 2.11 and Table 2.12 show the ABC analysis for the risk factors according to their weights.

In Table 2.11 we can see that most of the "A" category risk factors are contained in clusters 4 (*"Informative flow"*) and 6 (*"Distribution"*), while "C" risk factors are mainly concentrated in clusters 1 (*"Competitive Environment"*), 3 (*"Offer"*) and 7 (*"Knowledge of customers"*). These results confirm that supply chain efficiency, in terms of correct management of both material (i.e. distribution of fashion products to final consumers) and informative flow, needs most of the company's efforts for avoiding any possible disruption or delay. On the contrary, competition and the appropriate knowledge and management of the market are not considered highly risky fields, although fashion market trend and customer's tastes are always changing.
Table 2.12 instead, highlights that, despite the 85% of all the risk factors is related to the Pre-Season phase, they are almost equally distributed over the ABC classes, indicating that only the 35% of them is considered highly crucial for the company.

Table 2.10: Normalized weights for each risk factor

# factor	Risk Factor	Weight [$*10^3$]
1.1	Long-term horizon	4,494
1.2	Unstable demand	5,939
1.3	Competitive initiatives	3,247
1.4	High number of intern. competitors	3,276
1.5	Unstable pol./econ. conditions	0,08708
1.6	Weak infrastructures in new markets	0,05877
1.7	Inadequate logistic system for international expansion	0,1130
1.8	Poor brand recognition abroad	0,07086
1.9	Different purc. behaviour in each area	1,967
2.1	No comparison with fabric suppliers	12,51
2.2	Many actors between company and market	2,314
2.3	Bullwhip effect	3,321
2.4	Few different suppliers	25,921
2.5	"On-off" purchases	43,79
2.6	Exclusive use of "up-front buying"	0,4419
2.7	Different contractual terms for returns from wholesalers	8,177
2.8	Wholesaler's reputation inconsistent with brand image	40,79
2.9	Ineff. interaction Styling O./Suppl.	12,51
2.10	Delays in closing sales campaign	16,83
2.11	Increase in distributors orders	0,8547
2.12	Process misalignment between actors	21,46
2.13	Production of more items by one supplier	4,060
2.14	Production & delivery of whole lot before selling season	19,59
2.15	Orders launch close to the selling season	10,10
2.16	No sharing procedures for sales plans by main company	5,884
2.17	Returns procedures not shared with multibrand customers	60,64
2.18	Sole use of foreign suppliers	10,92
2.19	Wrong selection of intern. distributors	0,7786
3.1	Customisation in intern. markets	0,8058
3.2	Design of only two collections a year	0,4419
3.3	Limited assortment in outlet sores	0,5741
3.4	Excessive focus on continuative items	1,401
3.5	Poor diversification from competitor's products	8,120
3.6	Repl. solely based on stocks	12,18
3.7	Inefficient item classification	0
3.8	No eco-design	0
3.9	Limited use of excess fabrics	0,8058
3.10	Many new product launches failed	0,33762
4.1	Lack of information from wholesalers	26,32
4.2	Ineff. Interaction Styling O./Mkt O.	16,90
4.3	Poor "virtual integration"	67,01
4.4	No EDI system	30,44
4.5	Deviations between delivery notes and actual deliveries	8,556
4.6	No IT support to production	1,816
4.7	Difficult return identification	12,47

# factor	Risk Factor	Weight [$*10^3$]
4.8	Misalignment between virtual and physical inventory	10,81
5.1	Low service level	4,143
5.2	Lack of "key" sizes in stores	1,730
5.3	Long production lead time	7,284
5.4	Delivery delays	26,79
5.5	Inefficient item division in warehouse	4,299
5.6	Long lead time between returns and resending	2,943
5.7	Limited production capacity	1,749
5.8	Limited flexibility	4,500
5.9	No optimisation due to order differentiation	7,289
5.10	No control on prod. progress status	23,28
5.11	Errors in clients assortment	9,580
5.12	No control on suppliers environmental policies	0
5.13	No packaging recovery/recycling	0
6.1	Poor diversification of sales channels	5,403
6.2	Use of low cost transports	15,68
6.3	Short del. times for foreign clients	6,285
6.4	Urgent deliveries	10,34
6.5	Frequent replenishments	15,50
6.6	Forced markdowns due to late deliveries	10,87
6.7	Need to optimise lots of different suppliers	18,36
6.8	Items exchange between stores	0
6.9	Long dist. between raw materials & finished products producers	5,403
6.10	Wrong delivery scheduling	22,11
6.11	Limited storage capacity – No automated warehouses	37,12
7.1	Market heterogeneity	7,3643
7.2	Lack of historical data for fashion items	2,194
7.3	Absence of in-store mkt analysis	2,379
7.4	No use of real demand as replenishment driver	32,13
7.5	Lack of attention to "green" consumers	0
7.6	In-store shopping experience	2,937
7.7	Forecasting error for some items	20,94
7.8	Inability to expand clientele	0,3392
7.9	Unappropriate selection of stores location	0,08033
7.10	No sold/foreseen deviation analysis	0
8.1	Deviation between offered and expected product quality	4,499
8.2	Limited On-Shelf Availability	23,97
8.3	No accurate quality control in laboratories / suppliers	4,018
8.4	Poor raw material quality	35,81
8.5	Excessive defective percentage	35,81
8.6	High safety stock due to unreliable demand forecasts	4,207
8.7	Overload for receiving entire production lot	16,42
8.8	Lost sales due to stock-out	4,401
8.9	Forced Mark down due to over stock	4,207
8.10	Overload at the end of the season	7,668
8.11	Returns of entire lots for high defective percentage	32,44
8.12	Excessive production waste	0

Table 2.11: Percentage distribution of risk factors over the ABC classes for each cluster

	Category	A	B	C
	Cluster			
1	***Competitive Environment***	0%	22%	78%
2	***Relationship between SC actors***	47%	21%	32%
3	***Offer***	10%	10%	80%
4	***Informative Flow***	75%	13%	13%
5	***Process and timing control***	15%	38%	46%
6	***Distribution***	64%	27%	9%
7	***Knowledge of Customers***	20%	10%	70%
8	***Quality and Quantity Control***	42%	42%	17%

Table 2.12: Percentage distribution of risk factors over the ABC classes for the three time phases

	# factors	A	B	C
Pre-Season	78	35%	23%	42%
In-Season	6	33%	33%	33%
Post-Season	8	38%	25%	38%

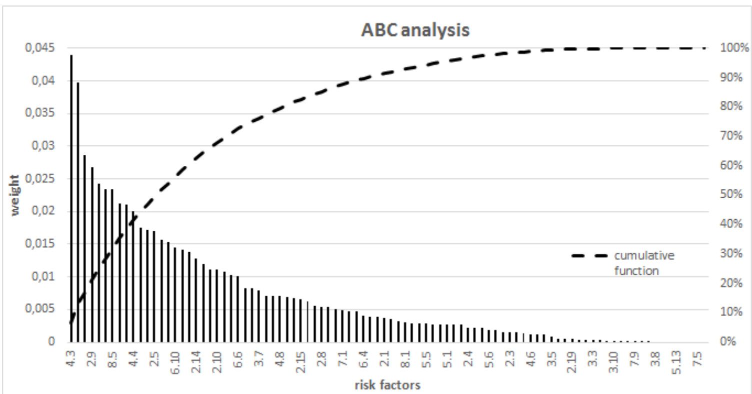


Figure 2.6: ABC analysis for the risk factors

2.4 Conclusions

The results of the ANP analysis described in this chapter show that the constant research for *Cost Reduction* and, in particular, for the reduction of the *Time to Market* is considered by the interviewed managers as the most crucial aspect for risk management and is not specific for fashion retailing but is shared by all industries. *Market driven orientation* is, instead, a specific issue for any demand-driven supply chain as those of the fashion industry, which is constantly seeking for customers tastes and needs. In this context, the next chapter focuses on this aspect and proposes a framework for the optimisation of performances. The proposed model is based on the analysis, during the sales season, of real-time demand data allowing companies to adapt their operations plans according to real market demand.
The risk analysis also showed that, besides *Information Flow*, the *Distribution* process is essential for ensuring a high level of customer satisfaction and avoiding any possible disruption or delay. This process will be better analysed in Chapter 6 where a heuristic optimisation model is proposed.

Chapter 3

Framework for Optimisation of Supply Chain performances

Contents

3.1 Introduction

This chapter presents a framework which defines and analyses all the processes, material and informative flows that are characteristics of a fashion company operating with a dense network of direct-operated or franchising mono-brand stores. Unlike previous chapter, in this part of the study wholesalers are neglected since their orders are defined and fixed before the beginning of the sales season. The attention is instead focused on the stores that are directly managed by the company. For these stores the company is responsible for defining operations plans and bears all the risk connected to possible errors.
Main purpose of this model is to optimise Supply Chain performances through a responsive approach which, during the sales season, analyses actual market demand and adjust operations plans according to it. In order to compare different scenarios, a set of technical and economic Key Performance Indicators (KPIs) is defined.
The opportunity of performing simulation experiments which try to assess

the risks connected to all the possible decision alternatives and try to optimize the performances of the whole Supply Chain, becomes a crucial factor for a company that has to manage at least two seasonal collection per year; this means that at least twice a year the company has to define purchasing and delivery plans almost entirely based on unreliable forecasts and on experts opinion trying to maximise its profit and to satisfy market requirements in terms of newness, variety and speed.

3.2 Definition of the framework

The proposed optimisation model is shown in Figure 3.1.

The process starts from the development of the *New Collection* (A) by the styling office and the definition of the *Demand Forecasts* (C). While the *New Collection* is considered as a simple input for the framework, forecasting is one of the pillars on which all further planning activities are based. In the Fashion & Apparel Industry this process is crucial and particularly complex due to high volatility and unpredictability of demand and is based on historical sales data and characteristics of the new collection (*Classification* - B) and stores. Next step is the drafting of *Merchandise Orders* (D), which define purchasing quantities for each item, and *Delivery Orders* (E), which define time and place for products deliveries from *Suppliers* (F). For simplicity, we suppose that the k-th supplier produces the k-th item and delivers it all to the area warehouses in quantity Q_{kj}. The supply process ends with the delivery of goods to the *Area Warehouses* (G) according to the Delivery Orders. At this point, warehouse staff has the task of preparing personalized kits of items to send to the *Stores* (I) according to the *Replenishment Orders* (H). The j-th warehouse supplies only a specific set of n_j stores pertaining to its area. The process described so far defines the material and informative flow that characterizes the Pre-Season phase that, as the name implies, is performed before the beginning of the sales season. For example, in the case of Fall/Winter (FW) Season this phase starts in October, with the development of the new collection before the most important sector fairs, and ends in September with the first deliveries to the

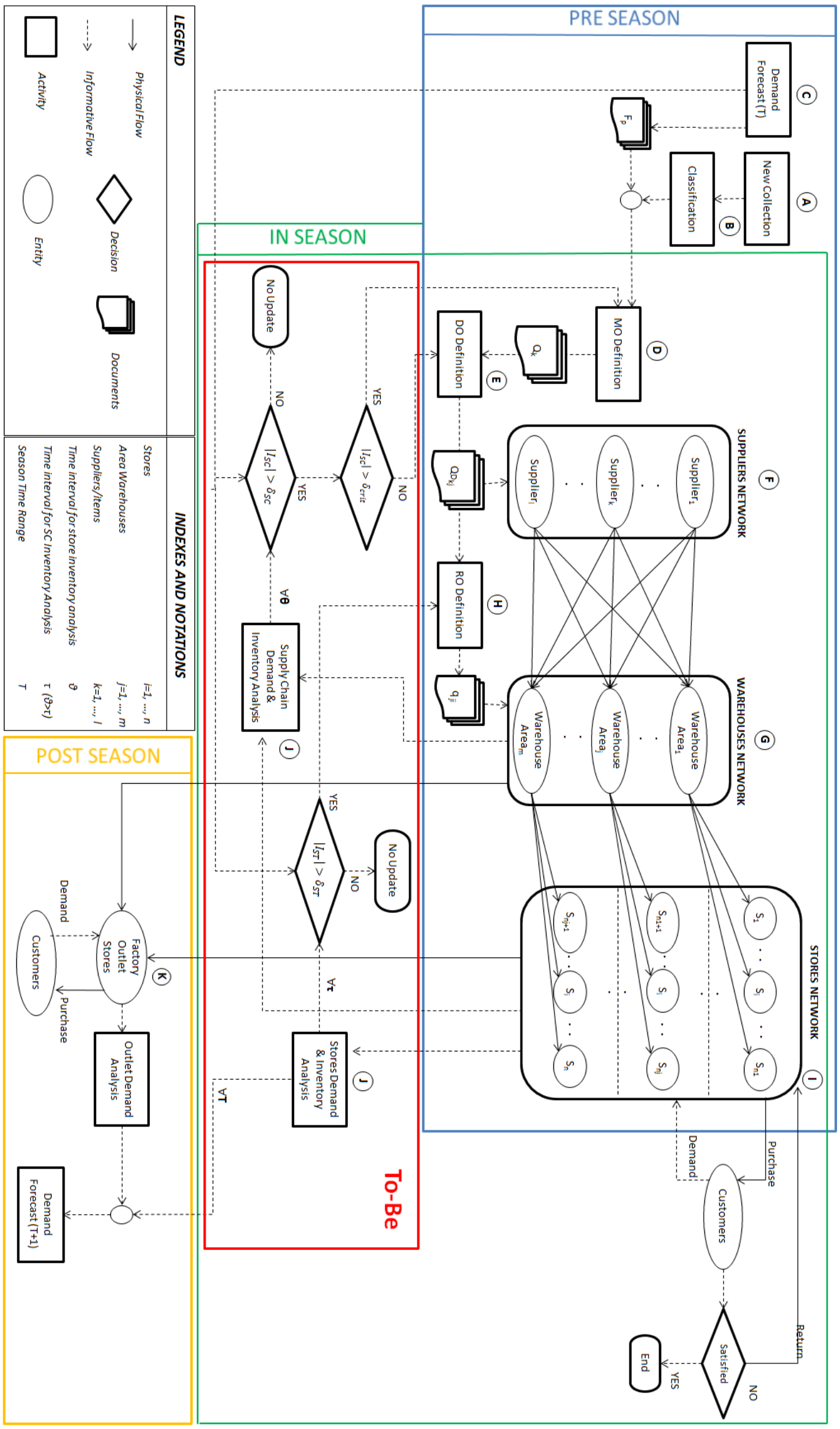


Figure 3.1: Framework for the Optimization of the Supply Chain in the Fashion Retail Industry

stores (Table 3.1).

The In-Season phase, instead, starts with the first sales recorded in the stores. We suppose that both deliveries form suppliers and replenishments to stores are also performed during the selling season even if they are scheduled before it. Thank to sales data recorded in the stores, it is possible to assess deviations between real sales and forecasts. This analysis represents the core of the proposed approach (To-Be) and defines in real-time how much the demand was under-estimated or over-estimated. If this deviation is higher than a fixed threshold, the model will update all the *Merchandise Orders* and possibly cancel some orders or issue new ones; otherwise it will simply update *Replenishment Orders*, increasing or reducing quantities to be delivered to stores. This adjusting procedure is called *Update Process*. The In-Season phase ends with the collection of unsold goods from stores and warehouses. These unsold items will be then delivered to *Factory Outlet* stores (K) and disposed during the following seasons (Post-Season). It is clear that each item will have a fall in price in proportion to the time of storage in the outlet store, which results in a reduction of the contribution margin. In addition, during this phase, all sales data recorded will be collected and used to draft demand forecasts for the following season (T+1). In the following paragraphs we will describe in detail the different steps of the proposed framework.

3.2.1 Development of the New Collection (A)

The definition of the collection primarily concerns to the Styling Office and is performed down line of a long phase of studies of trend, fair attendance, etc. This activity will not be part of this study but it will be just considered as an input to the model. It is, in fact, responsibility of fashion designers to define materials, design clothing items and decide in which colours, sizes and variations to replicate them. Table 3.2 shows an example of the information items needed for the definition of the collection.

In more complex cases of worldwide companies, the collection could also be substantially modified according to the reference market (European, Asian or American).

Table 3.1: Example of activity schedule for a Fall/Winter Season

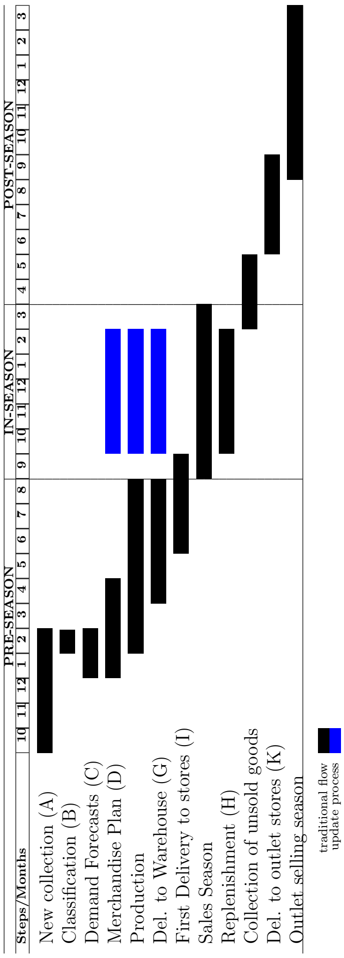


Table 3.2: Example of characteristics of collection items

Item code	**Materials**	**Colors**	**Sizes**	**Process**	**Accessories**
001	Wool	Blue Black Brown	40-46	Knitting	Buttons Brooch Belt
002	Denim	Blue Black	38-44	Cutting Scouring	-
...	...	...	...	...	...

Generally, after its development and before starting procurement and production, the collection is presented to buyers during the most important sector fairs (Milano Fashion Week, Première Vision in Paris, etc.); from this moment on sales to wholesalers begin.
Starting production after having acquired orders from the market obviously increases time to market; this can only be accepted for high level brands or for collection with an important stylistic content. Sophisticated and expensive items, in fact, cannot be produced without reliable sales data; wrong demand forecast can lead to heavy losses and capitals fixed in stocks.
Companies that work with a direct retail distribution network, as the case described in this thesis, could also avoid this phase of presentation to buyers, or perform it but without time constraints, just to acquire image on the market and to promote the company to the press. In this case, there are no long waits for acquiring final orders and no specific delivery commitments since the company issues internal orders for its Retailers and delivers goods according to its internal plans. On the other hand, procurement and purchase orders are performed based on demand forecasts, forcing the company to take the risk connected to forecast errors and to be sure that products are available in stores when the market demands them, so as not to lose sales.

3.2.2 Classification (B)

For specific business needs, each item is generally identified with a unique code. For our purposes and given the aim of the proposed framework, instead, each clothing item is classified according to Product Category, Price Range and Seasonality.
It is important to underline that all real case data and examples showed in the present work refer to an Italian Fashion Company which works in the whole national territory with hundreds of stores both franchising or monobrand direct-operated stores.
Researches on these past sales data show that, depending on the position of the store (in a Shopping Mall, on the Street or in an Airport), customer's purchase behaviour is different for both Product Category and for Price

Range [Iannone et al., 2013].
In particular, for products we identified three macro-categories:

- *Clothing*: products that can be quickly purchased without trying them on in the dressing room. This may reduce the time spent by the customers for the purchasing activities and by the shop assistants for serving clients;

- *Clothing to Try on*: trousers, t-shirts, dresses and all the other items that require the use of the dressing room and a longer stay of customers in the stores;

- *Accessories*: handbags, scarves, jewellery, etc. For this articles customers do not have the choose size which best fits them, but just the color.

The list of clothing items included in each Product Category is shown in Table 3.3.

As regards the price, instead, we defined three different ranges:

- *Cheap*: from 0 to 50 Euro;

- *Intermediate*: from 51 to 100 Euro;

- *Expensive*: more than 100 Euro.

According to seasonality characteristics of items, we can distinguish (Sen [2008], Nuttle et al. [1991]):

- *Basic* products which are sold throughout the year. They amount approximately 25% of all apparel;

- *Seasonal* products, with a 20-week product life, which represent almost 45% of apparel. Those products are replaced by new lines twice or three times per year;

- *Fashion* products, with 10-week product life and more than four seasons per year. Fashion items are steadily increasing their share of

Table 3.3: Product category classification

CLOTHING		CLOTHING TO TRY ON		ACCESSORIES	
Code	**Description**	**Code**	**Description**	**Code**	**Description**
21	Wool Cardigan	11	Trousers	90	Accessories
31	Cotton Cardigan	12	Denim Trousers	92	Handbag/Clutch
47	Synthetic shawl	13	Bermuda shorts	93	Foulards/scarves
23	Bodysuit	15	Pedal pusher	94	Hats
59	Nightwear	17	Denim pedal pusher	95	Umbrellas
73	Eco sheepskin coat	18	Leggings	96	Belts
78	Eco leather jacket	20	Wool sweater	98	Necklace
79	Denim jacket	30	Cotton sweater	99	Sunglasses
80	Vest	41	Shirt	100	Wallet
81	Blazer	43	Denim shirt	101	Bracelet
82	Quilted jacket	42	Top and Undershirt	102	Gloves
83	Coat	48	Caftan	103	Brooch
84	Jacket	51	T-shirt	106	Beauty
85	Raincoat	60	Skirt	107	Spectacles
86	Sheepskin coat	62	Denim skirt	112	Trolley
87	Cloak	70	Dress	199	Mobile cover
89	Fur coat	71	Suit	792	Basic handbag
91	Shoes	72	Tracksuit	906	Agenda
192	Boots			907	Photo holder
194	Slippers				
195	Pantyhose				

the market at the expense of both seasonal and basic goods since consumers always demand greater variety and more frequent changes. Some major retailers argue that customers visit their store, on average, once every two months and they want their customers to see new lines of products during each visit.

This decision to deal with product categories and price ranges instead of single item codes is primarily due to the need of having forecasts as accurate as possible; a lower detail level, that is aggregated forecast for few groups of products instead of detailed forecast for thousands of codes, in fact, allows committing a lower error.
Furthermore, we observed that, depending on the store location, customer's purchasing choices can be substantially different toward the different categories indicated (refer to paragraph 3.2.3.2).

3.2.3 Demand Forecasts (C)

Next step of the model is demand forecasting; this is one of the pillars on which all planning activities are based. All financial plans, timing for purchases, definition of production and inventory levels, sale plans etc., in fact, derive from forecasts.
In the fashion industry this process is crucial and particularly complex due to high volatility and unpredictability of demand.
In this section we will first describe main and most recent studies on the subject and then we will propose several parameters needed to prepare forecasts.

3.2.3.1 Forecast Techniques in the Fashion Industry

Forecasting methods and techniques used in the fashion and apparel sector are numerous, ranging from personal experience [Noh and Ulrich, 2013] to more advanced statistical algorithms. The process is complicated due to different products and market circumstances that require or allow different reasoning. Besides particularities already described, other important constraints in this sector are that:

- items are declined in many colour alternatives - which is a very fashionable attribute and not widely examined in previous works [Liu et al., 2013] - and in various sizes, which should match with morphologies of the target consumers [Thomassey, 2010];
- most of the items are substituted in each collection [Thomassey and Hapiette, 2007], which implies that historical data are not always available.

To overcome these challenges, several advanced methods have been presented in last years and most of them use artificial intelligence. For example, Wong and Guo [2010] propose a hybrid intelligent model for medium-term sales forecasting which is also applicable when irregularity and seasonality occurs, but cannot reflect effects of exogenous factors such as weather or economic indexes. Hybrid methods, instead, are based on extreme learning

machine (ELM) which is a modern heuristic method using artificial intelligence [Xa et al., 2012], or use a clustering technique and decision tree classifier to group similar historical items and obtain mid-term forecasts [Thomassey and Fiordaliso, 2006]. Other forecasting support systems are based on soft computing techniques such as fuzzy logic, neural networks and evolutionary procedures and is able to perform forecasts for various time horizons and at different aggregation levels [Thomassey et al., 2005]. In the end, also a Fourier analysis for sales forecasting was presented [Fumi et al., 2013]; this is an easier and more effective forecasting method compared to other widespread heuristics normally used.
From the analysis of many forecasting approaches proposed in this sector in the past years [Nenni et al., 2013], it derives that it is still very challenging to have reliable previsions with such a level of uncertainty that characterizes this market. This is one of the main reasons of the great development of Fast Fashion, which does not try to predict and anticipate trends but tries to follow them.

3.2.3.2 Forecasting Factors and data

In the proposed model, *Demand Forecasts* provide the basis on which all operations plans are compiled and are drawn up according to historical data collected from stores.
In order to draft reliable forecasts, it is useful to distinguish if product is basic/continuing or seasonal/fashionable since forecasting methods can be substantially different in these two cases. In the first case, in fact, historical data are quite reliable and stable; this means that forecasts can nearly be exclusively based on them. In the second case, instead, historical data are not available since the product is new and it is difficult to anticipate sales results.
Inputs required for this step fall into three classes: the first one is related to physical characteristics of stores, the second one concerns historical data and the last one regards characteristics of the new collection.

1. ***Physical characteristics*** of stores are defined just once, when open-

ing the stores, and remain unchanged over time. They are:

- *Dimension (Dim)*, both of the exhibition area and of the internal warehouse. This factor is important to define maximum level of stocks that stores are able to accept and manage without overloading;
- *Location (Loc)*, which can be on the Street (ST), in a Shopping Mall (SM) or in an Airport (ARP). As already introduced in the previous paragraph, customer's purchasing behaviour is considerably different for different cases.
  Initial analysis of data coming from all the stores highlighted that, depending on the position, the three product categories - Clothing, Clothing to Try On and Accessories - record different sales levels. Accessories, for example, are highly sold in airports because customers are passing by and the purchasing must be very quick, while in shopping malls and on the street, accessories have very little success. Opposite behaviour is showed for clothing to try on, while clothing which do not require the use of the dressing room are equally sold in all stores.
- *Geographical Area (Geo)*, in which stores are located. In this paper, since we are referring to a company that works nationwide in Italy, we consider three different areas: North, Centre and South; but it can be simply adjusted considering regions, counties, etc., in other cases. This parameter is used to evaluate socio-economic factors that influence purchasing behaviour mainly towards different price ranges;
- *Competitor (Comp)*, which defines how many nearby competitors are located in the same area.

2. ***Historical sales data***, instead, are processed at the end of each season thank to EDI (Electronic Data Interchange) and EPOS (Electronic Point of Sale). They are:

- *Turnover (Turn)*, recorded during the previous comparable season. It is meaningless, in fact, to evaluate the previous season; it means considering turnover of Spring/Summer season for drafting forecasts for Fall/Winter season and vice versa. For stores located in tourist areas this can lead to significant errors if we do not consider the alternation between off-season and tourist season.
- *Sales percentage* (%Sales) related to deliveries, defined as:

$$\%Sales = \frac{Sales}{DeliveredQuantities} \tag{3.1}$$

  It is clear that sales will increase with the availability of goods in stores (ref. paragraph 3.4.5), this makes this parameter more relevant than the pure sales data.

Hence, given l the number of handled items and n the number of active stores during the season, demand forecasts ($\bar{F}_{ki}$) for the k-th item and the i-th store will be a complex function of all the above-mentioned parameters:

$$\bar{F}_{ki} = f(Dim_i, Loc_i, Geo_i, Comp_i, Turn_i, \%Sales_{ki}) \tag{3.2}$$

Table 3.4 shows an example of the above mentioned forecast data.

Table 3.4: Input factors for Demand Forecasts

Store code	Geo	Turn [K€]	Dim [mq]	Loc	%Sales [%] ACCESSORIES Ch.	Int.	Exp.	CLOTHING Ch.	Int.	Exp.	CL. TO TRY ON Ch.	Int.	Exp.
44	South	88	66	ARP	71	96	-	91	84	98	87	92	93
210	South	113	113	SM	57	90	100	73	67	71	86	71	68
76	South	59	58	ST	55	93	100	67	65	61	74	64	76
41	South	217	62	SM	68	93	100	80	73	69	72	65	67
37	North	124	343	SM	66	86	67	69	73	66	82	64	56
47	North	57	82	ST	65	67	90	79	76	78	82	76	77
233	North	126	100	SM	68	93	100	81	73	61	80	60	71
...	...	...	...	...	...	...	...	...	...	...	...	...	...

3. ***New Collection*** parameters are the last ones that have to be considered; they are expressed as a percentage deviation from the previous

season and are defined as [Bini, 2011]:

- *Attractiveness (Δ_{att})*: which has a positive value if the Styling Office thinks that the new collection will be more successful than the previous one, negative in the opposite case. This impact is estimated on the ratings of customers to which the collection is shown during sector fairs.
- *Investment in marketing and communication (Δ_{mrk})*: if the company intends to carry out a powerful advertising and communication campaign, this will increase brand awareness and directly influence final client's purchasing. Unlike previous factor that can only be subjectively assessed, the budget devoted to advertising is defined in advance by the company and Δ_{mrk} can be easily calculated as:

$$\Delta_{mrk} = \frac{Mkt_T - Mkt_{T-1}}{Mkt_{T-1}} \tag{3.3}$$

  Where T is the index related to the season and *Mkt* is the budget assigned to the marketing campaign.

Then ultimately, sales forecasts previously defined must be adjusted as:

$$F_{ki} = \bar{F}_{ki} * (1 + \Delta_{att} + \Delta_{mrk}) \tag{3.4}$$

All remarks made so far do not include either size or colour of the clothing item. For sizes, generally demand trend follows a Gaussian curve centred on a particular size which varies according to the customer target and the reference market (see an example in Figure 3.2).

All colors, instead, are treated in the same way: equal quantity for each variation of color is purchased. Nevertheless, it may be defined the "trendy" color for the season under exam and increase its forecasts of a small percentage.
A summary of the characteristics of the forecasting factors previously described is reported in Table 3.5.

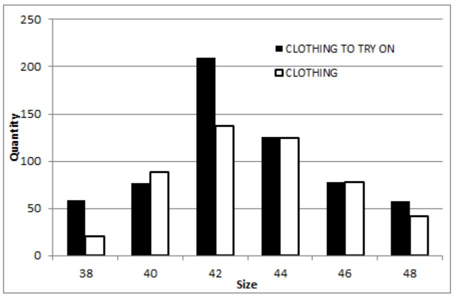


Figure 3.2: Gaussian curve representing demand trend according to sizes

Table 3.5: Summary of the forecasting factors and their characteristics

Degree of detail	**Level of detail**	**Parameters**	**Unit of measure**	**Forecasting characteristics**
↓	COLLECTION	Impact	%	Deviation from previous season
		Marketing		
	POS	Dimension	m^2	Non changing physical characteristics
		Position	ST SM ARP	
		Geogr. Area	North Centre South	
		Turnover	€	Historical Data
	SEASONALITY	Basic	%	Consolidated Historical Data
		Seasonal		Historical Data
		Fashion		NO Historical Data
	PRODUCT CATEGORY	% Sales Clothing % Sales Cl. to try on % Sales Accessories	%	Historical Data
	COLOR	Trendy	-	Historical Data from trendy color of previous season
		Basic		Consolidated Historcal Data
	SIZE	Gaussian Distribution	-	Target Market

The Purchasing Office will, then, receive sales forecasts for each k-th clothing item defined as:

$$F_k = \sum_{i=1}^{n} F_{ki} \tag{3.5}$$

These quantities will represent a kind of internal order for the company whereby launching orders to suppliers.
It is important to underline that, if the company plans to open new stores, it must evaluate its impact by considering past sales of a real store which is equivalent in terms of dimension and location. In this case, forecasts will

be partially reduced due to the necessary start up.

3.2.4 Definition of the Merchandise Orders (D)

The main Operations Plan that a fashion company must issue is the *Merchandise Plan* which defined purchase quantities for each item code. For its definition the Purchasing Office evaluates, besides sales forecasts, possible volume discounts granted by suppliers, company's economic and financial capacity and a need to ensure a certain unsold stock in order to conveniently manage factory outlets, defined as *Outlet Compensation Stock* (OS).
Therefore, the purchase quantity Q_k will be defined as:

$$Q_k = (F_k + AS_k) * (1 + OS + SS) \tag{3.6}$$

Where:

- AS_k is the *Assortment Stock* and represents the quantity to be added to the forecasts in order to guarantee availability of all sizes and colors for each item. Then:

$$\begin{cases} AS_k > 0 & \text{if} \quad \bar{F}_k < AS_{min,k} \\ AS_k = 0 & \text{if} \quad \bar{F}_k > AS_{min,k} \end{cases} \tag{3.7}$$

- OS is the *Outlet Compensation Stock* and is expressed as a percentage of the quantities defined by forecasts and assortments. As described following (ref. paragraph 3.2.11), factory outlet stores are used to absorb the risk of overestimation of the demand which can be important when managing hundreds of stores. At the same time, therefore, to be attractive for customers, outlet stores as well must guarantee a fixed assortment of sizes and colours, at least at the beginning of the season.

- SS is the *Safety Stock* defined according to the service level that the company wants to ensure and to the demand rate.

Then the total quantity will be:

$$Q = \sum_{k=1}^{l} Q_k \tag{3.8}$$

Before issuing these orders to suppliers, the Purchasing Office must evaluate:

- *Purchasing Budget*, which is fixed when defining the collection;
- *Discounts on quantities*, that you can obtain from suppliers.

Each order must contain the following information:

- *Suppliers*: they are chosen with a precise procedure that evaluates stylistic and technical requirements (ref. paragraph 3.2.6);
- *Quantities* Q_k: we are supposing that each item is produced by one and only supplier, then the index k refers both to the item and to the supplier.

3.2.5 Definition of the Delivery Orders (E)

These orders define, for each supplier, quantities and times for deliveries to the central warehouse. It is clear that, in the simplest case, there is a single central warehouse, for example when companies operate only at national level. For global companies, instead, warehouses will be numerous and located all over the world. In this case, defining delivery plans will be more complex since it will be necessary to optimize those plans according to sales forecasts for the different geographical areas served by the warehouse. The orders that define deliveries to the central warehouse are issued by the Purchase Office in agreement with the suppliers. These plans, in fact, must combine two conflicting requirements. On one hand, the company requires frequent deliveries for medium-small lots so as not to overload warehouse and its resources. In addition, for more complex collections, which involve many clothing items of different warmness, the company prefers to have at

stock items appropriate to the temperature of the moment, in order to be able to respond quickly to customers' requests. During the Spring/Summer season, warmer items are generally shipped at the beginning of the season (late January/early February) because weather is still cold and those items are then more requested, while lighter ones are delivered in early spring when milder weather justifies their purchasing. In the Fall/Winter season the opposite case occurs. In August/September it is better to have lighter clothing in stores for still high temperatures, while only later, when weather gets colder, stores will receive winter clothes.
On the other hand, suppliers would prefer less frequent deliveries for larger lots in order to reduce shipping costs.
Hence, it is possible to define, together with the suppliers, the quantities to be delivered at time t to the j-th warehouse as:

$$Q_{D,j}(t) = \sum_{k=1}^{l} Q_{D,kj}(t) \tag{3.9}$$

$$with \quad \sum_{j=1}^{m} \int_{0}^{T} Q_{D,kj}(t)dt = Q_k \qquad \forall k \in 1, ..., l \tag{3.10}$$

3.2.6 Suppliers (F)

Outsourcing is becoming an unavoidable trend in cost cutting for Fashion & Apparel companies, especially when purchasing activities involve multiple international suppliers overseas located. This means that establishing an efficient relationship between buyers and suppliers is a critical factor.
It is clear that, for our purpose, two are the unavoidable feature that suppliers must respect:

- *Qualification and Quality Assurance*: the initial hypothesis on which the described model is based is that collection is already defined by stylists and consequently all materials and manufacturing processes requested are already known. It is clear that suppliers must possess all the skills and equipment needed to produce a clothing item respecting all the company's specifications;

- *Productive capacity*: selected suppliers must be able to produce the required quantities on schedule. Then it is necessary to verify that they are not already saturated due to other client's orders.

Other discriminant factors are:

- *Cost*: a factor of paramount importance is clearly the purchase cost of the clothing item and is one of the main elements of suppliers choice;
- *Location*: the geographical position of the supplier is important to evaluate shipping time and cost and any custom duties;
- *Flexibility*: which represents the capability of the supplier to respond to unexpected requests or variations in terms of volume and mix of products;
- *Reliability*: which evaluates the supplier's ability of respecting contractual requirements in terms of delivery dates, quality etc.

In the proposed model we consider the case of complete outsourcing of the production process. Actually, some companies outsource only a part of the entire process while internally performing finishing steps. In this case we should also consider a suppliers' network, a warehouse for semi-finished products and the resources needed for final phases of production.
Several studies were proposed in this context for evaluating and selecting suppliers; in the apparel industry most used models are based on AHP [Chan and Chan, 2010, Teng and Jaramillo, 2005] and use several areas of evaluation such as delivery, quality, assurance of supply, flexibility, cost and reliability.

3.2.7 Central Warehouses (G)

The central warehouse is responsible for receiving goods from different suppliers, for storing and for inventory managing. Then, through the picking and sorting process, personalized kits of items will be prepared and shipped

to the different stores. Besides material flows, warehouses must manage the information flow concerning delivery and replenishment plans provided by the Department.
The stock level for the j-th warehouse (ST_j) at the time t can be calculated as:

$$ST_j(t) = ST_j(t-1) + \sum_{k=1}^{l} Q_{D,kj}(t) - \sum_{i=1}^{n} Q_{POS,ji}(t) \qquad (3.11)$$

where $Q_{POS,ji}$ is the quantity delivered from the j-th warehouse to the i-th Point of Sale (POS). We suppose that each warehouse supplies only a specific set of n_j stores pertaining to its area. Then $Q_{POS,ji}$ is null for the i-th stores not pertaining to the j-th warehouse.
We also need to consider physical limits of the central warehouse concerning storage capacity:

$$ST_j(t) \leq ST_{max,j} \qquad (3.12)$$

and concerning materials handling capacity:

$$\sum_{k=1}^{l} Q_{D,kj}(t) + \sum_{i=1}^{n} Q_{POS,ji}(t) \leq HC_{max,j} \qquad (3.13)$$

Where $HC_{max,j}$ is the maximum materials handling capacity.
It is important to underline that some items may require additional treatments (such as for example ironing) before delivery to the stores; this obviously creates another time constraints that has to be respected before shipment to POS.

3.2.8 Definition of the Replenishment Orders (H)

Against the delivery plan to the central warehouse, the company must define personalized kits of items to deliver to each store for each k-th item. Given n the total number of POS directly managed by the company and $q_{ki}(t)$ the quantity of the k-th item delivered to the i-th store at the time t, we can say that the total quantity delivered to the POS i is:

$$Q_{POS,ji}(t) = \sum_{k=1}^{l} q_{kji}(t) \tag{3.14}$$

$$where \qquad \sum_{i=1}^{n} \int_{0}^{T} Q_{POS,ji}(t)dt \leq \sum_{k=1}^{l} \int_{0}^{T} Q_{D,kj}(t)dt \tag{3.15}$$

It is important not leave stores lacking in some requested items or sizes but neither to overload them, thus respecting the capacity restriction:

$$ST_{POS,i}(t) \leq ST_{POS,max,i} \tag{3.16}$$

where $ST_{POS,i}$ is the Stock Level in the i-th POS and is defined as:

$$ST_{POS,ki}(t) = ST_{POS,ki}(t-1) + \sum_{j=1}^{m} q_{kji}(t) - s_{ki}(t) \tag{3.17}$$

where $s_{ki}(t)$ are the sales of the k-th item in the i-th store at time t. Even if a first schedule is defined during the In-Season phase, stores are not replenished in a unique solution before the selling season. Then, plans drafting is a process which needs to be performed before each replenishment. The first draft, before the selling seasons, is based on sales forecasts while the following ones, during the season instead, are based both on forecasts and on real sales data.

3.2.9 Stores (I)

The stores are the final ring of the supply chain and represent the point of direct interface with customers offering not only a mix of goods but also services. In this study they are considered as passive recipients of products allocated by the company but have the essential role of recording actual sales through EDI and EPOS systems. The only way of implementing an effective demand driven approach is, in fact, real time information sharing between retailers and the Logistic Department.
Real sales recorded in the stores can be evaluated as:

$$s_{ki} = min\{d_{ki}(t); ST_{POS,ki}(t)\} \tag{3.18}$$

where $d_{ki}(t)$ is the demand of the k-th item in the i-th store. Actually, this parameter is difficult to measure; in most cases, in fact there is no awareness of the entity of the potential lost sales since the only available information on customer demand derives from sales data [Battista et al., 2011].

3.2.10 Deviation analysis (J)

In order to update in real time all merchandise, delivery and replenishment plans, it is necessary to analyse the deviation between actual recorded sales and forecasts. This process represents the core of the proposed approach (To-Be case). For this purpose, two different analysis must be performed at different time intervals. The first one, *Stores Demand & Inventory Analysis*, allows us to evaluate in real-time how much stores demand was under-estimated or over-estimated.

$$\Delta_{ST,ki} = \frac{F_{ki} - s_{ki}}{F_{ki}} \tag{3.19}$$

It is performed at time intervals τ and evaluates not only actual sales but also any return, defective or stolen item. If this deviation is higher than a fixed threshold (δ_{ST}), the model will update the replenishment plans adjusting them in order to meet customers' requests. The replenishment quantities are updated according to the following equation:

$$\begin{cases} if \quad |\Delta_{ST,ki}| > \delta_{ST} \qquad \bar{q}_{kji} = q_{kji} * [1 - (\Delta_{ST,ki} * u)] \\ if \quad |\Delta_{ST,ki}| < \delta_{ST} \qquad \bar{q}_{kji} = q_{kji} \end{cases} \tag{3.20}$$

where $\bar{q}_{kji}$ is the updated quantity and u is a parameters which defines how much replenishment plans can change and it has to be appropriately set. It is important to underline that if Δ_{ST} is negative, it means that demand was under-estimated then the replenishment quantity ($\bar{q}_{kji}$) must

be incremented, and vice versa.
The second analysis, *Supply Chain Demand & Inventory Analysis*, evaluates in aggregate data from stores and warehouses at each time interval θ (with $\theta > \tau$).

$$\Delta_{SC,k} = \sum_{i=1}^{n} \frac{\bar{F}_{ki} - s_{ki}}{\bar{F}_{ki}} \tag{3.21}$$

If this deviation is higher than threshold δ_{SC}, it means that we have to revise Merchandise Orders and possibly cancel some orders or issue new ones.

$$\begin{cases} if \quad |\Delta_{SC,k}| > \delta_{SC} \qquad \bar{Q}_k = Q_k * [1 - (\Delta_{SC,k} * u)] \\ if \quad |\Delta_{SC,k}| < \delta_{SC} \qquad \bar{Q}_k = Q_k \end{cases} \tag{3.22}$$

3.2.11 Factory Outlet stores (K)

Main role of outlet stores is to absorb the risk of incorrect demand forecasts, especially in case of demand overestimation. Factory Outlet stores sell at significantly discounted prices thus greatly reducing contribution margins for each item and involving additional costs for the management of other stores and for the withdrawal of unsold goods from main stores and delivery to outlets. Therefore, when it comes to hundreds of main POS, unsold items reach such high volumes that it is unavoidable the use of an effective system for their disposal. On the other hand, to conveniently run an outlet, you can not simply offer unsold items from main stores; it would be a poor and not assorted offer that would not attract customers. Many companies, then, complete this offer by producing additional items to replace missing colors and sizes or just to offer new maybe simpler and cheaper items.

3.3 The Causal Loop Diagram for he analysis of interactions between variables

After the definition of the processes and flows, in order to evaluate the performances of the Supply Chain for the proposed approach, it is necessary to define an appropriate set of KPIs. For this purpose, the problem was analysed using the principles of System Dynamics for the analysis of the interactions and cause/effect relationships between variables.

3.3.1 Principles of System Thinking and System Dynamics in Supply Chain Management

System dynamics (SD) is a methodology developed by Forrester to understand the structure and dynamics of complex systems [Forrester, 1961]. This approach has been used in several fields, from project management [Toole, 2005] and Supply Chain management [Gnoni et al., 2003] to product lifecycle management [D'Amico et al., 2013] and capacity planning [Vlachos et al., 2007], and describes a system behaviour through the structure of its feedback loops.
Basic elements of this methodology are causal loop diagrams and stock and flows diagrams. The first ones represent the feedback structure of the system while stock and flow diagrams are tools for assessing variables dynamics through a period [Gnoni and Lanzilotto, 2012].
Main elements of these diagrams are [Sterman, 2000, Georgiadis et al., 2006]:

- *Variables* which are relevant for the system description;
- *Oriented arches* which suggest causal relationships. The + and - sign indicate that the effect is positively or negatively related to the cause;
- *Positive loops*: they are self-reinforcing loops, identified with R. In a positive feedback loop, an initial disturbance leads to further change, suggesting the presence of an unstable equilibrium;
- *Negative loops*: they are self-correcting or balancing loops, identified with B. In a negative feedback loop, after a disturbance, the system

seeks to return to an equilibrium situation;

- *Delays* which describe the inertia of physical system, according to which it is not possible that a quantity changes instantaneously;
- *Stocks* which represent quantities that are accumulated or disposed over time;
- *Flows* which indicate an entity flow from/to one or more Stocks.

All these elements will be part of the Causal Loop Diagram (CLD) which graphically illustrates causal relationships and major feedback loops among variable of the system.
In next sections, the Pre-Season and In-Season phases will be analysed into detail identifying variables and related causal relationships.
In the diagrams, Stocks will be represented in capital letters, Flows in italic underlined letters and Delays with the symbol //.

3.3.2 Pre-Season phase

a) *Definition of New Collection*

Many companies operating in the fashion industry highlight that the most relevant core competences to keep in house are those related to the design phase, which defines material requirements, aesthetic aspect and style of the product [Brun et al., 2008]. Then, this phase, also named as New Product Development (NPD) is considered crucial and very time consuming, since it usually begins almost two years before production [Bandinelli et al., 2013].
Main output data of the collection definition process which are considered relevant to our model are the *Number of Items* and their *Price*. The first variable has a positive relationship with the *Number of Suppliers*. Since it is likely that each clothing item requires one or more specific manufacturing skills or processes, their production will be committed to the most suitable supplier. To simplify, we consider that each item is produced by one specific supplier. The variable *Price*, instead, has a

clear relationship of direct proportionality with *Revenues*.
Another significant variable is the *Collection Attractiveness*, which is evaluated in terms of design, quality and assortment (i.e. the number of different clothing items). Not less significant is the *Price* factor [Mariany et al., 2012]. To increase attractiveness there is also *Marketing Investment (Mkt)*, intended as the planned investment in advertising and communication campaigns, which is defined as a percentage of the *Budget* allocated to the entire selling season.

b) *Forecasting*

As already mentioned in previous paragraph, demand for fashion items is highly unpredictable, since isolating external effects such as season, weather conditions or mediatic phenomena can be extremely complex [Souza et al., 2014]. In last years several sophisticated models have been proposed [Fumi et al., 2013, Nenni et al., 2013] and most of them use generic algorithms based on the assumption that demand can be predicted uniformly for all companies and across all industries, product lines and geographies. This one-size-fits-all approach yields a forecast that fails to reflect the relative impact of different demand drivers and to adapt as market conditions and consumer behaviours evolve [Myerholtz and Caffrey, 2014].
Nevertheless, all researchers agree in basing sales forecasting on historical data, which in our case are represented by *Demand* data of the *Previous Sales Seasons*. This idea is represented in our CLD (refer to Fig. 3.3) by a delay. It is clear that these demand data are aggregate data coming from all the stores of the network, then the global *Demand* is positively related to the*Number of Stores* managed by the company.

c) *Merchandise Planning*

Main output of the merchandise planning process is the definition of the global *Purchase Quantity* for each item included in the collection.
The *Purchase Cost (C_P)* will be then calculated as:

$$C_P = \sum_{k=1}^{l} Q_k * cu_k \tag{3.23}$$

Where l is the *Number of Items*, Q_k is the *Purchase Quantity* for the k-th item and cu_k is the k-th item's unitary cost (*Items' cost*).
It is clear that this cost must fall within the *Budget (B)* allocated according to the following equation:

$$Mkt + C_P \leq B \tag{3.24}$$

where *Mkt* is the *Marketing Investment.*
Then, the CLD for these first three processes is shown in Fig. 3.3.

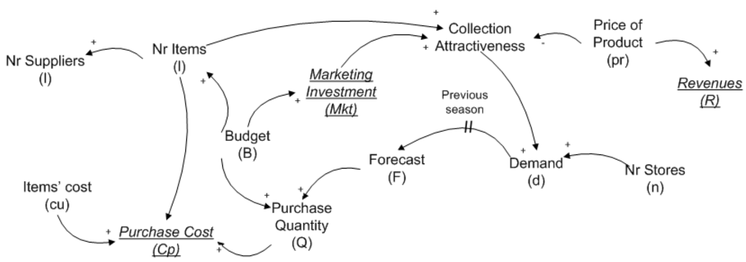


Figure 3.3: Causal relationships for Definition of New Collection, Demand Forecasting and Merchandise Planning

d) *Delivery*

The deliveries (or primary transport) from the suppliers to the Central Warehouse (*Deliveries to Warehouse* - Q_D), which are an incoming flow in the *Warehouse Stock (ST)*, are defined by the Delivery Plan which contains information concerning delivery quantity (*Purchase Quantity* - Q) and times for each supplier (*Number of Suppliers*).
The first balancing loop (**B1**) identified in this system is defined between Q_D and ST. The positive causal relationship (from Q_D to ST) is given by the material flow incoming into the warehouse with an unavoidable delay due to *Delivery Lead Time* increasing with *Suppliers Distance.* The negative feedback (from ST to Q_D), instead, refers to the updating

process in the delivery plans: warehouse physical limits, concerning both storage and material handling capacity, must not be overcome, then delivery quantities and times must be revised accordingly.
The cost item related to this process is the *Primary Transport Cost (C_{PT})* given by:

$$C_{PT} = \int_0^T \left[\sum_{k=1}^{l} \sum_{j=1}^{m} (C_{tf,k} + C_{tv,k} * Q_{Dkj}(h) * DIST_{kj}) \right] dh \qquad (3.25)$$

Where l is the number of suppliers, j is the number of warehouses, $C_{tf,k}$ and $C_{tv,k}$ are constant values and are respectively fixed and variable cost for primary transport for the k-th supplier, $Q_{D,kj}$ and $DIST_{kj}$ are respectively the quantity delivered and the distance from the k-th supplier to the j-th warehouse.

The CLD for this process is showed in Fig. 3.4.

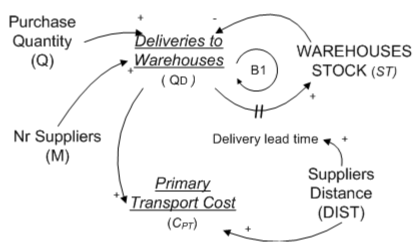


Figure 3.4: Causal relationships for Delivery process

e) *Replenishment*
The replenishment process (or secondary transport) principally aims at dynamically optimizing the assortment of the stores trying to minimize overstock or out of stock events. In this process we can identify two different balancing loops (refer to Fig. 3.5):

B2) between *Warehouse Stock (ST)* and *Deliveries to Stores (Q_{POS})*:

- The negative causal relationship (from Q_{POS} to ST) is given by the material flow out coming from the warehouse;
- The positive feedback (from ST to Q_{POS}) is given by the necessity to respect physical warehouse limits (refer to Delivery process). In order to avoid overloading of the warehouse, when stocks increase, deliveries to store must become bigger and more intensive.

B3) between *Deliveries to Stores* (Q_{POS}) and *Stores Stock (ST_{POS})*:

- The positive causal relationship (from Q_{POS} to ST_{POS}) is given by the material flow incoming in the stores, with a delay due to transport lead time increasing with *Stores Distance* - *dist* from the warehouse;
- The negative feedback (from ST_{POS} to Q_{POS}) is given by the necessity to respect physical internal stores' warehouse limits, such as for the central warehouse.

This second loop also reflects two conflicting requirements of the fashion retail environment. From one side, given customers' impulsive purchasing behaviour, we need to ensure high availability of products, not only in terms of product range but also in sizes and colours. From the other side, higher stock levels may lead to the overloading of internal stores' warehouses and consequent related costs, and to the increase in unsold stocks.
The two cost items related to this process are:

- Warehouse Management Cost (C_{MW}):

$$C_{MW} = \sum_{j=1}^{m} \left[C_{mf,j} + \sum_{k=1}^{l} ch_k * cu_k * \frac{1}{T} * \right. \\ \left. * \int_0^T \left(Q_{D,kj}(h) - \sum_{i=1}^{n} Q_{POS,ji}(h) \right) dh \right] \quad (3.26)$$

Where $C_{mf,j}$ is the fixed cost for the management of the j-th warehouse, ch_k is the warehouse holding cost for the k-th item expressed as percentage of its value and $Q_{POS,ji}$ is the quantity delivered from the j-th warehouse to the i-th store.

- Secondary Transport Cost (C_{ST}): This is the cost that the company supports for the delivery of quantity $Q_{POS,ji}(t)$ to the stores. Accepting a small approximation, we will suppose that this cost also includes the cost for the collection of unsold products.

$$C_{ST} = \sum_{i=1}^{n} \left[c_{tf,i} + c_{tv,i} * \int_0^T \sum_{k=1}^{l} q_{ki}(h) * dist_i dh \right] \tag{3.27}$$

Where, for the i-th store, c_{tf} and c_{tv} are constant values and are respectively fixed and variable cost for secondary transport, Q_POS, ji is the quantity delivered and $dist_i$ *(Stores Distance)* is the distance between central warehouse and the i-th store. For simplicity, we suppose that each warehouse replenishes only a fixed range of stores pertaining to its area.

The CLD for this process is showed in Fig. 3.5.

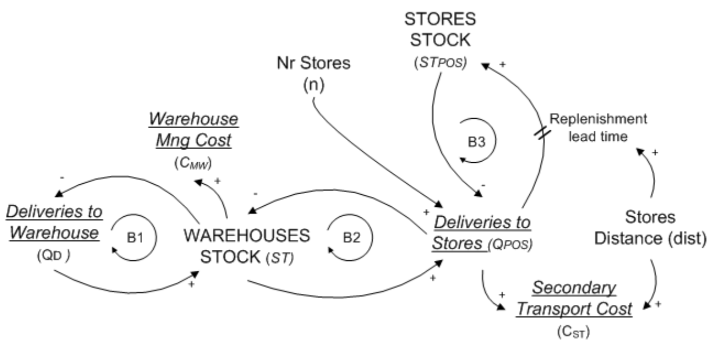


Figure 3.5: Causal relationships for Replenishment process

3.3.3 In-Season phase

a) *Sales*

The *In Season* phase starts with the first *Sales* recorded in the Stores. In this process we can clearly identify a balancing loop (**B4**) between *Demand (d)*, *Sales (s)* and *Stores Stock (ST_{POS})*:

- The negative causal relationship (from s to ST_{POS}) is given by the real Sales which represent a material flow out going from the stores;
- The positive causal relationship (from ST_{POS} to d) reflects customers' impulsive and compulsive purchasing behaviour (refer to *Replenishment* process), then an increasing demand will be observed with a higher assortment level;
- The positive feedback (from d to s) shows the direct proportionality between Demand and Sales (refer to equation 3.28).

In addition, in order to estimate uncensored customer requests, Caro and Gallien [2007] define *Demand* as the sales that would have been observed had all merchandise been displayed without any *Out of Stock (OOS)*. Then we can define the following equation:

$$d_{ki} = s_{ki} + OOS_{ki} \tag{3.28}$$

The cost item connected to this process are:

- *Stores Management Cost (C_{MS})*:

$$C_{MS} = \sum_{i=1}^{n} c_{mf,i} + \sum_{k=1}^{l} \overline{ch}_k * cu_k * \frac{1}{T} \int_0^T (\sum_{j=1}^{m} q_{kji}(h) - s_{ki}(h))dh \tag{3.29}$$

  - $c_{mf,i}$ is the fixed management cost of the i-th store. It is greater than zero only if the store is directly managed by the company, otherwise, in case of a franchising store, it is null since all the fixed costs are supported by the franchisee;

- $\bar{ch}_k$ is the store holding cost for the k-th item expressed as percentage of its value. This value changes if we are considering a main store or a factory outlet store but it is always higher than the same ch_k for the central warehouse, since products stored in the stores can not be used any more for the replenishment of other stores and other possible transfers will generate higher costs.

- *Out of Stock Cost (C_{OOS})*:

$$C_{OOS} = \int_0^T \sum_{k=1}^{l} \sum_{i=1}^{n} OOS_{ki}(h) * (pr_k - cu_k) * c_{sh} dh \qquad (3.30)$$

Where c_{sh} is the unitary shortage cost expressed as a percentage of the difference between price and unitary purchase cost.

Another variable that must be considered in this process is *Revenues (R)*, expressed as:

$$R = \int_0^T \sum_{i=1}^{n} \sum_{k=1}^{l} s_{ki}(h) * pr_k(h) dh \qquad (3.31)$$

Revenues are time depending since products suffer a depreciation according to the time of permanence in the store. In general, the price will follow a step function decreasing over time (see an example in Figure 3.6).

In addition to revenues resulting from sales, other incomes from franchisee (typically royalties) must be included.

The CLD for this process is showed in Fig. 3.7.

b) *Deviation analysis*

Supply and demand are easily matched if demand is steady over time with no change in volume or mix. As soon as demand changes, however,

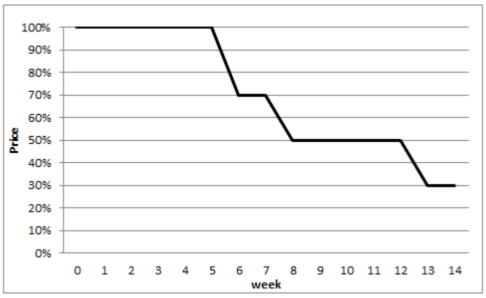


Figure 3.6: Price trend

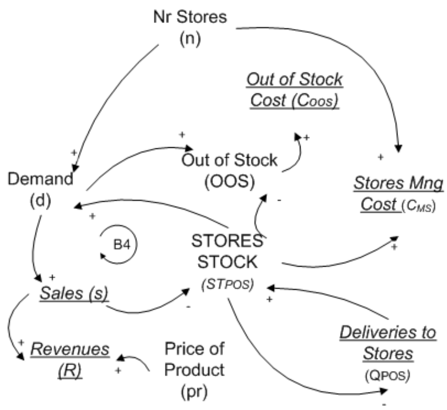


Figure 3.7: Causal relationships for Sales process

a company must adjust the supply levels accordingly at each step of the supply chain [Budd et al., 2012].
This adjusting process is based on the comparison between real *Demand* and *Forecasts*, which allows us to perform two different deviation analysis (ref. paragraph 3.2.10):

- *Supply Chain Deviation*: it evaluates aggregate data from *Warehouse Stock* and *Stores Stock* and, if this deviation is higher than a fixed threshold, the system will update *Purchasing Quantity* possibly cancelling some orders or issuing new ones;
- *Replenishment Deviation*: through the analysis of current *Stores Stock*, it evaluates in real time how much *Demand* was under or

over estimated and, if it overcomes a fixed threshold, we will have to adjust the replenishment plans (*Deliveries to Stores*).

The CLD for this process is showed in Fig. 3.8.

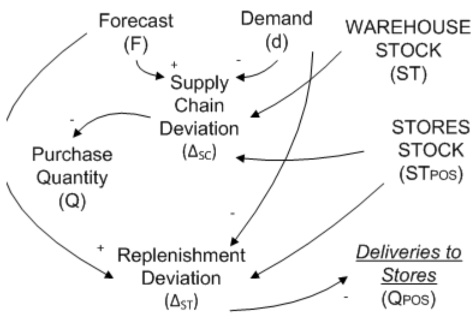


Figure 3.8: Causal relationships for Deviation Analysis

3.3.4 Economic Performance

For each Retail SC and, generically, for each Supply Chain, main purpose is the maximization of the *Profit (P)* expressed as:

$$P = R - C_{OOS} - C_P - C_{PT} - C_{MW} - C_{ST} - C_{MS} - Mkt \qquad (3.32)$$

The causal relationships representing this economic evaluation are showed in Fig. 3.9.

3.3.5 The Final Causal Loop Diagram

Integrating all the variables and interactions previously described, the final CLD of the system under exam is shown in Fig. 3.10.

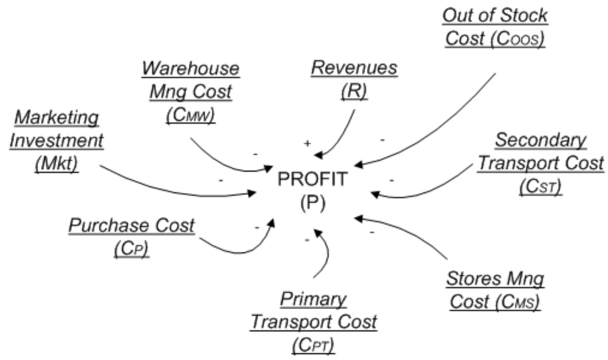


Figure 3.9: Economic relationship

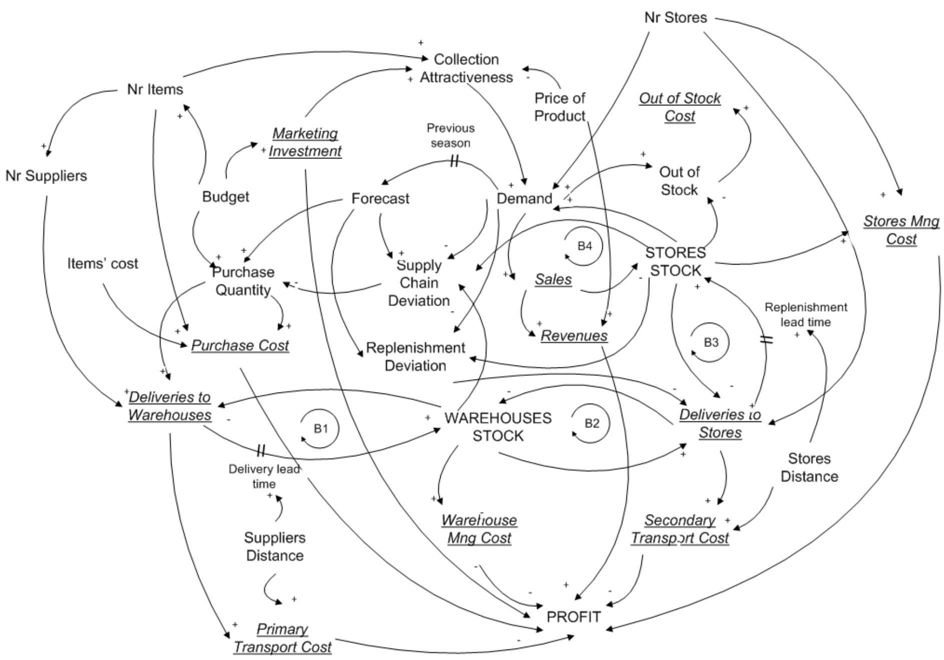


Figure 3.10: The Final Causal Loop Diagram for a Fashion Retail Supply Chain

3.4 Technical Key Performance Indicators

Besides the cost items defined in the previous paragraph, for a correct analysis and optimisation of the performances of the entire Supply Chain, it is necessary to define a complete set of Key Performance Indicators (KPI) also including some technical aspects. For this purpose, we referred to the SCOR Reference Model 11.0 [Council, 2012] which defines six primary management processes (Plan, Source, Make, Deliver, Return and Enable - ref. Figure 3.11) and five Performance Attributes (Reliability, Responsiveness, Agility, Costs and Asset Management Efficiency).

Figure 3.11: Six Major Management Processes of the SCOR Model

In Figure 3.12 the selected technical KPIstogether with the cost and revenues items are listed and related to one Performance Attribute and metric defined by the SCOR model.

In the following sections we will better describe all the above-mentioned KPIs and other two additional ones specifically defined for the application in the fashion industry.

3.4.1 Service Level

It is usually defined as the ratio between orders fulfilled and total orders received. In this context, for the i-th store, it is expressed as the ratio between actuals sales recorded (s_{ki}) and demand received (d_{ki}):

$$SL_i = \frac{\sum_{k=1}^{l} s_{ki}}{\sum_{k=1}^{l} d_{ki}} \tag{3.33}$$

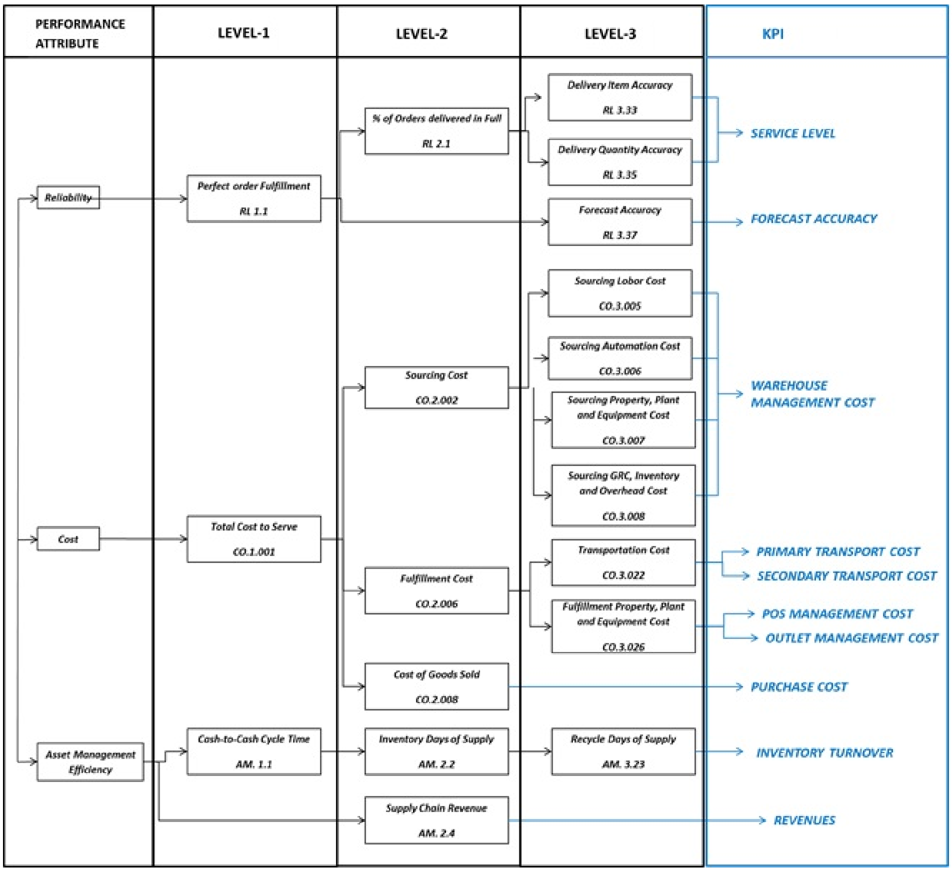


Figure 3.12: KPIs identification from SCOR 11.0 model

In current practice, companies try to guarantee, for each POS, a Service Level at least equal to 0,8.

3.4.2 Forecasting Accuracy

Forecasting accuracy is calculated for each item and is defined as one minus the percentage of error compared to actual sales:

$$FA_k = 1 - \frac{\sum_{i=1}^{n}(s_{ki} - F_{ki})}{\sum_{i=1}^{n} s_{ki}} \tag{3.34}$$

It is important to control this indicators in order to always improve sales forecasts over time.

3.4.3 Inventory Turnover

It represents the number of times that inventory is sold or used in a fixed time period and is expressed by the ratio between quantity outgoing the warehouse and average stock ($\bar{ST}_j$).
We evaluate this indicator both for the central warehouse (in this case outgoing quantities are the item delivered to POS):

$$IT_{W,j} = \frac{\sum_{k=1}^{l}\sum_{i=1}^{n} q_{kji}}{\bar{ST}_j} \tag{3.35}$$

and for POS' internal warehouses (in this case outgoing quantities are sales):

$$IT_{POS,i} = \frac{\sum_{k=1}^{l} s_{ki}}{\bar{ST}_{POS,i}} \tag{3.36}$$

3.4.4 Sales Percentage

For the k-th product and for the i-th store, it is defined as the ratio between actual sales and quantities delivered to each POS:

$$\%Sales_{ki} = \frac{s_{ki}}{\sum_{j=1}^{m} q_{kji}} \tag{3.37}$$

This indicator is not derived from the SCOR model but it is specifically defined for the application in the fashion industry (ref. paragraph 3.2.3.2). In this sector, in fact, it is meaningless to evaluate the pure data on actual sales since, given the impulsive purchasing behavior of customers, sales will increase with the availability of product in stores.

3.4.5 Availability

The concept of availability in the retail industry refers to three different aspects [Centro di Ricerca sulla Logistica, 2011] :

- *Shelf availability*: it is a measure of the event whereby the requested item is not available on the shelf and not accessible to the customers, although it may available in a different position of the store (for example in the internal warehouse);

- *Store availability*: it is a measure of the event whereby the requested item is not available in the store but it can be available in the central warehouse/distribution center or incoming in the store;

- *Warehouse availability*: it is a measure of the event whereby there are no available stocks for the requested item either in the central warehouse.

In this context we consider that Store Availability coincides with Shelf availability, since we imagine that shop assistants can replace sold out items on the shelves in a very short time, if obviously they are available in the store i.e. in their internal warehouse.
This indicator is defined for each item code, and also for each POS for the shelf availability, by the following relations:

$$\begin{cases} Shelf & A_{s,ki} = \sum_{j=1}^{m} q_{kji} - s_{ki} \\ Warehouse & A_{w,kj} = (Q_{Dkj} - \sum_{i=1}^{n} q_{kji}) \end{cases} \tag{3.38}$$

3.4.6 Out of Stock

This parameter is strictly connected to the availability (ref. paragraph 3.4.5) and to the service level (ref. paragraph 3.4.1). It is the define as the number of orders that can not be fulfilled (ref. equation 3.28). the cost connected to this parameters (ref. equation 3.30) is related to the possible lost sale and connected revenue. In case of out of stock, in fact, the customer can act in different ways [Sloot et al., 2005]:

a. Buy the same item in a different store;

b. Buy a different item in the same store;

c. Wait until the product is available in the store;

d. E-commerce;

e. Not buy.

In order to reduce the percentage of lost sales, i.e. the percentage of customers which choose the last alternative (not buy), in last years companies are trying to implement a combination of the physical stores with e-commerce ("bricks-and-clicks") [Agatz et al., 2008, Lanzilotto et al., 2014]. This solution is commonly called "Omni-Channel Retailing" and involves the integration between physical, mobile and on-line channel, thus increasing sales and profit-making opportunities [Bermn and Thelen, 2004, Elia et al., 2014]. This new strategy will be better analysed in the following chapter.

3.5 Conclusions

The coordination and management of the Supply Chain has always been a challenging task especially in case of retailing and in such fast changing conditions as the Fashion and Apparel Industry. In this context, this chapter presented a comprehensive and flexible model for the definition of the physical and informative flows from the development of the collection by the styling office until the withdrawal of unsold items from the stores.

This model may represent a useful Decision Support System for the optimisation of performances of all supply chain's actors by conveniently acting on decision variables involved in the whole process. These variables are several and connected to each other thus making difficult the definition of their values.
The main decision variables are:

- *Order Quantity (Q)*: when increasing Q, it will also increase the opportunity to receive volume discounts by suppliers. At the same time, however, there will be a higher risk connected to unsold items which will have to be disposed in factory outlet stores. In addition, bigger volumes of purchased goods involve higher primary transport costs, wider areas devoted to storage and more resources in the central warehouse;

- *Delivery policy from Suppliers*: from one side it is better to have few deliveries for big lots in order to reduce primary transport costs, from the other side warehouse and its resources cannot be overloaded, then seizing for more frequent deliveries for smaller lots;

- *Replenishment policy*: it is necessary to ensure high availability of items in the stores in order to reduce stock-outs but, at the same time, company wants to reduce secondary transport cost and to avoid the overload of stores' internal warehouses;

- *Threshold (δ) assessment*: low thresholds may lead to too frequent and unnecessary changes in the Merchandise Plans thus requiring an accurate management of Purchasing Orders. On the other hand, higher thresholds may involve more stable Merchandise Plans but may fail in properly assessing under or over-estimation of demand.

Given the highly unpredictable demand and impulsive purchasing behaviour, Supply Chain in this industry should follow a model which can quickly follow changes in trends and marked demand. In this context, in order to assess how the proposed model may improve Supply Chain performances in terms of responsiveness, it has been implemented and simulated.

The next chapter will then present and discuss the results of the simulation by varying decision variables.

Chapter 4

Design of the Simulation model

Contents

4.1 Introduction

This chapter describes the process flow of the simulation model. It was implemented through Excel and reproduces a real case study of an Italian Fashion Retail company. After a sensitivity analysis, decision variables were set at appropriate values and different scenarios were simulated.

4.2 Definition of the simulation model

In order to evaluate Supply Chain performances of the proposed framework, the simulation model was developed and implemented in Excel. Its general diagram is represented in Figure 4.1 and has the main purpose of comparing the previously defined KPIs (ref. paragraphs 3.3 and 3.4) in the As-Is and To-Be cases. While the To-Be case involves the In-Season deviation analysis and consequent adjusting of the operations plans, in the As-Is case instead, those plans are defined before the sales season and kept fixed throughout the time range.

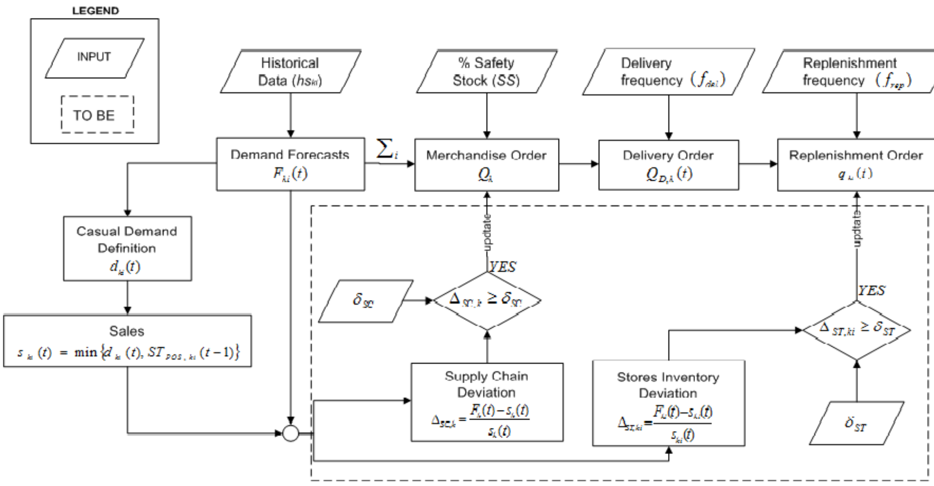


Figure 4.1: General Diagram of the simulation model

A summary of the nomenclature already used in paragraph 3.2 and that will be used in the following sections is reported in Table 4.1.

Table 4.1: Nomenclature

$i = 1, ..., n$	nr. of stores	Q_k	purchase quantity
$j = 1, ..., m$	nr. of warehouses	$Q_{D,kj}$	quant. delivered to warehouse
$k = 1, ..., l$	nr. of items	q_{ki}	quantity delivered to the store
hs_{ki}	historical sales data	d_{ki}	demand
SS	percentage of safety stocks	s_{ki}	sales
f_{del}	delivery frequency	ST	Stock level in central warehouses
$del = 1, ..., n_{del}$	nr. of deliveries	ST_{POS}	Stock level in stores
f_{rep}	replenishment frequency	$\Delta_{ST,ki}$	Stores deviation
$rep = 1, ..., n_{rep}$	nr. of replenishments	δ_{ST}	Stores deviation threshold
F_{ki}	sales forecasts	$\Delta_{SC,k}$	Supply Chain deviation
		δ_{SC}	Supply Chain deviation threshold

The model uses as inputs:

- *historical sales data* (h_{ki}) of the k-th item in the i-th store;

- percentage of *Safety Stocks* (SS);

- *frequency of deliveries* to the warehouse (f_{del}) and of *replenishment* to stores (f_{rep});

- *deviation thresholds*, both for stores (δ_{ST}) and for Supply Chain (δ_{ST});

and defines:

- *demand forecasts* F_{ki}: for simplicity we suppose that forecasts are equal to historical sales data hs_{ki}:

$$F_{ki}(t) = hs_{ki}(t) \tag{4.1}$$

- *merchandise orders* Q_k: they are given by the total quantity that we are supposing to sell during the season (F_k) adding safety stocks:

$$Q_k = \int_0^T \sum_{i=1}^{n} F_{ki}(t) * (1 + SS) \tag{4.2}$$

- *delivery orders* $Q_{D,kj}$: we are supposing that each delivery is performed at time:

$$t_{del} = 1 + f_{del} * (del - 1) \qquad for \quad del = 1, ..., n_{del} \tag{4.3}$$

where $n_{del} = T/f_{del}$ and the delivered quantity is given by the total quantity that we are supposing to sell until the next delivery:

$$Q_{D,kj}(t_{del}) = \int_{t_{del}}^{t_{del+1}} \sum_{i=1}^{n_j} F_{ki}(t) * (1 + SS) \tag{4.4}$$

it is important to underline that in this evaluation, we have to only include demand forecasts for the n_j stores pertaining to the j-th warehouse.

- *replenishment orders* q_{ki}: as for the delivery orders, we are supposing that each replenishment is performed at time:

$$t_{rep} = 1 + f_{rep} * (rep - 1) \qquad for \quad rep = 1, ..., n_{rep} \tag{4.5}$$

where $n_{rep} = T/f_{rep}$ and the replenishment quantity is given by the total quantity that we are supposing to sell until the next replenishment:

$$q_{ki}(t_{rep}) = \int_{t_{rep}}^{t_{rep+1}} F_{ki}(t) \tag{4.6}$$

These steps reproduce the Pre-Season phase, while for the In-Season phase the model generates a casual demand ($d_{ki}(t)$). If the demand is lower than the stocks available the item can be sold otherwise we will have an Out of Stock.
The process described so far defines the As-Is case. For the To-Be case we have to include the *Deviation Analysis*, described in paragraph 3.2.10. In summary, the To-Be model analyses how much demand was under or over-estimated, both at Supply Chain level and at Stores level. If this deviation ($\Delta_{SC,k}, \Delta_{ST,ki}$) is higher than a fixed threshold (δ_{SC}, δ_{ST}) the model updates the replenishment and/or merchandise orders by increasing or decreasing quantity by a defined percentage (u).

4.2.1 Key performance Indicators

A summary of the KPIs already described in Chapter 3 is reported in Table 4.2. They will be used for comparing AS-Is and To-Be cases.

It is important to underline that whenever one of the operations plans undergoes a variation, the company will have to incur a cost. In the To-Be case, this *Penalty Cost* (C_{pen}) is added to purchase cost and calculated as:

$$C_{pen} = pen * |\Delta Q| \tag{4.7}$$

where pen is the unitary penalty cost ([€/pcs]) and ΔQ is the variation ([pcs]) of the updated purchase plan compared to the one defined before the

Table 4.2: Key Performance Indicators

	Technical KPIs
Service Level	$SL_i = \frac{\sum_{k=1}^{l} s_{ki}}{\sum_{k=1}^{l} d_{ki}}$
Forecasting Accuracy	$FA_k = 1 - \frac{\sum_{i=1}^{n}(s_{ki} - F_{ki})}{\sum_{i=1}^{n} s_{ki}}$
Inventory Turnover	$IT_{W,j} = \frac{\sum_{k=1}^{l}\sum_{i=1}^{n} q_{kji}}{ST_j}$ $IT_{POS,i} = \frac{\sum_{k=1}^{l} s_{ki}}{ST_{POS,i}}$
Sales Percentage	$\%Sales_{ki} = \frac{s_{ki}}{\sum_{j=1}^{m} q_{kji}}$
Shelf Availability	$A_{s,ki} = \sum_{j=1}^{m} q_{kji} - s_{ki}$
Out of Stock	$d_{ki} = s_{ki} + OOS_{ki}$
	Economic KPIs
Purchase Cost	$C_P = \sum_{k=1}^{l} Q_k * cu_k + C_{pen}$
Primary Transport Cost	$C_{PT} = \int_0^T \left[\sum_{k=1}^{l}\sum_{j=1}^{m}\left(C_{tf,k} + C_{tv,k} * Q_{Dkj}(h) * DIST_{kj}\right)\right] dh$
Warehouse Mng. Cost	$C_{MW} = \sum_{j=1}^{m}\left[C_{mf,j} + \sum_{k=1}^{l} ch_k * cu_k * \frac{1}{T} * \int_0^T ST_k dh\right]$
Secondary Transport Cost	$C_{ST} = \sum_{i=1}^{n}\left[c_{tf,i} + c_{tv,i} * \int_0^T \sum_{k=1}^{l} q_{ki}(h) * dist_i dh\right]$
Stores Mng. Cost	$C_{MS} = \sum_{i=1}^{n} c_{mf,i} + \sum_{k=1}^{l} \overline{ch}_k * cu_k * \frac{1}{T}\int_0^T ST_{POS,i} dh$
Out of Stock Cost	$C_{OOS} = \int_0^T \sum_{k=1}^{l}\sum_{i=1}^{n} OOS_{ki}(h) * (pr_k - cu_k) * c_{sh} dh$
Revenues	$R = \int_0^T \sum_{i=1}^{n}\sum_{k=1}^{l} s_{ki}(h) * pr_k(h) dh$
Profit	$P = R - C_P - C_{PT} - C_{MW} - C_{ST} - C_{MS} - C_{OOS}$

sales season.

4.3 Introduction to the case study

In order to compare Supply Chain performances of the proposed model we used real data from an Italian Fashion Company which works in the national territory with hundreds of franchising and direct operated mono-brand stores and just a single central warehouse. The data collected from the above-mentioned company concern characteristics of 10 selected clothing items (Table 4.3) and 10 selected stores (Table 4.4).

Table 4.3: Clothing items characteristics of the case study

item	**Category**	**Description**	**Price (pr)**		**Cost (cu)**
			€	range	
1	Clothing to try on	Trousers	28	Cheap	8
2	Clothing to try on	Shirt	26	Cheap	8
3	Clothing to try on	Dress	125	Expensive	40
4	Clothing to try on	Denim Trousers	45	Cheap	14
5	Clothing to try on	Denim Trousers	60	intermediate	16
6	Clothing	Cotton Cardigan	27	Cheap	8
7	Clothing	Jacket	72	Intermediate	20
8	Accessories	Necklace	65	Intermediate	18
9	Accessories	Handbag	85	Intermediate	25
10	Accessories	Foulard	18	Cheap	4

Table 4.4: Stores characteristics of the case study

Store	**Geographical Area**	**Location**	**Dimension**	
			m^2	category
1	South	Airport	66	Small
2	South	Shopping Mall	113	Medium
3	South	Street	180	Medium
4	South	Street	58	Small
5	South	Shopping Mall	62	Small
6	Centre	Shopping Mall	343	Large
7	Centre	Street	82	Small
8	North	Shopping Mall	100	Small
9	North	Street	84	Small
10	North	Street	41	Small

Parameters related to transport are reported in Table 4.6 for the primary transport (from supplier to central warehouse) and in Table 4.5 for the secondary transport (from central warehouse to stores). For simplicity, we suppose that each clothing item is produced and delivered by one single supplier.

Table 4.5: Stores characteristics related to secondary transport for the case study

Store	**Distance** ($dist$)	**Transport Cost**	
		Fixed (c_{tf})	**Variable** (c_{tv})
	[Km]	[€]	[€/Km*pcs]
1	50	10	0,02
2	90	10	0,02
3	70	10	0,02
4	30	10	0,02
5	60	10	0,02
6	120	15	0,02
7	150	15	0,02
8	400	20	0,02
9	450	20	0,02
10	500	20	0,02

Table 4.6: Suppliers characteristics related to primary transport for the case study

Supplier/ item	**Distance** ($DIST$)	**Transport Cost**	
		Fixed (C_{tf})	**Variable** (C_{tv})
	[Km]	[€]	[€/Km*pcs]
1	500	50	0,01
2	1700	70	0,001
3	5000	150	0,001
4	2500	130	0,0015
5	700	50	0,01
6	1000	50	0,0025
7	1500	70	0,005
8	2000	100	0,005
9	5000	150	0,005
10	900	50	0,003

The related Historical sales data were collected over a time range of 6 months (24 weeks) corresponding to the whole Fall/Winter season (from September to February) and are reported in Figure 4.2 and Table 4.7.

A summary of other parameters used in the simulation model is reported in Table 4.8.

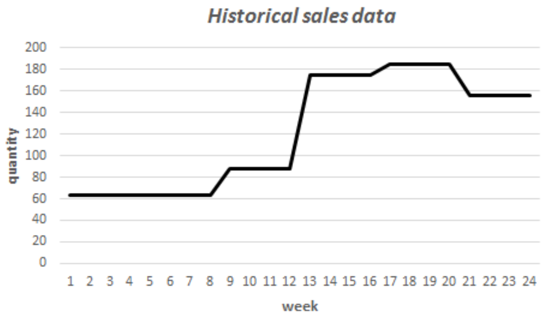


Figure 4.2: Case study historical sales data for the whole sales season

Table 4.7: Case study historical sales data for each item and each store

store	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
item										
1	23	14	40	10	25	17	12	9	5	1
2	76	38	59	26	62	27	17	16	24	18
3	27	25	69	26	18	27	28	32	22	19
4	1	1	5	0	3	0	0	0	1	1
5	27	47	54	17	39	48	15	40	20	29
6	15	15	16	3	18	18	4	11	10	4
7	5	2	42	4	9	7	3	0	2	0
8	0	0	1	0	1	0	1	1	0	1
9	121	32	50	15	55	42	40	80	34	23
10	272	78	190	52	80	90	57	103	85	67

4.3.1 Definition of the scenarios

Main aim of the simulation model is to evaluate if the proposed model is able to quickly follow changes in demand trend and to consequently adapt operations plans. With this purpose different demand profiles were defined that may summarise any possible real case: highly variable demand and increasing or decreasing trends.
Six different scenarios were defined and simulated by varying the demand profile:

Scenario 1 : the demand follows a gaussian distribution with mean equal to the demand forecast and standard deviation equal to 1% of the mean (Figure 4.3(a));

Scenario 2 : it is equal to the previous case with a higher standard devi-

Table 4.8: Parameters of the simulation model

General parameters		***Deviation Analysis parameters***	
i	10	δ_{ST}	0,3
j	1	δ_{SC}	0,2
k	10	u	10%
T	24 weeks	pen	0,01 [€/pcs]
SS	10%		
f_{del}	8 weeks		
f_{rep}	4 weeks		
c_{sh}	50%		
C_{mf}	100 €		
c_h	5%		
c_{mf}	150 €		
$\bar{c_h}$	10%		

ation: 10% of the mean value (Figure 4.3(b));

Scenario 3 : from week 10 to 17 the demand has a peak (3 times greater than forecasts) while during the other weeks it follows Scenario 1 (Figure 4.4(a));

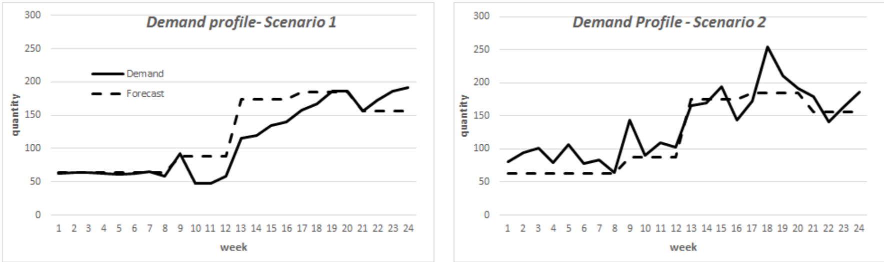
Scenario 4 : from week 10 onwards, the demand has a growing trend equal to 1% (Figure 4.4(b));

Scenario 5 : from week 10 onwards, the demand has a decreasing trend equal to 1% (Figure 4.5(a));

Scenario 6 : from week 10 onwards, stores 1 to 5 have a growing trend - as Scenario 4 - while store 6 to 10 have a decreasing trend - as Scenario 5 - (Figure 4.5(b)).

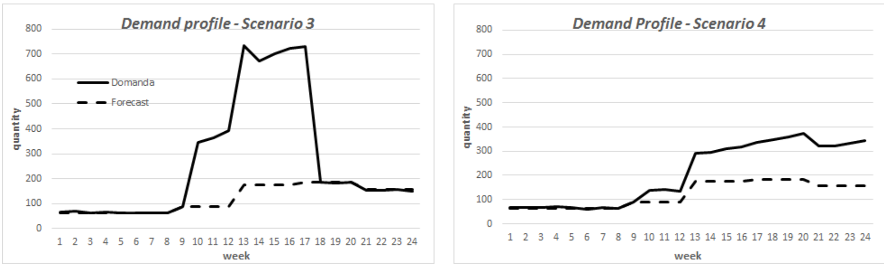
4.4 Sensitivity Analysis

In order to set appropriate values for the deviation analysis parameters (δ_{ST}, δ_{SC}, u), a sensitivity analysis was performed by changing one-factor-at-a-time. Table 4.9 shows the values used in the analysis while Table 4.10 shows minimum, maximum and mean value of the percentage variation of



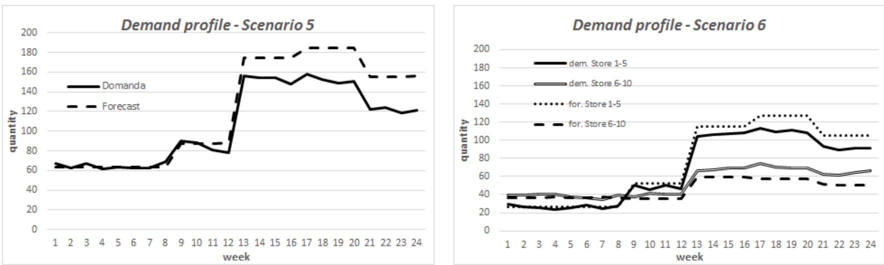
(a) (b)

Figure 4.3: Demand Profile of Scenario 1 and 2



(a) (b)

Figure 4.4: Demand Profile of Scenario 3 and 4



(a) (b)

Figure 4.5: Demand Profile of Scenario 5 and 6

Table 4.9: One-factor-at-a-time Sensitivity Analysis

		Parameter		
		δ_{ST}	u	δ_{SC}
Cases	*base case*	0,3	10%	0,2
	δ_{ST} +50%	0,45	10%	0,2
	δ_{ST} -50%	0,15	10%	0,2
	u +50%	0,3	15%	0,2
	u -50%	0,3	5%	0,2
	δ_{SC} +50%	0,3	10%	0,3
	δ_{SC} -50%	0,3	10%	0,1

the KPIs. While technical KPIs were individually analysed, the economic performance is globally evaluated through the Profit value.

It is clear from the result that the most critical value is u which causes the highest percentage variation in all the KPIs. The detailed results of the analysis for the percentage of variation in the operations plans (u) are shown in Figure 4.6: increasing u by 50% will improve Supply Chain performances and in particular will increase Profit by approximately 70%.

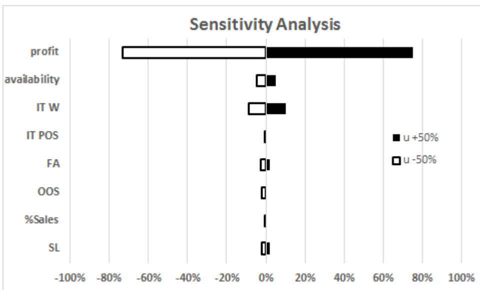


Figure 4.6: Results of the sensitivity analysis for the parameter u (percentage of variation of the operations plans)

This value ($u = 15\%$) will then be used for all the next simulations.

4.5 Analysis of the results

From the analysis of the KPIs in the six different scenarios it emerged that:

- for all the six scenarios in the As-Is case, costs for *Primary Transport* (Figure 4.7(a)), *Secondary Transport* (Figure 4.7(b)), *Purchase* (Figure

Table 4.10: Results of the Sensitivity Analysis

		SL	$\%Sales$	OOS	FA	IT_{POS}	IT_W	A_S	P
$\delta_{ST}+50\%$	min	0%	0%	0%	0%	0%	-1%	0%	-5%
	max	0%	0%	1%	0%	0%	1%	0%	0%
	mean	0%	0%	0%	0%	0%	0%	0%	-1%
$\delta_{ST}-50\%$	min	0%	0%	-1%	0%	0%	0%	0%	0%
	max	0%	0%	0%	0%	0%	0%	0%	1%
	mean	0%	0%	0%	0%	0%	0%	0%	0%
$u+50\%$	min	0%	-1%	-7%	0%	-3%	0%	0%	-1%
	max	2%	0%	1%	2%	0%	10%	5%	75%
	mean	0%	0%	-2%	1%	-1%	4%	1%	15%
$u-50\%$	min	-2%	-1%	-2%	-3%	-1%	-9%	-4%	-73%
	max	0%	1%	7%	0%	3%	-1%	1%	0%
	mean	-1%	0%	1%	-1%	1%	-4%	-1%	-14%
$\delta_{SC}+50\%$	min	0%	0%	0%	0%	0%	0%	0%	0%
	max	0%	0%	0%	0%	0%	0%	0%	0%
	mean	0%	0%	0%	0%	0%	0%	0%	0%
$\delta_{SC}-50\%$	min	0%	0%	0%	0%	0%	0%	0%	0%
	max	0%	0%	0%	0%	0%	0%	0%	0%
	mean	0%	0%	0%	0%	0%	0%	0%	0%

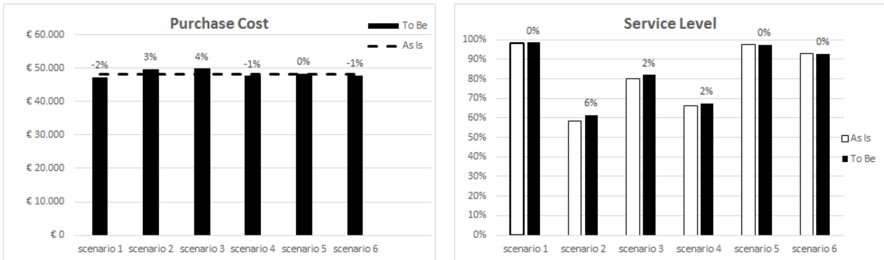
4.8(a) a) and *Warehouse Management* (Figure 4.13(b) a) are constant. This is due to the fact that operations plans are defined according to demand forecasts and do not change in the different simulated scenarios;

- *Transport Costs* (Figure 4.7(a) and 4.7(b)) may result higher than the As-Is case in some scenarios (in particular where a peak in demand - Scenario 2 - or a higher uncertainty - Scenario 3 - occur). This is due to the fact that, in order to cope with market demand, the company needs to buy (Figure 4.8(a) - *Purchase Cost*) and consequently deliver greater quantity;

- despite the number of *Out of Stock* and related cost (Figure 4.9) are very high for Scenario 2, 3 and 4, the *Service Level* (Figure 4.8(b)) is always higher than the As Is case;

(a) (b)

Figure 4.7: Comparison of the results for the Primary and Secondary Transport Costs



(a) (b)

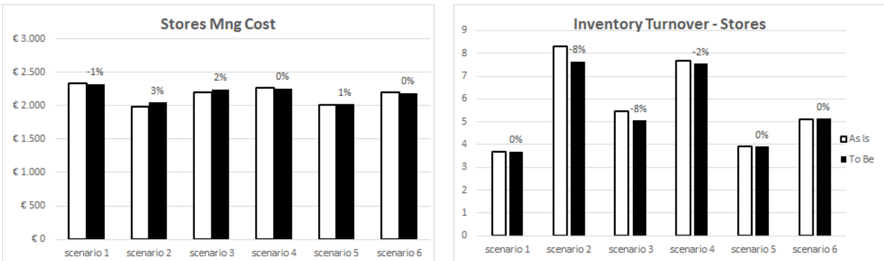
Figure 4.8: Comparison of the results for Purchase Cost and Service Level

- from the stores perspective, Figure 4.11(a) shows an increase up to 14% in Scenario 2 even if *Stores Management Cost* stays almost constant (Figure 4.10(a)). This means that the average stock in the stores is higher on average, as demonstrated by the slightly lower values in the *inventory Turnover* (Figure 4.10(b));

- *Sales Percentage* (Figure 4.11(b)) is strictly connected to the stores performance and *Revenues* (Figure 4.12(a)). This value is, in fact, given by the ratio between sales and quantities delivered to the stores. As demonstrated by the higher value in Revenues (Scenario 2 and 3), sales increase in the To-Be case. This implies that the quantity delivered to the stores are higher, as confirmed by the lower value in the Stores Inventory Turnover;

(a) (b)

Figure 4.9: Comparison of the results for Out of Stock and OOS Cost



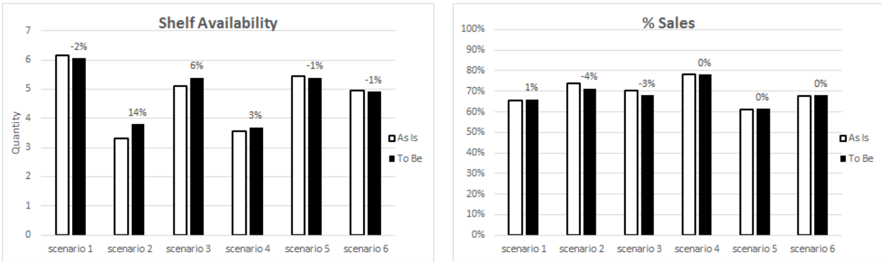
(a) (b)

Figure 4.10: Comparison of the results for Management Cost and Inventory Turnover for Stores

- thank to the adjusting process, also the *Forecasting Accuracy* (Figure 4.12(b)) results slightly higher in the proposed model, since it is able to follow market changes;

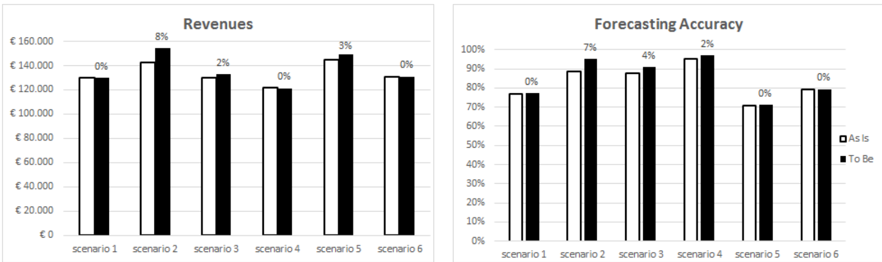
- both technical and economic performances of the central warehouse improve when introducing the proposed model: *Inventory Turnover* (Figure 4.13(a)) increases at least of 5% compared to the As-Is case and *Warehouse Management Cost* (Figure 4.13(b)) is always lower;

- from a global economic perspective, the proposed model (To-Be) guarantees better performances. The *Profit* is, in fact, always higher than the As-Is case and in particular it is more than 5 times greater in the Scenario 2, that represents an unexpected peak in demand (Figure 4.14).



(a) (b)

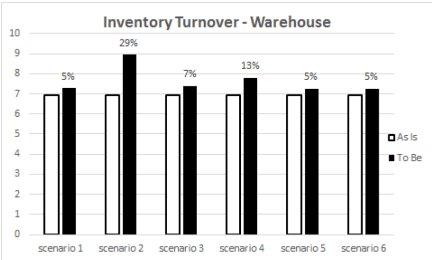
Figure 4.11: Comparison of the results for Shelf Availability and Sales Percentage



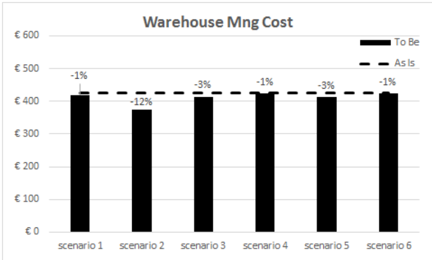
(a) (b)

Figure 4.12: Comparison of the results for Revenues and Forecasting Accuracy

This implies that the proposed model is able to follow demand variations during the sales season by adjusting operations plans according to that. This behaviour is also confirmed by the number of *Out of Stock* (Figure 4.9 a), that is on average lower than the As-Is case.



(a)



(b)

Figure 4.13: Comparison of the results for Inventory Turnover and Management Cost for Warehouse

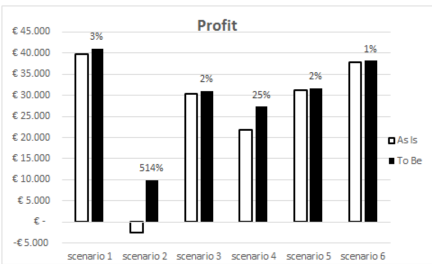


Figure 4.14: Comparison of the results for the Profit

Chapter 5

Impact Analysis of the Introduction of an Omni-Channel Retailing System

Contents

5.1 Introduction

The last decades have been characterized by the wide spread of e-commerce and mobile channel purchasing that have deeply changed retail business and management strategies. According to Keller et al. [2014], in fact, Global apparel and footwear market has grown 5% from 2002 to 2015, but online channel have grown 3-4 time faster (Figure 5.1).

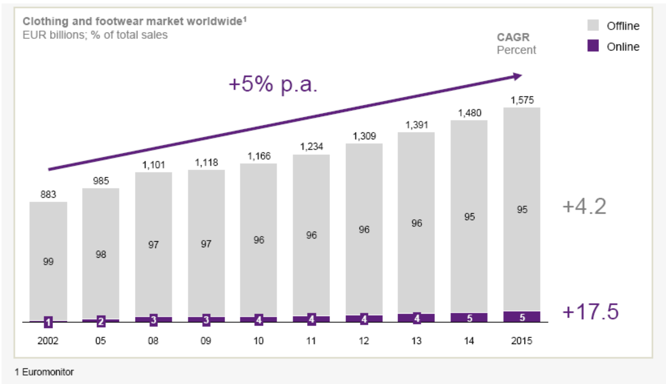


Figure 5.1: Compound Annual Grow Rate (CAGR) for online and offline apparel market

In the fast changing environment of the retailing industry, adapting to changing and always increasing customer requirements can make the difference in being a highly successful and profitable market leader. Then, in the recent years, one of the main challenge to meet customers' needs is the integration of traditional stores with mobile channels in a new synchronized

operating model called omni-channel retailing [Lanzilotto et al., 2014].
The diffusion of ICT based tools of retail supply chain has contributed to modify retail operations [Elia and Gnoni, 2013]. Traditional brick and mortar companies have, in fact, attempted to increase sales and improve profitability by adding online retail channels for consumers [Bretthauer et al., 2010]. Many small businesses, use platforms like eBay and Amazon Marketplace on one hand, and a self-managed online store on the other hand, as sales channels [Schneider and Klabjan, 2013]. On the other side, "pure-play" Internet retailers are also opening physical stores or cooperating with traditional retailers [Agatz et al., 2008].
It is clear that the simultaneous and integrated management of both physical and mobile channels is not simple and assumes that the supply chain meets the requirements of visibility, accuracy and control of information, flexibility and efficiency. Furthermore, some processes such as inventory management and logistics become extremely critical by adopting an omni-channel retailing strategy. In this context, this chapter analyses the main advantages and critical issues related the integration of traditional physical stores with e-commerce, and describes the possible purchasing paths. After that, for the particular case of the "buy online, pick-up in store" case we analysed the impact that this new integrated strategy may have on the performances of the traditional Fashion Supply Chain.

5.2 An overview on Omni-Channel retailing strategy

The omni-channel retailing can be defined as a synchronized operating model in which all of company's channels, i.e. traditional stores and mobile channels, are aligned and present a single face to the customer, allowing companies to meet customers' requirements and to be more competitive. The eCommerce B2c [2014] distinguish three different purchasing paths according to the combination of online, mobile and physical stores (Figure 5.2 and 5.3):

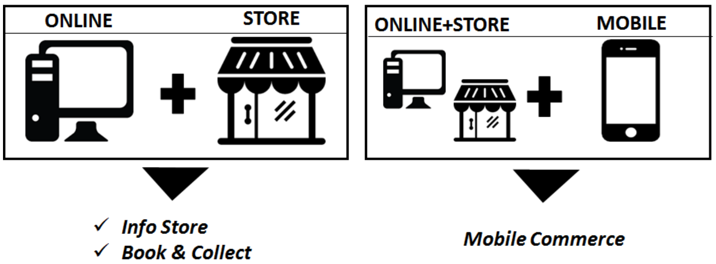


Figure 5.2: Omni-Channel strategies

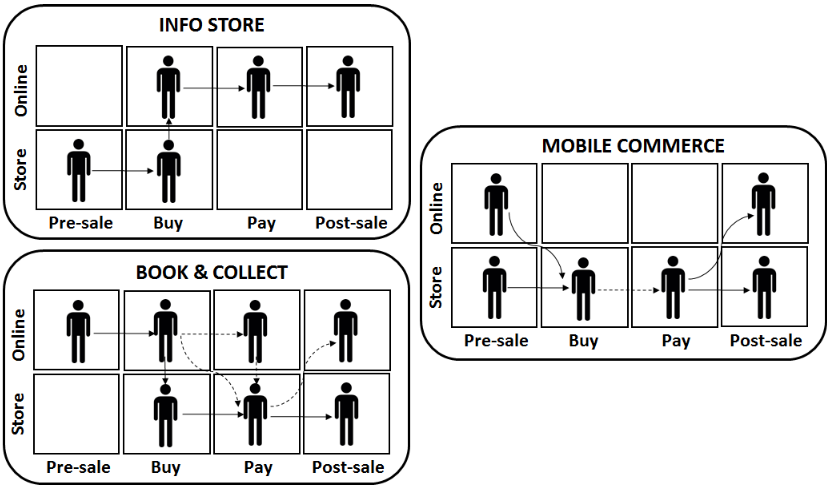


Figure 5.3: Customer path for "Info Store", "Book & Collect" and "Mobile Commerce" strategies

- *Info Store*, that can be distinguished in:
  - "opportunistic": it refers to those customers who take information about the product in the physical store before finalizing the purchase online, at a lower price. According to Mangiaracina [2015] two out of three consumers belong to this category;
  - "induced": it refers to those customers who buy online products that are not available in the stores. This drastically reduces lost sales due to in-store stock out;
- *Book & Collect*, that can be distinguished in:

- "convinced": it refers to those customers who pick the product up in the store after having paid it online to reduce waiting times;
- "prudent": it refers to those customers who pay and pick the product up in the store to maintain the offline perceived security without sacrificing online convenience. For this purchase path it, the company must guarantee the perfect alignment in online and offline prices.

This strategy may lead to logistical complexity in the shared management of stocks and in the organization of stores operations.

- *Mobile Commerce*, that also involves the use of mobile devices. According to Mangiaracina [2015], 89% of smartphone users, use the device in the store, 42% of them to compare prices while 30% of them send photos pf products to friends. This strategy may be distinguished in:

  - "urgent": it refers to those customers who buy product online for a sudden need or to seize a time-limited special deal;
  - "opportunistic": it refers to those customers who directly buy products through mobile devices in the stores to have access to lower prices or to products no longer available;
  - "standard": it is the traditional web purchase through mobile devices.

From customer point of view, main benefit due to Omni-Channel application is to provide a seamless experience across all channels, translating benefits characterizing the online experience in physical stores and vice versa. Main advantages of the web channel can be observed in the reduction of buyer's search costs, in providing detailed information to the customer and offering a very large range of products. From traditional channel perspective, the proximity to the customer is considered the key element: the brick-and-mortar is not dead, it just plays a different role. In fact, in an Omni-Channel world, physical stores can provide a competitive advantage.

The aspects of a store that matter most to customers are [Hering et al., 2014]:

- *Convenience and proximity*: customers can easily and quickly visit a store and get what they need. In addition the company can offer a flexible choice of fulfilment and return options [Consulting, 2014];

- *Efficiency*: clients may see the store as a place that helps them make better use of their time — for example, by enabling them to make faster decisions or by serving as a pickup location for something they ordered online;

- *Inspiration*: a store is a place where to discover new ideas and new products;

- *Instant Gratification*: in the stores, customers have the chance to make impulse purchases and get things immediately;

- *Experiencing brands and product*: customers have the chance to touch and feel products and brands.

Considering delivery options instead, the logistic services offered to customers are:

1. *"buy in store, pick up in store"*: it is the traditional in store purchase and pick up;

2. *"buy in store, home delivery"*: after buying the item in store, an additional home delivery service is provided by the retail firm;

3. *"reserve in store, pick up in the same or another store"*: when the item required is not available in the store, the retailer verifies availability in another nearby store. In case of success, the product is booked and the customer can pick it up in the store where it is available or wait for the delivery to the first visited store;

4. *"buy online, home delivery"*: it is the traditional e-commerce. The user buys the product online and it is delivered to its home;

5. *"buy online, pick up in store"*: the customer buys the product online and then picks it up in a physical store or in a pick-up point, thus cancelling home delivery costs;

6. *"reserve online, pick up in store"*: customer books product online, then pays and picks it up in the physical store; this model differs from the previous one just in the purchasing process which is not performed online in advance but in the physical store at the moment of the pick-up.

The analysis of different logistic paths highlights the processes that could become critical by adopting an omni-channel retailing and several capabilities are required for a successful implementation [Mercier et al., 2014]:

- accurate and real-time inventory management: online purchase and booking processes require an effective inventory visibility. Any actor in the supply chain should be able to see which products are available and in which channels they are located [Motorola, 2013]. Not less important are accuracy of this information, real time accessibility to the entire inventory and ability to control it;

- lean warehouse operations: combining the each picking that predominates in e-fulfillment with the case and pallet replenishment that is done to support store replenishment, clearly creates more complex warehouse processes [Banker, 2014], then an appropriate layout and management of warehouse operations becomes crucial;

- reliable and quick distribution network: the logistics network becomes articulated and complex due to the great number of connections among the actors in the supply chain.

- efficient return flow: it involves authorization, transportation from customer to return destination, processing and settlement.

Information sharing and synchronization among channels is the distinctive element of the management strategies. It is possible to clearly distinguish two management models of retailing systems with several sales channels [Elia et al., 2014] :

1. *multi-channel model*: the management of channels is separate, i.e. each channel manages independently information on its products, customers and distribution network;

2. *omni-channel model*: the management of the channels is integrated and coordinated. This means a high level of integration in operations which implies the adoption of a single and shared information system containing real-time updated information on purchases and stock levels in each warehouse or store.

Main differences between Multi- and Omni-Channel are summarised in Table 5.1.

Table 5.1: Multi-Channel versus Omni-Channel Management [Verhoef et al., 2015]

	Multi-channel	***Omni-channel***
Channel focus	Interactive channels only	Interactive and mass-communication channels
Channel scope	Retail channels: store, online website, and direct marketing (catalog)	Retail channels: store, online website, and direct marketing, mobile channels (i.e., smart phones, tablets, apps), social media, Customer Touchpoints (incl. mass communication channels: TV, Radio, Print, C2C, etc.).
Separation of channels	Separate channels with no overlap	Integrated channels providing seamless retail experiences.
Brand versus channel customer relationship focus	Customer – Retail channel focus	Customer – Retail channel – Brand focus
Channel management objectives	Per channel objectives (i.e., sales per channel; experience per channel)	Cross-channel objectives (i.e., overall retail customer experience, total sales over channels)

5.3 Omni-Channel Impact on a traditional Fashion Supply Chain

Main purpose of this chapter is to evaluate how the introduction of an Omni-Channel strategy may impact on the technical and economic performances of a traditional Fashion Supply Chain. The framework (Figure 5.4) focuses on the "Click and Collect" strategy and represents an evolution of the traditional Supply Chain model presented in paragraph 3.2. It disregards the deviation analysis and adjusting process but introduces all the processes and flows related to online purchases.

With the modality "buy online, pick up in store", also called "Click and Collect" strategy, the customer chooses products online and then picks them up in the physical store or dedicated facility. Management approach of this channel changes according to the retailing model applied. If a *multi-channel* model is implemented, the product bought online is shipped from a central warehouse to the store selected by the customer; no control is carried out at the store level to verify the product availability. On the contrary, if *omni-channel* model is implemented, central warehouses and stores' inventories are synchronized as a centralized inventory works. In this case, the cornerstone of the system is the *Virtual Inventory System*: it contains data of all central warehouses and stores' inventories updated in real time. It also performs availability checks as shown in Figure 5.5.

It starts from a *Global Check*, i.e. it verifies whether the product is available in one of the firm's locations or not. If it is available, the "check phases" follow in order to identify where the item is. In chronological order they are: *Store Check* and *Warehouses Check*. If the product is available in the selected store, the customer can buy it and go to pick it up in a short time range (e.g. less than an hour). Otherwise, the system switches to verify in which warehouses the product is and plans its shipping from the nearest warehouse to the store chosen by the customer. If the *Global Check* fails, the system verifies if the required product is among incoming goods. If the answer is affirmative, the system, based on when the arrival product is foreseen, offers customer the due date for product pick up in store giving

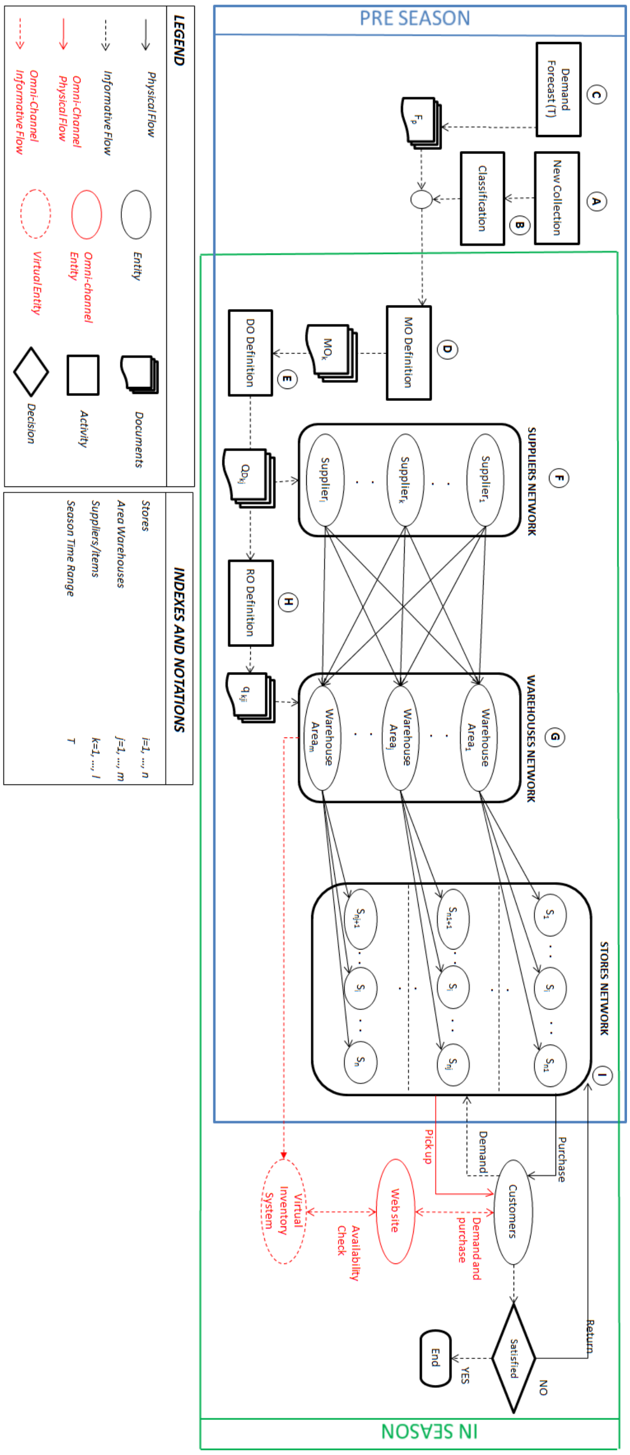


Figure 5.4: Supply Chain of the Fashion Retail Industry - Traditional and "Buy Online, Pick up in Store" channels

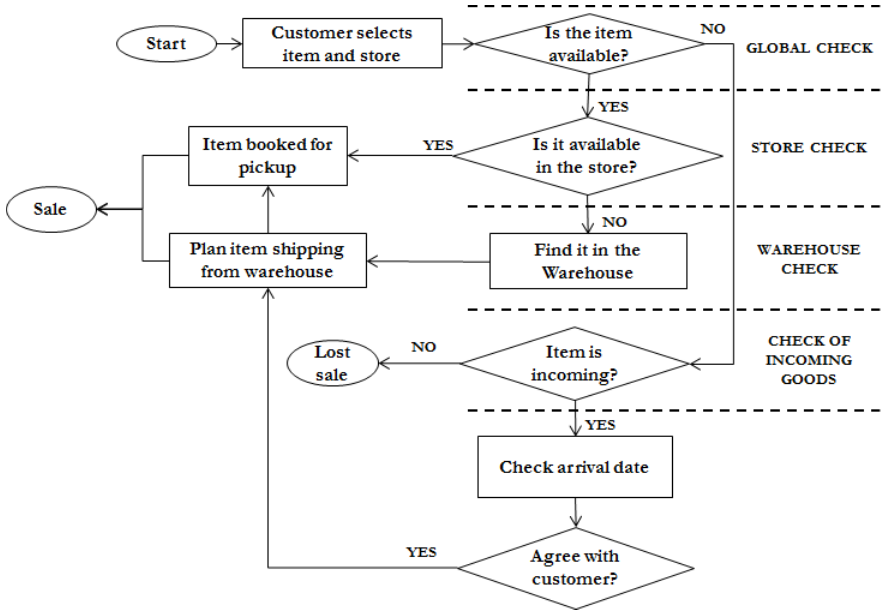


Figure 5.5: Availability check process in the virtual inventory system

him the opportunity to decide whether to proceed with the purchase or not.

5.4 Design of the simulation model

Main purpose of the developed simulation model was to analyse how performances of a fashion retail supply chain can change when introducing an integrated strategy between traditional physical stores and online sales. The model developed with Rockwell Software Arena has the main purpose of simulating the supply, delivery and sales process and its general diagram is represented in Figure 5.6. Similarly to the model described in Chapter 4, it uses as input data:

- *historical sales data* (h_{ki}) for each item (k) and for each item (i);

- percentage of *Safety Stocks* (SS);

- *frequency of deliveries* to the warehouse (del) and of *replenishment* to stores (rep);

and defines:

- *Demand Forecasts* F_{ki} (ref. equation 4.1): for simplicity we suppose that forecasts are equal to historical sales data hs_{ki};
- *Merchandise Orders* Q_k (ref. equation 4.2): they are given by the sum of total demand forecasts (F_k) and Safety Stocks (SS);
- *Delivery Orders* $Q_{D,kj}$ (ref. equation 4.4): they define quantity and time for deliveries from suppliers to the central warehouses;
- *Replenishment Orders* q_{kji} (ref. equation 4.6): they define quantity and time for deliveries from the central warehouse to the stores. We suppose that replenishments are weekly performed until the beginning of the discounts. In addition we suppose to to deliver to the stores only the 80% of the total quantity purchased in order to absorb possible fluctuations in demand.

The model starts with the casual generation of the daily demand for each item and for each store both for the traditional channel ($d_{ki}(t)$) and for the online channel ($do_{ki}(t)$). They are generated from a gaussian distribution whose mean value is equal to the historical sales data (h_{ki}). Even though in current practice not always shop assistants record real demand (which means also recording missed sales) through Electronic Point of Sales (EPOS) devices, this information is highly important for always improving sales forecasts. Given demand, the model checks availability of the requested product by verifying that demand is lower or equal to the inventory level. While for the traditional channel we check availability in the store internal warehouses ($ST_{POS,ki}(t)$), for the online purchases we have to distinguish the two logistics strategies:

- Multi-channel: the two channels – traditional and online – are separate, then purchases and deliveries are independently managed. The retailer does not satisfy on line purchases with stores' on-hand inventory, but always ships the requested items from the warehouse, previously performing a check for availability in central warehouse stock ($ST_k(t)$).

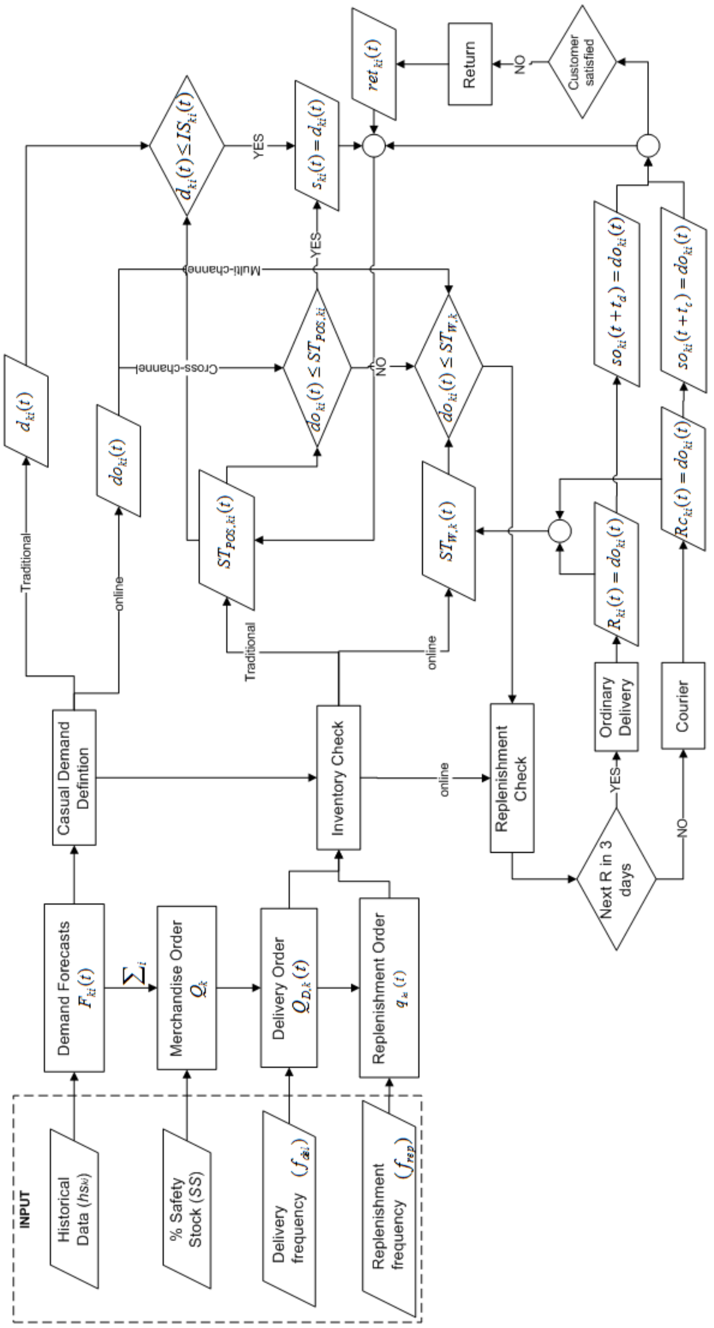


Figure 5.6: General Diagram of the Simulation Model

- Omni-channel: in this actually integrated strategy the company has a single and shared information system containing real-time updated information on all stock levels. In this case, the model first performs an availability check in the store internal warehouse ($ST_{POS,ki}(t)$), and then, only in case of unavailability, delivers the requested product from the central warehouse.

For online purchases which are shipped from the central warehouse, we need to perform a further check for replenishment schedule: if there is an ordinary shipment to store already scheduled in the next three days the requested item will be unified with the pre-defined shipment ($R_{ki}(t)$) otherwise it will delivered through a dedicated courier ($Rc_{ki}(t)$). Another crucial variable that has to be considered when dealing with online purchases are returns ($ret_{ki}(t)$). While this phenomenon can be disregarded for physical stores, it becomes important in integrated strategies since customers do not physically see or try the item and may simply do not like or fit it. In our model the returned goods will stay in the store increasing stock level and will not be shipped back to warehouse for recovery since we disregard defective products return. The return rate is fixed as the 15% of the online total demand.

5.5 Introduction to the case study

The case study used for the simulation is the same that was described in Chapter 4 with 10 items (ref. Table 4.3), 10 stores (ref. Tables 4.4 and 4.5), 1 central warehouse and 10 suppliers (ref. Table 4.6) each producing a different item. Historical sales data refer to a whole Fall/Winter season (ref. Figure 4.2 and Table 4.7). The other parameters used in the simulation model are reported in Table 5.2.

5.5.1 Definition of the scenarios

By progressively increasing the historical sales data, and the consequently the demand, coming from the online channel, 11 different scenarios were

Table 5.2: Parameters of the Omni-Channel simulation model

Parameter	***Value***
i	10
j	1
k	10
T	24 weeks
SS	40%
f_{del}	8 weeks
f_{rep}	1 week (from week 1 to 18)
c_{sh}	50%
C_{mf}	100 €
c_h	5%
c_{mf}	150 €
$\bar{c_h}$	10%

simulated (Table 5.3).

Table 5.3: Simulated Scenarios

Scenario	***Forecasts***	
	Online	***Physical***
0	0	
1	$10\% * hs_{ki}$	
2	$20\% * hs_{ki}$	
3	$30\% * hs_{ki}$	
4	$40\% * hs_{ki}$	
5	$50\% * hs_{ki}$	hs_{ki}
6	$60\% * hs_{ki}$	
7	$70\% * hs_{ki}$	
8	$80\% * hs_{ki}$	
9	$90\% * hs_{ki}$	
10	$100\% * hs_{ki}$	

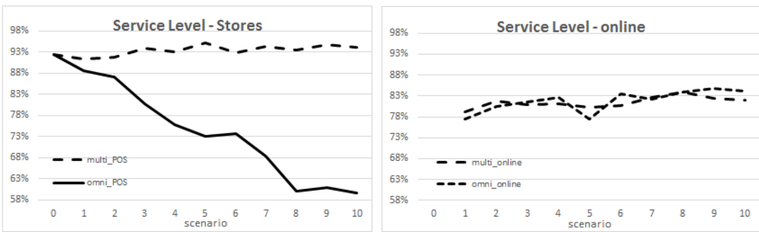
It is clear that, according to the sales forecasts, the quantity purchased from the suppliers and delivered to the central warehouse will increase while the replenishment plan remains unchanged. As already mentioned, in fact, items sold online will be shipped to stores with ordinary deliveries when possible; in this case the replenishment plan will be updated accordingly, otherwise they will be delivered by courier. Each scenario is simulated both with a multi-channel and a omni-channel strategy, for a total of 22 simulation.

5.6 Analysis of the results

In this section we show and analyse the trend of the selected KPIs (ref. Table 4.2) in all the simulated scenarios.

5.6.1 Service level

As shown in Figure 5.7, for both retailing strategies, service level of the online market does not significantly change. For the traditional physical stores, instead, this KPI drastically decreases when adopting an omni-channel approach. In this case, in fact, stores stocks are consumed by online purchases as well, then also out of stock increases (ref. section 5.6.6) since scheduled delivered items are not able to satisfy traditional demand. This trend is due to a not optimized replenishment strategy, since quantity supposed to be sold online are not delivered to the stores but stays at the central warehouse waiting for the actual request.

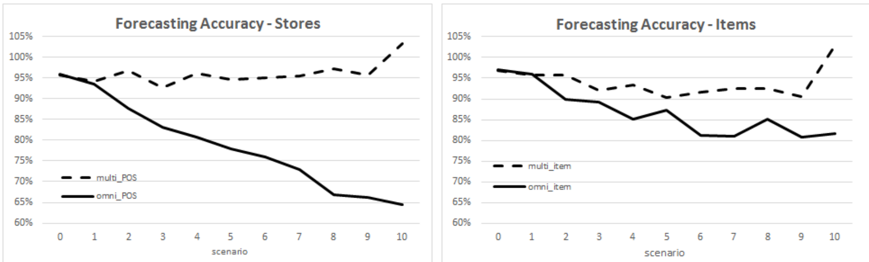


(a) (b)

Figure 5.7: Service level for physical stores and online channel

5.6.2 Forecasting Accuracy

As shown in Figure 5.8, the mean forecasting error grows with the online purchasing both for items and for stores. This is clear since we have a return rate which contributes to increase deviation between forecasts and actual sales. In addition, when introducing an omni-channel strategy, this deviation will further increase since all the items supposed to be purchased online are not delivered to the stores but stocked in the central warehouse and shipped only when requested. It implies that all stores on-hand stock are quickly consumed thus increasing the possibility of stock outs.

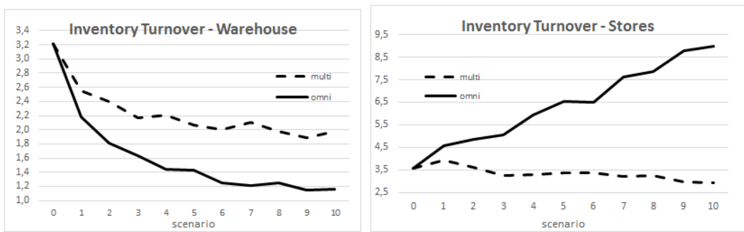


(a) (b)

Figure 5.8: Forecasting accuracy for stores and items

5.6.3 Inventory turnover

Figure 5.9 shows an opposite trend of the inventory turnover in central warehouse and stores for the omni-channel strategy. This is due to the fact that, with this approach, before delivering an item from the central warehouse all stores stocks must be consumed. This obviously leads to an increase in inventory turnover for the stores and a decrease for the warehouse.



(a) (b)

Figure 5.9: Inventory turnover for warehouse and stores

5.6.4 Sales Percentage

As shown in Figure 5.10, in the multi-channel strategy the mean value is almost constant at more than 85% despite the increasing rate in returned goods. Whit this approach, in fact, both sales and deliveries to stores will increase. When introducing a omni-channel approach, additional items will be delivered only if necessary then this ratio will obviously increase.

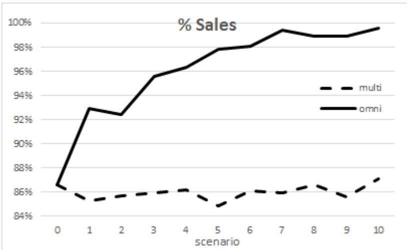


Figure 5.10: Sales percentage

5.6.5 Shelf Availability

Figure 5.11 shows that in the multi-channel strategy, shelf availability is almost constant while it decreases when introducing omni-channel. This trend is similar to the Service Level for stores (Figure 5.7), meaning that stores stocks are not enough to satisfy online demand too.

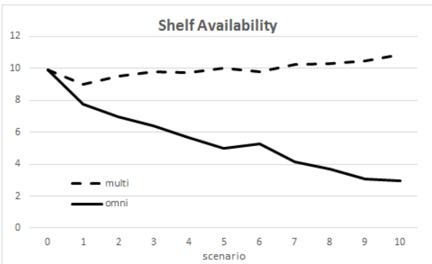
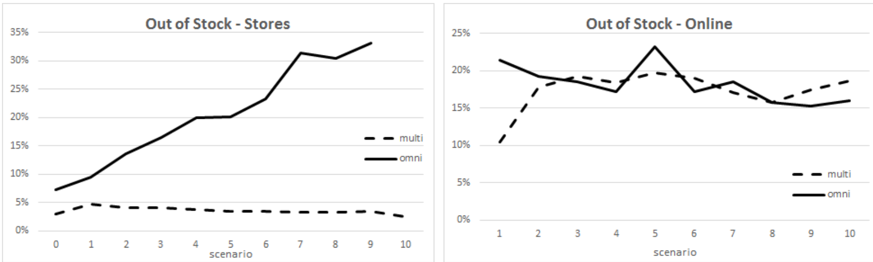


Figure 5.11: Shelf Availability

5.6.6 Out of Stock

In order to take into account the increasing demand in the different simulated scenarios, the Out of Stock value is divided for the value of demand. This resulting percentage value is reported in Figure 5.12 and shows that for the online purchases this value is equal for multi- and omni-channel and is almost constant to 20%. For the stores, instead, the value is very low (around 3%) for the multi-channel approach, while increases up to 30% in the omni-channel.



(a) (b)

Figure 5.12: Out of Stock for physical stores and online channel

As already mentioned, this is due to the fact the replenishments are not optimised for the omni-channel strategy, then stocks are consumed by online purchases before they are appropriately restored.

5.6.7 Purchase Cost

This value is equal for multi- and omni-channel since we suppose that purchasing and delivery plans do not change for the two strategies (ref. 5.13).

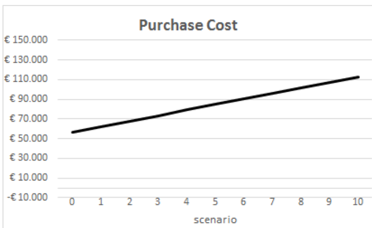


Figure 5.13: Purchase Cost

5.6.8 Primary Transport Cost

Figure 5.14 shows the values of the unitary primary transport cost, i.e. the total transport cost compared to the quantities delivered to the central warehouse. This value is equal for multi- and omni-channel since we suppose that purchasing and delivery plans do not change for the two strategies. The slightly decreasing trends reflects the higher saturation of the transport means when quantities increase.

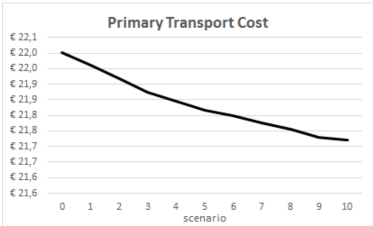


Figure 5.14: Primary Transport Cost

5.6.9 Warehouse Management Cost

As for previous sections, in order to appropriately compare the different scenarios, the value of the warehouse management cost is compared to quantities delivered to it, i.e. the total purchased quantity. It is clear that in the omni-channel strategy, items are delivered to stores only when they are actually requested resulting in a higher average stock level (ref. section 7.5). This implies a higher cost for their holding (Figure 5.15).

Figure 5.15: Warehouse Management Cost

5.6.10 Secondary Transport Cost

Figure 5.16(a) shows the values of the unitary secondary transport cost, i.e. the total transport cost compared to the quantities delivered to the stores through ordinary weekly deliveries. This value decreases when online purchases increase, demonstrating a higher saturation of transport means. On the other hand, this unitary costs remains higher in the omni-channel strategy since on average we deliver lower volumes. It is important to underline that, for online purchases, we need also to evaluate courier costs (Figure 5.16(b)) since we need to guarantee deliveries within three days even if there is no scheduled ordinary delivery in this time range. We are supposing that the Courier Cost (C_C) is independent from the quantity delivered in a single solution but it is only proportional to the number of deliveries. It is calculated as:

$$C_C = \sum_{i=1}^{n} n_{cour,i} * (dist_i * c_{cv,i} + c_{cf,i}) \tag{5.1}$$

where n_{cour} is the number of courier deliveries, $c_{cv,i}$ and $c_{cf,i}$ are respectively variable and fixed courier costs (ref. Table 5.4).

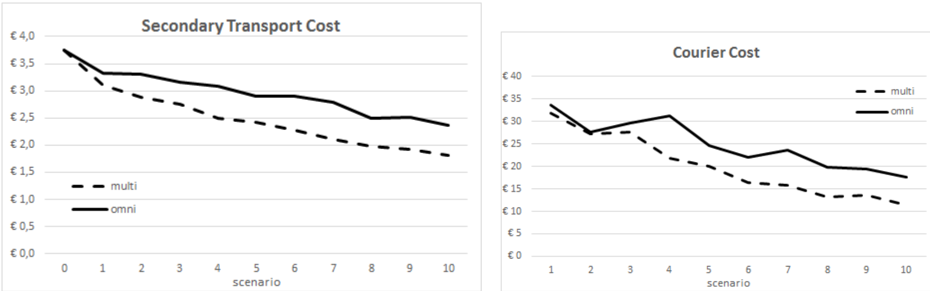
Table 5.4: Parameters used for the evaluation of Courier Costs

store	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
$c_{cv,i}$					0,1 [€/km]					
$c_{cf,i}$ [€]	12	12	12	12	12	23	23	28	28	28

The Courier Cost decreases when online purchases increase; in fact, only the quantity delivered through courier increases but not the number of deliveries. In the multi-channel strategy this value always remains lower since quantities delivered through courier are higher, then it is possible to optimise shipments.

5.6.11 Stores Management Cost

Figure 5.17 shows the value of the store management cost compared to quantities delivered to them. This cost has an opposite trend than the previous one, since in the omni-channel strategy, replenishments to stores, considering both ordinary deliveries and courier shipments, increase and, at the same time, the average stock level in the stores' internal warehouses decreases. This results into a lower holding cost.



(a) (b)

Figure 5.16: Secondary and Courier Transport Costs

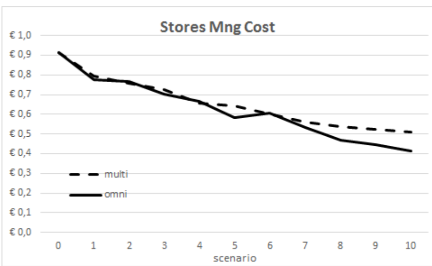
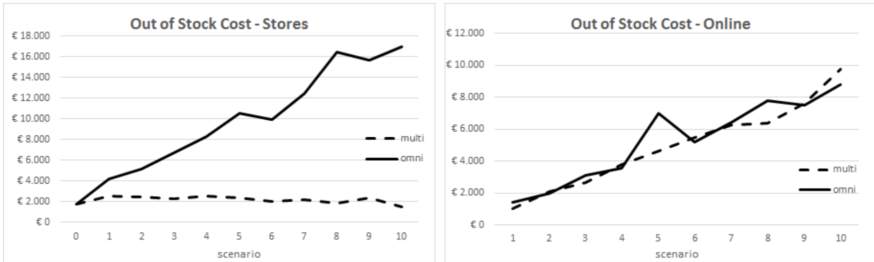


Figure 5.17: Management Costs for Warehouse and Stores

5.6.12 Out of Stock Cost

Figure 5.18 shows the Out of Stock Cost and reflects what already explained in section 5.6.6.



(a) (b)

Figure 5.18: Out of Stock Costs

5.6.13 Revenues

Figure 5.19 shows that for Revenues there is only a slight difference between the two approaches.

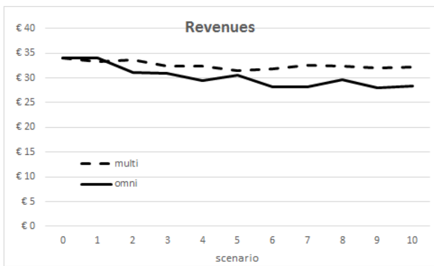


Figure 5.19: Revenues

5.6.14 Profit

All the cost and revenues items were evaluated together through the Profit (Figure 5.20). The graph shows that, compared to a traditional Supply Chain (Scenario 0), the multi-channel strategy is increasingly better when online purchases grow. The opposite situation occur for the omni-channel strategy. The factor that mostly causes this difference is the Out of Stock Cost (ref. section 5.6.6).

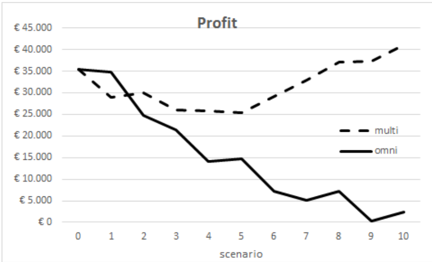


Figure 5.20: Revenues

5.7 Conclusions

The integration between physical stores and mobile channel is the new frontier for retail: customer expectations are always increasing, then operational requirements and supply chain configuration must be considered in the design and management of an omni-channel system. This chapter shows how the introduction of another fulfilment path, in addition to the traditional one, impacts on the performances of a Fashion Retail Supply Chain. The first requirement for the implementation of this integrated strategy is coordination and proper management of the information flow which becomes an enabling factor. The role of the virtual inventory system is, in fact, crucial for the access to data on availability and location of products. In addition, the analysis of the set of technical and economic KPIs highlights that Out of Stock represents the most significant cost item making the multi-channel strategy more convenient than the integrated one. The reduction of the Out of Stock may be obtained by optimising the replenishment policy, i.e. by varying replenishment plans, in terms of frequencies and quantities. Risk analysis (Chapter 2) already identified the replenishment as one of the most crucial processes for a Fashion Retail Industry and the introduction of the omni-channel retailing confirms that first result. In this context, in the next chapter a meta-heuristic algorithm is proposed for the optimisation of the replenishment problem.

Chapter 6

Optimisation of the Replenishment Problem using the Bees Algorithm

Contents

6.1 Introduction

In the fast changing environment of the Retailing Industry, the generic problem of allocating inventory from a central warehouse to several locations satisfying separate demand streams, is considered one of the most crucial issue, especially for companies that manage an extended network of stores. This so-called “Replenishment or Distribution Process” principally aims at dynamically optimizing stores assortment, in terms of items, colours, and sizes, trying to ensure high product availability and to minimize overstock or out of stock events [Iannone et al., 2015]. With particular attention to the Fashion and Apparel Industry, market demand is significantly affected by the inventory level, i.e. by the availability of products in the stores [Martìnez-de Albèniz and Boada Collado, 2014]. Specifically, with lower inventory levels, customers may not find the right size, or the desired colour and thus the sales will be lower. Concerning out-of-stock events, instead, customers may behave differently: deciding to buy another product in the same store, to buy the same product in another store or through web and mobile channels [Lanzilotto et al., 2015], to wait until the product is available or not to buy at all. All these cases of course generate customer dissatisfaction. A different case is represented by overstocks. Since fashion items suffer a strong depreciation over time, in particular at the end of the sales season, unsold stock will be disposed at highly discounted prices thus significantly reducing contribution margins. This demand-supply mismatch is highly important in the last ring of the supply chain, i.e. retailers, since any corrective action may be late, difficult, and costly [Flores et al., 2014]. In this context, the purpose of this chapter is to optimise the replenishment process using a new version of the Bees Algorithm which includes Tabu-Search principles and is called Tabu-Bees Algorithm.

6.2 The Replenishment Problem in the Retail Industry

Although there is a wide range of literature on both supply chain and retailing replenishment planning and optimisation, only few researchers have focused their attention on the particular case of the fashion retail industry [Iannone et al., 2013] or on fashion luxury firms [d’Avolio et al., 2015]. This industry, in fact, presents several issues such as: a wide product and customer variety, a very short product life cycle, a highly unpredictable, seasonal, and impulsive demand also influenced by shelf availability [Lanzilotto et al., 2014]. Concerning the replenishment problem, some of these problems have been separately analysed by different authors:

- Grewal et al. [2015] and Al-Zubaidi and Tyler [2004] focused on the seasonality of the demand using a discrete event simulation;
- Coelho and Laporte [2014] and Novotna and Varysova [2015] analyse the joint problem of replenishment and inventory for perishable or deteriorating products;
- Zhu [2013] evaluate both supply and demand uncertainties in a price-sensitive demand context;
- Bijvank et al. [2015] include lost sales costs in the replenishment policies;
- Anily and Hassin [2013] focuses on customer heterogeneity related to purchasing choices;
- Pan et al. [2009] consider uncertain factors, such as market changes, in an agent-based model to define the optimal reorder point and replenishment quantity between retailer and manufacturer;
- Abbott and Palekar [2008] study single store multi-product problem in which product sales are influenced by shelf availability and display-space.

Besides the sole replenishment process, other researchers dealt with the joint problem of replenishment and delivery/transportation for a retail supply chain with several different products [Cardòs and Garcìa-Sabater, 2006], with different locations and distribution centres [Qu et al., 2015] and with heterogeneous items [Qu et al., 2013]. In addition, the introduction of a RFID technology in those processes [Cui et al., 2014, Condea et al., 2012, Thiesse and Buckel, 2015] or the use of collaborative mechanisms [Lyu et al., 2010] may improve efficiency. Other related studies, instead, investigate only on single location single product [Rossi et al., 2011] or single retailer multiple suppliers [Adeinat and Ventura, 2015] cases. Given these considerations, the main purpose of the presented study is to analyse a complete problem with a multi-product multi-store configuration, stochastic demand, lost sales, and budget constraint. The problem cannot be solved by an exact method since demand is not a deterministic variable in this analysis but it derives from a casual distribution.

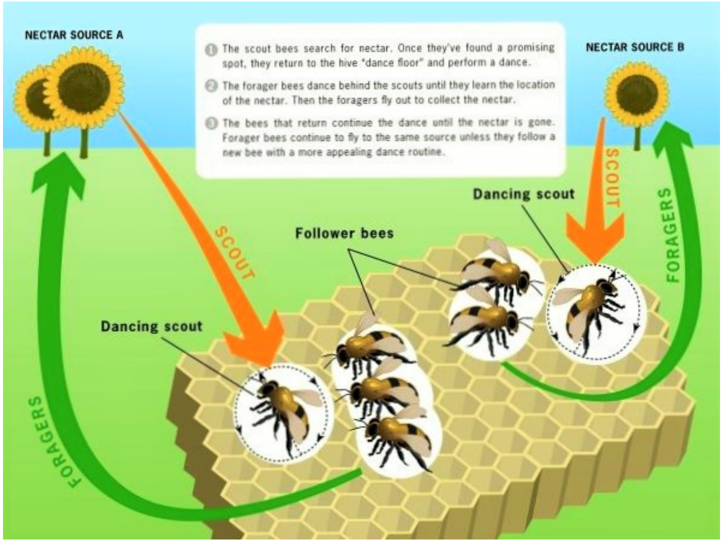
6.3 The Basic Bees Algorithm

The Bees algorithm is a population-based optimisation algorithm imitating the natural foraging behaviour of honey bees (ref. Figure 6.1). During the harvesting season, in fact, bees are able to discover food sources employing part of the colony's population (called *scout bees*) in a random search [Tereshko and Loengarov, 2005]. Once the potential nectar sources are discovered, these bees return to the hive and start the ritual "waggle dance" to communicate to the other bees the location of the nearest food source and its quality [Seeley, 1996]. After that, the dancer bee goes back to the food source with its followers (called *recruited bees*) to perform a local search in the neighbourhood of the patch. The number of recruited bees for each patch depends on its quality: patches with more and more easily available nectar will attract more bees. While the recruited bees are locally searching, other scout bees will continue the random global search to look for other possible food sources.

This bee colony behaviour is reproduced in the basic Bees Algorithm [Yuce et al., 2013, Pham and Castellani, 2009] to search for the best solution to a given optimisation problem. Each point in the search space (i.e. each potential solution) is thought of as a food source following the pseudo-code reported in Table 6.1.

The model requires some initial parameters to be set: number of scout bees (ns), number of elite (e), and best (b) patches and their size (ngh), number of recruited bees for elite (ne) and best (nb) patches. The first step of the algorithm is the random search of the scout bees, which are randomly placed in the defined space (step 1). For each of the random points, the model evaluates the objective function (step 2) and sort them (step 3) from the highest to the lowest for a maximisation problem (vice versa for a minimisation problem). The first points, elite and best patches,

Figure 6.1: The Natural Foraging Behaviour of Honey Bees [Vaishali, 2014]



are selected for the local search (step 5) and recruited bees (step 6) are sent in the neighbourhood (ngh) of these patches to explore other near points (step 7). All the other bees will continue the random global search (step 8). The iteration of the algorithm will stop when the stopping condition is met. Most used stopping conditions are:

- Maximum number of iteration;
- Maximum number of iterations without significant improvements;
- Expected value achievement;
- Minimum gradient value.

The basic Bees algorithm was used to solve several optimisation problems: Supply Chain configuration problem with multi-objective optimisation function [Mastrocinque et al., 2013], data clustering [Pham et al., 2007b], detection of wood defects [Pham et al., 2006], single machine scheduling with different jobs and common due date [Pham et al., 2007a], for feeder arrangement and component placement sequencing in an assembly optimisation problem [Pham et al., 2007c], etc.

Table 6.1: Pseudo-code of the basic bees algorithm

1.	Generate initial population of n random solutions
2.	Evaluate the objective function for the initial population
3.	Sort the initial population based on the objective function
4.	While (stopping criterion not met) // forming new population
5.	Select e elite patches and b best patches for neighbourhood search
6.	Recruit ne forager bees for the elite patches and nb for the best patches
7.	Evaluate the objective function for the foragers bees and select the representative bee for each patch
8.	Assign the remaining (n-e-b) bees for the random search and evaluate their objective function
9.	Sort the population based on their objective function
10.	End while

6.4 The proposed Tabu-Bees algorithm

In order to make the basic algorithm more efficient, some modified versions were developed:

- Packianather et al. [2009] propose a pheromone-based approach for recruiting bees for the local search in the best patches;

- Yuce et al. [2014] use a dynamic resizing of the neighbourhood and an abandoning strategy for useless sites, when there is no improvement in a particular site.

The algorithm proposed in this thesis , instead, uses the principles of the Tabu Search [Glover et al., 2007] which involves an adaptive memory and a responsive search. As the Basic Bees, also the Tabu Search performs a local or neighbourhood exploration but its main purpose is to allow classic methods to overcome local minima. For this reason, Tabu Search also allows non-improving moves and prevents going back to previously visited solutions by memorizing them in the *Tabu-List*. For our particular purpose, the Tabu-Search is used in the selection of the *elite* and *best* patches to avoid stopping in the same points for too many iterations without any improvement.
The pseudo-code of the Tabu-Bees Algorithm is reported in Table 6.2.

Table 6.2: Pseudo-code of the Tabu-Bees algorithm

1.	Generate initial population of n random solutions
2.	Evaluate the objective function for the initial population
3.	Sort the initial population based on the objective function
4.	While (stopping criterion not met)//forming new population
5.	Select e elite patches and b best patches for neighbourhood search
6.	If (any of the elite or best patches is repeating more than n_tabu times)//creating Tabu-List
7.	Include the repeating point in the Tabu-List
8.	Generate r random points and evaluate the objective function
9.	Select the best of these random points
10.	If (the best random point is better than the Tabu-List)//updating patches
11.	Replace the patch with the new random value
12.	Else keep the old patch value
13.	End if
14.	End if
15.	Recruit ne forager bees for the elite patches and nb for the best patches
16.	Evaluate the objective function for the foragers bees and select the representative bee for each patch
17.	Assign the remaining (n-e-b) bees for the random search and evaluate their objective function
18.	Sort the population based on their objective function
19.	End while

The main difference of this proposed model with the basic bees algorithm is represented by the two "if" loops (point 6-14 and 10-13). When one or more of the *elite* or *best* patches are repeating more than n_tabu times, these points are memorized in the *Tabu-List* (step 7), while the model generates other random points (step 8). If any of these random points are better than Tabu-List points, these new values will replace the old ones as *best* or *elite* patches (step 11), otherwise the algorithm will use the old values for one more iteration (step 12).

Even if it does not actually allow non-improving moves, the proposed model uses a memory [Imanguliyev, 2013] for recording repeating local minima points and tries to avoid these cases by searching for new better random points.

6.5 Design of the Optimisation process: the replenishment problem

Main objective of the replenishment problem is the maximisation of the profit, intended as the difference between Revenues and total Costs, trying to satisfy the whole market demand. For this particular study, we are referring to a multi-product, multi-store, and multi-period model with a marked demand that follows a uniform distribution in a fixed range and is independent from other items or stores. The replenishment problem also evaluates lost sales and is subject to a budget constraint.
The objective function (*Profit*) is defined as:

$$\max_{q_{kit} \in q \subseteq Z^+} \{P(q_{kit})\} = R - C_P - C_{ST} - C_{MS} - C_{OOS} \tag{6.1}$$

where R are the Revenues (ref. equation 3.31), C_P is the Purchase Cost (ref. equation 3.23), C_{ST} is the secondary Transport Cost (ref. equation 3.27), C_{MS} is the Stores Management Cost (ref. equation 3.29) and C_{OOS} is the out of Stock Cost (ref. equation 3.30).
The objective function is subject to the *Budget Constraint*:

$$C_P \leq B \tag{6.2}$$

where B id the Budget allowed by the company to buy products from suppliers and is fixed before every sales season. In this analysis, the attention is focused only on the economic problem then the Budget is the only constraint included. Other constraints that may be added in future developments may be related to warehouse capacity, inventory turnover, service level, etc.

6.6 Experimental results

The case study used for the simulation experiments is the same that was described in the previous chapters (Chapter 4 and 5) and in particular it refers to 10 clothing items (Table 4.3), 10 store (Table 4.4 and 4.5) and 1 central warehouse. Historical sales data (hs_{kit}) refer to a whole Fall/Winter season (ref. Figure 4.2 and Table 4.7). It was assumed that the Budget is equal to 1.000.000 €, that the company performs only 4 replenishments during the whole sales season and that sales for the analysed selling season are randomly generated in the following interval:

$$s_{kit} = [hs_{kit} * (1 - 0,2) \div hs_{kit} * (1 + 0,2)] \tag{6.3}$$

Table 6.3 shows the set parameters for the Bees and Tabu-Bees Algorithms.

Table 6.3: Parameters of the Bees and Tabu-Bees Algorithms for the replenishment problem

Parameter	**Symbol**	**Value**
Nr. Scout Bees	ns	100
Nr. Elite patches	e	2
Nr. Best patches	b	5
Nr recruited bees for elite patches	ne	30
Nr recruited bees for best patches	nb	15
Neighbourhood size	ngh	3
Nr. of iterations	itr	500
Nr. of iterations before including a point in the Tabu List	n_{tabu}	5
Nr. of random points generated for replacing Tabu points	r	100

We considered different configurations by varying the number of items and stores (k and i) from 1 to 10. Due to the randomness of the demand, each configuration is simulated 10 times. Figure 6.2 shows the average result, i.e. the profit, for the different configuration related to the number of iterations of the algorithm. The percentage in the graphs represent the improvement of the Tabu-Bees compared to the basic bees algorithm. It is clear from the graphs that the new proposed model always presents an average of 10% improved results since it allows to overcome local minima and reach better results in a lower number of iterations.

6.7 Conclusions

In the Fashion Retail Industry the replenishment process is considered the most crucial one in order to guarantee high availability of products in the stores but at the same time in order to reduce holding and transportation costs. Purpose of this analysis is to optimise company's profit, including cost items connected to purchase, transportation, holding and shortage. To solve this problem, a meta-heuristic approach was adopted since the stochastic demand does not allow using an exact method. A new version of the Bees Algorithm, which uses Tabu-Search principles, has been proposed and applied to a multi-product, multi-store and fixed period configuration. This more responsive research method allows the algorithm to overcome local minima and to reach on average 10% better results than the basic model.

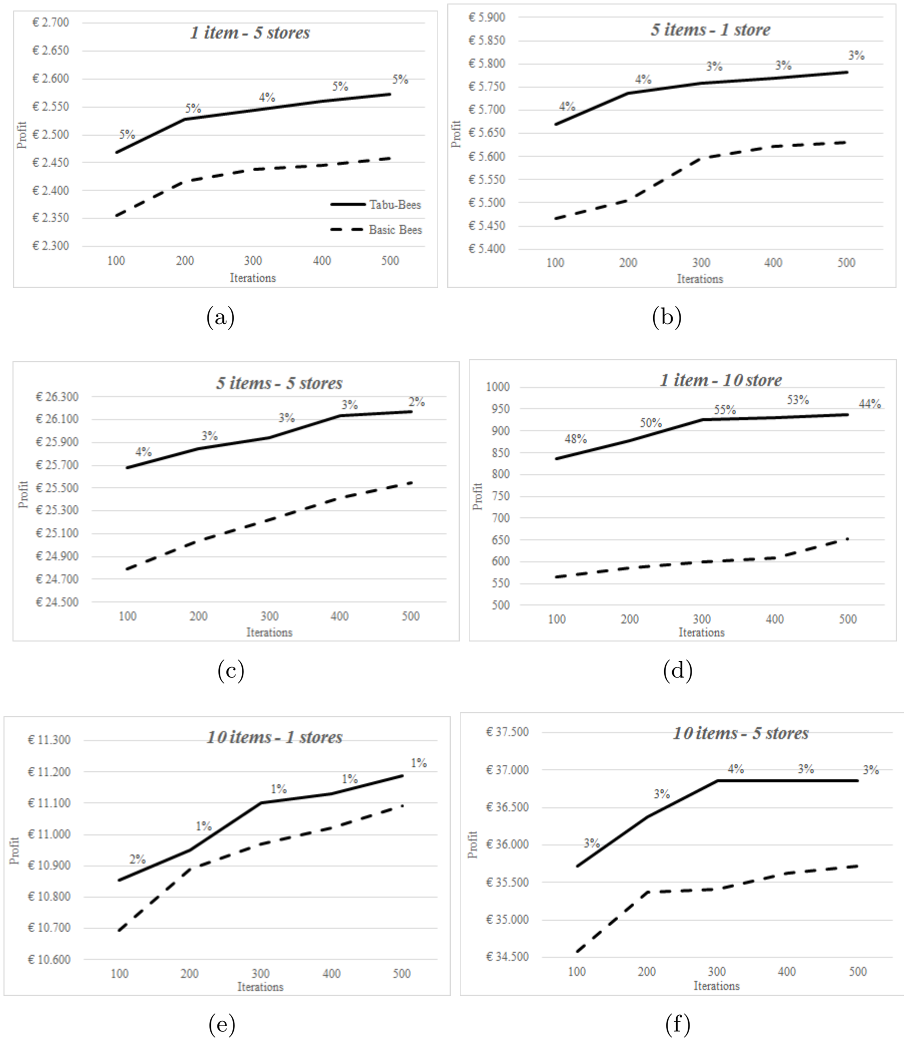


Figure 6.2: Comparison between basic bees and Tabu-Bees results: Profit value for 6 different configurations of items and stores

Conclusions

Fashion and Apparel market, characterized by fast changes in trends and demand, by short product life-cycles and by broad assortments, requires a responsive/demand driven Supply Chain focused on products availability, real-time information sharing and speed in matching customers' requests. In this context, this thesis presents different analysis and models that, integrated in an efficient Decision Support System, may allow companies to optimise performances of their Supply Chains.

After a first risk analysis of the overall structure of a traditional supply chain operating in this sector, it emerged that the most critical target is the correct time management - i.e. the ability of being responsive to market fluctuations - and, to perceive this goal, the most crucial process is the replenishment, i.e. the distribution of products to the network of direct-operated stores. To face these problems, this thesis proposes a model for the optimisation of Supply Chain performances through an in-season deviation analysis and an adjusting process. This model shows an improvement, especially from an economic perspective, in all the simulated scenarios and in particular in the case where an unexpected peak in demand occurs.

Nevertheless, this framework focuses on a brick-and-mortar only Supply Chain model which has been overcome by the wide spread of online and mobile purchasing. This "e-commerce revolution" forced companies to evolve in the so-called Omni-Channel Retailing strategy which implies management of both physical and online purchase channel and requires the adjustment of the operations according to it. To include this new integrated strategy, the framework was revised and extended and shows the for the appropriate and convenient management of both online and physical channel, a well optimised replenishment policy is mandatory. To perceive this goal an heuristic optimisation model was adopted and represents the last ring for the definition of a complete system for supporting companies in the strategic decision making process for the definition of the purchasing quantities and operations plans well ahead of the sales season.

Appendix A

Correlation matrix which defines relationships among risk factors.

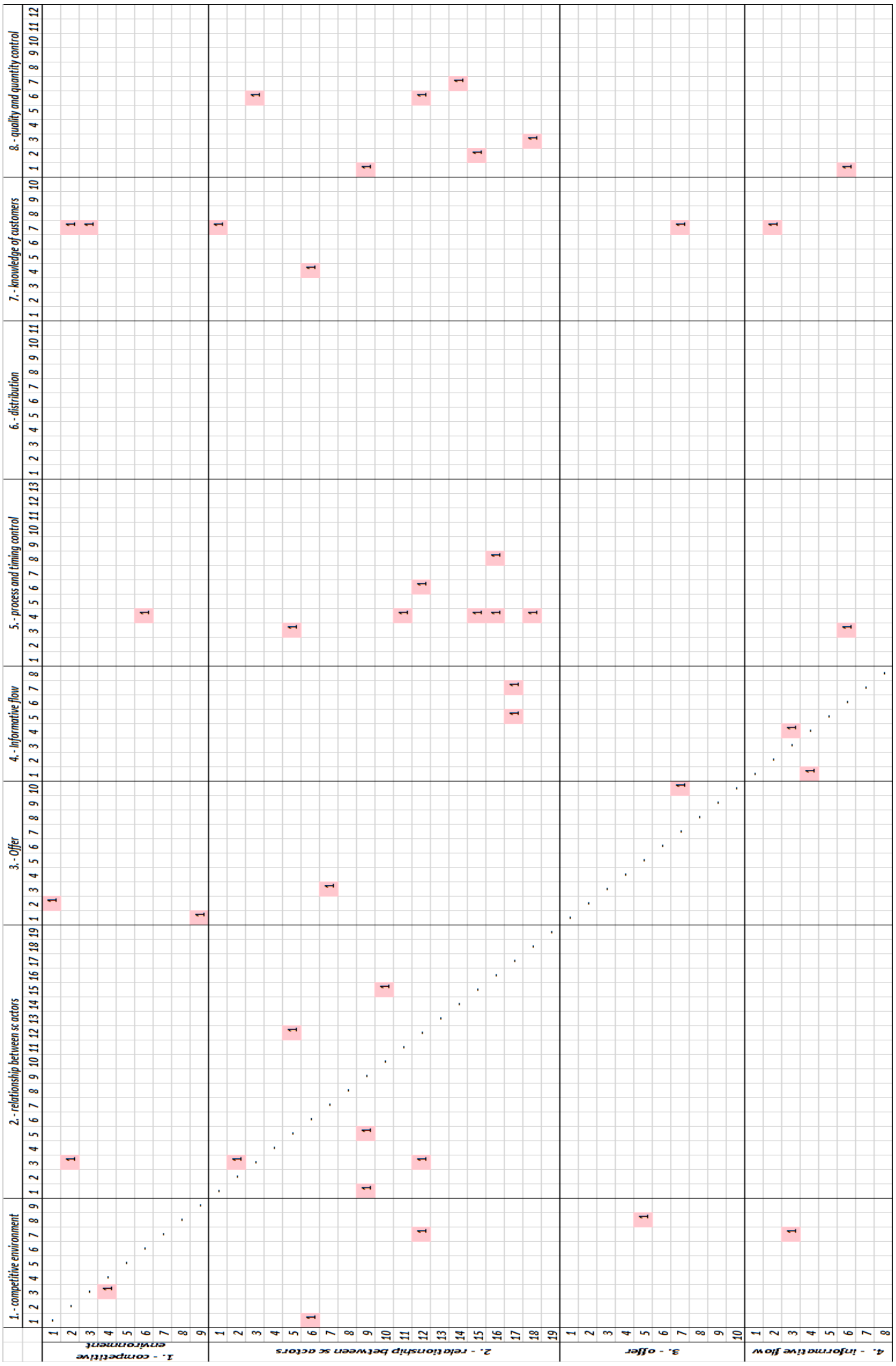


Figure 6.3: Correlation matrix - part 1

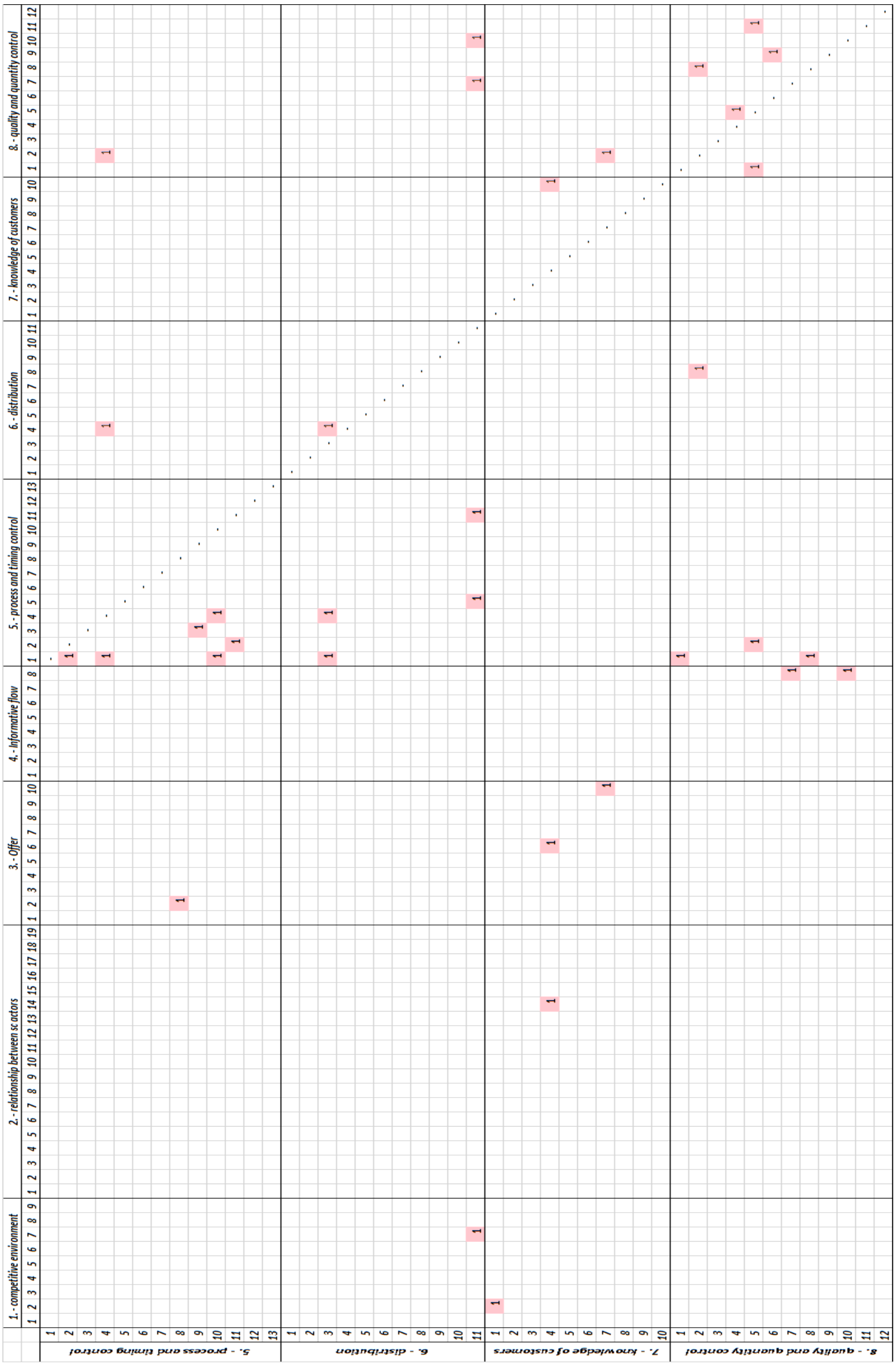


Figure 6.4: Correlation matrix - part2

Appendix B

Table 6.4: Summary of the nomenclature used in the thesis

$i = 1, ..., n$	nr. of stores
$j = 1, ..., m$	nr. of warehouses
$k = 1, ..., l$	nr. of clothing items/suppliers
T	duration of the sales season
F_{ki}	demand forecast for the k-th item in the i-th store
F_k	total demand forecast for the k-th item in all the stores
Q_k	purchase quantity for the k-th item
Q	total purchase quantity for all the items
SS	percentage of safety stocks
$Q_{D,kj}$	quantity delivered from the k-th supplier of the k-th item to the j-th warehouse
$Q_{D,j}$	total quantity delivered to the j-th warehouse
ST_j	stock level in the j-th warehouse
$\bar{ST}_j$	average stock level in the j-th warehouse
$ST_{POS,ki}$	stock level for the k-th item in the i-th store
$\bar{ST}_{POS,i}$	average stock level in the i-th store
$Q_{POS,ji}$	quantity delivered from the j-th warehouse to the i-th store
q_{kji}	quantity of the k-th item delivered from the j-th warehouse to the i-th store

Table 6.4: Summary of the nomenclature used in the thesis

s_{ki}	sales of the k-th item in the i-th store
d_{ki}	demand of the k-th item in the i-th store
$\Delta_{ST,ki}$	deviation between demand forecast and actual sales for the k-th item in the i-th store
δ_{ST}	threshold for stores deviation
$\Delta_{SC,k}$	global deviation between demand forecast and actual sales for the k-th item
δ_{SC}	threshold for demand deviation
u	percentage of variation in operations plans
C_P	purchase cost
cu_k	unitary purchase cost of the k-th item
C_{PT}	primary transport cost
$C_{tf,k}$	fixed primary transport cost from the k-th supplier
$C_{tv,k}$	variable primary transport cost from the k-th supplier
$DIST_{kj}$	distance from the k-th supplier to the j-th warehouse
C_{MW}	warehouse management cost
$C_{mf,j}$	fixed management cost for the j-th warehouse
ch_K	holding cost of the k-th item in the warehouse
C_{ST}	secondary transport cost
$c_{tf,i}$	fixed secondary transport cost to the i-th store
$c_{tv,i}$	variable secondary transport cost to the i-th store
$dist_i$	distance from the j-th warehouse to the i-th store
OOS_{ki}	out of stock for the k-th item in the i-th store
C_{MS}	stores management cost
$c_{mf,i}$	fixed management cost of the i-th store
$\bar{ch}_k$	store holding cost for the k-th item
C_{OOS}	out of stock cost
pr_k	price of the k-th item
c_{sh}	shortage cost
R	revenues
P	profit

Table 6.4: Summary of the nomenclature used in the thesis

SL	service level
FA	forecasting accuracy
$IT_{W,j}$	inventory turnover in the j-th warehouse
$IT_{POS,i}$	inventory turnover in the i-th store
$A_{s,ki}$	shelf availability of the k-th item in the i-th store
$A_{w,kj}$	warehouse availability of the k-th item in the j-th warehouse
h_{ki}	historical sales data for the k-th item in the i-th store
f_{del}	frequency of delivery from suppliers to warehouses
n_{del}	nr. of deliveries from suppliers to warehouses
f_{rep}	frequency of replenishment from warehouses to stores
n_{rep}	nr. of replenishments from warehouses to stores
C_{pen}	penalty cost for changing purchase plans
pen	unitary penalty cost

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