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Fashion retailing: A framework for supply chain optimization

Giada Martino[a*], Raffaele Iannnone[a], Marcello Fera[b], Salvatore Miranda[a], Stefano Riemma[a]

[a]*Department of Industrial Engineering, University of Salerno, Via G. Paolo II, Fisciano (SA), Italy*
[b]*Department of Industrial and Information Engineering, Second University of Naples, Via Roma 29, Aversa (CE), Italy*

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A B S T R A C T

Fashion and Apparel Supply Chains work in a very fast-changing environment and always demand better quality, higher availability of products, broader assortments and shorter delivery times. An efficient Supply Chain Management can make a difference between success and failure in the market. In this context, the main purposes of the presented work are: (i) to define the physical and informative flows, together with connected cost and revenue items, which characterize a Fashion Supply Chain working with a wide network of direct-operated or franchising mono-brand stores and (ii) to optimize Supply Chain performances through a responsive approach which, during the sales season, analyses actual market demand and adjusts operations plans accordingly. The framework aims at becoming a decision support system for the optimization of the performances of a process that starts from the development of the collection by the Styling Office and ends with the withdrawal of unsold items from the stores. In order to analyze the performances under different scenarios, a set of Key Performance indicators, partially selected from the SCOR Model, is defined.

Nomenclature

$i=1,\ldots,n$	nr. of stores
$j=1,\ldots,m$	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 stock
$Q_{D,kj}$	quantity delivered from the k-th supplier og 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
$\overline{ST_j}$	average stock level in the j-th warehouse
$ST_{POS,ki}$	stock level for the k-th item in the i-th store
$\overline{ST}_{POS,ki}$	average stock level in the i-th store
$Q_{POS,ji}$	quantity delivered from the j-th warehouse to the i-th store

* Corresponding author
E-mail address: gmartino@unisa.it (G. Martino)

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q_{kji}	quantity if the k-th item delivered from the j-th warehouse to the i-th store
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 for 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 fixed management cost of the i-th store
$c_{mf,i}$	fixed management cost for the i-th store
$\overline{ch}_k$	Store holding cost fot the k-th item
C_{OOS}	Out of stock cost
pr_k	Price of the k-th item
c_{sh}	Shortage cost
R	Revenue
P	Profit
SL	Service level
FA	Forecasting accuracy
$IT_{w,j}$	Inventory turnover for the j-th warehouse
$IT_{POS,i}$	Inventory turnover for 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 deom suppliers to warehouses
C_{pen}	Penalty cost for changing purchase plans
pen	Unitary penalty cost

1. Introduction

In modern Fashion and Apparel Supply Chains, customers are demanding better quality, higher availability of products, broader assortments and shorter delivery times. In this complex context, the main challenge is to gain value through supply chain management, allowing to respond quickly, efficiently and with flexibility to demand fluctuations (Battista & Schiraldi, 2013; Martino et al., 2016a). This obviously requires (Masson et al., 2007):

- *market sensitivity*, connection to the customer and capacity to capture trends as they emerge (Martino et al., 2015);
- *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.

Based on these considerations, this work presents a framework which defines and formalizes physical and informative flows that are characteristics of a fashion company operating with a dense network of direct-operated or franchising mono-brand stores. The model analyses the entire supply chain process, from the definition of the seasonal collection to the withdrawal of unsold goods from stores. This model is used to propose a more reactive approach which is based on a real-time updating process in order to quickly respond to changes in market demand and to optimise a set of Key Performance Indicators. The paper is organized as follows:

- section 2 analyses the fashion market and its features in order to highlight its complexity and to define the context in which the framework fits;
- the third section presents the framework and describes each block into details with the related main cost items;
- section 4 presents a set of Key Performance Indicators (KPI) selected from the Supply Chain Operations Reference (SCOR) model used to evaluate and optimize performances of the entire Supply Chain;
- section 5 describes the simulation model implemented in Excel;
- the sixth section presents the case study and all the data used in the simulation model;
- a sensitivity analysis is performed (section 7) before analysing results in section 8;
- in the end, in section 9, the results obtained in this research work are discussed.

2. The fashion market and its characteristics

The Fashion and Apparel (F&A) 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 (Fig. 1). Given that 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; Martino et al., 2016b).
- *Unpredictable and Volatile Demand* since it is driven by extremely unstable phenomena, such as weather, movies, sports, etc. Consumer's demand could change completely in a short time because an increasing star leads a new fashion trend (Wang et al., 2012), 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 & 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.

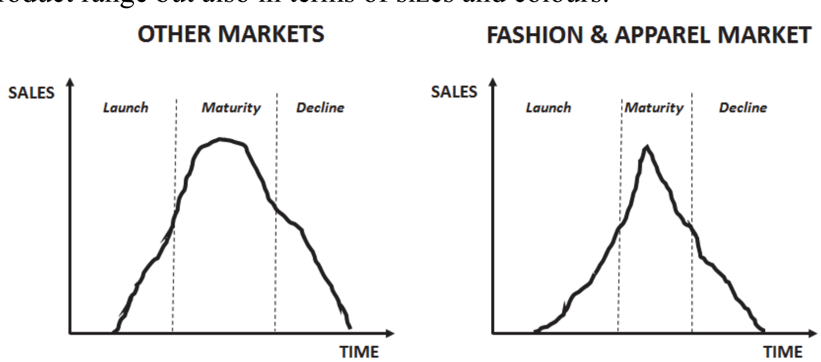


Fig. 1. Fashion product life cycle compared to other markets (Bandinelli et al., 2011)

Other characteristics highlighted by several studies in this sector are:

- *Extremely Wide Product Variety* (Vaagen & 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): 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 & 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 its introduction in the stores. 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 (Xiao & Jiao, 2011) (Fera et al., 2017);
- *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. This generates 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 the product. If this cannot be a critical issue for companies working in the luxury market, given the very high contribution margins that they can achieve, for large mass productions, instead, these costs may critically influence on profits defining company's economic success or failure.

3. Definition of the framework

In this section, the traditional approach, solely based on sales forecasting, is analysed (As-Is - ref. section 3.1). Then, in section 3.2 the proposed approach (To-Be) is described, which is based on a deviation analysis and an adjusting process of the operations plans with the main purpose of making the Supply Chain more reactive to market changes. The models are developed according to the following hypotheses:

a. the seasonal collection is unique, developed almost a year before its introduction in the market;

b. the production is launched based on sales forecasts and not on consolidated orders;

c. Points of Sale (POS) are replenished more than once during the sales season.

3.1. As-Is model

The process flow in the traditional approach is shown in Fig. 2 and 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 F&A 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 to the j-th area warehouse 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 stores (Table 2).

The IN SEASON phase, instead, starts with the first sales recorded in the stores. We suppose that both deliveries from the suppliers and replenishments to the stores are also performed during the selling season even if they are scheduled before it. This phase ends with the collection of unsold goods from stores and warehouses. These un- sold 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).The different steps of this framework will be described in detail in the following paragraphs and the nomenclature is summarised in Appendix.

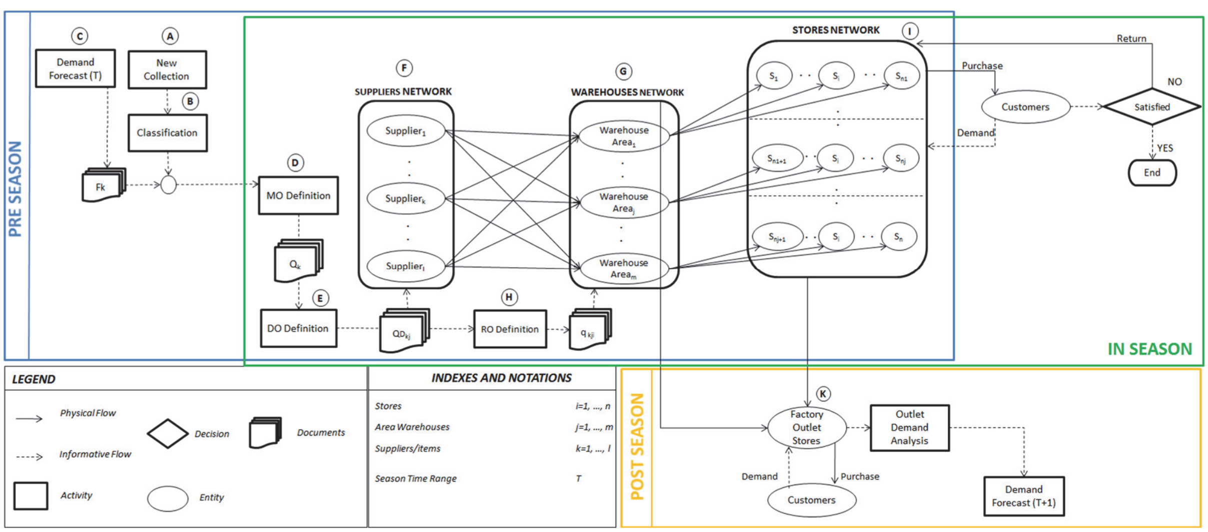


Fig. 2. Framework for the definition of the As-Is model

3.1.1. Development of the New Collection (A)

The definition of the collection primarily concerns to the Styling Office and is per- formed down line of a long phase of studies of trends, 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 1 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). 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, Premiere 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.

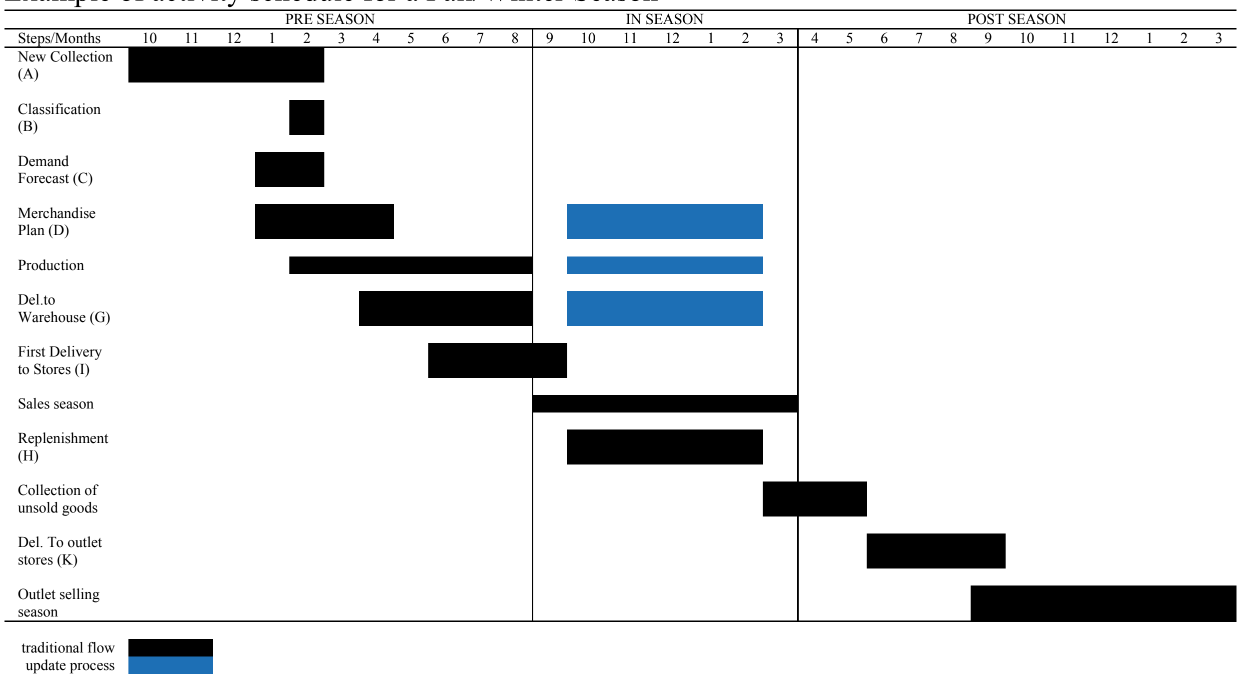
Table 1

An 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	-
…	…	…	…	…	…

Table 2

Example of activity schedule for a Fall/Winter Season



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, as the case described in this paper, 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.

3.1.2. 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*. 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), customers purchase behaviour is different both for 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 aspect allows to reduce the time spent by the customers for the purchasing activities and by the shop assistants for serving clients;

- *Clothing to Try on*: trousers, dresses and all 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 color.

As regards the price, instead, we defined three different ranges: *Cheap*, *Intermediate* and *Expensive*.

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

- *Basic* products, sold throughout the year, which 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 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 3.1.3).

3.1.3. Demand Forecasts (C)

Next step of the model is demand forecasting. In the fashion industry this process is crucial and particularly complex due to high volatility and unpredictability of demand. In the proposed model, *Demand Forecasts* provide the basis in which all operations plans are compiled and are drawn up according to historical data collected from stores. In order to compile reliable forecasts, it is useful to distinguish whether 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 only 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 opening 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, customers 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 in stores on the street, accessories have very little success. Opposite behaviour is shown 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 toward 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 Electronic Data Interchange (EDI) and Electronic Point of Sale (EPOS). 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:

$$\%Sales = \frac{Sales}{DeliveredQuantities} \quad (1)$$

It is clear that sales will increase with the availability of goods in stores (ref. paragraph 4.7), thus making 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 for the *k*-th item and the *i*-th store ($\overline{F_{ki}}$) will be a complex function of all the above-mentioned parameters:

$$\bar{F}_{ki} = f(Dim_i, Loc_i, Geo_i, Comp_i, Turn_i, \%Sales_{ki}) \quad (2)$$

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 the 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:

$$\Delta_{mrk} = \frac{Mkt_T - Mkt_{T-1}}{Mkt_{T-1}}, \quad (3)$$

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:

$$F_{ki} = \bar{F}_{ki} * (1 + \Delta_{att} + \Delta_{mrk}), \quad (4)$$

All remarks made so far do not include either size or color of the clothing item. For sizes, generally demand trend follows a Gaussian curve centered on a particular size which varies according to the customer target and the reference market. 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. All forecasting factors and their characteristics are summarised in Table 3. The Purchasing Office will, then, receive sales forecasts for each k-th clothing item defined as:

$$F_k = \sum_{i=1}^{n} F_{ki} \tag{5}$$

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, you have to 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.

Table 3
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	%	Historical Data
		% Sales Cl. To try on		
		% Sales Accessories		
	COLOR	Trendy	-	Historical Data from trendy color of previous season
		Basic		Consolidated historical data
+	SIZE	Gaussian Distribution	-	Target Market

3.1.4. 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:

$$Q_k = (F_k + AS_k) * (1 + OS + SS) \tag{6}$$

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:

$$\begin{cases} AS_k > 0 & if\ F_k < AS_{min,k} \\ AS_k = 0 & if\ F_k > AS_{min,k} \end{cases} \tag{7}$$

- ✓ *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 3.1.10), 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 you want to ensure and to the demand rate. Then the total quantity will be:

$$Q = \sum_{k=1}^{l} Q_k \,. \tag{8}$$

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

- ✓ *Purchasing Budget*, which is fixed when defining the collection;
- ✓ *Discounts on quantities* that we 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 3.1.6);
- ✓ *Quantities Qk*: 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.

3.1.5. 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 total quantities to be delivered at time t to the j-th warehouse as:

$$Q_{D,j}(t) = \sum_{k=1}^{l} Q_{D,ki}(t) \tag{9}$$

With $\sum_{j=1}^{m}\int_{0}^{T} Q_{D,kj}(t)dt = Q_k \qquad \forall k \in 1,\dots,l$ (10)

Eq. (10) means that the purchased quantity for each k-th item has to be totally delivered to the warehouse during the considered time range T.

3.1.6. Suppliers (F)

Outsourcing is becoming an unavoidable trend in cost cutting for F&A 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. Two are the unavoidable features 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:

- ✓ *Cos*t: 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 (Tend & Jaramillo, 2005; Chan & Chan, 2010; Fera & Macchiaroli, 2010) and use several areas of evaluation such as delivery, quality, assurance of supply, flexibility, cost and reliability.

3.1.7. Central Warehouses (G)

The central warehouse is responsible for receiving goods from different suppliers, storing and inventory managing (Fera & Macchiaroli, 2009). Then, through the picking and sorting process, personalized kits of items will be prepared and shipped to the stores network. Besides material flows, warehouses must manage the information flow concerning delivery and replenishment plans provided by the Department. The stock level (ST) at the time *t* for the j-th warehouse can be calculated as:

$$ST_j(t) = ST_j(t-1) + \sum_{k=1}^{l} Q_{D,kj}(t) - \sum_{i=1}^{n} Q_{POS,ji}(t) \tag{11}$$

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:

$$ST_j(t) \leq ST_{max,j} \tag{12}$$

and concerning materials handling capacity:

$$\sum_{k=1}^{l} Q_{D,kj}(t) + \sum_{i=1}^{n} Q_{POS,ji}(t) \leq HC_{max,j} \tag{13}$$

where HC_{max} 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 stores.

3.1.8. 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 the i-th store for the k-th item (d'Avolio et al., 2015). Given *n* the total number of stores directly managed by the company and $q_{kji}(t)$ the quantity of the k-th item delivered from the j-th warehouse to the i-th store at the time *t*, we can say that the total quantity delivered to the i-th store is:

$$Q_{POS,ji}(t) = \sum_{k=1}^{l} q_{kij}(t) \tag{14}$$

where $$\sum_{k=1}^{l} \int_0^T Q_{POS,ji}(t)dt \leq \sum_{k=1}^{l} \int_0^T Q_{D,kj}(t)dt \tag{15}$$

Eq. (15) means that, for each k-th item, quantity delivered to the i-th store in the considered time range T cannot obviously overcome total quantity delivered to the warehouse.

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

$$ST_{POS,i}(t) \leq ST_{POS,i,max} \tag{16}$$

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

$$ST_{POS,i}(t) = \sum_{k=1}^{l} [ST_{POS,ki}(t-1) + \sum_{j=1}^{m} q_{kij}(t) - s_{ki}(t) \tag{17}$$

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 sales season. In the As-Is case plans drafting is a process which is performed only once according to forecasts, while in he proposed approach (To-Be case - ref. section 3.2) it is performed before each replenishment according to actual market demand.

3.1.9. Stores (I)

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:

$$s_{ki}(t) = \min\{d_{ki}(t); ST_{POS,ki}(t)\}, \tag{18}$$

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).

3.1.10. Factory Outlet stores (K)

The primary 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, we cannot 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.

3.2. To-Be model

As discussed in previous sections, the As-Is model is solely based on forecasts thus making it difficult to adjust purchasing and operations plans according to high fluctuations in demand during the sales season. To overcome this limit, the proposed model defines plans according to actuals sales data rather than only forecasts. Thank to sales data recorded in the stores, in fact, 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*.

3.2.1. 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). 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.

$$\Delta_{ST,ki} = \frac{F_{ki} - s_{ki}}{F_{ki}} \tag{19}$$

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:

$$\begin{cases} if \ \ |\Delta_{ST,ki}| > \delta_{ST} & \bar{q}_{ki} = q_{ki} * [1 - (\Delta_{ST,ki} * u) \\ if \ \ |\Delta_{ST,ki}| < \delta_{ST} & \bar{q}_{ki} = q_{ki} \end{cases} \tag{20}$$

where $\bar{q}_{ki}$ is the updated quantity and u is a parameters which defines how much the replenishment plans can change and 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 ($\bar{q}_{ki}$) must be incremented, and vice versa.

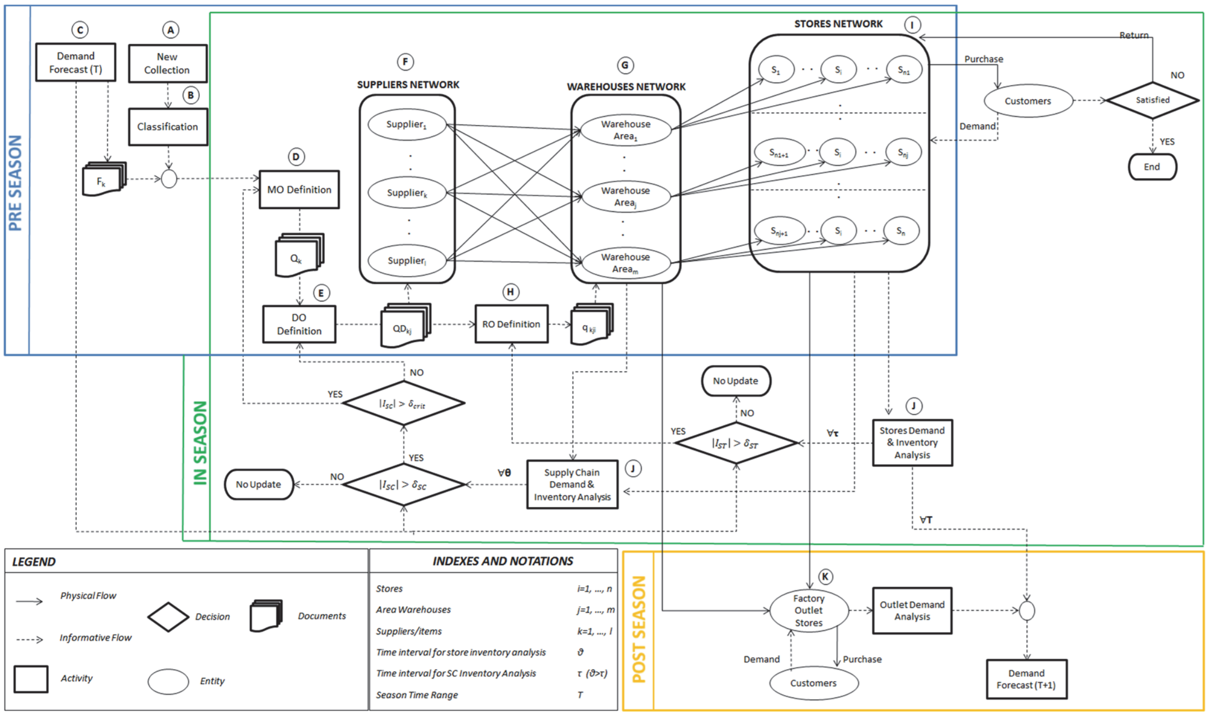


Fig. 3. Framework for the definition of the To-Be proposed approach

The second analysis, *Supply Chain Demand & Inventory Analysis*, evaluates in aggregate data from stores and warehouses at each time interval θ (with θ > τ).

$$\Delta_{SC,k} = \sum_{i=1}^{n} \frac{F_{ki} - s_{ki}}{F_{ki}} \tag{21}$$

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 according to the following equation:

$$\begin{cases} if \ \ |\Delta_{SC,k}| > \delta_{SC} & \bar{Q}_k = Q_k * [1 - (\Delta_{SC,k} * u) \\ if \ \ |\Delta_{SC,k}| < \delta_{SC} & \bar{Q}_k = Q_k \end{cases} \tag{22}$$

4. Key Performance Indicators (KPI)

After the definition and description of all the Supply Chain processes, it is necessary to define a set of Key Performance Indicators (KPIs) in order to analyse and optimise performances of the entire Supply Chain. These KPIs are selected from the SCOR Reference Model 11.0 (Supply Chain Council, 2012) which defines six primary management processes (Plan, Source, Make, Deliver, Return and Enable) and five Performance Attributes (Reliability, Responsiveness, Agility, Costs and Asset Management Efficiency). According to the most used industrial indicators and to (Lanzilotto et al., 2015), the KPI are selected and listed in Fig. 4; each of them is related to one Performance Attribute and metric defined by the SCOR model. In the following sections the above-mentioned KPIs will be better described and other two additional KPIs, specifically defined for the application in the fashion industry, will be proposed.

4.1. Service Level (SL)

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

$$SL_i = \frac{\sum_{k=1}^{l} s_{ki}}{\sum_{k=1}^{l} d_{ki}} \tag{23}$$

4.2. Forecasting Accuracy

Forecasting accuracy is calculated for each product category and is defined as the percentage of error compared to actual sales:

$$FA_k = \sum_{i=1}^{n} \frac{s_{ki} - F_{ki}}{s_{ki}} \tag{24}$$

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

4.3. Costs

The main cost items identified for this particular problem are (Iannone et al., 2015)**:**

- ✓ *Warehouse Management Cost ($C_{M\,W}$):*

$$C_{MW} = \sum_{j=1}^{m} \left[C_{mf,j} + \sum_{k=1}^{l} \frac{ch_k * cu_k}{T} * \int_0^T \left(Q_{D,kj}(h) - \sum_{i=1}^{n} q_{kij}(h) \right) dh \right] \tag{25}$$

where ch_k is the holding cost expressed as a percentage of the unitary purchase cost (cu_k) of the products in stock at time t and $C_{mf,j}$ is the fixed management cost of the j-th warehouse.

- ✓ *Primary Transport Cost* (C_{PT}) (from suppliers to central warehouse):

Given $C_{tf,k}$ and $C_{tv,k}$ fixed and variable primary transport costs for the k- th product (we are supposing that product k is manufactured by one specific supplier) at the time *t* and given $DIST_k$ the distance from the supplier to the central warehouse, primary transport cost will be:

$$C_{PT} = \int_0^T \left[\sum_{k=1}^{l} \left(C_{tf,k} + C_{tv,k} * \sum_{j=1}^{m} Q_{D,kj}(h) * DIST_{kj} \right) \right] dh \tag{26}$$

- ✓ *Secondary Transport Cost (CST)* (from central warehouse to POS):

$$C_{ST} = \sum_{i=1}^{n} \left[c_{tf,i} + c_{tv,i} * \int_0^T \sum_{k=1}^{l} \sum_{j=1}^{m} q_{kij}(h) * dist_{ij} dh \right] \tag{26}$$

This is the cost that the company supports for the delivery of quantity q_{kij} to the stores network.

Accepting a small approximation, we will suppose that this cost also includes the cost for the collection of unsold products. Given $c_{tf,i}$ and $c_{tv,i}$(t) the fixed and variable costs for secondary transport to the i-th store and $dist_{ij}$ the distance from the j-th warehouse to the i-th POS, we have that the secondary transport cost is equal to:

- ✓ *POS management cost* (C_{MS}), including both main stores and Factory Outlet stores:

$$C_{MS} = \sum_{i=1}^{n} c_{mf,i} + \sum_{k=1}^{l} \overline{ch}_k * cu_k * \frac{1}{T}\int_0^T (q_{ki}(h) - s_{ki}(h))dh \quad (28)$$

where:

- ✓ $\overline{ch}_k$ is the holding cost for products in the POS. It is higher than the same ch_k for the central warehouse since products stored in the POS can not be used anymore for the replenishment of other POS;
- ✓ $c_{mf,i}$ is the fixed management cost for the i-th POS; it is greater than zero only if POS is owned by the company, otherwise, in case of a franchising store, $c_{mf,i}$ is null since all the fixed costs are supported by the franchisee.
- ✓ *Purchase Cost* (C_P): Defined as the product of the quantities purchased Q and the unit cost cu.

$$C_P = \sum_{k=1}^{l} Q_k * cu_k \quad (29)$$

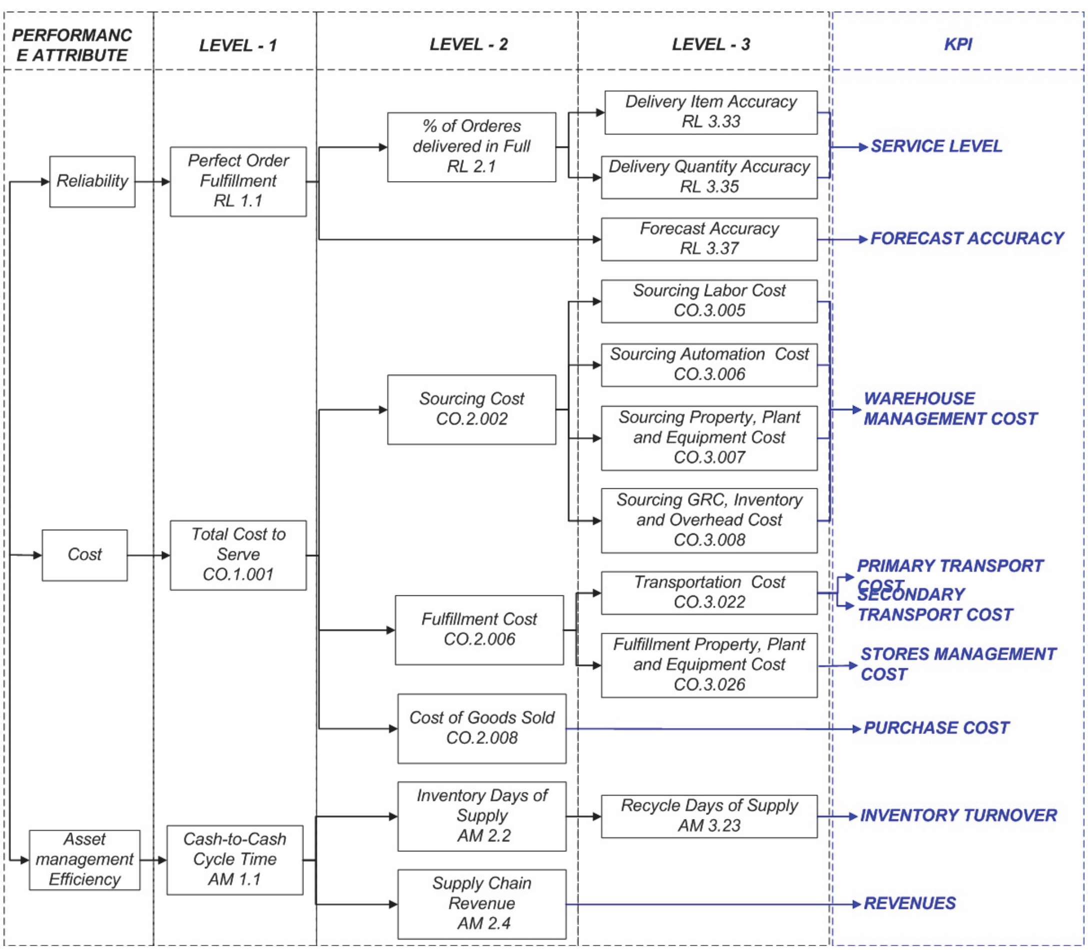


Fig. 4. KPIs identification from SCOR 11.0 model*4.4. Inventory Turnover*

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 ($\overline{ST}$). We evaluate this indicator both for the central warehouse (in this case outgoing quantities are the item delivered to POS):

$$IT_W = \frac{\sum_{k=1}^{l}\sum_{i=1}^{n}\sum_{j=1}^{m} q_{kij}}{\overline{ST}} \quad (30)$$

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

$$IT_{POS,j} = \frac{\sum_{i=1}^{n} s_{ij}}{\overline{ST}_{POS,j}} \quad (31)$$

4.5. Revenues

Besides costs, it is also important to evaluate revenues, which 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 Fig. 5).

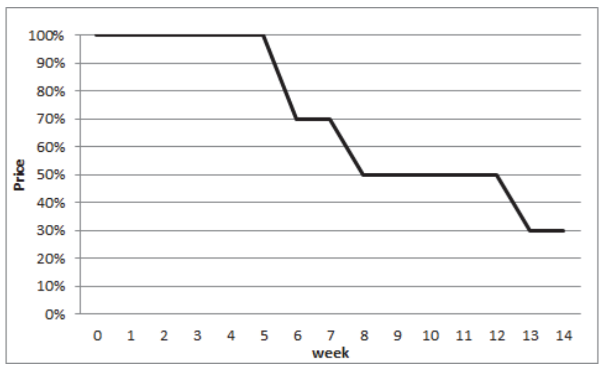


Fig. 5. Price trend over the sales season

Then, given $pr_k(t)$ the selling price of the product k at time t, total revenues can be expressed as:

$$R = \int_0^T \sum_{i=1}^{n}\sum_{k=1}^{l} s_{ki}(h) * pr_k(h)dh \quad (32)$$

4.6. 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:

$$\%Sales_{ki} = \frac{s_{ki}}{q_{ki}} \quad (33)$$

This indicator is not derived from the SCOR model but it is specifically defined for the application in the fashion industry (ref. paragraph 3.1.3). 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.

4.7. Availability

The concept of availability in the retail industry refers to three different aspects (LIUC 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 centre 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:

$$\begin{cases} Shelf \quad A_{s,ki} = \sum_{j=1}^{m} q_{kij} - s_{ki} \\ Warehouse \quad A_{w,j} = \sum_{k=1}^{l} \left(Q_{D,kj} - \sum_{i=1}^{n} q_{kij} \right) \end{cases} \tag{34}$$

4.8. Out of Stock (OOS)

This parameter is strictly connected to the availability (ref. paragraph 4.7) and to the service level (ref. paragraph 4.1). It is defined as the number of orders that cannot be fulfilled and is given by:

$$OOS_{ki} = d_{ki} - A_{s,ki} \tag{35}$$

In case of out of stock, the customer can act in different ways (Slot et al., 2005; Zeppetella et al., 2016):

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. 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 recent years, companies have been trying to implement a combination of "bricks-and-clicks" (Agatz, 2008; Lanzilotto et al., 2014; Lanzilotto et al. 2015). This solution is commonly called "Multi-Channel Retailing" and involves the integration between physical, mobile and on-line channel, thus increasing sales and profit-making opportunities (Bermn & Thelen, 2004; Elia et al., 2014). The damage caused by OOS to the company (in terms of customer dissatisfaction, image damage, etc.) can be economically evaluated through the following equation:

$$C_{OOS} = \int_0^T \sum_{k=1}^{l} \sum_{i=1}^{n} OOS_{ki}(h) * (pr_k - cu_k) * s_{sh}\, dh \tag{36}$$

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

5. Definition of the simulation model

In order to evaluate Supply Chain performances of the proposed framework, a simulation model was developed and implemented in Excel. Its general diagram is represented in Fig. 6 and has the main purpose of comparing the previously defined KPIs (ref. section 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 this case instead, those plans are defined before the sales season and kept fixed throughout the time range. A summary of the nomenclature already used in previous sections and that will be used following is reported in Table 4.

Table 4
Nomenclature

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

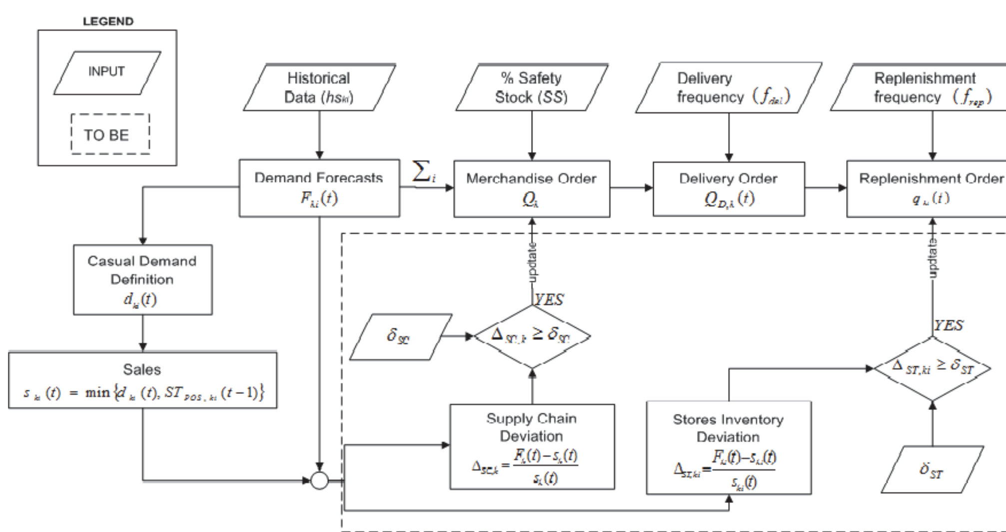


Fig. 6. General Diagram of the simulation model

The model uses as inputs:

- *historical sales data* (h_{ki});
- *percentage of Safety Stocks (SS);*
- *frequency of deliveries* to the warehouse (*del*) and of *replenishment* to stores (*rep*);
- *deviation thresholds*, both for stores (δ_{ST}) and for Supply Chain (δ_{SC});

and defines:

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

$$F_{ki}(t) = hs_{ki}(t) \tag{37}$$

- *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:

$$Q_k = \int_0^T \sum_{i=1}^{n} F_{ki}(t) * (1 + SS) \tag{38}$$

- *Delivery orders QD,kj* : we are supposing that each delivery is performed at time:

$$t_{del} = 1 + f_{del} * (del - 1) \qquad for \quad del = 1, \dots, n_{del} \tag{39}$$

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:

$$Q_{D,kj}(t_{del}) = \int_{t_{del}}^{t_{del}+1} F_{ki}(t) * (1 + SS) \tag{40}$$

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

$$t_{rep} = 1 + f_{rep} * (rep - 1) \qquad for \quad rep = 1, \dots, n_{rep} \tag{41}$$

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:

$$q_{kij}(t_{rep}) = \int_{t_{rep}}^{t_{rep}+1} F_{ki}(t) \tag{42}$$

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 stocks available in the stores are given by:

$$ST_{POS,ki}(t) = \int_0^T \sum_{j=1}^{m} q_{kij}(h) - s_{ki}(h) dh \tag{43}$$

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 3.2.1. 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*).

5.1. Key performance Indicators

A summary of the KPIs already described in section 4 is reported in Table 5. 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* (C_P) and calculated as:

$$C_{pen} = pen * |\Delta Q| \quad (44)$$

where *pen* is the unitary penalty cost ([e/pcs]) and ΔQ is the variation ([pcs]) of the updated purchase plan compared to the one defined before the sales season. All the cost items and revenues can also be globally evaluated through the *Profit*.

6. Introduction to the case study

In order to compare Supply Chain performances of the proposed model we used the real case of 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 (m=1). The data collected from the above-mentioned company concern characteristics of 10 selected clothing items (k=10 - Table 6) and 10 selected stores (i=10 - Table 7).

Table 5
Key Performance Indicators

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

Table 6
Clothing items characteristics

Item	Category	Description	Price (*pr*) €	Price (*pr*) range	Cost (*cu*)
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 7
Stores characteristics

Store	Geogr. 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 9 for the primary transport (from supplier to central warehouse) and in Table 8 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 8
Stores characteristics related to secondary transport

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

Table 9
Suppliers characteristics related to primary transport

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

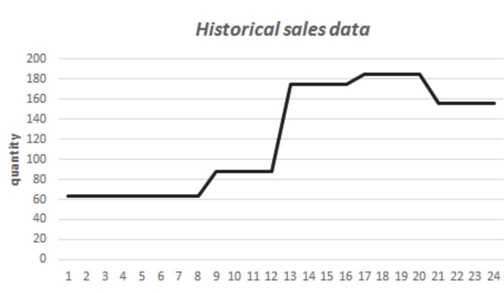


Fig. 7. Case study historical sales data for the whole sales season

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 Fig. 7 and Table 10.

Table 10
Case study historical sales data for each item and each store

	Store									
Item	1	2	3	4	5	6	7	8	9	10
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

A summary of other parameters used in the simulation model is reported in Table 11.

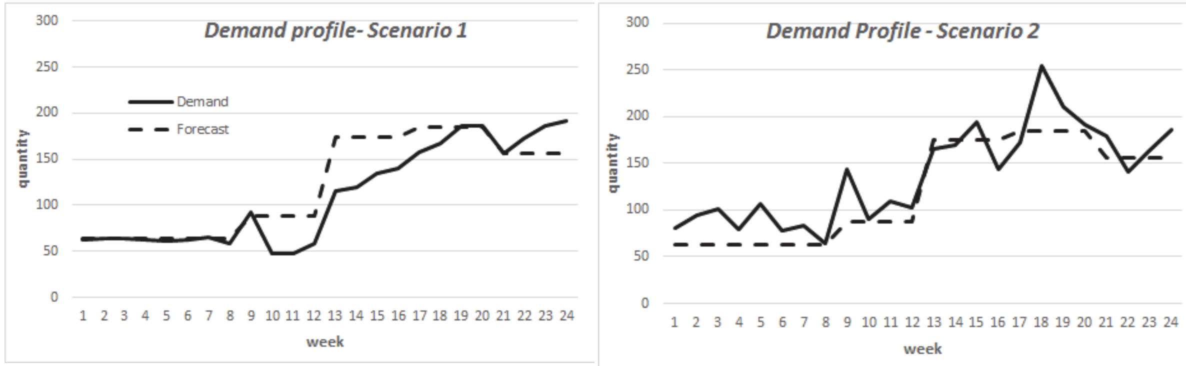
Table 11
Parameters of the simulation model

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

6.1. Definition of the scenarios

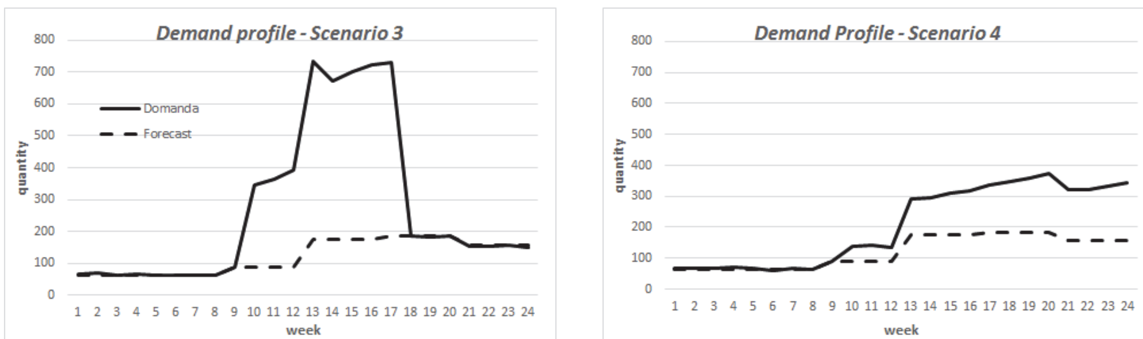
The primary objective of the simulation model is to evaluate if the proposed model is able to quickly follow changes in demand trend and to consequently adapt operations plans. With this purpose different demand profiles were defined that may summarise any possible real case: highly variable demand and 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 (Fig. 8(a));
Scenario 2: it is equal to the previous case with a higher standard deviation: 100% of the mean value (Fig. 8(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 (Fig. 9(a));
Scenario 4 : from week 10 onwards, the demand has a growing trend equal to 1% (Fig. 9(b));
Scenario 5 : from week 10 onwards, the demand has a decreasing trend equal to 1% (Fig. 10(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 - (Fig. 10(b)).



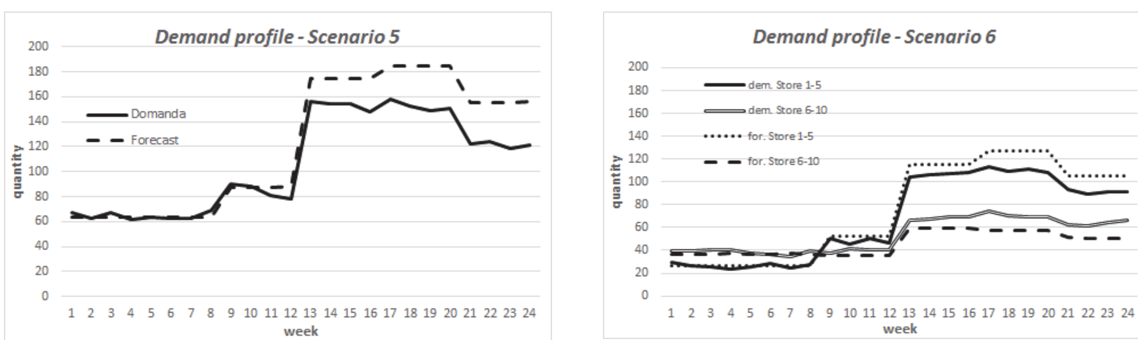
(a) (b)

Fig. 8. Demand Profile of Scenario 1 and 2



(a) (b)

Fig. 9. Demand Profile of Scenario 3 and 4



(a) (b)

Fig. 10. Demand Profile of Scenario 5 and 6

Table 12
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

7. Sensitivity Analysis

In order to set appropriate values for the deviation analysis parameters (δ_{ST} , δ_{SC} and u), a sensitivity analysis was performed by changing one-factor-at-a-time. Table 12 shows the values used in the analysis while Table 13 shows minimum, maximum and mean value of the percentage variation of the KPIs. While technical KPIs were individually analysed, the economic performance is globally evaluated through the Profit value.

Table 13
Results of the Sensitivity Analysis

		SL	*%Sales*	*OOS*	*FA*	IT_{POS}	IT_W	A_S	*P*
δ_{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%
δ_{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%
δ_{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%
δ_{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%

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 Fig. 11: increasing u by 50% will improve Supply Chain performances and in particular will increase Profit by approximately 70%. This value (u = 15%) will then be used for all the next simulations.

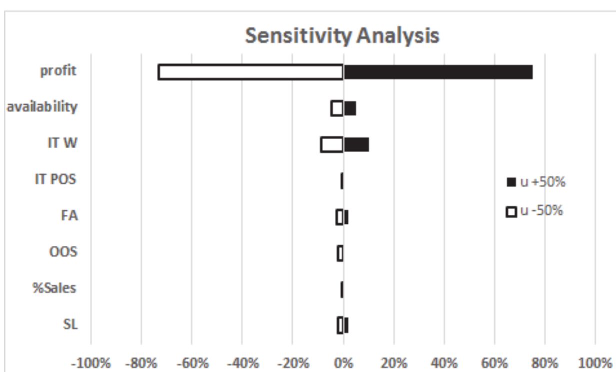


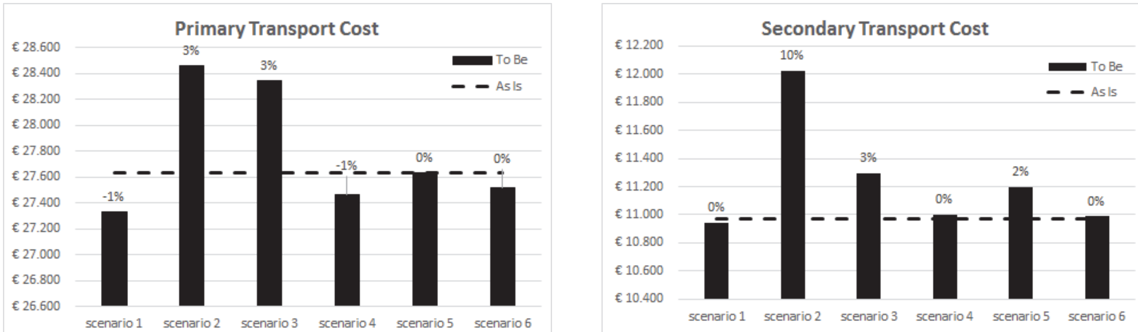
Fig. 11. Results of the sensitivity analysis for the parameter u (percentage of variation of the operations plans)

8. Analysis of the results

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

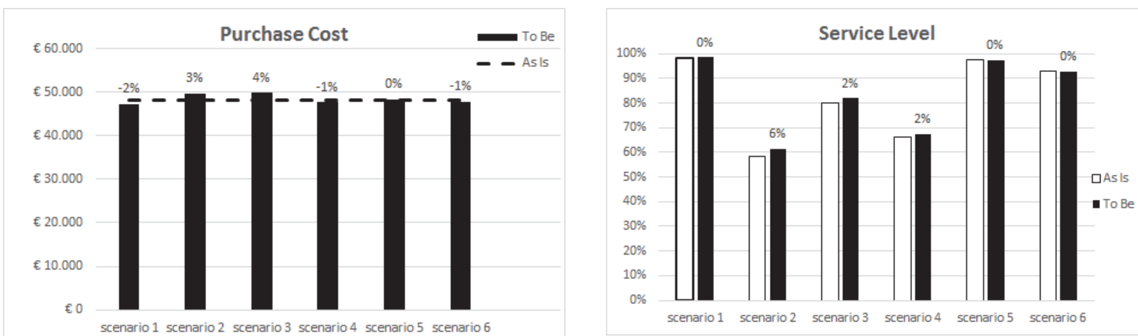
- ✓ for all the six scenarios in the As Is case, costs for Primary Transport (Fig. 12(a)), Secondary Transport (Fig. 12(b)), Purchase (Fig. 13(a) a) and Warehouse Management (Fig. 18(b) a) are constant. This is due to the fact that operations plans are defined according to demand forecasts and do not change in the different simulated scenarios;

✓ Transport Costs (Fig. 12(a) and 12(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 (Fig. 13(a) - Purchase Cost) and consequently deliver greater quantity;



(a) (b)

Fig. 12. Comparison of the results for the Primary and Secondary Transport Costs



(a) (b)

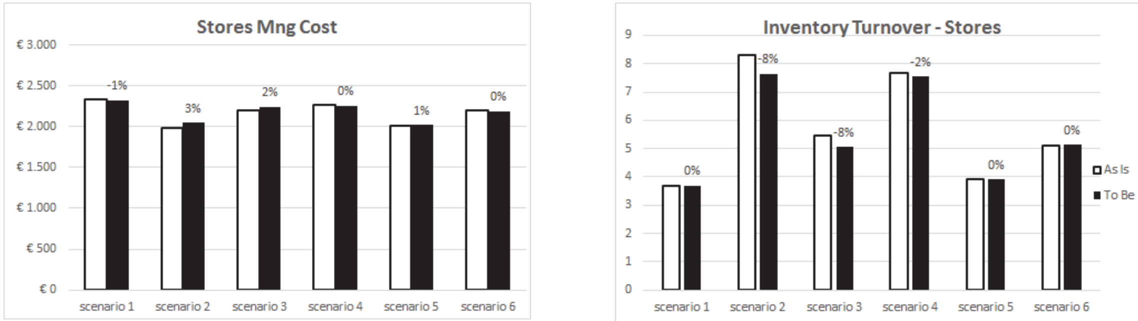
Fig. 13. Comparison of the results for Purchase Cost and Service Level

✓ despite the number of Out of Stock and related cost (Fig. 14) are very high for Scenario 2, 3 and 4, the Service Level is always higher than the As-Is case;

(a) (b)

Fig. 14. Comparison of the results for Out of Stock and OOS Cost

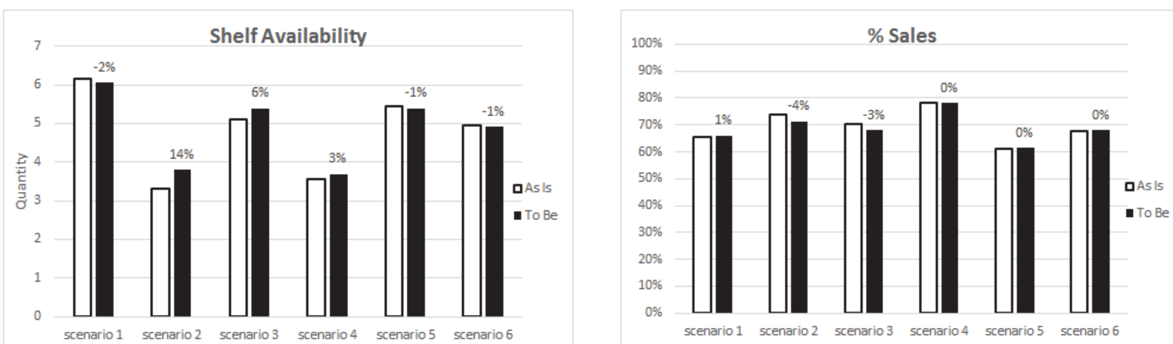
✓ from the stores perspective, Fig. shows that Shelf Availability (Fig. 16(a) a) increases up to 14% in Scenario 2 even if Stores Management Cost stays almost constant (Fig. 15(a)). This means that the average stock in the stores is higher on average, as demonstrated by the slightly lower values in the inventory Turnover (Fig. 15(b));



(a) (b)

Fig. 15. Comparison of the results for Management Cost and Inventory Turnover for Stores

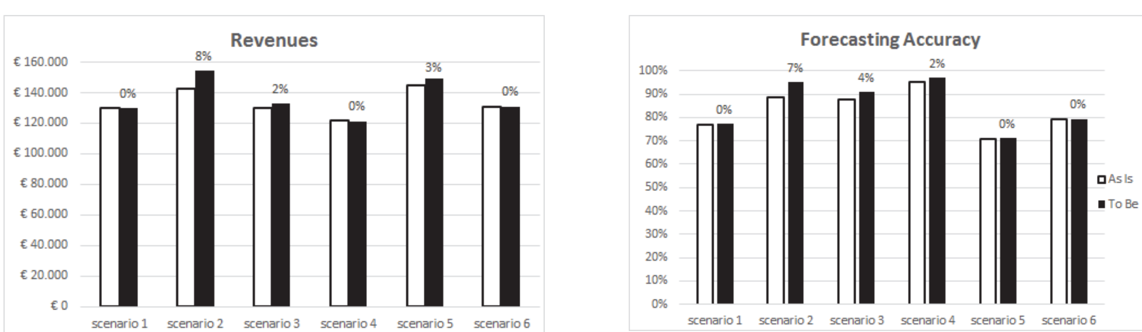
- ✓ Sales Percentage (Fig. 16(b)) is strictly connected to the stores performance and Revenues (Fig. 17(a)). This value is, in fact, given by the ratio between sales and quantities delivered to the stores. As demonstrated by the higher value in Revenues (Scenario 2 and 3), sales increase in the To Be 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)

Fig. 16. Comparison of the results for Shelf Availability and Sales Percentage

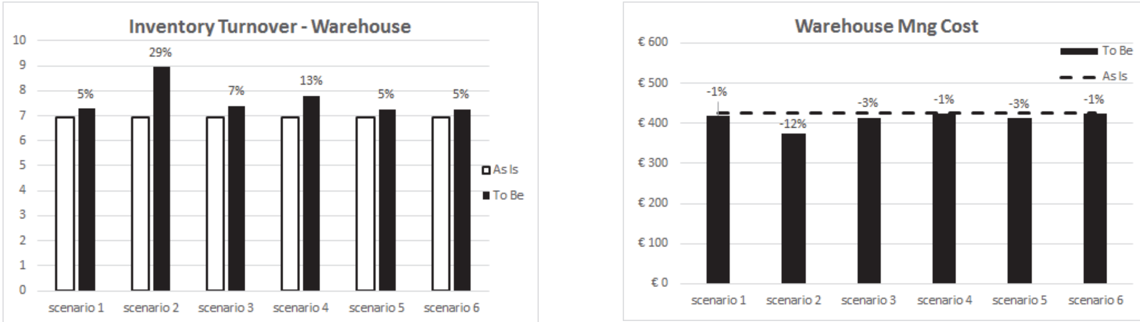
- ✓ thank to the adjusting process, also the Forecasting Accuracy (Fig. 17(b)) results slightly higher in the proposed model, since it is able to follow market changes;



(a) (b)

Fig. 17. Comparison of the results for Revenues and Forecasting Accuracy

- ✓ both technical and economic performances of the central warehouse improve when introducing the proposed model: Inventory Turnover (Fig. 18(a)) increases at least of 5% compared to the As Is case and Warehouse Management Cost (Fig. 18(b)) is always lower;



(a) (b)

Fig. 18. Comparison of the results for Inventory Turnover and Management Cost for Warehouse

- ✓ 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 (Fig. 19). 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 (Fig. 14 a), that is on average lower than the As-Is case. 9. 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 paper presents 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 stores network (As-Is case). The model also proposes a responsive approach which, during the sales season, analyses actual market demand and adjust operations plans according to it. The proposed model was implemented in Excel and used to compare As-Is and To-Be cases for an Italian Fashion company working with a dense network of direct- operated and franchising mono-brand stores. Results show that the proposed adjusting process guarantees improved performances both in economic terms (Profit is always higher than the As-Is case especially when a peak in demand occurs) and in terms of customer satisfaction, with an increased Service level. This work, then, may represent a useful Decision Support System for the optimisation of performances of all supply chain's actors thank to the ability of quickly following changes in market demand.

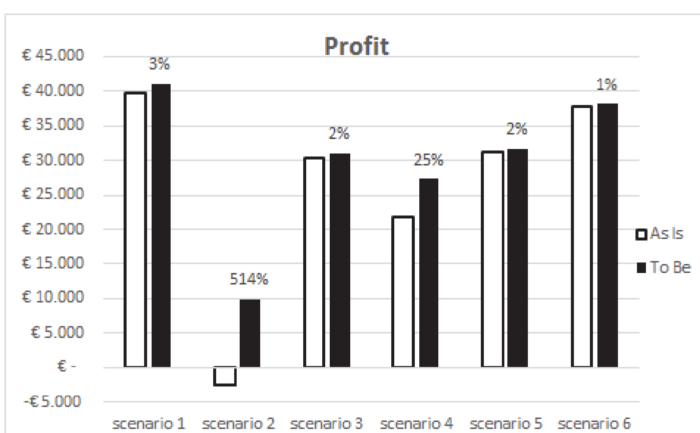


Fig. 19. Comparison of the results for the Profit

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