Chapter 9
Fast Fashion Retail: Dynamic Sub-models for Replenishment and Assortment Problem

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Abstract With few historical data and quick response of the market, fast fashion apparel retailers should make decisions about replenishment policies and assortment strategies. Deciding the quantity to deliver for each point of sales, in term of quantity and assortment mixture, is one of the big retailers challenges, and keys of success. In this paper, our proposal is about a mathematical model, for fast fashion retail planning chain. Our model is a dynamic tool to make the loop on the assortment, replenishment and inventory quantities, to help decision makers delivering the right product in the right point of sales with the right quantity, by maximizing the profit. It constitutes a flexible tool, allowing retailer to add new items in the optimization process, or even to renew the product range regularly, for fast fashion retailers, who aim for just in time production models. The replenishment supply chain is fragmented into strategic, tactic and operational levels. Each level is modeled as an integer linear program. Looping is made from Head Quarters, through countries until stores. Chorological horizon is sub divided according to season collections, monthly and weekly basis. Our integer linear programs are developed and solved with IBM Cplex Optimizer. Model validation is established with random data instances, inspired from real case studies.

Keywords Fast fashion · Apparel retail · Replenishment · Assortment
Mathematical model · Integer programming · Supply chain management

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9.1 Introduction

The fast fashion industry has been developed in the last few decades, and demonstrates a great success since consumers have a positive attitude towards fast fashion retailers due to the affordable prices (Cook and Yurchisin 2017). The fast fashion work frame of apparel supply chains requires fast turning models proposals and frequently changes in the displayed styles, with a large product range (Martino et al. 2017).

The phenomenon raises question marks about replenishment and assortment policies. In fact, this work makes the loop on replenishment and assortment model for a fast fashion retailer.

In a first place, a literature survey is presented in Sect. 9.2, followed by the problem definition in Sect. 9.3. The model formulation and validation are detailed respectively in Sects. 9.3.2 and 9.4. Finally, experimental results and model discussion are shown in Sect. 9.4.2 before concluding in Sect. 9.5 by opening the eventual work perspectives.

9.2 Literature Survey

Despite the present researches in the literature, working on retail supply chain (Martino et al. 2016), rare of them deal with a fast fashion industry framework (Iannone et al. 2013) or on fashion luxury (D'Avolio et al. 2015).

Martino (2016) presented an heuristic using Tabu-Bees algorithm for the replenishment problem. The authors quoted some references, such as Grewal et al. (2015) and Al-Zubaidi and Tyler (2004) who worked on the seasonality of the demand, Coelho and Laporte (2014) and Novotna and Varysova (2015) focused on deteriorating products replenishment problem; while Zhu (2013) and Bijvank et al. (2015) focused on price policies and supply chain mechanisms.

The authors named as well Abbott and Palekar (2008) in dealing with store multi-product problem with shelf availability and display-space constraints, and Pan et al. (2009) in defining the optimal replenishment level for retailers. In this context, Yu and Kunz (2010) examined, in a framework of assortment diversity, the capability of minimizing the merchandising errors.

Generally, in fast fashion Heikki et al. (2002) sourcing, buying, and forecasting replenishment might have a powerful impact overall planning chain.

In this work frame, several works focused on replenishment problem linked to other pillars of decision-making (Dandeo et al. 2004) and (Mattila et al. 2002). This will lead us to stand on below researches in the literature:

- Spragg (2017) established a forecasting framework based on Newsvendor model and Bass Diffusion model, dedicated for fashion seasonal demand.

- Chaudhry and Hodge (2012) explored the applications of postponement strategy in the textile and apparel industry, with a particular focus on the supply chain structure.
- Cinar and Martinez-de-Albéniz (2013) worked on a dynamic programming formulation, as a support of decision-making. As an alternative of binary decisions (Caro and Martinez-de-Albéniz 2014), continuous feature of products values was introduced.
- Sefra (2013) presented in her thesis an integral approach for production and distribution planning in textile industry.
- Iannone et al. (2013) clothing categories on the basis of the trying speed (accessories, underwear …).
- Choi et al. (2014) suggested a fast fashion forecast tool with limited data size and time range.

To our knowledge, the replenishment problem of fast fashion retail has never been smoothly modeled as our proposal in this work paper.

9.3 The Problem Definition and Model Formulation

9.3.1 The Problem Definition

The study presented in this article is about a multi store, multi product and multi period retailer.

It focuses on international retailers model, that need to maximize their profit among an international stores network, not only replenishment and assortment decisions, but also inventory level modeling, on the basis of sales and consumer behavior forecasts. It is both art and science: our model stands on qualitative and quantitative features of data, dynamically hybridized in integer linear programs.

KPIs of the model are suggested below, to enhance functionally the customer demand learning through the season, and to make the loop on the main development areas accordingly.

9.3.2 The Model Formulation

We fragmented the program on 3 sub models. The subsequence is established between the 3 parts dynamically (Fig. 9.1).

We developed our model as an extension of Martino et al. (2016), based on the model they suggested.

In fact few papers in the literature focused on supply chain of fast fashion retail specifically, and namely on the replenishment problem in that field. Martino et al.

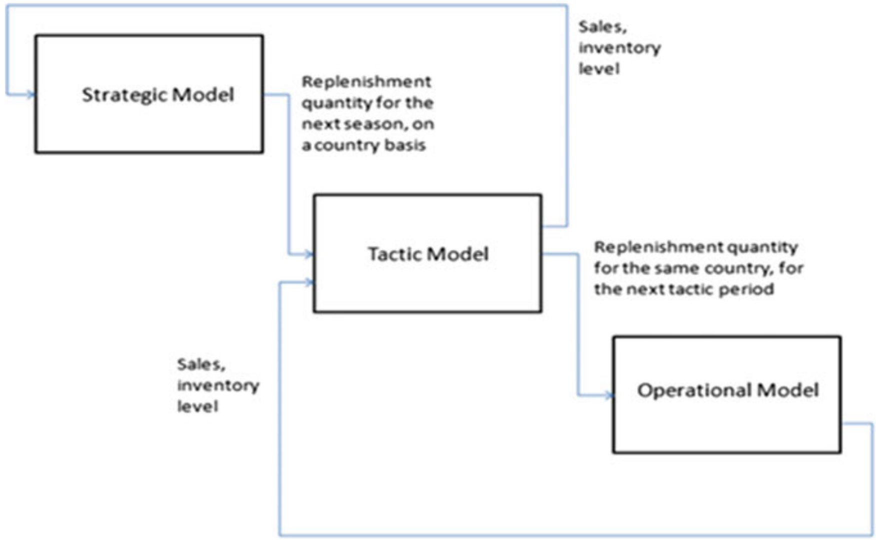

Fig. 9.1 The sub-models scope

(2016) presented in fact a dedicated research in this work frame, thus the choice of this research, and our ambition to present our work as its perspective.

The main goal of Martino et al. (2016) is to present a mathematical model, to determine the optimal quantity for replenishment, on model basis, in order to maximize the profit, and as per the relevant constraints.

Our work is a detailed multi-scope model, which presents the replenishment issues on all the stages, from central warehouses until the points of sales. It takes into consideration the specific constraints of each node of the supply; furthermore, it is resolved as integer model, by giving the exact mathematical model solution without any approximation.

While Martino et al. (2016) gave a general work frame for replenishment problem, approximately resolved using heuristics.

Thus the value added of our work.

9.3.2.1 Strategic Model

This part is the most global model scope. It might be run over head quarter (HQ) office functionally, chronologically once a semester or a quarter, to determine the replenishment and assortment policies globally during the next season on a country basis for items macro categories. At this first scope, we take into study:

Item macro categories replenishment quantities: pants, coats, t-shirts, shoes….

The storage capacity of each country central warehouse.

Combinations: set of products, separately sold but which correlation sales is extremely high, due to the design. They are composed of several macro categories elements, giving the customer a full combination suggestion.

The next table denotes the model nomenclature (Table 9.1):

While costs are defined as below:

- Average stock out cost: if the macro category is not displayed in a country while it is requested by its customer, it generates the below cost:

$$c_{s1} = \left\{ \begin{array}{ll} \sum_{i=1}^{I} c_{su1} * cu_i * \sum_{c=1}^{C} \sum_{t_1=1}^{T_1} (d_{ict_1} - Inv_{ict_1}) + \sum_{g=1}^{G} c_{su1} * cu_g * \sum_{c=1}^{C} \sum_{t_1=1}^{T_1} (d_{gct_1} - Inv_{gct_1}) & if\ d_{ict_1} > Inv_{ict_1}\ and\ d_{gct_1} > Inv_{gct_1} \\ 0 & if\ d_{ict_1} \le Inv_{ict_1}\ and\ d_{gct_1} \le Inv_{gct_1} \end{array} \right\}$$

- Average purchase cost: the purchase cost of macro categories

$$C_{P1} = \sum_{i=1}^{I} cu_i * cu_i * \sum_{c=1}^{c} \sum_{t_{1=1}}^{T_1} Q_{ict_1} + \sum_{g=1}^{G} cu_i * \sum_{c=1}^{c} \sum_{t_{1=1}}^{T_1} Q_{gct_1}$$

- Average transport cost: the transport cost from HQ central warehouse to the countries central warehouses

$$C_{T1} = C * T_1 * c_{tf1} + c_{tv1} * \sum_{c=1}^{C} dist_c * \sum_{i=1}^{I} \sum_{t_1=1}^{T_1} Q_{ict_1} + c_{tv1} * \sum_{c=1}^{C} dist_c * \sum_{g=1}^{G} \sum_{t_1=1}^{T_1} Q_{gct_1}$$

- Average handling cost: handling cost in the countries central warehouses

$$C_{H1} = C * c_{hf1} + \sum_{i=1}^{I} c_{hv1,i} * cu_i \sum_{i=1}^{I} \sum_{t_1=1}^{T_1} \frac{Inv_{ict_1}}{t\_range\ t_1} + \sum_{g=1}^{G} c_{hv1,g} * cu_g \sum_{g=1}^{G} \sum_{t_1=1}^{T_1} \frac{Inv_{gct_1}}{t\_range\ t_1}$$

Since we are dealing with macro categories and not with the final product at exact level, and since the prices are at final product level, the costs are calculated on an average manner, based on average prices. Our decision variables are the quantity Q to replenish and the inventory level Inv, for every combination g and macro category i, in the defined time range. The strategic model is formulated as:

Decision variables:

$$\mathrm{Q}_{\mathrm{ict}_1}; \mathrm{Q}_{\mathrm{gct}_1}; \mathrm{Inv}_{\mathrm{ict}_1}; \mathrm{Inv}_{\mathrm{gct}_1}$$

Objective function:

$$\text{Maximize Profit} = R_{1i} + R_{1g} - (C_{S1} + C_{P1} + C_{T1} + C_{H1}).$$

Table 9.1 Strategic model nomenclature

g = 1...G	Number of combinations	c = 1...C	Number of countries
i = 1...I	Number of items macro categories	t_1_*range*	Number of days in each time range t_1
$t_1 = 1 \ldots T_1$	Number of time ranges	B_Country	Total budget defined for the head quarter
$Capacity_{c1}$	Capacity of central warehouse of country c for initial inventory storage	$dist_{country}$	Distance of central warehouse of country c from HQ countries
$Capacity_{c2}$	Capacity of central warehouse of country c for new replenished products storage	C_{tv1}	Variable transport cost from HQ to central warehouses of countries
C_{tf1}	Fixed transport cost from HQ to central warehouses of countries	C_{su1}	Unitary stock out cost
		unc_1	Strategic forecast uncertainty
C_{hf1}	Fixed holding cost in countries central warehouses (logistic costs)	C_{hv1}	Variable holding cost in countries in central warehouses (logistic costs)
cu_i	Average purchase cost of the macro category i	pr_i	Average market price of the macro category i.
Cu_g	Average purchase cost of the combination g	pr_g	Average market price of the combination g
$f_{ic\,t_1}$	Forecast of the macro category sales for the macro category i in the country c during the t_1	d_{ict_1}	Market demand estimation of the macro category i in the country c during the time range t_1. It has a uniform distribution: $d_{ict_2} = [f_{ict_2} - unc_1; f_{ict_2} + unc_1]$
$Inv_{ic\,t_1}$	$Inv_{ict_2} = Q_{ict_2} - S_{ict_2} + Inv_{ic(t_2-t_1)}$		
R_{1i}	Revenue: $R_{1i} = \sum_{i=1}^{I} \sum_{c=1}^{C} \sum_{t_2=1}^{T_2} s_{ijt_2} * pr_i$	s_{ict_2}	Sales estimation: $s_{ict_2} = min\{Inv_{ict_2}; d_{ict_2}\}$
$f_{gc\,t_1}$	Sales forecast of combination g in the country c during the t_1	d_{gct_1}	Market demand estimation of the combination g in the country c during the time range t_1. It has a uniform distribution: $d_{gct_2} = [f_{gct_2} - unc_1; f_{gct_2} + unc_1]$
Inv_{gct_1}	$Inv_{gct_1} = Q_{gct_1} - s_{gct_2} + Inv_{gc(t_1-2)}$		
R_{1g}	Revenue: $R_{1g} = \sum_{g=1}^{G} \sum_{c=1}^{C} \sum_{t_1=1}^{T_2} S_{gct_2} * pr_g$	s_{gct_2}	Sales estimation: $s_{gct_2} = min\{Inv_{gct_2}; d_{gct_2}\}$

Subject to:

- $$\forall c \in [1; C], \forall t_1 \in [1; T1] : \sum_{i=1}^{I} Inv_{ict_1} + \sum_{g=1}^{G} \mathrm{Inv}_{\mathrm{gct}_1} \leq \mathrm{capacity}_{c1} \tag{9.1.1}$$

- $$\forall c \in [1; C], \forall t_1 \in [1; T1] : \sum_{i=1}^{I} Q_{ict_1} + \sum_{g=1}^{G} \mathrm{Q}_{\mathrm{gct}_2} \leq \mathrm{capacity}_{c2} \tag{9.1.2}$$

- $$C_{P1} \leq \mathrm{B\_Country} \tag{9.1.3}$$

where (9.1.1) and (9.1.2) define the capacity constraints and (9.1.3) defines the budget constraint.

9.3.2.2 Tactic Model

The second model scope focuses on the replenishment policies for each country. The model had as an output the replenishment and assortment decision, for every store on a weekly basis. At this stage, our model takes in consideration following points:

- The styles of macro categories: formal, casual, classic…
- The total storage capacity of each store, covering both store warehouse and sales area stocks.
- The weather parameters: at this stage, we have a better visibility on current quarter year weather forecast than like for like prediction. We define the weather parameters as segmentation of the weather state (windy, rainy…). We model them with Boolean variables, set in the model, and consider them for forecast.
- The capacity of each style: according to the store layout and potential customer profiles, each style had a special defined, to ensure a consistent supply and demand matching. Nomenclature is defined in below table (Table 9.2):

  Similarly, average costs are defined as below:

- Average stock out cost: if we don't meet the customer need, or if the customer requests a product I in the store j at the time range j, and doesn't find it, it generates a cost represented as below:

$$C_{S2} = \left\{ \begin{array}{ll} \sum_{j=1}^{J} c_{su2} * cu_j * \sum_{s=1}^{S} \sum_{t_2=1}^{T_2} \left(weather_j * d_{jst_2} - Inv_{jst_2} \right) & d_{jst_2} > Inv_{jst_2} \\ 0 & d_{jst_2} \leq Inv_{jst_2} \end{array} \right\}$$

- Average purchase cost: the cost for buying the products to the stores

Table 9.2 Tactic model nomenclature

j = 1 . . . J	Number of styles	s = 1 . . . S	Number of stores
$t_2 = 1 \ldots T_2$	Number of time ranges	B_Store	Budget defined for the store s
$Capacity - wh_s$	Warehouse of store s	$dist_{store}$	Distance of central warehouse of country c from the store s
$C_{tf}2$	The capacity of each style j		
$C_{hf}2$	Average fixed transport cost from central warehouse to stores for the set of style j	C_{tv_2}	Average variable transport cost from central warehouse to stores for the set of style j
$C_{su}2$	Average fixed holding costs in the store for the set of style j	C_{hv_2}	Average variable holding costs in the store s for the set of style j
$C_{su}2$	Unitary stock out cost: if the style is not displayed in a store while it is requested by its customer	unc_2	Tactic forecast uncertainty
		$weather_j = function\left(\alpha_{st_2}, \beta_{st_2}, \gamma_{st_2}\right)$	Style weather parameters
		$\alpha_{st_2}, \beta_{st_2}, \gamma_{st_2}$	Time range weather parameters (Boolean variables)
cu_j	Average purchase cost of the style j	pr_j	Average market price of the style j
f_{jst_2}	Forecast of the macro category sales for style j in the store s during the t_2	d_{jst_2}	Market demand estimation of the style j in the store s during the time range t_2. It has a uniform distribution: $d_{ict_1} = \left[f_{ict} - unc_1; f_{ict_1} + unc_1\right]$
Inv_{jst_2}	$Inv_{jst_2} = Q_{jst_2} - s_{jst_2} + Inv_{js(t_2-1)}$	full_prm$_j$	
R_2	Revenue: $R_2 = \sum_{j=1}^{J} \sum_{s=1}^{S} \sum_{t_2=1}^{T_2} s_{jst_2} * pr_j$	s_{jst_2}	Sales estimation: $s_{jst_2} = min\left\{Inv_{jst_2}; d_{jst_2}\right\}$

$$C_{P2} = \sum_{j=1}^{J} cu_j * \sum_{s=1}^{S} \sum_{t_2=1}^{T_2} Q_{jst_2}$$

- Average transport cost:

$$C_{T2} = S * T_2 * c_{tf2} + c_{tv2} * \sum_{j=1}^{m} dist_j * \sum_{i=1}^{m} \sum_{t_2=1}^{T_2} Q_{jst_2}$$

- Average handling cost:

$$C_{H2} = S * c_{hf2} + \sum_{j=1}^{n} c_{hv2,j} * cu_j \sum_{s=1}^{S} \sum_{t_2=1}^{T_2} \frac{Inv_{jst_2}}{t_{range}}$$

This model decides similarly on the quantity of replenishment Q and the inventory level Inv. The tactic model is formulated as below:

Decision variables:

$$Q_{jst_2};\ Inv_{jst_2}$$

Objective function:

$$\text{Maximize}\, R_2 - (C_{S2} + C_{P2} + C_{T2} + C_{H2})$$

Subject to:

-
$$\forall s \in [1; S], \forall t_2 \in [1; T2] : \sum_{j=1}^{J} Inv_{jst_2} \leq capacity - wh_s \tag{9.2.1}$$
-
$$C_{p2} \leq \text{B\_Store} \tag{9.2.2}$$

where (9.2.1) denotes the capacity constraint and (9.2.2) defines the budget constraint.

9.3.2.3 Operational Model

Finally, this model is the most rich in data, due to the highly dependence to the shop floor, and short time period. The program might be run on a weekly basis by merchandisers or at head offices level and fed with field data from stores. It is expected that this level reports the most detailed needed features and run on a weekly basis.

Table 9.3 Operational model nomenclature

$m_j = 1 \ldots M_j$	Number of models m of the style j	pr_{mjxz}	The revenue of item k
x = 1 . . . X	Number of colors	z = 1 . . . Z	Number of sizes
C_{tf3}	Fixed transport cost from central warehouse to stores for the model j	C_{tv3}	Variable transport cost from central warehouse to stores for the model j
C_{hf3}	Fixed holding costs in the store s for the model j	C_{hv3}	Variable holding costs in the store s for the model j
C_{su3}	Unitary stock out cost: if the style is not displayed in a store while it is requested by its customer	unc_3	Operational forecast uncertainty
		pr_{mj}	Average market price of the model m
cu_{m_j}	Purchase cost of the model m of the style j	d_{mjxz}	Market demand estimation of the style m_j in the store s during the time range t_2. It has a uniform distribution: $d_{m_jxz} = \left[f_{m_jxz} - unc_3; f_{m_jxz} + unc_3\right]$
f_{m_jxz}	Forecast of the style m_j in the store s during the t_2		
Inv_{m_jxz}	$Inv_{m_jxz} = Q_{m_jxz} - s_{m_jxz} + Inv_{m_jxz}(t_2 - t_1)$		
R_3	Revenue: $R_3 = \sum_{m_j=1}^{M_j} \sum_{x=1}^{X} \sum_{z=1}^{Z} s_{m_jxz} * pr_{mjxz}$	s_{m_jxz}	Sales estimation: $s_{m_jxz} = min\left\{Inv_{m_jxz}; d_{m_jxz}\right\}$

Each model is run for a specific store considering:

- Colors and sizes.
- Fit (normal, slim…) and patterns (checked, stripped…).
- Fashion attractiveness: it is highly expected that a fast fashion retailer display very frequently new models. Products attractiveness decreases along they are displayed in the store. We determine the order of displaying according to the final products revenue (Caro et al. 2014).

We consider the same nomenclature considered in the tactic model, and add the below parameters (Table 9.3):

At this model, we are dealing at unique product reference level. Thus, the depth treatment of data is highly delicacy, and costs are exactly modeled not on an average basis. They are defined as below:

- Stock out cost:

$$C_{S3} = \left\{ \begin{array}{cc} \sum_{m_{j=1}}^{M_j} C_{su3} * Cu_{m_j} * \sum_{x=1}^{X} \sum_{Z=1}^{Z} \left(d_{m_jxz} - Inv_{m_jxz} \right) & d_{m_jxz} > Inv_{m_jxz} \\ 0 & d_{m_jxz} \leq Inv_{m_jxz} \end{array} \right\}$$

- Purchase cost: the cost for buying the products to the stores

$$C_{P3} = \sum_{m_{j=1}}^{M_j} cu_{m_j} * \sum_{X=1}^{X} \sum_{Z=1}^{Z} Q_{m_jxz}$$

- Transport cost: C

$$C_{T3} = C_{tf3} + C_{tv3} * \sum_{m_{j=1}}^{M_j} dist_j * \sum_{m_{j=1}}^{M_j} \sum_{Z=1}^{Z} Q_{m_jxz}$$

- Handling cost:

$$C_{H3} = c_{hf3} + \sum_{m_j=1}^{M_j} c_{hv3,m_j} * cu_{mj} \sum_{x=1}^{X} \sum_{z=1}^{Z} \frac{Inv_{m_jxz}}{t_{range}}$$

The model, which decides on the replenishment quantity Q and the inventory level Inv, is formulated as below:

Objective function:

$$\text{Maximize}\, R_3 - (C_{S3} + C_{P3} + C_{T3} + C_{H3})$$

Decision variable:

$$Q_{m_jxz}; Inv_{m_jxz}$$

subject to:

- $$\forall x \in [1; X], \forall z \in [1; Z] : \sum_{j=1}^{J} Inv_{mjxz} \leq capacity_s \tag{9.3.1}$$

- $$C_{P3} \leq \text{B\_store} \tag{9.3.2}$$

where (9.3.1) and (9.3.2) define respectively: capacity and budget constraints.

9.3.3 The Framework Forecast KPIs

In order to gauge its inventory management, the retailer may refer to establish key performance indicators (KPIs) that measure the estimations exactitude toward real data. We suggest 4 KPIs according to the forecasts and terminal stock. Actually, forecast is initially analyzed based on historical sales, while it is mentored and might be frequently modified by decision makers above the 3 levels. Once the period passed, sales vs. forecast ratios will evaluate the decision makers forecast performance, and will led us to define the uncertainty forecast parameters to be set in the next period program.

Finally, the terminal stock, which indicates the remaining inventory at the end of the season, and the input that is the inventory level data of the next season, is a pillar of replenishment performance. Retailers should emphasis the transition period by mentoring the replenishment quantities, and injecting the markdown prices strategies, by having as an objective to tend the terminal stock value to 0.

- Initial forecast data KPI $= \frac{f_{ict_1}}{sales_{ict_1}}$
- Tactic forecast KPI $= \frac{f_{ist_2}}{sales_{ist_2}}$
- Operational forecast KPI $= \frac{fm_jxz}{scales\ m_jxz}$
- Terminal stock KPI $= Inv_{ic}(t_1 - 1)$.

9.4 Model Validation and Results

9.4.1 Data Instances Description

As per model validation purpose, we run the model with experimental data, inspired from real case studies. We test each program under 3 data configurations, leading to instances referring to low demand, average and high demand (Table 9.4). The test data are used for validation purpose; it does not affect the model or the case study. The data covers 3 countries, with 5 stores in each country, and 4 time periods from t1 to t4. It covers a range of 10 items macro categories, 5 item styles for each macro category and 100 models for each style.

9.4.2 Experimental Results and Model Discussion

In order to test the appropriateness of the models, they were programmed within Cplex IBM software.

The below figures indicate an extract of the replenishment results for strategic, tactic and operational models (Fig. 9.2).

Table 9.4 Extract of data: macro categories forecast

	f_{ict1}											
Time ranges	$t_1 = 1$			$t_1 = 2$			$t_1 = 3$			$t_1 = 4$		
MacroCategory i/country c	1	2	3	1	2	3	1	2	3	1	2	3
100000	12197	10909	14248	14912	10031	10493	12440	13544	10161	13441	13190	12893
200000	14532	14265	11425	14498	14198	14581	13110	10568	12096	12431	10100	13388
300000	11412	14442	10812	11031	14336	13805	11852	11424	12868	13252	12965	13744
400000	13054	12181	12492	13840	11704	14997	14689	12030	12840	10479	13308	10566
500000	12137	10806	10003	14727	14732	10899	10733	11105	13927	12588	14900	11144
600000	13488	13847	14095	10623	13418	14291	10231	14175	12781	13965	10581	12263
700000	14009	13584	11623	12828	12615	10568	14399	10906	10318	12451	11074	10402
800000	10869	14306	10537	14020	14281	11599	11255	12273	10004	10483	13215	12474
900000	11975	13779	14372	10830	13970	13424	14007	14941	11326	11905	13646	11902
1000000	11764	12578	13457	11050	13920	14165	14428	14521	12182	14278	12738	12379

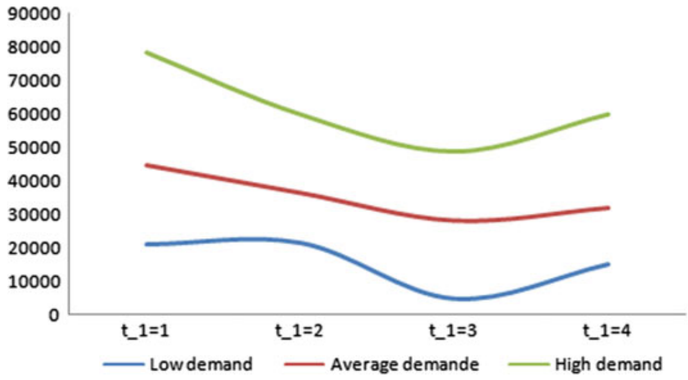

Fig. 9.2 Extract of result: replenishment quantity for macro category 1 in country1

The results are consistent according to the entry data, which demonstrates the model validation. The model was run in few seconds. The test data is going to be relevant for brand applications, according to their forecast calculations, costs and distances between stores and warehouses.

It was suggested that the strategic model covers 3 months as per the season length. The period covered might be changed according to the retailer policies. For instance, some retailers are working with a horizon of 6 months, namely: spring-summer and autumn-winter periods. The time range may also refer to a particular period of event, which impact directly on the sales (back to school, holidays, special festivals…).

Furthermore, the model is not imperatively run once 3 months. It is likely that several fluctuations occur within the season, which might affect the model parameters. Running the model for 3 months lengths within the season, will allow the retailer to model the transition period; in terms of inventory level and sales. Furthermore, it will support in mentoring markdowns and sales strategies mechanism.

9.5 Conclusion and Perspectives

In this paper, we proposed a set of integer linear programs, to optimize dynamically the replenishment problem of fast fashion retail. The model allows even for the just in time trend, enabling the retailer to change the set of the products in the study on the basis of the time range defined, on which the loop might be at a weekly basis or even daily basis if needed.

In work environments where fast fashion brands might have a huge number of models, the model execution delay can be longer.

Future eventual perspectives of the work might focus on a heuristic development of the model, to assure its responsiveness on a big data size in a short delay.

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