Publié par : Faculté des sciences de l'administration
Published by: 2325, rue de la Terrasse
Publicación de la: Pavillon Palasis-Prince, Université Laval
Québec (Québec) Canada G1V 0A6
Tél. Ph. Tel. : (418) 656-3644
Télec. Fax : (418) 656-7047

Disponible sur Internet :
Available on Internet
Disponible por Internet : **http://www4.fsa.ulaval.ca/la-recherche/publications/documents-de-travail/**

DOCUMENT DE TRAVAIL 2016-016

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Document de travail également publié par le Centre interuniversitaire de recherche sur les réseaux d'entreprise, la logistique et le transport, sous le numéro CIRRELT-2016-61

Novembre 2016

Dépôt legal – Bibliothèque et Archives nationales du Québec, 2016
Bibliothèque et Archives Canada, 2016

ISBN 978-2-89524-443-1 (PDF)

Dynamic Inventory Management for Large Retail Chains

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ABSTRACT

Inventory management is critical for many economic systems, especially those related to highly seasonal products, such as in the retail industry. To deal with very dynamic demands of a large retail chain, we have developed a method to aggregate stock-keeping units (SKUs) based on their common features. This greatly reduces the number of units to manage, allowing the efficient development of forecasting methods. Based on different statistics and on the forecasts of the aggregated SKUs, we develop a *success-failure index* which provides managers with information on the product lines that are most likely to succeed or fail, thus providing a valuable operational tool for practitioners. This is especially useful for highly seasonal products or for distribution centers serving satisfying online orders, for which managers must make decisions quickly. Our contribution focuses on inventory decisions centered on the range individual SKUs offered by one firm. Using our tools, a manager would be able to quickly visualize which products are likely to succeed, and more importantly, which ones are likely to fail and should thus be discontinued as soon as possible. Our methods are parametrized to work with different statistics, namely a confidence level around the demand forecast, quartiles of the demand, or a percentage of the average demand, imposing constraints on absolute values of minimum number of items that should be sold for an SKU to be maintained. In general, the confidence level option is more conservative and keeps more products under observation, while the percentage alternative is more sensitive and determines to discontinue certain product lines more often. We provide insights on how managerial decisions may change in the light of demand forecasts.

Keywords: Forecast, inventory, replenishment, retail, logistics.

Acknowledgments: This work was partly funded by the Canadian Natural Sciences and Engineering Research Council (NSERC) under grant 2014-05764. This support is greatly acknowledged.

1 Introduction

Large retailers offering tens of thousands of stock-keeping units (SKUs) like Carrefour and Walmart actively pursue aggressive global strategies to jump-start growth and diversify their geographical risk. On a continental level, other retailers have done very well. S.A.C.I. Falabella, a Chilean retailer operating hundreds of stores in South America is reinforcing its position as a retail powerhouse in the southern cone [8]. Despite these success stories, retailers seldom succeed at internationalizing their activities [4]. The recent example of American retailer Target failed attempt to expand into the Canadian market is a case in point [6]. From the start, this venture had been plagued with inability to replicate the American parent business model and strategy. Moreover, poor inventory management led to severe customer dissatisfaction with its Canadian subsidiary. Yet, despite such setbacks, the retail industry remains an important one.

The American retail industry is estimated to reach around $5 trillion in sales for 2016 [5], making it one of the largest in the world. Given the difficulty of internationalizing their activities and that the US has many established retail players on a national level vying for growth, this highly competitive market allows regional retail chains room to grow provided they show higher levels of productivity than the national chains they compete harshly with (see Foster et al. [10]).

Fulfilment is a challenge in time of growth as the number of DCs and stores continuously increase while at the same time, the time window for selling individual SKUs, especially seasonal ones, is fast decreasing [14], putting pressure on the supply chain and the overall business model. In an environment characterized by razor thin margins and high competitive intensity, inventory management decisions are crucial.

Many traditional brick and mortar retailers are entering the online world and offering their products over the internet. They realize it is easy to showcase a myriad of products, many of which were not available in physical stores. While this has evident positive effects for the customers, who have a wider variety of options, it pressures distribution center managers in many different ways: 1) it requires better inventory management with tens of thousands of new products; 2) it immobilizes more capital in inventory; and 3) some of the products might offer only marginal value, and should not be continued.

American retailers that succeed over the long run also sustain their investments as those who do not invest on a regular basis typically reap benefits over a short period only [32]. The literature on retail industry management typically focuses on inventory-related problems; on channel selection issues; on the impact of seasonality; and on particular conditions that affect demand. These factors are examined below in that order.

Inventory management is key to retailer performance [31]. Indeed, inventory optimization is a central element in evaluating the performance of a supply chain [1]. Yet classical inventory measures and ratios have their limitations. Indeed, Gaur et al. [13] emphasize the importance of moving beyond reliance on measures like inventory turns. They mention the necessity for more sensitive and fine-grained indicators. Moreover, new approaches in order to generate measures in inventory management are being put forward. For instance, Tsai and Chen [34] have proposed a posterior-type and a progressive-type approaches to solve the multi-objective inventory problem in the context of simulation optimization. Furthermore, some techniques like bundling or grouping SKUs (as proposed in this paper) can be beneficial in the face of specific demand conditions [12]. Such techniques may create an impulse to use transshipment to solve inventory challenges. Unfortunately, transshipments are contingent on individual store capacities in a given store network [30]. These make channel selection especially important.

In the era of an increasingly connected consumers, shopping habits are now multi-channel with the Internet gaining traction even in premium and traditionally conservative categories like designer clothing [9]. These channel-related habits are not set in stone as Gallino and Moreno [11] explain differentiated behavior with cross-selling effects and channel shift effects. Indeed, retailers can focus on m-commerce, on e-commerce, or on brick and mortar stores.

The simultaneous uses of these channels create challenges for firms. An added difficulty is that some segments, like perishable products, have their particular idiosyncrasies like unique or non-standard seasonality. Retailers decisions under high levels of uncertainty have been examined in the literature for large retailers [15]. Seasonal products for their part induce mixed behaviors from manufacturers centering around rebates or capacity expansion [19].

Beyond seasonality, there are often particular demand conditions that influence how a retailer's supply chain is managed. Players like Dell try to use or to balance product configuration and business forecasts, including financial metrics [27], while Kroger seems to have focused on simulations [37].

As seasonality may influence costs including inventory-related borne by retailers as well as their reordering systems [7], this paper deals with this issue by framing the problem in terms of random demand, ensuring that the presence or absence of seasonality for certain products does not affect our model, and that our solution procedure is robust with respect to the shape of the demand.

Past research has also examined the cases where demand is modeled as stock-dependent [16]. Some authors go further and suggest a modulation of the sales efforts according to lifecycle of the products [17]. In the case of products with short lifecycles, evidence suggests that better collaborative behavior in the supply chain leads to better outcomes related to demand forecasts [28], especially when collaborative planning initiatives are implemented [35].

In this sense, demand forecasting among various channels is an intricate problem for retailers as it contains many discrete decisions on a variety of levels (DCs, stores and down to individual SKUs). Many methods rely on forecasting accuracy expected from the aggregation of increasing volumes of sales data [23]. Some have examined vendor-managed inventory (VMI) models [33] even if it does not necessarily outperform retailer-managed inventory (RMI) on many cost-related performance indicators [36].

This paper's contribution is a simpler yet more comprehensive perspective. We do not focus on forecasting per se, but rather on identifying early-stage sales patterns. The objective of this paper is threefold. First, we develop a method to aggregate SKUs based on their common features. This greatly reduces the number of units to manage, allowing the efficient development of forecasting methods. Second, based on different statistics and on the forecasts of the aggregated SKUs, we develop a *success-failure index* which provides managers with information on the product lines that are most likely to succeed or fail, thus providing a valuable operational tool for practitioners. This is specially useful for highly seasonal products, for which managers must make decisions quickly. Third, we disaggregate the forecasts for the products which have been determined to keep in the system, breaking it down to the most granular level (individual SKU) per store and per DC. Instead of focusing on category planning itself through an all-encompassing review of software and models [20], our contribution focuses on inventory decisions centered on the range individual SKUs offered by one firm [26].

The remainder of this paper is organized as follows. In Section 2 we formally define the problem at hand. In Section 3 we present the details of all the procedures proposed to manage inventory items that should be kept in business and the ones that should be discontinued. This is followed in Section 4 by detailed simulated numerical, and by our conclusions in Section 5.

2 Problem description

In this section, we formally describe the problem at hand. We consider a fictional retail chain in the clothing industry with a strong regional position. This retailer has a set $\mathcal{D} = \{1, \dots, D\}$ of distribution centers and a set $\mathcal{B} = \{1, \dots, B\}$ of branches. Let $\mathcal{N} = \mathcal{D} \cup \mathcal{B}$ denote all the nodes of the problem.

The retailer sells a set $\mathcal{S} = \{1, \dots, S\}$ of SKUs. Each SKU $s \in \mathcal{S}$ is represented by a combination of its features including its supplier, the product type, size, gender and color. A selling price for each SKU is known. Demand for each SKU in each branch occurs in periods, typically intervals of five hours, with the set of the planning horizon periods being $\mathcal{T} = \{1, \dots, T\}$. Each distribution center and each branch keep inventory of a subset of the SKUs. Demand is unknown, and after each period it is realized, allowing for the update of the inventory levels. When demand occurs, the branches either satisfy the demand or it is lost in case of stockout.

At each period of the planning horizon, the objective of the problem is decide which SKUs to keep in the system, which product lines to stop selling, and which ones to manage more carefully in a watch list.

3 Solution procedure

Our algorithm works with three main steps. First, the demand forecasting is developed at an aggregated level, described in Section 3.1. Then, we develop a success-failure index allowing to determine which products to keep in the system and which products to remove, as described in Section 3.2. Finally, the disaggregation of the forecasts into individual SKUs per stores and DCs is described in Section 3.3.

3.1 Aggregation of SKUs and demand forecast

The forecasts are developed at an aggregated level, in order to reduce the variance and increase the confidence level of the calculations. Thus, we have aggregated SKUs from the same type (e.g., shirts of different colors, sizes), from the same supplier, and the same gender (male, female or unisex). This aggregation gives rise to what we refer to as a *product line*.

The forecasting method used in our algorithm is based on time series analysis [2]. We have chosen the exponential smoothing technique, which assigns exponentially smaller weights to past observations. This is a simple yet powerful method capable of identifying changes in the mean, trend or seasonalities in time series. It provides a point forecast, i.e., a single value representing the expected future demand, and a prediction interval, i.e., an estimated variance [21].

Once the forecasting model is fit to the aggregated historical data, one can generate forecasts for several periods ahead. Here, a compromise must be made between a short horizon which yields faster computations but lower solution quality, and a longer horizon which considers more information but requires more extensive computations [3]. We have then parametrized our algorithm to generate forecasts for the next f periods and to provide not only a point forecast but a whole probability distribution of the forecast for each of the next f periods, comprising a mean and a standard deviation of the forecast for a given parametrized confidence level.

3.2 Success-failure index

Based on the forecasts obtained previously, we have used the ABC analysis [18], that is an application of what is known as the Pareto principle, for all product lines. The idea is to identify the products of the C class, i.e., the ones that are not critical and have a small contribution to the inventory management challenge and to the profits. These products composing the C class will be used to create the success-failure index.

This index is composed of three zones. Products in the green zone have a good contribution and volume, and should be continued; products in the orange zone are intermediate ones and must be closely managed; finally, products in the red zone have a very poor contribution to the volume and profit and should be discontinued. A visualization of the success-failure index is shown in Figure 1.

Figure 1: Graphical visualization of the success-failure index

These three intervals were established using three different strategies, namely the confidence level, the quartiles, or a percentage of the average. These three options are described next:

- Confidence level: the green zone represents the first interval, that is the average ($\overline{X}$) to the upper bound of the confidence level, represented by the equation $\overline{X} + z_{\alpha/2}\frac{\sigma}{\sqrt{n}}$. The orange zone is represented by the interval between the average ($\overline{X}$) and the lower bound of the confidence level, represented by the equation $\overline{X} - z_{\alpha/2}\frac{\sigma}{\sqrt{n}}$. The red zone, is the interval below the lower bound of the confidence level.

- Quartiles: here we have divided the zone by frequency, dividing C class in quartiles. The first interval contains the first quartile, that is the first 25% of the product lines. The second interval contains values between the first and the second quartiles. The third interval contains values beyond the second quartile, that is, the bottom 50% of the product lines.

- Percentage of the average: The last type of division of the interval was done based on the percentage of the average. It is necessary to chose two cut offs: the first one should be the value that represents product lines that will be rejected. The second cut off will establish the interval for the product lines that will be observed. Lastly, the product lines that lie above this second cut off will be kept.

Furthermore, we add two constraints to the index, indicating, in absolute number of units, product lines that must be considered and ones that must be rejected. Mathematically, we impose that if a demand value for a product line is greater than a given value, we will keep it; likewise, if a demand value is lower than a given parameter, we will reject it.

3.3 Disaggregation of the forecasts into individual SKUs

After the classification of the product lines in A, B and C classes, we can identify which ones have been maintained (classes A, B, and C-green), which ones were rejected (C-red zone), and which product lines should be observed (C-orange zone). The aggregate demand forecast can then be disaggregated by SKUs following the same features such as supplier, type of product, gender, size and color.

Since the forecast was performed by *product line*, we can compute for each SKU in that product line what was its individual demand and what was the demand for the whole product line. By keeping the same proportion, we can compute the contribution of the forecast for each individual SKU. For example, if an SKU had a demand equal to 50, the total demand of its product line is 1000, and the forecast for its product line equals 2000, the contribution of the global forecast to the forecast of the individual SKU must be kept constant, and can be computed as $2000 \times \frac{50}{1000} = 100$. Likewise it is possible to compute the forecast for each SKU individually by store.

4 Numerical example

In this section we provide some implementation specifications, we describe the generation procedure for the test instances, and we present results of extensive computational experiments.

4.1 Instances and implementation details

Instances were generated with 28 past periods of demand information before the future p periods such that it can be used as historical data. Our set is generated according to the following data, estimated based on stylized information from composite data of leading industry players:

- number of distribution centers: 2
- number of stores: 9
- number of SKUs: 6864
- number of suppliers: 5
- number of types of products: 16
- genders: equal to 0, 1 or 2 (male, female, unisex)
- number of sizes: 7
- number of colors: 14
- horizon: equal to 28 periods
- demand distributions: mean demand μ is a random normal number with mean 0 (centered) and variance 10000, that is generated as an integer random number

following a discrete uniform, and standard deviation σ as an integer random number following a discrete uniform distribution in the interval [0, 100]. The demands are generated following a normal distribution with these parameters. If a negative demand value is generated, it is substituted by zero

This configuration has led to the aggregation of SKUs based on the supplier, the product type, and gender, yielding 225 product lines. The ABC analysis was performed using standard values: 70% of the items for the A class, 20% for the B class, and the remaining 10% for the C class.

Demands were created randomly for each SKU and all stores. These demands of SKUs of the same supplier and type were then combined. Forecasts were carried out using the forecast package available for R Language and Environment for Statistical Computing. We allowed the software to run under its default settings, searching through all the 30 variants of the exponential smoothing models described in Makridakis et al. [26]. We have made use of the 28 past periods immediately before the current period as historical data for the chosen forecasting method for each product line.

4.2 Results of computational experiments

We now report the results of our extensive computational experiments. For each method we present the total of SKUs, the number of product lines, and the numbers of SKUs for the A and B classes. For the C class we show the percentage of items for each interval.

The first method was calculated from the quartiles, for which each quartile represents 25% of total. The second method used a 95% confidence level. The third method imposed 80% of average as the point for cut off. Moreover, demands below $x = 5000$ were set to be rejected and above $y = 100000$ were set to be kept. These results are presented in Table 1.

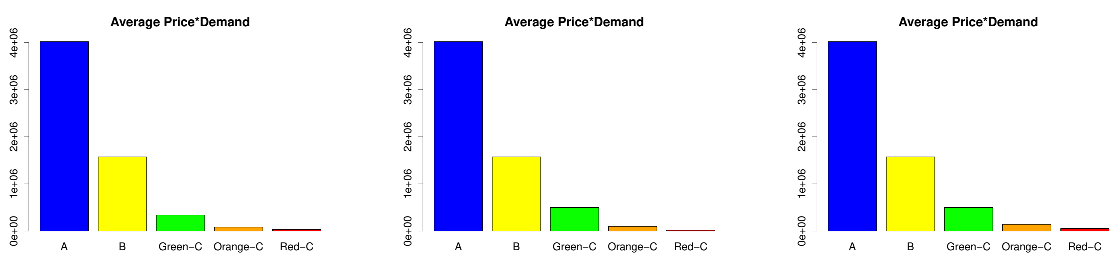
Results from Table 1 indicate that the quartile method, which is based on the frequency of the product lines, will always reject 25% of the total items, even for the product lines with a reasonable demand (given they are higher than x). On the other hand, the confidence

Table 1: Summary of computational results

SKUs	Product lines	Method	Constraints		Classes %					Time
			x	y	A	B	C-Green	C-Orange	C-Red	(s)
6864	225	Quartile	5000	100000	22	16	31	16	16	12.34
6864	225	Confidence Level	5000	100000	22	16	17	39	6	12.49
6864	225	Percentage	5000	100000	22	16	17	16	29	12.68

level method with the parameters we have chosen is much more conservative and adds more than double the number of items in the orange zone. In this case, the parameter used was the 95% for the confidence level. Finally, the percentage method was used like a cut off, and demands 50% below the average were rejected; the SKUs between 50% and 80% were set to the watch list in the orange zone, and SKUs above the 80% will be kept. The most conservative method was the confidence level, because it rejected only 6% of the SKUs. However, we emphasize that all methods are fully parametrized and could be adjusted to fit the expectations and policies of any company.

Figure 2 shows for each method, the average price multiplied by the demand. For the quartile method, the C green class presents the lowest average; the lowest C red class is obtained with the confidence level method; finally, the C orange class is the highest with the percentage method.



(a) Quartile **(b)** Confidence Level **(c)** Average

Figure 2: Average Price times Demand for each Method

Figures 3, 4 and 5 show the minimal demand for the quartile, the confidence level and the percentage methods, respectively. The percentage method presents the highest minimal demand for the C orange watch list, whereas it presents the lowest demand value in C red class.

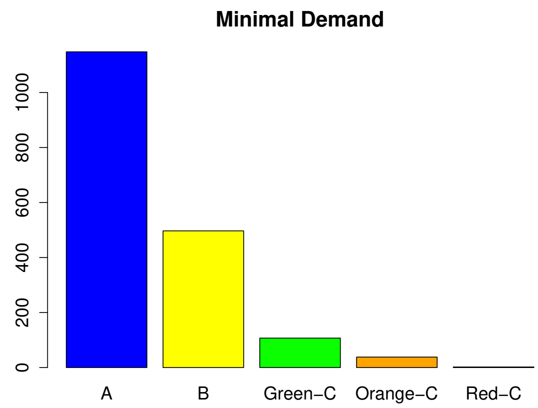


Figure 3: Graphical visualization of Minimal Demand for the Quartile Method

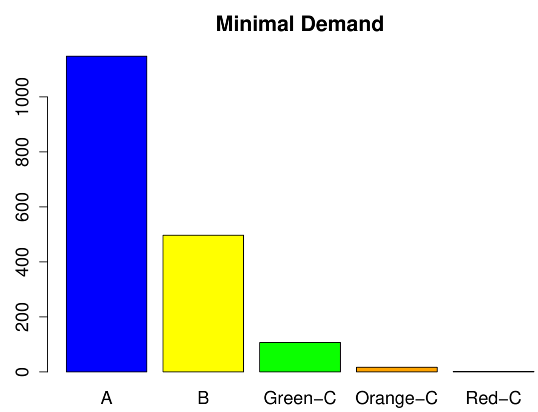


Figure 4: Graphical visualization of Minimal Demand for the Confidence Level Method

5 Conclusion

In this paper we have presented three main contributions: we have paved the way for novel research implications; we have provided new tools for practitioners; and we have opened new avenues for future research.

This paper has many implications for managers. First, it presents a novel way of tracking

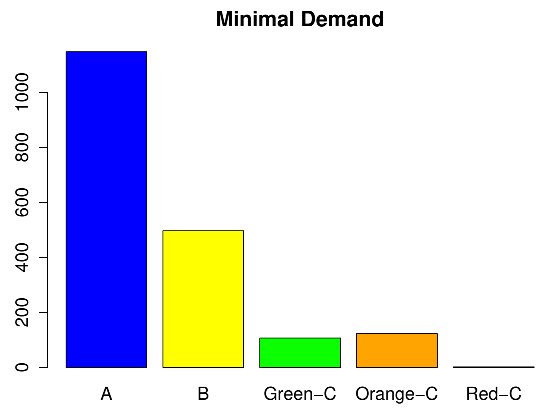


Figure 5: Graphical visualization of Minimal Demand for the Average Method

variations in demand to make quick and efficient inventory decisions. Second, managers now have a model and index that can keep up with fluctuations in the number of SKUs and the firm's infrastructure, namely DCs and stores.

Our dynamic approach towards inventory management, specially for high seasonal items, is adaptable to a wide range of DC-store-SKU combinations. Another advantage is the increased sensitivity and highly parametrized methods in the approaches presented here. Our methods work very well for managers whether they are well-versed in the mathematical details behind it or not. The mathematical solution coupled with the graphical/visual sensitivity of the success-failure index makes for an easy to use tool.

Examining the relationship between replenishment management, inventory management, pricing and financial performance for retailers would help push this research stream further. Past work has suggested the link between pricing and inventory, the former depending on the latter when dealing with non-perishable products [22]. Others have suggested to delay warehouse replenishment decisions in order to better manage stock out risks [38] or to focus on the concurrent consideration of pricing and procurement [24] or of the interactions between channels and pricing [29]. Indeed, pricing considerations for suppliers can shape order quantities from retailers [25]. However, the sensitivity of the link for fast-moving consumer goods or fashion still represents an interesting research opportunity.

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