

Fashion luxury retail supply chain: determining target stock levels and lost sale probability

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Expensive product sales in fashion luxury industry companies typically show peculiar demand patterns, most of all when recorded at the store level: disaggregated data show sporadic demand with a relatively high coefficient of variation, which causes classical inventory theories and control policies to be ineffective or to give unsatisfactory results. However, companies which face the need to automatically set the target stock levels in hundreds of stores for thousands of products cannot reasonably analyze sales demand patterns by choosing the most suitable customized inventory management model one by one. As a consequence, the common practice is to choose a unique approach, most of the times based on normal distribution assumption. This may lead to evaluation errors that can reflect on business results, because service level in stores – more commonly, availability rate – is directly impacted. This paper analyses when traditional inventory management models along with their related assumption, are suitable or not to determine target stock levels in stores in fashion luxury industry. Particularly, we focus on the so-called permanent products, i.e. those products which have to always be present in stores throughout the year and, despite their sporadic demand, are managed by the traditional base-stock policy, with periodic replenishment. Two stochastic models, respectively based on Poisson and Normal distribution assumptions, are assessed through an extensive numerical comparison, in order to understand if one may lead to an over or under stock setting in store. Scenario parameters are inspired by the case of a major luxury company operating with a three-echelon distribution network, with local warehouses quite near the final point of sales. Results show that the application of the most common normal-distribution-based approach is suitable until the target availability rate in store is below 98% when average demand ranges from 10 units/SKU/store/week to 2 units/SKU/store/year.

Keywords: fashion luxury industry; supply chain; inventory control; target stock level; base stock policy.

1 Introduction

Fashion luxury is considered one of the fastest-growing industries worldwide: the luxury goods industry has tripled its market, from 73 billion EUR in 1994 to 218 billion EUR in 2013 (Bain & Co, 2014). This was especially due to the economic growth in emerging countries (Kim, et al. 2014). However, since 2009 Atwal and Williams indicated how it is becoming increasingly difficult to compete in such a dynamic industry because market growth may lead to saturation. Cavender & Kincade (2015) analyzed the challenging business environment where luxury companies operate; D'Avolio et alii (2015) outlined how managing fashion industry products is challenging, not only for designers and stylists, but also for supply chain managers; and when considering the fashion *luxury* industry, the challenge gets even worse. Indeed, Kapferer & Bastien (2009) pointed out that there seems to still be confusion on how the supply chain should be managed in this industry. Just during the last few years some authors have started exploring this subject, especially through survey and case study analysis. Researchers dealing with supply chain issues try to describe current practice in the fashion luxury industry and to highlight how the decision-making process in this area relies on key marketing aspects. Researchers have analyzed how supply chain configuration and management decisions can affect critical success factors (Brun et al., 2008) and it emerges that the operative level

supply chain management seems not to have been completely explored. The fashion luxury supply chain shows innate issues, mainly originating from the complexity of marketing, branding and sociological aspects that characterize luxury goods purchasing. Literature has widely dealt with supply chain management in mass markets but contributions in luxury business seem to be quite limited. Indeed, despite the fact that big players are reported to aim for integrated approaches in their supply networks (Macchion, Danese, & Vinelli, 2015), the fashion luxury industry seems to not truly realize the need for operative cost control and reduction in this area.

One of the key processes in the day-to-day supply chain management consists of replenishment: these operations are greatly affected by demand and market complexity, and could deeply influence company margins through lost sales or, conversely, unsold items. Obviously, this process' effectiveness relies on demand planning and consequently optimized replenishment parameter setting. This work aims at providing some useful help to effectively set inventory levels according to demand characteristics in fashion luxury industry stores, avoiding over or underestimating service level and, as a consequence, affecting brand image.

Therefore, after a brief review of literature on the replenishment process in the fashion luxury industry, the customer demand at store level in this specific context will be analyzed. The concept of service level will be

investigated along with its practically used translations, i.e. availability rate or fill rate. Then, focusing on the “lost sale” concept, the paper introduces the two alternative stochastic models most commonly adopted to compute store inventory parameters in this industry, the Normal model, based on the normal distribution, and the Poisson model, with its namesake distribution. Because normal and Poisson distributions are often straightforwardly adopted in fashion-luxury companies without appropriate hypothesis validation, the rest of the paper will show the quantification of the eventual errors arising from the assumption of an unsuitable demand distribution pattern. Specifically, we focus on stock management for permanent products at store level.

2 Replenishment process in fashion luxury industry

In the fashion industry, merchandising and replenishment processes mainly deal with demand planning and fulfilment activities. Indeed, the purpose of demand planning is to improve decisions affecting demand accuracy and buffer or safety stock calculations in order to reach a predefined service level (Stadtler & Kilger, 2004). Once the demand plan is determined, the demand fulfilment process is executed. Iannone, Ingenito et alii (2013) proposed a model to support optimization for merchandising and replenishment processes in the fashion industry. D'Avolio et alii (2015) explored the merchandise and replenishment planning in the Italian luxury fashion industry, focusing on how companies try to coordinate replenishment processes upstream and downstream for seasonal products. They found that - differently from companies in Australia and the USA - Italian companies perform merchandise planning just in the pre-season period, using the “open to buy” (OTB) approach, but often in an unstructured way; only few companies among an interviewed panel were able to restart production during the in-season period; on top of this, it turns out that Italian companies find it difficult to adopt quick response methods, and this results in manual replenishment processes as well as manual approaches to SCM. The authors suggest that companies improve their ability to perform in-season planning and point out the importance of developing tools to optimize merchandise planning, especially the OTB management and replenishment process. Unfortunately demand of fashion luxury products presents some specific difficulties that hamper effective demand management.

3 Fashion luxury demand characteristics

Fashion industry products can be categorized into two main groups: seasonal and unseasonal (often called permanent). The first ones are characterized by short life-cycles. In this case stock management bases its strategies on “news boy” problem solutions (Hadley & Whitin, 1963) as, at the end of the season, products will be phased out. While permanent products stay at stores the whole year and sometimes for multiple years too. In the *luxury* fashion industry, both categories may typically show rare demand events. Indeed, in most fashion luxury companies, even top seller products often sell less than one piece per store per week. A growing field of literature is related to specific problems associated with low and very low consumption items (Wanke 2014): the greatest part of this literature

focuses on spare parts (Kocer & Tamer 2011; Kourentzes, 2014; Syntetos & Boylan 2006) or on those cases where there is a large fragmentation of customers' requests within a broad product mix. However, slow movers or sporadic sales products also include high-value retail goods (Hill, 2007). Indeed, Hahna & Leuch (2015) explicitly state that spare parts and decentralized retail supply chain items with large assortments frequently exhibit similar demand patterns. The intrinsic characteristics of fashion luxury products, i.e. low stock turnover, difficult demand predictability, high service-level requirements, contribute to an increase in the difficulties of planning and managing demand (Wanke, 2014). Carmignani and Zammori (2015) pointed out that in such an environment, make to order (MTO) strategies could represent a solution for certain fashion luxury companies; however, due to the typical long production lead times in this industry, MTO approach is often abandoned in favor of the simpler make to stock (MTS). And because MTS is based on forecasting, over-planning has been found to be a common practice to face uncertainty; eventual production excess is then absorbed by outlet retail channels (Brun, et al. 2008). Indeed, in the luxury fashion industry as well as in many high margin businesses, focusing on inventory reduction is often considered a low priority with respect to sale increase. However, even if overstock costs may be underestimated, they may entail some significant aftermath, among which there are non-negligible losses from markdown practice, reverse logistics and/or disposal/destruction costs. Inventory management in slow moving product context shows some criticalities because classical inventory theories and control policies are often ineffective or give unsatisfactory results (Kocer & Tamer, 2011; Eaves, 2002). Indeed, here the sales pattern recorded during the time bucket cannot always be modeled by a normal distribution as it is almost always done with mass products: normal distribution is often chosen thanks to its convenient properties (Iannone et al., 2009), as it allows the quick and easy computation of several parameters in inventory management (Strijbosch & Moors, 2006). However, normal distribution has two essential characteristics: it is symmetrical and has a left tail including negative values. By contrast, sales distribution is always non-negative (unless assuming the possibility of product returns) and frequently appears to be skewed to the right side (Janssen et al., 2009). These two problems may be negligible when the coefficient of variation of demand (σ/μ) is very low; in other cases, disadvantages become relevant. Strijbosch and Moors (2006) proposed two different adjustments to normal distribution in order to cope with the left distribution tail problem, but some limitations still remain when a high coefficient of variation is recorded. The majority of authors have used a different distribution in order to model specific demand patterns, but it emerged that these depend on the chosen data aggregation rule: indeed, for example the same customer behavior clearly results in different demand distributions if sales events are sampled on a daily or monthly basis, or if data are aggregated at store or at worldwide level.

Because in the fashion luxury industry production lead times can reach several weeks, some authors introduced the

“lead-time demand” concept to indicate replenishment lead time between distribution points. International fashion luxury companies often establish a multi-echelon supply chain, setting global warehouses, local warehouses and points of sale. Replenishment lead time from local warehouses to points of sale can be very short, sometimes only one day. Analyses performed by the authors of this paper on the case of a top multinational company operating in the fashion luxury industry showed, for example, that customer sales recorded on a daily basis at store level followed a Poisson distribution in nearly 93% of cases related to all the combinations of 20 luxury products at 200 stores at a worldwide level (data collected over one year; confidence level: 95%); on the contrary, when customer sales were aggregated on a weekly basis at store level, the normal distribution fit nearly 60% of cases. Differently, operating at market level instead of store level, the Poisson distribution hypothesis on weekly sales was rejected in 90% of cases. Indeed, Poisson distribution – or its variations – has been often used to model demand or sales distribution in contexts where events are extremely rare (Silver et al., 1998; Hill, 2007; Porras & Dekker, 2008; Nenes et al., 2015). It seems that this mathematical model could be suitable to be used in most fashion luxury contexts for representing daily sales at store level, also given that the Poisson distribution operates on the discrete dominion. On top of this, its application in common spreadsheets is quite straightforward, especially to compute service levels and lost sales probability. In practical contexts, companies have to face the need to automatically manage the inventory systems (thus, setting the target stock levels in stores according to management specified service levels) for thousands of products at a time (Iannone, Lambiase et al., 2013), choosing the most appropriate stochastic model from product to product is almost impossible. Moreover, often it makes no sense to choose a specific model for different product categories, because within a product category, fashion luxury companies may include products with very different sales volumes and frequencies. Thus, the most common practice is to choose a global approach – often based on a normal distribution assumption – and directly apply it to the entire product list. This practice may or may not lead to evaluation errors that can reflect on business results, because service level can be over or underestimated.

4 Service level indicators in fashion luxury industry

Undoubtedly, one of the most important indicators in fashion luxury supply chain management is service level. There exist different definitions for this concept: among the most widespread, α -service level (or “cycle-service-level” to stress that stock-out should be avoided during the replenishment cycle time) describes the fraction of time in which no stock-out occurs (Stadtler & Kilger, 2004). In common practice, this is often used in measuring service level in the store echelons and it is referred to as “availability rate”: e.g. if a store has zero stock for 3 days out of one week for a given product, the availability rate for that product is computed as $3/7 \cong 43\%$. While, when computing the fraction of demanded quantity that has been fulfilled with available stock, the term “fill-rate” is generally used. Unfortunately, demanded quantities are usually not

recorded in retail contexts, while there is an abundance of historical sales data series and inventory levels. Thus, it is much easier to compute the availability rate instead of fill rate. If the applied inventory model is the base-stock (i.e. a *TSL* “target stock level” is defined and replenishments follow the order-up-to-level rule) – which happens many times at store level for permanent products – lost sale probability can be computed as the probability to receive more requests than the *TSL* during the replenishment lead time. Replenishment lead time (*RLT*) includes the interval between stock control on top of the time for performing the replenishment operation.

Excluding the case where backorder is allowed, if:

$d(\mu_{d,T}; \sigma_{d,T})$ indicates the demand in time T , with its average and standard deviation;

RLT indicates the replenishment lead time from local warehouse to points of sale;

hence, lost sales probability (P_{LS}) is defined as:

$$P_{LS} = P(d_{RLT} > TSL) = 1 - P(d_{RLT} \leq TSL)$$

In cases where normal distribution is assumed, lost sale probability has been estimated with Microsoft Excel, computing both the average value and the standard deviation of the demand during the replenishment time with the formula:

$$P_{LS} = 1 - \text{norm.dist}(TSL; \mu_{d,RLT}; \sigma_{d,RLT}; 1)$$

Where the last term set to 1 implies the computation of the cumulative function. When the demand is distributed according to the Poisson model, lost sale probability has been estimated with Microsoft Excel again, using the average value of demand during the replenishment time as follows:

$$P_{LS} = 1 - \text{poisson}(TSL; \mu_{d,RLT}; 1)$$

On the contrary, the chance of not reaching zero-stock given a certain target stock level – converting from frequency to probability – can be assumed equal to availability rate (AR):

$$AR = P(d_{RLT} < TSL)$$

However, because the normal distribution operates on a continuous dominion, the computation of the availability rate is difficult, due to the need to introduce an infinitesimal value ε which makes no sense when dealing with contexts where products are sold in units:

$$AR = \text{norm.dist}(TSL - \varepsilon; \mu_{d,RLT}; \sigma_{d,RLT}; 1)$$

While, with Poisson distribution – which operates on discrete values – the availability rate can be estimated with:

$$AR = \text{poisson}(TSL - 1; \mu_{d,RLT}; 1)$$

Nevertheless, it is important to point out that, in practice, a stock-out condition is very different from a lost-sale event (Battista et al., 2011), especially in this context where customers usually buy no more than one piece at a time and sale events are extremely rare. As a consequence, saying that a given product had a 43% availability rate in a given

store in a certain week clearly does not mean that 57% of customers were unsatisfied: service level (SL) may be greater than 43% because any demand may occur while being out-of-stock, thus generally it stands:

$$AR < SL = 1 - P_{LS}$$

In the following paragraph, the two stochastic models, Poisson and Normal, are compared in order to understand strengths and weaknesses in managing fashion luxury product inventory systems and, specifically what the error may be in defining the target stock level originating from using the Poisson model rather than the normal distribution and vice versa.

5 Comparing Poisson versus normal distribution

The normal and Poisson models are applied to a simple inventory system operating with a base stock policy and periodic order-up-to-level replenishment with deterministic replenishment lead time and stable discrete demand, where service level is intended as the complement to lost sale probability and is set as input. In order to perform a fair comparison between the two models, the demand average and standard deviation during the replenishment lead time $d(\mu_{d,RLT}; \sigma_{d,RLT})$ are the same in both cases and

$$\sigma_{d,RLT} = \sqrt{\mu_{d,RLT}}$$

in order to cope with Poisson distribution characteristics.

A total amount of 136'000 numerical computations have been performed varying $\mu_{d,RLT}$ (and, of course, $\sigma_{d,RLT}$ as a consequence) and finding the target stock level TSL to be kept in store in order to grant a target service level.

The value of $\mu_{d,RLT}$ ranges between the following interval:

$$0.005 \leq \mu_{d,RLT} \leq 10$$

with an increase step of 0.005. An average demand of 0.005 units in a replenishment lead time of two days is representative of a product selling about 1 piece per year per store, which can be considered a characteristic value for a very slow moving product in the fashion luxury industry. On the other side, an average demand of 10 units in a replenishment lead time of one week is representative of a product selling about 500 pieces per year per store, which can be considered an upper bound for a blockbuster product in this industry.

The value of SL ranges between the following interval:

$$50\% \leq SL \leq 99.9\%$$

with different decrease steps: 1% step increase between $50\% \leq SL \leq 98\%$ and 0.1% step increase between $98\% \leq SL \leq 99.9\%$. A target service level of 99.9% is representative of those cases when the store should never run out of stock for that specific product and can be considered a theoretical upper bound in fashion luxury retail context.

The aim of the analysis is to determine when the adoption of Poisson model (i.e. the assumption of Poisson distribution) results in overestimating or underestimating the target stock level TSL with respect to the case in which

the Normal model is adopted (i.e. a normal distribution is assumed).

This analysis is extremely useful in practice because it allows for a quick evaluation of the robustness of a TSL setting in the stores of a fashion luxury company.

In the following Figure 1, the red cells indicate times when normal distribution assumption results in underestimating the TSL . Thus, these are those cases when, facing a Poisson distributed demand, using the normal assumption may expose the store to a higher lost sales probability than expected. On the contrary, green cells indicate when the Poisson distribution assumption results in underestimating the TSL . Thus, these are those cases when, facing a normal distributed demand, the use of the Poisson assumption may expose the store to a higher lost sales probability than expected.

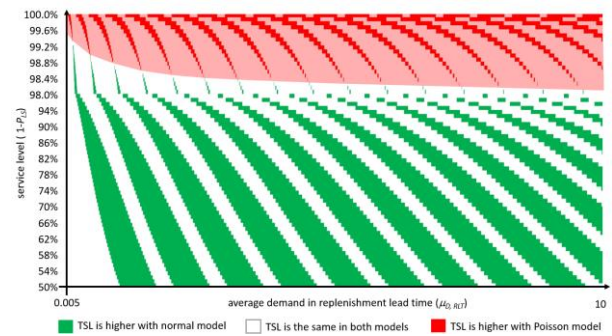


Figure 1: comparison between Poisson and normal distributions

Clearly, this result can also be read in another way: red areas correspond to those scenarios in which the Poisson model is safer to use (from a service level perspective, i.e. returns a higher TSL) and, conversely, green areas correspond to those scenarios in which the normal assumption allows a safety right-sizing of the target stock level in store. In white areas, the two models return the same TSL . The white stripes in the graph originate from the round-up approximation needed to compute an integer value of TSL when using the normal distribution, which by definition returns values in a continuous co-dominion.

Results show that assuming normal demand distribution (thus, in practice, inputting service level in the *norm.dist* Excel function) leads to a safety right-sizing of TSL s in stores until target service level is lower than 98.1%. Otherwise, if the store is aiming to reach higher service levels, the Poisson computations may be needed - especially when dealing with fast-moving products.

Interestingly, the TSL difference between the two models was never higher than 1 unit. If this result permits for good confidence in choosing one model rather than the other when TSL s in stores are high, it is important to point out that, for slow-moving items and service levels lower than 98.1%, when TSL s in store are generally set to 1 or 2 pieces, the choice of normal distribution may lead to respectively, a 100% or 50% increase in stock level.

6 Conclusion

This paper presented the results of an extensive numerical computation of target stock levels to be set for permanent

products in fashion luxury stores in order to reach established service levels (i.e. limiting lost sales probability) according to the two most commonly applied stochastic models, the Poisson and the normal model.

Because, in practical contexts, companies need to automatically set the target stock levels for thousands of store-product combinations at a time, and because demand pattern could fit Poisson or normal distributions depending on data aggregation, it is of paramount importance to know the gravity of the potential errors originating from the choice of an unsuitable model.

The paper showed that, when target service level is lower than 98.1%, the use of the most common normal distribution assumption leads to the same results provided by the Poisson model or, possibly, to a slight overestimation of TSLs, thus generating a safer condition due to an overstock of one piece per product per store at most. On the contrary, when target service level is higher than 99.1%, TSL setting according to Poisson model will generate higher stock levels than desired. Finally, in the 98.1%-99.1% service level interval, a more careful evaluation should be performed in order not to underestimate the target stock levels needed in stores.

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