Demand Forecasting in the Fashion Industry: A Review

Regular Paper

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Abstract Forecasting demand is a crucial issue for driving efficient operations management plans. This is especially the case in the fashion industry, where demand uncertainty, lack of historical data and seasonal trends usually coexist. Many approaches to this issue have been proposed in the literature over the past few decades. In this paper, forecasting methods are compared with the aim of linking approaches to the market features.

Keywords Demand Forecasting, Fashion, Supply

1. Introduction

Demand forecasting plays an important role in basic Operations Management as an input for planning activities. Poor forecasting effects are stock outs or high inventory, obsolescence, low service level, rush orders, inefficient resource utilization and bullwhip propagating through the upstream supply chain. As such, demand forecasting is a popular research topic and many models for forecasting fashion products have been proposed in the literature over the past few decades.

Typically, high performance companies focus on robust demand forecasting approaches; however, the challenge of demand forecasting varies greatly according to company and industry. In the fashion industry, products are usually characterized by long replenishment lead times, short selling seasons and nearly unpredictable demand and therefore, inaccurate forecasts [1]. All these features make the issue of forecasting demand particularly challenging. Companies in the fashion industry have been trying to manage the demand for many years, which has brought about the development of a number of specific forecasting methods and techniques.

Much of this earlier work was intended to create insights and tools for improving the demand forecasting of fashion products. However, the reality that is now gradually being accepted both by those who work in the industry and those who research forecasting is that the demand for fashion products cannot be forecast. Instead, we need to recognize that fashion markets are complex open systems that frequently demonstrate high levels of 'chaos'. In such conditions, managerial efforts may be better expended on devising strategies and structures that enable products to be created, manufactured and delivered on the basis of 'real-time' demand [2].

The difficulty in predicting demand has led companies to focus on the improvement of the supply chain [3, 4] and the traditional newsvendor-type overage-underage trade-off. This is one of the factors in the success of brands such as H&M and Zara, which have the shortest market lead times. Over the past few years, fashion companies have worked on strategies and inventory, and the framework of the industry has been radically changed.

The research question that therefore arises is: does it make sense to continue to study demand forecasting? What are the approaches and methods that may be more fitting with the actual context?

The purpose of this paper is to discuss the actual state of the context in the fashion industry compared with the demand forecasting approaches developed over the last few years. The most important literature on forecasting demand of recent years is confronted with recent findings on strategies of the main supply and demand-oriented firms in the fashion industry and on consumer behaviour. The aim is to understand which forecasting methods are more effective under the current conditions.

The main expected findings from the literature review will aim to propose a new framework for forecasting demand.

The paper is structured as follows: section 2 is devoted to analysing the actual supply chain features and firm context and what have been the main motivating factors of change. Section 3 introduces and discusses in depth the features of demand. Section 4 yields an analysis of the main works in the literature presented. Section 5 summarizes the findings and provides some final remarks. Finally, section 6 proposes a new conceptual framework for forecasting demand and discusses some open issues.

2. Development in the global fashion industry

The fashion industry has been in a state of transition over the past 20 years [5] due to pressure from many factors:
- Needs for reducing cost: as with many other industries, fashion has needed to reduce its cost base to increase competitive advantage; the main result of this tendency has been to buy materials and move production to developing nations where production is cheaper due to lower labour cost.
- Globalization: in terms of both production and retailing, this is a growing trend in many companies for gaining a substantial cost advantage. However, to source product and materials off-shore has in many cases led to significantly longer lead-times.
- Increase of customer requirements: the market has evolved from mass fashion into the segmented

fashion [6]. Moreover, in the fashion industry, customer tastes change dynamically and their expectations are varied [7, 8]. Companies are expected to meet the requirements of the customer on both a product and service level. For instance, fast fashion has increased its share in the apparel market, as customers expect greater variety and frequent design changes [9]. Retail stores have a critical role in creating brand image and have an influence on customer satisfaction [10]. Finally, service level quality, as noted by Rayman et al. [11] is one of the major parameters for customer satisfaction.
- Technology: has impacted the fashion industry in many ways and has contributed to the increase in customer requirements through a dramatic rise in the instantaneous knowledge of new trends and brands. Additionally, it has improved the capability of retailers, wholesalers and manufacturers for sharing data and making better business decisions. Out of this came two important advances: *(i)* Automatic replenishment, allowing manufacturers to automatically ship goods when inventory falls below agreed upon thresholds and *(ii)* Value Chain Initiative (VCI), where standardized codes and linkage have been developed throughout the industry [12].

As a result of the above-mentioned factors, the fashion industry is now synonymous with rapid change and the organization's flexibility and responsiveness [13]. Recent trends across the fashion industry are:
- Vertical integration and outsourcing: the traditional chain of suppliers to manufacturers to retailers to consumers is blurred. Many companies experience vertical integration in an effort to increase efficiency, eliminate intermediaries and better understand consumer needs. Other manufacturers choose to have all production outsourced in order to gain a competitive advantage [14]. Manufacturers and retailers have also recognized that cooperation leads to quicker product development, production and distribution and higher profits.
- Agile Supply Chain: an agile organization embedded within an agile supply chain performs better than conventional organizational structures and forecast-driven supply chains that are not adequate for meeting the challenges of the fashion industry [15-17].
- Quick Response: in order to reduce the inventory level, fashion retailers have adopted various measures such as the quick response policy [18–21]. Responsiveness is the ability to scale up (or down) quickly and the rapid incorporation of consumer preferences into the processes of a supply chain.

Relevant from the last trend is the recognized capability of Quick Response to counter the negative impacts of

uncertainty. Ideally, a Quick Response system would enable the manufacturer to adjust the production of different styles, colours and sizes in response to retail sales during the season; responsiveness can then be used to effectively substitute forecasting ability and/or inventory required for operating under uncertainty.

3. Analysis of the products

Many authors [22, 23] agree on characteristics typically exhibited by products in the fashion industry.

- Short life-cycles: the product is often ephemeral, designed to capture the mood of the moment; consequently, the period in which it will be saleable is likely to be very short and seasonal, measured in months or even weeks.
- Short selling season: today's fashion market place is highly competitive and the constant need to 'refresh' product ranges means that there is an inevitable move by many retailers to extend the number of 'seasons', i.e., the frequency with which the entire merchandise within a store is changed. In extreme cases, typified by the successful fashion retailer Zara, there might be twenty seasons in a year. The implications of this trend for supply chain management are clearly profound.
- Long replenishment lead times.

Regarding the features of the demand:
- High impulse purchasing: many buying decisions by consumers for these products are made at the point of purchase. In other words, the shopper, when confronted with the product is stimulated to buy it; hence the critical need for 'availability'.
- High volatility: demand for these products is rarely stable or linear. It may be influenced by the vagaries of weather, films, or even by pop stars and footballers. There are numerous sources of uncertainty in a fashion supply pipeline, starting with demand through to the reliability on the part of suppliers and shippers, etc.
- Low predictability: because of the volatility of demand it is extremely difficult to forecast with any accuracy even total demand within a period, let alone week-by-week or item-by-item demand.
- Tremendous product variety: demand is now more fragmented and the consumer more discerning about quality and choice.
- Large variance in demand and high number of stock keeping units: as a result, the volume of sales per SKU is very low [24] and demand for SKUs within the same product line can vary significantly [25]. Thus, even if aggregate demand can be predicted with some certainty, it is very difficult to predict how that demand will be distributed over the many products that are offered [26].

Obviously, the categorization of alternative demand patterns facilitates the selection of a forecasting method. In addition to the general features of the products, Varghese and Rossetti [27] have proposed classifying demand according to the following attributes:

- Smoothness: demand is quite stable.
- Intermittence: intermittent demand is generally defined as demand occurring randomly with many time periods with zero demands. Johnston et al. [28] propose that if the mean interval between non-zero demands is 1.25 times greater than the inventory review period, the demand series could be considered as intermittent.
- Lumpiness: the feature of tending to have periods of very low or zero demand and then spikes of demand. A lumpy demand is variable, sporadic and nervous [29].
- Erraticness: demand is described as patterns with high variability in non-zero demands [30]. Erraticness relates to the demand size rather than demand per unit time period.
- Slow-moving: demand is usually defined as having infrequent demands, which occur in very few units [30]. Slow demands are usually intermittent demands.

Most of the authors agree on the features of products or supply chain in the fashion industry. On the contrary there is no largely recognized link between demand in fashion and a specific attribute or pattern. Only Bartezzaghi [31] hazards a guess on the basis of correlation as a cause of lumpiness. Correlation may be, for example, due to imitation in fashion, which will lead to sudden peaks in demand.
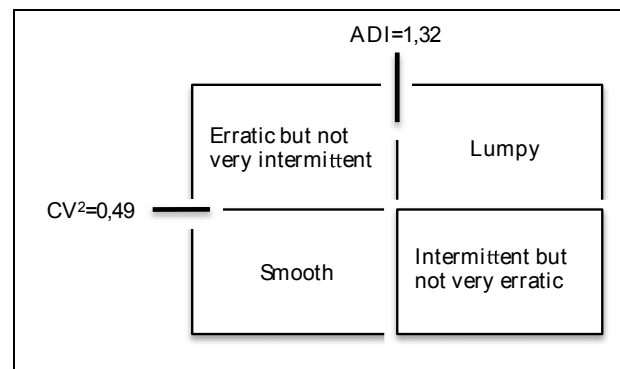

Figure 1. Items demand attributes.

As a result, many authors [30, 32, 33] propose different sets of indicators in order to classify demand. The most popular is based on two cut-off parameters:

- Average inter-Demand Interval (ADI): measures the average number of time periods between two successive demands.
- Coefficient of Variation (CV): represents the standard deviation of period requirements divided by the average period requirements.

ADI and CV distinguish the different attributes as in Figure 1. Recognizing the demand pattern is useful in order to select the forecasting technique.

4. Analysis of forecasting approaches

Demand forecasting is one of the biggest challenges for retailers, wholesalers and manufacturers in any industry, and this topic has received a great deal of attention from both researchers and practitioners. The question is whether the forecasting approaches are applicable and useful within the fashion industry.

Traditional forecasting methods, such as exponential smoothing [34], are designed for smooth, high-volume demand and don't work well with intermittent, erratic or lumpy demand.

There are many papers that propose the use of statistical methods in order to forecast demand [35]. This first group includes the extension of standard methods and variants of the Poisson model [36], a model based on binomial distribution [37], as well as Croston's model and its variants [28, 38, 39] and bootstrap methods [27]. Many authors [40, 41] have compared models and the general consensus is that performance should vary significantly according to the level of attributes. Particularly, if the demand pattern has a high level of lumpiness or erraticness, which is likely in fashion demand and often causes poor performance with statistical methods.

Moreover, Gutierrez et al. 2008 [42] clearly demonstrated that traditional time-series methods may not always capture a nonlinear pattern in data. Expert systems, such as an Artificial Neural Network (ANN), are a logical choice for overcoming these limitations.

Many authors have obtained impressive results through ANN [43, 44] and we can even count some interesting applications to fashion demand among these [45-47]. However, the same authors found that while the ANN model can yield accurate forecasts, the required forecasting time can be a large barrier to its real-world applications. This is because the training time required by ANN strongly increases according to the complexity or variety of the data. This limitation renders it impractical with the feature of the short selling season in the fashion industry and the requirement of responsiveness, too.

The last group of papers we have analysed discusses various techniques in managing the level of uncertainty [48, 49, 30]. Such papers focused on the development of a single algorithm or framework and attempted to measure the performance of such a framework against existing ones, often through a simulative approach.

Though somewhat dated, the most interesting contribution comes from Bartezzaghi [48]. In his paper, the author includes the main causes of demand lumpiness as:

- High numerousness of potential customers
- High heterogeneity of customers
- Low frequency of customer requests
- High variety of customer requests
- High correlation between customer requests

It is easy to verify that the above-mentioned features are common in the fashion industry and it is logical to presume that the main attribute of demand in the fashion industry is in fact lumpiness.

Bartezzaghi [49] even proposes two approaches for managing uncertainty typically present in lumpy demand:

- Early sales: this method exploits information from actual orders that have already been received for future delivery. Making Bayesian use of information from actual orders already received provides some degree of correlation between the unknown and known portions of the demand.
- Order over-planning: another approach for anticipating future lumpy requirements is to exploit the early information that a customer generates during his purchasing process before he places his actual order. Order over-planning uses as forecasting unit each single customer order instead of the overall demand.

5. Final remarks and future research

Lesson learned from both the context analysis and literature review proposed in this paper is that there are many different methods for and approaches to forecasting. However, product and supply chain features of the fashion industry remain dominant factors. It is therefore not surprising that the most famous brands have decided to focus on improving their supply chain performance. This does not mean that Zara or H&M do not forecast demand; more likely, they instead rely on marketing approaches. Main barriers in forecasting demand are:

- Short selling seasons
- Level of uncertainty (lumpiness)
- Lack of historical data

The last barrier results from the level of product innovation that can be found at t each season in fashion. That is the main reason for the considering the order overlapping method. The idea to use the customer as a forecasting unit has the power to overcome this problem. Under the hypothesis of a relatively stable set of customers, the historical series are then populated.

From this observation arises the starting point for future research. Having a more populated historical series is a key point for facilitating the use of a range of effective forecasting methods. The basic idea is then to use the features of products (colour, size, etc.) that are repetitive in each season as forecasting units. In fact, Zara has just demonstrated that colour is a more important feature than model or type of clothes [50]. Expected advantages of this idea are:

- Decrease the level of lumpiness through an effective choice of product features
- Improve performance of statistical forecasting methods

Main limits are likely to be:

- After forecasting a specific feature, how can we translate it into a product forecast? The problem then becomes distributing an expected demand of features among products that possess them. One answer could be a Bayesian approach.
- The performance should vary significantly on a case by case basis. Therefore, an extensive validation campaign could be conducted in order to fine-tune the approach. The risk is to fall into generalizing the approach.

The last issue should be to focus analysis on trend and cyclic nature of demand, using again the product features in order to have more populated historical series.

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