Chapter 2
Sales Forecasting in Apparel and Fashion Industry: A Review

Sébastien Thomassey

Abstract The fashion industry is a very fascinating sector for the sales forecasting. Indeed, the long time-to-market which contrasts with the short life cycle of products, makes the forecasting process very challenging. A suitable forecasting system should also deal with the specificities of the demand: fashion trends, seasonality, influence of many exogenous factors, ... We propose here a review of the different constraints related to the sales forecasting in the fashion industry, the methodologies and techniques existing in the literature to cope with these constraints and finally, the new topics which could be explored in the field of the sales forecasting for fashion products.

2.1 Introduction

The clothing industry includes many companies from the spinning to the distribution which are involved from the transformation of the fibre until the final garment (Fig. 2.1). Consequently, the creation of a garment requires a quite long and complex process with many manufacturing steps. The fashion and ephemeral aspect of the finished products contrasts with this long manufacturing process. However, the main actor of this network is the distributor downstream of the process. It makes orders for the upstream companies and supplies the consumer with their products: it is the driver of the all flows in the process.

These different stages with quite long and fluctuated manufacturing times involve a management based on a push flow strategy which makes the supply chain very sensitive to the bullwhip effect. In this context, sales forecasting emerges as a key

S. Thomassey (✉)
ENSAIT-GEMTEX, University Lille Nord of France, 2 allée Louise et Victor Champier, 59100 Roubaix, France
e-mail: sebastien.thomassey@ensait.fr

T.-M. Choi et al. (eds.), *Intelligent Fashion Forecasting Systems: Models and Applications*, DOI 10.1007/978-3-642-39869-8_2,

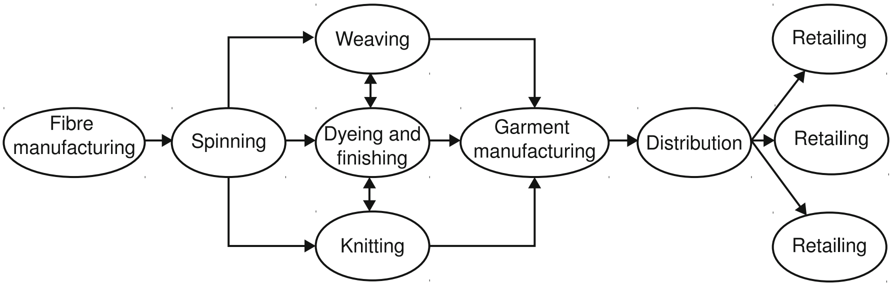

Fig. 2.1 The apparel supply chain

success factor of the supply chain management [59, 68]. However, the specificities of sales in the clothing sector make the forecasting process very complex. Indeed, the long and incompressible manufacturing and shipping lead times required to be provided with long term forecasts. Forecasting systems have also to take into account the particularities of the clothing itself:

- Strong relationships between most garments and the weather make the sales very seasonal. Seasonal data give general trends but unpredictable variations of weather involve significant peaks or hollows.
- Sales are disturbed by many exogenous variables such as end-of-season sale, sales promotion, purchasing power of consumers, etc. . . .
- Fashion trends provide very volatile consumer demands [55]. The design and style should be always up to date and most of the items are not renewed for the next collection. Consequently, historical sales are often not available since most of items are ephemeral.
- Product variety is huge. Indeed items are declined in many colour alternatives to meet the fashion trend, and in various sizes which should match with morphologies of the target consumers.

All these constraints make the sales forecasting for apparel companies very specific and complex. Therefore the implementation of such forecasting systems requires not only a strong background in the field of forecasting, but also a full and precise knowledge of the operations and challenges of the fashion industry and its supply chain.

For these reasons, this exciting topic has led to many works in the literature for decades [33, 68].

The next section deals with the main features of the fashion industry and more particularly the requirements in term of sales forecasting. It describes the specificities of the fashion sales which should absolutely be taken into account in the forecasting systems.

The Sect. 2.3 deals with the impacts of forecast errors on the supply chain. A review of the literature of simulations of supply combined with a forecasting system enables to show the real benefits of the reduction of forecast errors.

The Sect. 2.4 investigates the methods used by companies to respond to the constraints of the fashion industry and then suggests existing advanced methods to perform more accurate and reliable sales forecasts. These methods include fuzzy logic, neural networks and data mining.

The last section concludes and suggests some topics which currently arise for the sales forecasting in fashion industry. Sales discount, unsold management, new products, ... are specific cases in the sales forecasting point of view which should be deeply investigated in the near future.

2.2 The Fashion Industry and Its Requirements for Sales Forecasting

Usually, the decision process in the fashion company starts with the definition of budget for the collection and/or the sourcing. When designers have selected the items which should be included in the collection, the mix of budget and sales forecasting enables managers to launch the purchases or the production [67].

In fashion industry, it is commonly known that consumer demands are very volatile [21, 55]. Indeed, consumers are very unfaithful and generally their selection is first based on the price of the product. Facing these constraints, companies try to reduce their production costs by keeping a high service level. Thus, most of manufacturing processes, detailed in Fig. 2.1, are performed in far away and low cost countries. This strategy leads to the increase in the lead time and the lot size of supplies. Consequently, the supply chain management has to be optimized to avoid delay, out of stock, unsold and to keep the right inventory level. Therefore, many supply chain management tools have enabled companies to improve scheduling and synchronizing of material and information flows. Most of these tools can be customized to the specific constraints of the clothing retailing, however their efficiency is mostly dependent of the accuracy of sales forecasts.

In order to perform suitable sales forecasting for the supply chain management, it is crucial to perfectly know the product, the sales features and how the distributor will use the forecasts [8], especially in the very specific environment of the fashion industry.

The following subsections describes the main characteristics which should be taken in account to design a sales forecasting system for the fashion industry.

2.2.1 Horizon

The forecast horizon is one of most important feature of the forecasting system. Indeed, higher is the horizon, better is the anticipation, but higher are the errors of forecasts. Consequently, it is important to rigorously define the required horizon.

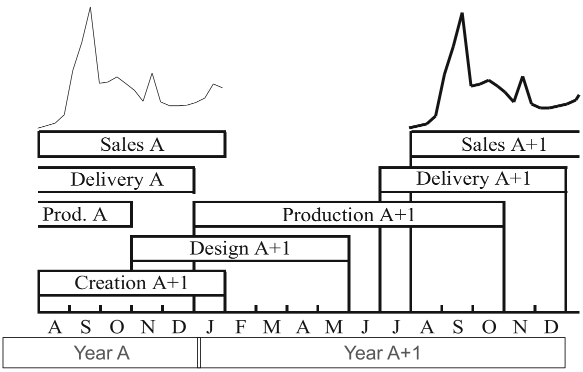

Fig. 2.2 Example of planning for autumn-winter items

With the supply strategy defined previously, many decisions are based on sales forecasting: purchases, orders, replenishments, inventory allocations, ... All these decisions should be considered in a sufficient time according to the incompressible lead times for production, shipment,transportation, quality control, ...

Furthermore, the supply strategy of clothing companies is generally composed on two steps:

1. A first order at the beginning of the season to enable the supply of the stores and to achieve to a right inventory level in warehouse.
2. One or more replenishments for some items during the season.

Considering the schedule of design/production/distribution of clothing items given for instance in Fig. 2.2, this strategy involves two horizons of forecast:

- A long term horizon, i.e. 1 year, to plan the sourcing and the production,
- A short term horizon, i.e. a few weeks, to replenish if necessary and to adjust the orders and deliveries of local stores.

Consequently, the sales forecasting system should provide two forecasts with two different horizons. The methods and models used to compute the forecast are obviously different according to the considered horizon.

2.2.2 Life Cycle

For most of the products, the life cycle is generally composed of four phases: the launch (or the implantation), the rise, the maturation and the decline. However in fashion industry, it is commonly known that life cycle of products is quite short especially compared with their long supply process [21, 55, 64].

Furthermore for clothing products, different categories should be differentiated according to the nature of items:

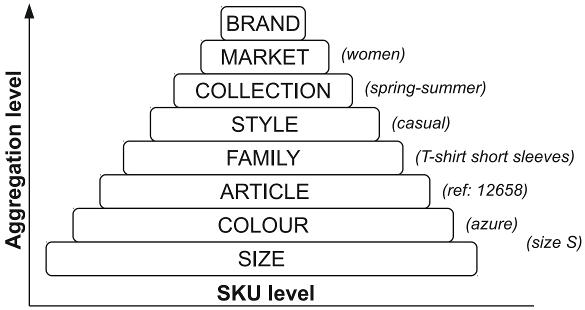

Fig. 2.3 Example of data aggregation by topology of products

- Basic items which are sold throughout the year (for instance denims) or each year (for instance basic white T-Shirt).
- Fashion items, including "one shot" items, which are sold punctually in a short period. They are generally not replenished.
- Best selling items are sold each year with slight modifications according to the fashion trends and could be replenished during the season.

The high variety of products generates strong differences in term of life cycles and it would be simplistic to assume that they all have the same behaviour.

In terms of forecasting, basic items and "best-selling" items are usually taken into account in sales forecasting system, while fashion items with "one shot" supply are often not considered in the "traditional" forecasting process. In fact, this category of products, widely used by the "fast fashion" brands, has specific forecasts, especially for the allocation of stocks in the stores and management of shelves [16].

2.2.3 Aggregation

In fashion industry, the product variety is one of the heaviest constraint. Indeed, the fashion trends involve many styles and colours. Combined with the variations in sizes, the product variety becomes huge [55, 64] and makes the management of Stock Keeping Unit (SKU) very complex.

In the point of view of sales forecasting, this variety, the short lifespan and the reference changing for each collection, require the company to aggregate the data. The main issue is then to select the right level and criteria for the aggregation. Classification methods based on quantitative or qualitative attributes could be implemented (see Sect. 2.4.2.2), but companies usually prefer to conveniently aggregate their data from a hierarchical classification of the topology of products [24] (Fig. 2.3). The suitable level for sales forecasts based for instance on time series techniques, is the lower level which enables the company to get historical data of several years ("family" level in Fig. 2.3). In the lower levels, for instance the SKU level, data are ephemeral and no historical data are available. Thus, other techniques based on data mining and classification should be implemented.

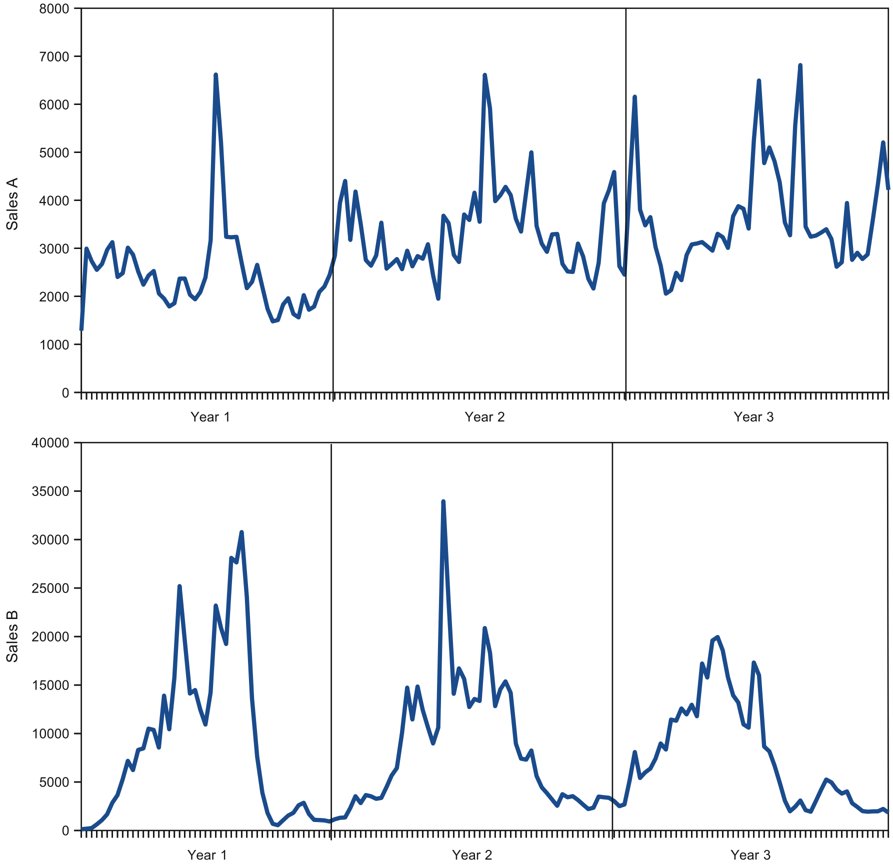

Fig. 2.4 Example of sensitivity to the seasonal variation: underpants (A) and short sleeve T-shirts (B) sales

2.2.4 Seasonality

Seasonality is also an important feature which has to be taken into account for every time series analysis, such as sales forecasting and which has been widely investigated in literature [18, 28, 36].

However in fashion industry, some items are logically very sensitive to the seasonal variation, such as swim wears or pull overs, others are not impacted, such as underpants. The Fig. 2.4 illustrates the sales of two basic items with a different behaviour in term of seasonality:

- (A) Underpants are not sensitive to seasonal variations. Their sales do not clearly show any periodic fluctuations

- (B) Short sleeve T-shirts are seasonal products. The amount of their sales is obviously larger during the hot period of each year.

Thus, according to the sensitivity of the considered item, the seasonality should be more or less integrated into the forecasting system for clothing sales.

2.2.5 Exogenous Variables

The clothing market is strongly impacted by numerous factors which make the sales very fluctuated. These factors, also called explanatory variables, are sometimes not controlled and even unknown. Some of them involve an increase of the purchase decision, others modify the store traffic [43]. Hence, the difficulty to exactly identify them and to quantify their impact [25].

Figure 2.5 illustrates the variables which are commonly taken into account by marketing experts (non-exhaustive list) for their influence on store traffic and/or purchase decision [43].

The impact of these factors could be very dissimilar on sales. Indeed, some factors generate punctual fluctuations without significantly affecting the overall volume of sales, for instance a temporal price discount produces peaks of sales as illustrated in Fig. 2.6. Others impact more globally the sales such as macro-economic data or strategy of retail. For instance, sales of the year 3 in Fig. 2.6 show an unexpected decline which could be explained from these kind of factors.

Regarding the previous remarks, practitioners have to keep in mind when building the forecasting system that [59]:

- Explanatory variables are essential to model the clothing sales and if possible the most relevant ones have to be integrated in the computation of the forecast.
- These variables are many and varied and it is not possible to establish an exhaustive list.
- The impact of each of these variables is particularly difficult to estimate and it is not constant over time.
- These variables can be correlated on them. This strongly complicates the understanding and the modelling of their impact on sales.
- Some variables are not available (i.e. competitor data) or predictable (i.e. weather data) and thus can not be integrated in the forecasting system.

2.3 Impacts of Forecast Errors

The direct effects of forecasting on efficiency, costs, inventory levels, or customer service levels is difficult to understand [4, 58]. In literature, many works rely on more or less complex simulations of a supply chain or more frequently a sample of a supply chain with different scenarios in many industrial fields.

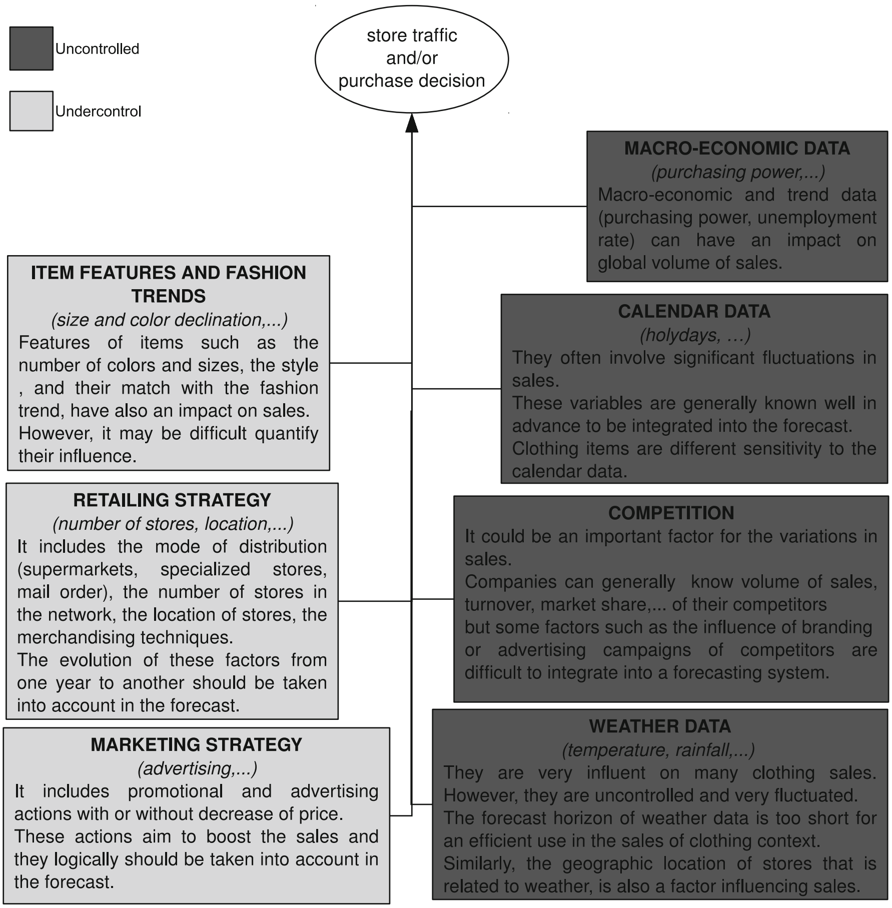

Fig. 2.5 Exogenous factors (non exhaustive list) related to the sales of clothing items

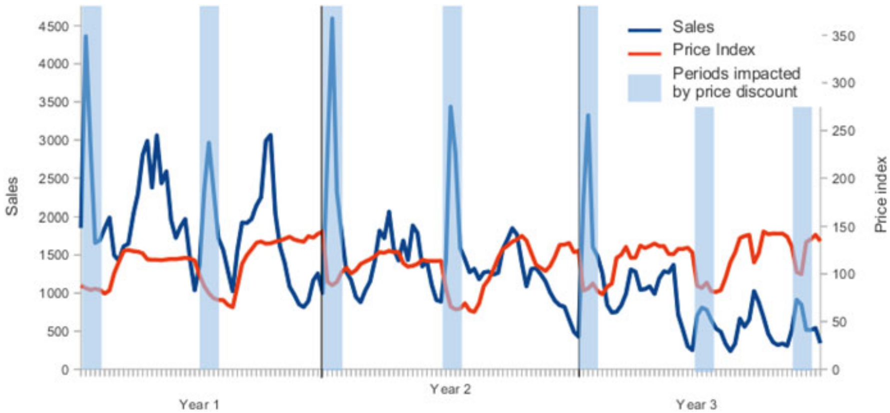

Fig. 2.6 Sales sensitivity to the price discount

It generally emerges that for most companies, based on push flow supply chain, sales forecasting arises as an important factor for the supply chain management. Indeed, many researches has demonstrated that a reduction of forecast errors leads to better supply chain performances [10, 29, 54, 75].

In [34], the authors investigate seven supply chains in different industrial sectors and they conclude that a suitable forecasting model enables to stabilize the supply chain especially for price-sensitive products.

In [9], an empirical analysis of the sales of more 300 SKUs of a superstore, clearly exhibits the relationship between forecast errors, inventory holdings and inventory costs.

In [29], the authors simulate a MRP method to understand and quantify the effect of forecasting on different indicators such as cost, inventory level, service level, ... they find that reducing the errors of forecast provides better benefits than choosing inventory decision rules. They also show that a misspecification of the forecasting method definitely increases costs.

In the same way, [2] investigates the relationship between forecasting and operational performances in the supply chain in chemical industry. They showed that the choice of the forecasting method strongly impacts the customer service and the costs.

Information sharing, and more especially the sharing of forecast data, also strongly impacts the supply chain management [3, 15, 42, 73]. In [78], a simulation is achieved on a sample of supply chain composed of a manufacturer and a retailer. Different scenarios are investigated including sharing information and forecast accuracy. They conclude that even if the manufacturer can get the same level of forecast accuracy as the retailer, the manufacturer would still prefer to share the forecasting demand of the retailer, instead of forecasting it himself. Thus, forecast effort should be done downstream of the supply chain, i.e. as close as possible of the demand of final users.

Some studies deal with the case of fashion industries with the constraints defined in Sect. 2.2 (long lead times, ephemeral and fashion items, etc. ...). It generally emerges that the forecast accuracy arises as one of the successful factors in supply chain management especially for fashion products [45]. The benefits of the implementation of advanced forecasting techniques can be evaluated at different levels:

- Reduction of the bullwhip effect [56, 71] without major supply chain reorganization [17].
- Possibility for the supplier to smooth out production, to optimize its resources, to decrease costs, and to improve the effectiveness of retailer's sourcing strategy [74].
- Reduction of lost sales, markdowns and consequently increase profit margin [45].

In [59] a simulation of the sourcing process of a retailer and a manufacturer is performed to quantify the impact of the forecast accuracy specifically on clothing supply chain. This simulation takes all the constraints into account described in

Sect. 2.2 and is implemented on real data of 20 items .... The sourcing strategy, including minimum reorder size, replenishment decision, ... is based on a Quick Response method [6].

Concerning the forecasts, this simulation implements sales forecasting at SKU level for a long-term horizon (a whole season). This forecasting system enables the retailer to estimate the sales in the stores at the beginning of the season. The forecasts of the whole season are shared with the manufacturer.

Different forecast scenarios are then simulated:

1. A scenario called "data mining based forecast" which uses the data mining based forecasting system developed in [60]. This system performs accurate forecasts.
2. A scenario called "average profile" forecast where forecasts are the average of the sales profiles of historical items of the same family. This method could be considered as the method commonly used technique in many companies.
3. A scenario called "flat profile forecast" where forecasts are the weekly average of the sales quantity of the whole season. This is a very basic forecast used as a benchmark.

The quantitative results of this study show that the scenario 1, using the more advanced forecasting system, enables significant reduction of the inventory level of the retailer (between 11.5 and 18 % according to the scenario), the inventory level of the manufacturer (around 11 %), the lost sales in stores (between 4.5 and 11 %) whereas the gross margin rises (between 8 and 14 %) (see [59] for more details).

Finally, these results obviously demonstrate the beginning of a bullwhip effect on a two stage supply chain and they suggest a significant amplification on the whole supply chain.

As per these studies, it seems obvious that fashion companies have to implement a suitable forecasting system and share their forecasts, and then have to try to restructure and/or rethink their supply chain to reduce the lead times and minimum order quantities.

2.4 Sales Forecasting Methods for Fashion Industry

Time series forecasting methods are probably the most used techniques for prediction of sales data. These statistical techniques include various well-known models that have formal statistical foundations [23]: exponential smoothing [13], Holt Winters model [66], Box & Jenkins model [12], regression models [51] or ARIMA. These methods have been implemented in different areas and they provide satisfactory results [40]. However, their efficiency strongly depends of the field of application, the forecast goal (especially the horizon) or the user experience [8]. Consequently, for the reasons described in Sect. 2.2, these methods are not easily and not efficiently implemented in the textile-apparel environment and more generally in any fashion sectors, especially because most of time series methods require large historical data sets, a complex optimization of their parameters, a certain experience of the operator, and they are limited to linear structure.

Many commercial softwares are based on these statistical techniques and enable the operator to automatically select the more suitable methods according to the considered data set [37]. Thus, ARIMA, Holt winters, Box & Jenkins or regression methods are implemented in various software such as *Autobox* of AFS, *Forecast Pro* of BFS, *SmartForecasts* of SmartSoftware, ... Few softwares, *SPSS Neural Networks* of IBM or *Forecaster* of Alyuda, use advanced computing techniques such as neural networks. In the last decade, the main trend is the implementation of forecasting tools into integrated softwares such as ERP: *Aperia Forecaster* of Aperia, *SAP Demand planning* of SAP, *TXT-Integrated Retail planning* of TXT Group, ... Some companies propose also specific systems for apparel and fashion industry: *Forecast Management* of Demand Solutions, *Optimate* of SEI. These softwares provide to the users useful tools which enable the management of the splitting by size and colour and the Point Of Store (POS) data.

2.4.1 Usual Methods

Despite of the various and advanced methods implemented in commercial softwares, they are seldom used in the textile-apparel industry. Their cost could be one reason but not only. Indeed, to obtain an optimized automatic treatment, the implementation of such systems on huge and customized databases could be very fastidious. Moreover, and maybe the main cause, practitioners want and need to keep control on their forecasts. No company agrees to let forecasting decision to a software, although it is very accurate. In fact, automatic forecasts from softwares, if they exist, are generally used as baseline for the final forecasts of the practitioners.

Due to the constraints described in Sect. 2.2, for ease of interpretation and understanding, and for cost reduction, companies have attempted to implement their own forecasting system. These customized systems, based on practitioner experiment, generally achieve relatively acceptable accuracy. Each companies use its own tips to perform what should be the best forecast.

The main frame is generally composed of a baseline forecast, extracted of a specific software or more basically sales of last year. The practitioner then reworks this baseline according to explanatory variables which are taken into account. For instance, the practitioner modifies the curves according to the price reduction periods and of course his knowledge of the market. The result could be very accurate since seasonality and impact of main explanatory variables are taken into account. However, this method has various drawbacks:

- The number of variables treated is limited, if not the analysis becomes too complex and imprecise,
- This work can be very tedious if the number of items is large,
- The results are fluctuating according to the experience of the operator.

For these reasons, the practitioner needs to use more advanced techniques to increase the accuracy of sales forecasts. These techniques are introduced in the following section.

2.4.2 Advanced Sales Forecasting Methods

The first parameter to take into account when designing a forecasting model is the availability of historical data. As shown in Sect. 2.2.3, fashion industry mainly needs forecasts at two levels of data aggregation:

- The "family level" composed of items of same category (T-Shirts, trousers, …) which enables companies to plan and to schedule purchase, production and supply at mid term. For this aggregation level, historical data usually exist.
- The "SKU level" which is required to replenish and to allocate inventory in stores at a shorter horizon. At this level, references (SKU) are ephemeral since they are created for only one season. Thus, historical data are not available, even if many items more or less similar have usually been sold in previous seasons.

2.4.2.1 Forecasting Methods with Historical Data

When historical data are available, the forecasting system has to extract the maximum information as possible from the past years. For fashion items such as garments, these information are the traditional trend and seasonality but also the impact of exogenous factors. If the two firsts should require many attentions and skills, the last one is very difficult to model and to control (see Sect. 2.2.5) and requires advanced techniques.

Among these techniques, neural networks (NN) are probably the more used techniques in sales forecasting especially for short-term forecast where the main issue is to be reactive to the last known sales [69]. NN perform generally well for sales forecasting if the demand is not seasonal and quite non fluctuating [67]. Consequently, if NN are directly implemented without advanced pretreatment of data or learning techniques, they are not suitable for fashion items. Therefore, many hybrid techniques based on NN have emerged to fit the features of the considered demand.

Recently, extreme learning machine (ELM) algorithms has been widely described and implemented in the literature for sales forecasting issues, and more especially for the learning process of NN [19, 35, 57, 67, 68, 77]. Comparing with NN based models with gradient learning algorithms, ELM should be better in generalization and faster in learning [67].

In [57], a NN model with extreme learning machine for fashion sales forecasting with a short term horizon is proposed. Their model enables to quantify the relationship between sales amount and some significant fashion product attributes such as colour, size and price.

In [67], the authors propose a sales forecasting method for fashion retailing, which performs mid-term forecasts (from annual to monthly forecasts) by item categories or cities. The proposed method relies on a hybrid intelligent model comprising a data pre-processing component and a forecaster (based on ELM). This method is claimed to overcome the limitations of NN and to tackle the sales forecasting problems in the fashion retail supply chain.

If ELM have demonstrated their effectiveness in sales forecasting problem, even in fashion industry, they still may suffer, like gradient or back propagation methods, of over-fitting or under-fitting especially for fashion sales data.

In [68], the authors have performed a hybrid model based on ELM with adaptive metrics of inputs to avoid over-fitting problem. Their model provides more accurate forecasts than other sales forecasting models (AR and ANN) implemented on fashion retailing data.

However, results obtained in this works only concern one-step-ahead point forecasting with monthly data.

In [19], another neural network methodology is proposed: a forecasting model based on a Gray relation analysis integrated with extreme learning machine (GELM) for the retail industry. According to experimental results, this hybrid system enables to select more significant influential factors, to increase the learning speed and to improve the forecasting performance comparing with other advanced models based on GARCH model and back-propagation network

Other soft computing techniques for sales forecasting have also been successfully implemented in fashion industry.

Fuzzy logic and Fuzzy Inference Systems (FIS) are commonly used to model uncertain knowledge and non-linear, fluctuating, disturbed and incomplete data [70]. These characteristics lead to implement fuzzy inference systems to model complex relationships between data, such as the influence of exogenous factors on sales [39].

For instance, a such system has been implemented on real data in [62]. The FIS is first used to quantify and to remove the influence of exogenous factors on historical sales. Statistical models based on seasonality can be then applied to forecast the sales of the future season without exogenous factors. The influence of exogenous factors existing in the future season are obtained by the FIS and are added on the seasonality based forecast to provide the final forecast. The inference rules and parameters of the FIS are extracted and optimized from the historical database with genetic algorithm. In this study, considered exogenous factors are the price, the holidays and season period.

Comparing with traditional forecasting models on real sales of 322 item families, this fuzzy based system improves significantly the accuracy of the mid-term forecast (one season ahead).

This result demonstrates that the right estimation of influences of exogenous factors is a key point for the sales forecasting of fashion items.

To conclude, advanced techniques such as ELM or FIS enable to improve the forecast accuracy compared with traditional time-series methods or traditional NN models. But different works never achieve a benchmark with real forecasts of retailers, which could be the only criteria for retailers to implement the model or not.

2.4.2.2 Forecasting Methods Without Historical Data

Most of fashion items are sold during only one season. Companies have to estimate the sales without any historical data: the forecasting system should be then designed for new product sales forecasting. New product forecasting is one of the most difficult forecasting problem [20]. Indeed, forecasting methods described in Sect. 2.4.2.1 are not suitable. In this context, a two-step methodology seems emerged:

1. To cluster and to classify new products to forecast their sales profile (mid-term forecast).
2. To adapt and to readjust this profile according to the first weeks of sales (short-term forecast).

If no historical data exists for the considered item, but similar products have already been sold in previous seasons. Indeed, new products usually replace old ones with almost the same style and/or functionality (i.e. T-shirt, pull over, …), it is thus possible to use historical data of similar products to estimate the sales profile of the new products [53].

Thus, to forecast the sales profiles of new products such as garments with clustering and classification techniques, descriptive attributes (price, life span, sales period, style, …) of historical and new products should be taken into account. The aim is to model the relationship between historical data, i.e. between sales and descriptive criteria of related items, and then to use these relationships to forecast future sales from descriptive criteria of new items.

These relationships are often complex and non-linear [5]. For this kind of problem, machine learning methods have demonstrated their efficiency for building simple and interpretable pattern classification models [41, 48].

This methodology has been successfully implemented in [60] and [61] for fashion sales forecasting. The process consists to:

1. Cluster the historical products which have similar sales profiles.
2. Establish links between sales profiles and descriptive criteria of historical products.
3. Assign each new product to one sales profile from its descriptive criteria.

The choice of the clustering and the classification methods varies according to the type and the number of data.

The clustering procedure could be based on the classic and straightforward k-means method if the number of data is reasonable, whereas more advanced techniques based on neural techniques such as Self Organizing Map (SOM) [38] should be preferred if dataset is larger, noisier or contains outliers [65].

For the classification procedure, neural networks and decision trees are considered as the most competitive techniques for this kind of applications [41, 63]. Neural networks are generally preferred for their generalization ability [76] and provide best results with numerical data. Decision trees obviously outperform neural networks in term of interpretability [72], seem less sensitivity to reductions in sample size and perform best with non-numerical data [14, 44].

As for any machine learning system, the main drawback of this method is that the data have to be reliable and relevant, especially for the descriptive criteria.

If the forecast of the sales profiles is very useful for a mid-term horizon at SKU level, it should be improved for short term forecasting. Indeed, allocation of inventory, replenishment of stores, . . . require accurate weekly and sometimes daily sales forecasting.

For this purpose, the strategy of "pre-sales" is often implemented for fashion products and more generally for new product forecasting.

Whenever it is possible, i.e. when replenishments are possible at low cost and with reasonable lead time, companies can supply some new products in a small sample of selected stores for a short period before the selling season. The analysis of these sales gives precious information for the whole supply.

In other cases, different models have been performed to extrapolate the future sales from few weeks of sales. In [30], pre-sales data enable to cluster stores of fashion merchandise. The pre-sales data at the representative stores is then used to estimate the sales at all the other stores in the same cluster.

In [31], 3 weeks of sales are used to determine the success or the failure of a new product. These 3 weeks enable them to define sales forecast ratio and to perform weekly forecasts.

Another method is based on a truncated Taylor Series [46]. The sales forecast is assumed as a Taylor Series where the first derivatives are the most important component. The final forecast is computed from a weighted sum of historical data with more weight to more recent data.

In [47], a diffusion model is implemented to forecast new product sales. Under some assumptions, the sales are extrapolated from a non-linear symmetric logistic curve considering saturation level, inflection point and delay factor of life cycle of products.

In [20], the authors propose an original decision support system for new product sales forecasting. This system automatically selects the best model according to the characteristics of the data and the requirements of the user. The models implemented are classical time-series models but also the specific models previously described. They obtained good results on real data but this system as not been tested on fashion items.

In any case, these methods require that products have already been classified according to their sales profiles.

2.5 Conclusion and Scopes

Sales forecasting in fashion industry is a challenging issue for many years. A lot of efforts has been done to improve the accuracy of forecasting systems with the specific constraints in this interesting field.

Advanced techniques such as extreme learning machine have enabled searchers to increase the capacity of systems to extract information from historical data, even if these data are strongly disturbed.

Data mining techniques and extrapolation techniques based on "pre-sales" can be very powerful when no historical data are available.

All these techniques will be improved again and again in the near future. However, other topics could be also very interesting to investigate. Indeed, the fashion industry is a very dynamic sector. New markets emerge and consequently new constraints and new requirements for the forecasting systems. These evolutions are attractive opportunities for researchers in the next decades.

Among these new trends, mass customisation strategy currently represents a small sample of products but could rise and change the needs in term of forecast and supply.

A further interesting trend is the fast fashion strategy [16]. Some famous brands successfully use this strategy and their requirements in sales forecasting are very specific.

Finally, another way of improvement for the fashion sales forecasting could be a deeper investigation of the management of the price discount, promotion, unsold, ... Indeed, fashion items are very price sensitive. Managers usually drive their sales with price discounts during the selling period to avoid end season inventory.

A decision support system based on sales forecasting to help companies to manage their sales and also their profits according to the price of the product could be very useful system. In a such system, the forecast engine should be able to accurately model the relationship between sales and price of a product.

Many studies have focused on the effect of promotions on sales in different industrial fields [1, 11, 22, 26, 27, 49, 50].

In [52], the authors implement a structural equation modelling [32] to understand how different demand factors, such as promotional factors, influence sales. Their proposed method was developed using weekly sales data of individual products of a leading Soft Drink Company.

In [7], a simulation of a two echelon supply chain with price sensitive demand is carried out. This simulation aims to investigate the impact of price discount on the profits of the manufacturer, the retailer and the consumer according to different strategies. This work demonstrates that relationships between price and the real profits of the actors of the supply chain is very complex.

Therefore, many profitable improvements specific to the fashion industry and using advanced forecasting techniques, could be done in this purpose.

References

1. Abraham M, Lodish L (1987) PROMOTER: an automated promotion evaluation system. Mark Sci 6(2):101–123
2. Acar Y, Gardner ES (2012) Forecasting method selection in a global supply chain. Int J Forecast 28(4):842–848
3. Agrawal S, Sengupta RN, Shanker K (2009) Impact of information sharing and lead time on bullwhip effect and on-hand inventory. Eur J Oper Res 192(2):576–593

4. Ali MM, Boylan JE, Syntetos AA (2012) Forecast errors and inventory performance under forecast information sharing. Int J Forecast 28(4):830–841
5. Altam EI, Macro G, Varetto F (1994) Corporate distress diagnosis: comparison using linear discriminant analysis and neural networks. J Bank Finance 18:505–529
6. Al-Zubaidi H, Tyler D (2004) A simulation model of quick response replenishment of seasonal clothing. Int J Retail Distrib Manag 32(6):320–327
7. Arcelusa FJ, Satyendra Kumar, Srinivasand G (2008) Pricing and rebate policies in the two-echelon supply chain with asymmetric information under price-dependent, stochastic demand. Int J Prod Econ 113:598–618
8. Armstrong JS (2001) Principles of forecasting – a handbook for researchers and practitioners. Kluwer, Norwell
9. Babai MZ, Ali MM, Boylan JE, Syntetos AA (2013) Forecasting and inventory performance in a two-stage supply chain with ARIMA(0,1,1) demand: theory and empirical analysis. Int J Prod Econ 143(2):463–471
10. Bayraktar E, Koh S, Gunasekaran A, Sari K, Tatoglu E (2008) The role of forecasting on bullwhip effect for E-SCM applications. Int J Prod Econ 113(1):193–204
11. Blattberg RC, Levin A (1987) Modelling the effectiveness and profitability of trade promotions. Mark Sci 6(2):124–146
12. Box GEP, Jenkins GM (1969) Time series analysis forecasting and control. Prentice Hall, Englewood Cliffs
13. Brown RG (1959) Smoothing forecasting and prediction of discrete time series. Prentice Hall, Englewood Cliffs
14. Bryson KMO (2004) Evaluation of decision trees: a multi-criteria approach. Comput Oper Res 31:1933–1945
15. Byrne PJ, Heavey C (2006) The impact of information sharing and forecasting in capacitated industrial supply chains: a case study. Int J Prod Econ 103(1):420–437
16. Caro F, Gallien J (2010) Inventory management of a fast-fashion retail network. Oper Res 58(2):257–273
17. Chandra C (2005) Application of multi-steps forecasting for restraining the bullwhip effect and improving inventory performance under autoregressive demand. Eur J Oper Res 166(2): 337–350
18. Chatfield C (2003) The analysis of time series: an introduction. Chapman & Hall/CRC, New York
19. Chen FL, Ou TY (2011) Sales forecasting system based on Gray extreme learning machine with Taguchi method in retail industry. Expert Syst Appl 38:1336–1345
20. Ching-Chin C, Ieng AIK, Ling-Ling W, Ling-Chieh K (2010) Designing a decision-support system for new product sales forecasting. Expert Syst Appl 37:1654–1665
21. Choi TM (2007) Pre-season stocking and pricing decisions for fashion retailers with multiple information updating. Int J Prod Econ 106(1):146–170
22. Christen M, Gupta S, Porter JC, Staelin R, Wittink DR (1997) Using market level data to understand promotion effects in a nonlinear model. Mark Res 34(3):322–334
23. Chu CW, Peter Zhang GQ (2003) A comparative study of linear and nonlinear models for aggregate retail sales forecasting. Int J Prod Econ 86:217–231
24. Correa J (2007) Optimization of a fast-response distribution network. M.S. thesis, LFM, Massachusetts Institute of Technology
25. De Toni A, Meneghetti A (2000) The production planning process for a network of firms in the textile-apparel industry. Int J Prod Econ 65:17–32
26. Divakar S, Ratchford BT, Shankar V (2005) CHAN4CAST: a multichannel, multi-region sales forecasting model and decision support system for consumer packaged goods. Mark Sci 24(3):334–350
27. Dube J-P (2004) Multiple discreteness and product differentiation: demand for carbonated soft drinks. Mark Sci 23(1):66–81
28. Franses PH (1996) Recent advances in modelling seasonality. J Econ Surv 10(3):299–345

29. Fildes R, Kingsman BG (2010) Incorporating demand uncertainty and forecast error in supply chain planning models. J Oper Res Soc 62:483–500
30. Fisher M, Rajaram K (2000) Accurate retail testing of fashion merchandise: methodology and application. Mark Sci 19(3):266–278
31. Goldfisther K, Chan C (1995) New product reactive forecasting. J Bus Forecast Methods Syst 13(4):7–9
32. Hair JF, Black WC, Babin BJ, Anderson RE, Tatham RL (2006) Multivariate data analysis, 6th edn. Prentice-Hall, New Jersey
33. Hammond JH (1990) Quick response in apparel industries. Havard Business school, Cambridge
34. Hill A, Doran D, Stratton R (2012) How should you stabilise your supply chains? Int J Prod Econ 135(2):870–881
35. Huang GB, Zhu QY, Siew CK (2004) Extreme learning machine: a new learning scheme of feedforward neural networks. In: Proceedings of the international joint conference on neural networks (IJCNN2004), Budapest, pp 25–29
36. Hylleberg S (1992) Modelling seasonality. Oxford University Press, Oxford
37. Jain, CL (2007) Benchmarking forecasting software and systems. J Bus Forecast Methods Syst 26(4):30–33
38. Kohonen T (2001) Self-organizing maps. In: Springer series in information sciences, 3rd edn. Springer, Berlin
39. Kuo RJ (2001) A sales forecasting system based on fuzzy neural network with initial weights generated by genetic algorithm. Eur J Oper Res 129:496–517
40. Kuo RJ, Xue KC (1999) Fuzzy neural networks with application to sales forecasting. Fuzzy Sets Syst 108:123–143
41. Lee KC, Oh SB (1996) An intelligent approach to time series identification by a neural network-driven decision tree classifier. Decis Support Syst 17:183–197
42. Lee H, So K, Tang C (2000) The value of information sharing in a two-level supply chain. Manag Sci 46(5):626–643
43. Little JDC (1998) Integrated measures of sales, merchandising and distribution. Int J Res Mark 15:473–485
44. Mak B, Munakata T (2002) Rule extraction from expert heuristics: a comparative study of rough sets with neural networks and ID3. Eur J Oper Res 136:212–229
45. Mattila H, King R, Ojala N (2002) Retail performance measures for seasonal fashion. J Fash Mark Manag 6(4):340–351
46. McLean, BL, Wortham AW (1988) Methodology aids forecasting with limited amounts of data. Ind Eng 20(2):18–22
47. Morrison J (1996) How to use diffusion models in new product forecasting. J Bus Forecast Methods Syst 15(2):6–9
48. Muller W, Wiederhold E (2002) Applying decision tree methodology for rules extraction under cognitive constraints. Eur J Oper Res 136(2):282–289
49. Naik PA, Raman K, Winer RS (2005) Planning marketing-mix strategies in the presence of interaction effects. Mark Sci 24(1):25–34
50. Nair H, Dube J-P, Chintagunta P (2005) Accounting for primary and secondary demand effects with aggregate data. Mark Sci 24(3):444–460
51. Papalexopoulos AD, Hesterberg TC (1990) A regression-based approach to short-term system load forecasting. IEEE Trans Power Syst 5:1535–1547
52. Ramanathan U, Muyldermans L (2010) Identifying demand factors for promotional planning and forecasting: a case of a soft drink company in the UK. Int J Prod Econ 128:538–545
53. Saaksvuori A, Immonen A (2005) Product lifecycle management, 2nd edn. Springer-Verlag, Berlin and Heidelberg GmbH & C
54. Saeed K (2008) Trend forecasting for stability in supply chains. J Bus Res 61:1113–1124
55. Sen A (2008) The US fashion industry – a supply chain review. Int J Prod Econ 114:571–593
56. So KC, Zheng X (2003) Impact of supplier's lead time and forecast demand updating on retailer's order quantity variablility in a two-level supply chain. Int J Prod Econ 86:169–179

57. Sun ZL, Choi TM, Au KF, Yu Y (2008) Sales forecasting using extreme learning machine with applications in fashion retailing. Decis Support Syst 46:411–419
58. Syntetos AA, Nikolopoulos K, Boylan JE, Fildes R, Goodwin P (2009) The effects of integrating management judgement into intermittent demand forecasts. Int J Prod Econ 118:72–81
59. Thomassey S (2012) Sales forecasts in clothing industry – the key success factor of the supply chain management. Int J Prod Econ 128:470–483
60. Thomassey S, Fiordaliso A (2006) A hybrid sales forecasting system based on clustering and decision trees. Decis Support Syst 42(1):408–421
61. Thomassey S, Happiette M (2007) A neural clustering and classification system for sales forecasting of new apparel items. Appl Soft Comput 7(4):1177–1187
62. Thomassey S, Happiette M, Castelain JM (2005) A short and mean-term automatic forecasting system – application to textile logistics. Eur J Oper Res 161(1):275–284
63. Tsujino K, Nishida S (1995) Implementation and refinement of decision trees using neural networksTsujinoK for hybrid knowledge acquisition. Artif Intell Eng 9:265–275
64. Vaagen H, Wallace SW (2008) Product variety arising from hedging in the fashion supply chains. Int J Prod Econ 114(2):431–455
65. Vesanto J, Alhoniemi E (2000) Clustering of the self-organizing map. IEEE Trans Neural Netw 11(3):586–600
66. Winters PR (1960) Forecasting sales by exponential weighed moving averages. Manag Sci 6:324–342
67. Wong WK, Guo ZX (2010) A hybrid intelligent model for medium-term sales forecasting in fashion retail supply chains using extreme learning machine and harmony search algorithm. Int J Prod Econ 128(2):614–624
68. Xia M, Zhang Y, Weng L, Ye X (2012) Fashion retailing forecasting based on extreme learning machine with adaptive metrics of inputs. Knowl Based Syst 36:253–259
69. Yoo H, Pimmel RL (1999) Short-term load forecasting using a self-supervised adaptive neural network. IEEE Trans Power Syst 14(2):779–784
70. Zadeh LA (1994) Soft computing and fuzzy logic. IEEE Soft 11(6):48–56
71. Zhang X (2004) The impact of forecasting methods on the bullwhip effect. Int J Prod Econ 88:15–27
72. Zhou ZH, Jiang Y (2004) NeC4.5: neural ensemble based C4.5. IEEE Trans Knowl Data Eng 16(6):770–773
73. Zhao X, Xie J (2002) Forecasting errors and the value of information sharing in a supply chain. Int J Prod Res 40(2):311–335
74. Zhao X, Xie J, Lau RSM (2001) Improving the supply chain performance: use of forecasting models versus early order commitments. Int J Prod Res 39(17):3923–3939
75. Zhao X, Xie J, Leung J (2002) The impact of forecasting model selection on the value of information sharing in a supply chain. Eur J Oper Res 142(2):321–344
76. Zhou ZH, Wu J, Tang W (2002) Ensembling neural networks: many could be better than all. Artif Intell 137(1–2):239–263
77. Zhu Q, Qin A, Suganthan P, Huang G (2005) Evolutionary extreme learning machine. Pattern Recognit 38(10):1759–1763
78. Zhu X, Mukhopadhyay SK, Yue X (2011) Role of forecast effort on supply chain profitability under various information sharing scenarios. Int J Prod Econ 129(2):284–291

Springer

http://www.springer.com/978-3-642-39868-1

Intelligent Fashion Forecasting Systems: Models and Applications
Choi, T.-M.; Hui, C.-L.; Yu, Y. (Eds.)
2014, VIII, 194 p. 76 illus., 39 illus. in color., Hardcover
ISBN: 978-3-642-39868-1