Ann Oper Res (2017) 257:335–355
DOI 10.1007/s10479-016-2204-6

A Comparative Study on Fashion Demand Forecasting Models with Multiple Sources of Uncertainty

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Published online: 23 April 2016

Abstract Fast fashion is a timely, influential and well observed business strategy in the fashion retail industry. An effective fast fashion supply chain relies on quick and competent forecasts of highly volatile demand that involves multiple stock keeping units. However, there are multiple sources of uncertainty, such as market situation and rapid changes of the fashion trends, which makes demand forecasting more challenging. Therefore, it is crucial for the fast fashion companies to carefully select the right forecasting models to thrive and to succeed in this ever changing business environment. In this study, we first review a selected set of computational models which can be applied for fast fashion demand forecasting. We then perform a real sale data based computation analysis and discuss the strengths and weaknesses of these versatile models. Finally, we conduct a survey to learn about the perceived importance of different demand forecasting systems' features from the fashion industry. Finally, we rank the fast fashion demand forecasting systems using the AHP analysis and supplement with important insights on the preferences on the demand forecasting systems of different groups of fashion industry experts and supply chain practitioners.

Keywords Industrial applications · Uncertainty demand forecasting systems · Computational models · AHP analysis · Fast fashion · RFID

1 Introduction

In fashion industry, fast fashion is a timely, influential and well observed business strategy implemented and advocated by many international companies such as Zara, H&M and Uniqlo (Choi 2013a; Choi et al. 2014a). Fast fashion retailers tend to react promptly to the market preferences changes and offer the trendy products to satisfy customer needs. Since they have to quickly respond to the customer demand, the characteristics of products offered by fast

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fashion companies include (i) short product life cycle, (ii) relatively simple product design, and (iii) possessing high demand uncertainty (Choi et al. 2014a). There is no doubt that the fast fashion retailers face multiple sources of uncertainty. The primary uncertainty that impacts the fast fashion supply chain operations would be the ever-changing nature of fashion trends. In addition, the unpredictable economic situation also imposes another source of uncertainty to the fast fashion supply chain. In the presence of these sources of uncertainty, fast fashion companies have to find the optimal demand forecasting techniques to drive growth.

In fact, demand forecasting is a critical area in fast fashion business models. As we note from the prior discussion, fast fashion products are featured by a high level of demand uncertainty (as it relates to the ever changing fashion trend and consumer preference) and the fast fashion companies have to make their production, and inventory and assortment planning decisions based on their forecasts with a very short lead time (and hence, the real-time data-driven approach (Wang 2011) for forecasting operations are highly desirable). As a result, fast fashion companies have to conduct demand forecasting (i) for their products in a nearly "real time" basis (Wang 2011) using technological devices such as RFID (Choi and Sethi 2010; Gaukler 2011), (ii) for a wide variety of products, and (iii) with a limited amount of available data (because of the short selling season of the related demand data for forecasting). For instance, Zara is one of the pioneers in fast fashion retailing and is able to offer trendy fashion products from conceptual design to ready-to-sell merchandise at sales floor in just two weeks time (Ghemawat et al. 2003). Besides, it is also capable to provide two replenishment shipments to each worldwide store every week (Caro and Gallien 2010). In light of these highly challenging business operations, Zara changes its demand forecasting practice and adopts both forecasting and optimization models to streamline and simplify the entire processes. It is estimated that such innovative demand forecasting strategy can increase the sales performance by 3–4 % (approximately $353 million), reduce the number of transshipments among individual stores, but prolong the fashion item's display time on the sale floor (see Caro et al. 2010 for details). This case study shows that the uncertainties and the risks of the fast fashion industry drive the fashion retailers to conduct demand forecasting in a more analytical way, and the use of appropriate demand forecasting model helps to achieve a better financial performance and improve operations efficiency.

Existing studies also suggest that demand forecast updating plays a crucial role to facilitate the Quick Response Program (QRP) and generates a better inventory management for fashion products. QRP is a strategy in which the fashion retailers can postpone the ordering decision and improve the initial demand forecast based on more accurate market information (Iyer and Bergen 1997). Under QRP, they can react quickly to the market preference changes by shortening the lead time, mitigate the bullwhip effect, and improve the customer service (Choi and Sethi 2010). Cachon and Swinney (2011) study game theory and analytically compare the performance of the quick-response-only systems, enhanced-design-only systems, and traditional systems (in the absence of both enhanced design and quick response features) in the equilibrium. For the quick-response-only system, the fashion retailer is able to update the demand forecasting information and determine whether additional inventory procurement is needed. They find that both systems can help to reduce the strategic purchasing behavior of the customers and reduce end-of-season markdown in different ways. Besides, fashion retailers can launch the products that customers desire under the enhanced-design-only system while they can better match the supply and demand under the quick-response-only system. Interestingly, they also reveal when the fast fashion retailers incorporate both systems for inventory planning can generate a higher benefit than that of single system adoption. Extensive literature also examines different operation strategies under the QRP, such as global sourcing (Choi 2013b, c; Liu and Nagurney 2013) and order quantity constraint (Chow et al.

2012), with the information updating capability. To be specific, Choi (2013b) examines the sustainability issue in the fashion supply chain and analytically illustrates the design of a carbon footprint taxation scheme under the QRP. He derives the optimal decision on the sourcing strategy (i.e., local sourcing or offshore sourcing) with the consideration of a carbon footprint tax in both single-ordering and dual-ordering setting. Through a risk analysis study, he finds that the carbon footprint taxation scheme not only could motivate the fashion retailers to seek for a local manufacturer for production but also be benefited by a lower risk level. Liu and Nagurney (2013) consider a supply chain network and develop an equilibrium model for the case with global outsourcing and quick response production capability. They analyze the impact of the demand and cost uncertainty toward the optimal decisions for the supply chain with competition. Chow et al. (2012) study the impact of the minimum order quantity (MOQ) requirement toward each supply chain member and address that the MOQ constraint can obstruct the information updating capability in the quick response system. Therefore, they propose a dynamic MOQ scheme that can coordinate the supply chain with Pareto improvement. To effectively capture the market information and customer preference for demand forecast updating, it is indispensable to adopt information technology. One of the well-discussed technologies is the Radio Frequency Identification (RFID) system (Zhu et al. 2012). RFID is an information system that transmits data automatically in real-time basis via the radio signals (Sarac et al. 2010). This system is now implemented by many renowned fashion retailers such as Zara, Marks and Spencer, and American Apparel to increase the inventory visibility (Chan 2016). Fashion retailers believe that the RFID system allows them to conduct fashion trends analysis and they can better cope with the highly volatile demand (Moon and Ngai 2008). Besides, with the ability of tracking the inventory level and capturing customer demand data at the retail shop floor, the RFID system can assist retailers in generating a better forecasting result (Lee and Özer 2007). For instance, Chan et al. (2015) propose facilitating the QRP with the support of the RFID system. In their model, they consider executing the RFID system to collect the demand information and then use it to update the forecasted demand determined at the preliminary stage. This approach can improve the forecast accuracy and better match the customer preference.

Recently, numerous studies also examine the impact of demand forecasting bias and information sharing on the supply chain performance. For instance, Zhu et al. (2011) examine the optimal pricing and forecasting accuracy (in terms of forecast variance) for different scenarios with a Stackelberg game model. Serel (2013) considers that the fashion retailers have two opportunities to place order with different wholesales prices before the selling season starts for determining the optimal inventory decision. The coarse demand forecast is adopted in the first order while the Bayesian theory is used to update the initial demand forecast. The model is extended to discuss the issues such as random purchase cost order cancellation, limited budget, and multiple products. Wang et al. (2013) assume the retailer has a demand forecasting bias and study its impact toward the optimal pricing and quality investment decision in the fashion supply chain. They also compare the optimal decision and address the supply chain coordination between the profit-loss sharing contract and traditional revenue sharing contract in the presence of forecasting bias. Interestingly, Xue et al. (2015) investigate a situation that the supplier can choose the time for selling the products (i.e., either before the production starts or after the production completion), and the retailers have their own private market demand information at the beginning of the selling season. They study three cases in which (i) there is only one retailer, (ii) there are multiple competing retailers with information sharing, and (iii) retailers are competing without information sharing; and explore how these cases affect the selling strategy of the supplier. Yang et al. (2015) consider that the manufacturer has private operational cost information of the equipment component and reserves the capacity of the component from the supplier prior to the final order. In their model, they analyze how the demand forecast accuracy affects the optimal decision on the reservation pricing strategy of the supplier in the fashion supply chain.

The above literature review shows that existing studies propose different measures for the fashion retailers to improve forecasting demand. Since the demand forecasting decision making processes is critical for fast fashion, in this study, we first review the recently published studies which employ scientifically sound analytical models to develop demand forecasting for fast fashion. We then systematically divide the review into different sub-sections with respect to the methods employed, perform a real sale data based computation analysis and discuss the strengths and weaknesses of these versatile models. Besides, we conduct an industrial survey to investigate the practitioners' preference towards demand forecasting systems. Finally, we rank the fast fashion demand forecasting systems using the AHP analysis and supplement with important insights on the preferences on the demand forecasting systems of different groups of fashion industry experts and supply chain practitioners.

It is noted that this study is not the only one that examines and reviews demand forecasting models for the fashion industry. The other related reviews include Choi et al. (2011), Liu et al. (2013), Nenni et al. (2013), and Thomassey (2014). However, this study aims to add value to this subject area and differs from the above studies because: (i) It reviews the specific advanced analytical models and conducts an analysis on their particular strengths and weaknesses, (ii) it focuses solely on the models that can be applied in fast fashion industry and hence emphasizes functional aspects on forecasting speed, data requirements, ease to use, etc, in addition to forecasting accuracy, and (iii) it aims to explore industry practitioner's preference for demand forecasting systems by conducting an industrial survey. To the best of our knowledge, this study is the first paper which specifically examines the analytical models for fast fashion demand forecasting in the presence of multiple sources of uncertainty. It is also the first paper which conducts industrial surveys and analyzes the practitioners' preference towards different criteria of the fast fashion demand forecasting systems. The findings generate significant insights to both practitioners and academicians.

The rest of this paper is organized as follows. Section 2 presents the detailed literature review of fast fashion demand forecasting models. Section 3 analyzes the strengths and weaknesses of the reviewed fast fashion demand forecasting models. Section 4 discusses the industrial survey and analysis. Section 5 concludes the paper with a discussion of future research direction.

2 Analytical forecasting models: a review

In this section, we examine various popular and important models for conducting fast fashion demand forecasting. Our discussion is based on their specific modeling characteristics.

2.1 Statistical panel-data based models

The classical approach for fashion products' demand forecasting starts by analyzing the product features (Nenni et al. 2013), and then determining the forecasting approach. In fast fashion, the time period of forecasting is critically important, and hence, a quick forecasting approach is more desirable. Being quick, intuitive and easy to apply, time-series based statistical methods such as Auto Regression Integrated Moving Average (ARIMA) and Seasonal Auto Regression Integrated Moving Average (SARIMA) approaches are commonly used for quick demand forecasting. Both ARIMA and SARIMA based models are well-examined by Box et al. (2011), Liu et al. (2013), and Thomassey (2014). However, the use of these time-series based methods is insufficient because demand of fashion products depends on other factors, such as price and other correlated products' demands. Based on this argument, recently, Ren et al. (2015) conduct a panel data analysis for time-series demand forecasting in fashion industry. Their model basically employs the popular panel data regression method in which multiple items' demand as well as other critically important factors (such as selling price) are incorporated into the time series forecasting model. The following is a review of the specific model.

First of all, they represent the demand of fashion product i at time interval t, by D_{it}:

$$D_{it} = L_{it} + NL_{it}, \tag{2.1}$$

where L_{it} represents the linear component of demand D_{it}, and NL_{it} denotes the nonlinear part. Under the panel data analysis, Ren et al. (2015) represent L_{it} as a linear function of the previous time period's linear component of demand D_{it-1} and the product selling price P_{it} as follows:

$$L_{it} = K_i + \gamma D_{it-1} + \beta P_{it} + \varepsilon_{it}, \tag{2.2}$$

where K_i is a constant and it is product item dependent, and ε_{it} is the white noise which is normally distributed with a constant variance and zero mean.

Conducting demand forecasting using the panel data model as shown in (2.1) and (2.2) above can incorporate (i) the demand correlation across multiple products, and (ii) the respective product selling price, into the forecasting process. This "pure panel-data (PPD)" method expectedly helps to provide more sophisticated and accurate demand forecast than the simple time-series based statistical methods such as ARIMA and SARIMA.

In Ren et al. (2015), they further explore a forecasting method called panel data particle-filter (PDPF) to have a forecasting on the non-linear part, i.e. NL_{it}. For the PDPF, they employ the well-known particle filter to help to predict NL_{it} and the final forecasting is done by combining the forecasted results on both L_{it} and NL_{it}. Based on real-data computational experiments, they report that both the PPD and the PDPF methods outperform the traditional statistical methods. They also show that increasing the amount of historical data does not necessarily improve forecasting accuracy under the PDPF. They hence propose that the PDPF method is suitable for conducting quick demand forecasting for fashion products with limited data available. This fits the requirements of fast fashion forecasting very well.

2.2 Extreme learning machines

Another popular set of forecasting models for predicting fashion product's demand is artificial neural networks (ANN) (Choi et al. 2014b; Banica et al. 2014; Hamzaçebi et al. 2009). It is well-known that even a simple ANN would take a substantial amount of time to complete a forecasting task (e.g., it may take several minutes, and evolutionary neural networks (ENN) may take hours (Au et al. 2008)). The long computational time becomes a major hurdle for the deployment of many ANN and ENN based forecasting models in real world fast fashion demand forecasting. Relatively recently, there is a proposal of a fast single-hidden layer feed-forward neural network (SLFN) called the extreme learning machine (ELM) (Sun et al. 2007, 2008; Hsu and Wang 2007; Huang et al. 2006; Rong et al. 2008; Xia et al. 2012). ELM is able to learn much faster than many conventional gradient-based learning methods that are reported in the classical neural networks literature. To the best of our knowledge, Sun et al. (2008) is the first study which applies ELM in conducting fashion demand forecasting. Yu et al. (2011) further include both ELM and traditional statistical measurement to develop a fast forecasting model for fashionable products. In the following, we review this pioneering demand forecasting model. For more details about the detailed illustrations and figures, please refer to Sun et al. (2008).

As we mentioned above, the ELM is an SLFN with the inputs of variables x_{ij}. By its nature, it randomly assigns the input weight matrix $\mathbf{W}$, and analytically determines the output weight matrix $\boldsymbol{\beta}$. To be specific, suppose that we want to train the "SLFN" of the ELM with K hidden neurons and an activation function vector $\mathbf{g}(x) = (g_1(x), g_2(x), \ldots, g_K(x))$ to learn from N distinct samples (x_i, t_i), where $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in R_n$ and $t_i = [t_{i1}, t_{i2}, \ldots, t_{im}]^T \in R_m$. If the SLFN in the ELM can approximate these N samples with a zero error, then we have $\sum_{j=1}^{N} ||\mathbf{y}_j - \mathbf{t}_j|| = 0$, where $\mathbf{y}$ is the SLFN's output.

In the ELM, the parameters $\boldsymbol{\beta}_i$, $\mathbf{w}_i$ and $\mathbf{b}_i$ satisfy the following equations:

$$\sum_{i=1}^{K} \boldsymbol{\beta}_i g_i(\mathbf{w}_i \cdot \mathbf{x}_j + b_i) = \mathbf{t}_j,\ j = 1, \ldots, N,$$

where $\boldsymbol{\beta}_i = [\beta_{i1}, \ldots, \beta_{im}]^T, i = 1, \ldots, K$ links the ith hidden neuron and the output neurons, $\mathbf{w}_i = [w_{i1}, \ldots, w_{in}]^T$ is the weight vector linking the ith hidden neuron and the input neurons, and b_i is the ith hidden neuron's threshold.

Note that in the ELM, by default, the input weights and hidden biases are all randomly generated instead of tuned. As a result, we can determine the output weights by finding the least-square solution to the given linear system of equations.

To employ ELM in fast fashion demand forecasting, from Sun et al. (2008), we have the following steps:

Step 1 Procure the demand data, and select the factors that have significant effects on the product demand as the inputs of ELM; note that the statistical analysis conducted in Ren et al. (2015) can be used to identify the factors which have significant effects on demand;
Step 2 With the given dataset, divide the data into training data, testing data, and forecasting data sets randomly. Normalize the training data and the testing data, and select the activation function of hidden neuron and choose the neuron number of hidden layer of ELM;
Step 3 Input training data and testing data, compute the outputs of ELM, un-normalize the outputs, then obtain the predicted demand time series of the training data and the testing data;
Step 4 Based on the input and output weights obtained by Steps 2 and 3 above, compute the predicted demand time series and the corresponding predicting error.

As a remark, even though ELM runs much faster than the classical ANNs and ENNs, it still requires a certain amount of time to complete the demand forecasting task and a sufficient amount of data for training in order to yield good demand forecasting results.

2.3 Grey models

To conduct time-series demand forecasting with insufficient historical data, the grey method (GM) provides a good framework (Choi et al. 2012; Hsu and Wang 2007; Chen and Ou 2009; Lei and Feng 2012; Lin and Lee 2007; Li and Xie 2014; Wang 2014; Xia and Wong 2014). The GM is derived from the systems science literature which proposes that a system often faces uncertainty, and it is often difficult, if not impossible, to classify the system purely as "black" or "white". Thus, based on this argument, Deng (1989) defines a system which has both "known" and "unknown" information as a grey system.

In the analytical model, the GM is usually represented by GM (l, k), where l is the order of differential equations employed, and k is the number of variables in the GM. Note that the simplest yet the most commonly used GM is GM (1,1), which is called the single-variable first-order grey model (SFGM) (Choi et al. 2012; Li and Xie 2014; Li et al. 2011). In Choi et al. (2012), the SFGM is used to conduct time-series forecasting for fashion demand. We review their analytical model as follows:

First, in the time series analysis by using SFGM, the original demand time series is represented by $X^0 = [x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)]$, where $x^{(0)}(i)$ is the demand data point of time series at time $i (i = 1, 2, \ldots, n)$. With X^0, we can get a new "aggregated demand time series" X^1 by the following simple operation:

$$X^1 = \left[x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\right], \text{ and } x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i). \tag{2.3}$$

Under the SFGM based demand forecasting method, the forecasting of X^1 at time k, given by $\hat{x}^{(1)}(k)$, can be derived using the method by Deng (1989), and the forecasted future demand value of X^0 at time $k + 1$ can be found by the following:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k). \tag{2.4}$$

Undoubtedly, the SFGM is a simple and easy to apply forecasting method. Together with other GM based methods, it is suitable for conducting time series demand forecasting with few historical data (which is commonly the case in fast fashion business operations). Thus, the GM is a good candidate with which one can develop fast fashion demand forecasting applications. However, the SFGM and other GM based methods are known to be unreliable. This is especially true for those time series which are highly volatile.

3 Analysis and comparisons

In Sect. 2, we discuss and review the recent and advanced analytical demand forecasting models that can be applied for conducting demand forecasting in fast fashion. In this section, we evaluate their performances in terms of the accuracy, speed, data sufficiency requirements, stability, and ease of use and other related parameters.

3.1 Accuracy

First of all, the most critical measure to compare the forecasting performance is accuracy (Yokuma and Armstrong 1995). From the prior studies reported by Ren et al. (2015), the forecasting accuracy results for ARIMA, ELM, and PPD are included in Table 1. For a fair and a scientific comparison among the models, we collect real sales data from a Hong Kong fashion boutique for analysis. To be specific, this set of data refers to six different kinds of fashion apparel items sold in a fashion boutique in Hong Kong. Since Ren et al. (2015) do not consider and analyze the performance of GM, we conduct a new analysis and also measure the forecast accuracy by mean squared error (MSE) and symmetric mean absolute percentage error (SMAPE). From Table 1, we can see that PPD has the smallest MSE and SMAPE among the models. Therefore, in terms of accuracy, PPD performs the best, followed by ELM and ARIMA, whereas GM performs the worst.

Table 1 Computational results of forecast accuracy among models

Item	ARIMA		GM		ELM		PPD	
	MSE	SMAPE	MSE	SMAPE	MSE	SMAPE	MSE	SMAPE
1	62.8	9.8	154.2	20.2	86.9	12.4	64.5	10.6
2	3.4	29.8	4.0	35.6	4.8	40.1	3.0	27.4
3	18.1	44.9	1.6	23.4	3.9	40.3	1.0	17.4
4	19.6	16.1	44.5	28.1	19.1	15.1	13.1	10.8
5	4.8	42.8	5.9	55.4	4.0	38.4	3.3	30.3
6	2.4	48.3	2.8	56.7	2.5	41.4	1.8	34.4
Mean	18.9	32.0	35.5	36.6	20.2	31.3	14.5	21.8

3.2 Speed

It has to be noted that all these methods are known to yield forecasting result in a timely manner and hence they are “fast”. While if we go deeper in terms of how fast each method performs, we can observe that in terms of speed, PPD and ARIMA are all the fastest (in seconds) because they are statistical methods. ELM and GM are also fast but definitely not as fast as ARIMA and PPD.

3.3 Data sufficiency requirements (DSR)

Regarding the data requirements, some methods have a higher requirement on the data sufficiency than the others. For example, ELM needs to have sufficient data for demand forecasting so as to achieve a good performance. Interestingly, PPD, ARIMA, and GM have much less demand for having substantial amount of data because: (i) For PPD, the panel-data puts a higher emphasis on correlation related information. Thus, there is not necessary to have many historical data of each item in forecasting; (ii) For ARIMA, it is the simplest and can be applied even if the number of data points are very little. (iii) For GM, it is known to be functional in the absence of enough data.

3.4 Stability

For stability of forecasting results, the case is rather clear. First of all, PPD and ARIMA can generate stable and reliable forecasting results as they are purely statistical methods (Ren et al. 2015). However, ELM and GM have several shortcomings such as yielding unstable forecasting results. Thus, PPD and ARIMA based demand forecasting models have high stability whereas ELM and GM have a low stability.

3.5 Ease of use and other related parameters

For the issue on whether the forecasting model is easy to use and implement, we find that ARIMA requires only simple analytical closed-form relationship to conduct forecasting and PPD requires only the basic regression of the available panel data. Both of these can be done automatically by many commercial software packages. Thus, ARIMA and PPD are the easiest models to be implemented and used in practice. For ELM and GM, they all can conduct demand forecasting in an automatic way after implementing the respective algorithms. Thus,

Table 2 Comparison of the reviewed models

Methods	Five factors				
	Speed	DSR	Stability	Ease of use	Accuracy
ARIMA	Fastest	Low	High	Easiest, intuitive	Medium
GM	Fast	Low	Low	Easy	Lowest
ELM	Fast	High	Low	Easy	Medium
PPD	Fastest	Low	High	Easiest, intuitive	Highest

they are also easy to use from that sense but are still less easy to use compared to ARIMA and PPD.

From the above discussion, we examine the performance of different demand forecasting models in terms of accuracy, speed, DSR, stability, and ease of use. As a summary, Table 2 shows the item-to-item systematic comparison among the reviewed fast fashion demand forecasting models.

4 Industrial survey and AHP analysis

In Sect. 3, we review and compare the performances of the demand forecasting models in terms of accuracy, speed, data sufficiency requirements, stability and ease of use. Among those forecasting models, it is interesting to determine which one is the most appropriate for demand forecasting from the industrialists' point of views. This is because they may have distinct priority and concern toward those five factors when selecting the model for forecasting products with different features or targeted market. Hence, by conducting an industrial survey, it can help to identify the best forecasting model systematically. In this section, we further examine how the individual decision makers perceive the importance level of each performance factor and rank those four demand forecasting systems. Firstly, a survey is conducted to analyze the perception from industrialists in the fashion industry regarding the importance of those five factors discussed in Sect. 3 (see Table 2). Next, a multiple criteria decision-making analysis is conducted and the performance of each analytical demand forecasting model is evaluated. Finally, the preferences of different groups of decision makers are analyzed followed by a discussion of the insights.

4.1 Analytic hierarchy process (AHP) analysis

A multiple criteria decision-making method, called AHP, is popularly used in the literature to measure the criteria applied in decision theory, conflict resolution and models (Vargas 1990). It can help assistant managers in making sound decisions by ranking alternatives (Golden et al. 1989). In this sub-section, we compare the four demand forecasting systems, i.e., ARIMA, ELM, GM and PPD, with respect to different evaluating criteria by using AHP analysis. To facilitate this multiple criteria decision-making, we develop an AHP structure which consists of three levels, namely, 'goal', 'criteria' and 'alternative' levels as shown in Fig. 1.

Figure 1 shows that our goal is to determine the best model with the consideration of multiple criteria and alternatives. For each criterion, we conduct an industrial survey to obtain the weighted average to indicate the relative importance (such as the work by Kaya et al. 2014). This survey is conducted through a convenience sampling method and all the

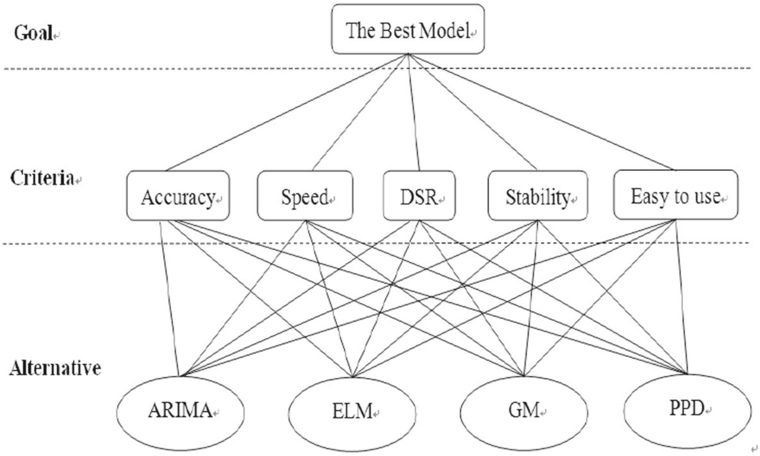

Fig. 1 The AHP structure

Table 3 Weights of forecasting performance in criteria level

Criteria	Accuracy	Speed	DSR	Stability	Ease of use
Weight	0.213	0.188	0.195	0.208	0.196

respondents have working experience in the fashion industry. In total, 123 questionnaires are collected and 114 of them are valid. Based on the collected data, we then calculate the weighted average of each forecasting performance criterion, w_j where j denotes the criteria. The results are summarized in Table 3. In Table 3, the larger the value of the weighted average, the higher the perceived importance level of the criteria. Therefore, we find that the respondents perceive "accuracy" is the most important criteria, following are stability, ease of use, DSR, and speed, respectively.

In order to study the preferences of different respondents, we further sort the collected data into different groups according to the respondents' position (i.e., manager and operator), product feature (i.e., fashionable product and basic product) and targeted market (i.e., high-end market and mass market) of the respondents' companies. The weighted average (i.e., relative importance) of each forecasting performance criterion with respect to different groups and categories are shown in Table 4. Table 4 illustrates that accuracy is the most important forecasting performance criterion (among those five criteria) no matter the forecasting model is used by which position group of users, used for forecasting which product or used in which targeted market. This finding is intuitive and consistent with the study by Thomassey (2014).

Table 4 Weights of forecasting performance in different groups

Group	Category	Accuracy	Speed	DSR	Stability	Ease of use
Position	Manager	0.212	0.189	0.196	0.204	0.199
	Operator	0.215	0.188	0.194	0.209	0.194
Product	Fashion	0.216	0.194	0.190	0.205	0.195
	Basic	0.212	0.183	0.199	0.210	0.196
Market	High-end	0.217	0.191	0.191	0.210	0.191
	Mass	0.213	0.186	0.196	0.207	0.198

Table 5 The fundamental scale

Intensity of importance	Definition
1	Very unimportant
2	Unimportant
3	Neutral
4	Important
5	Very important

Regarding the alternatives, the comparative forecasting performance of each method with respect to different criteria is measured by "experts", according to the scale listed in Table 5. The pairwise comparisons among forecasting models reveal the performance on how one is superior to others for each criterion in the 'criteria' level. Thus, five 4×4 matrices of judgments are developed as there are five elements in 'criteria' level, and four forecasting models undergo pairwise comparison under each criterion. The comparison matrices together with priority vectors are shown in Tables 6, 7, 8, 9 and 10. The calculating process of priority vectors follows Saaty (1990). To give a better overview, we lay out the priorities in Table 11. Since the above judgment matrices are obtained by pairwise comparison, the consistency in each matrix should be further checked (Wang et al. 2005). Consistency ratio (CR) is a commonly used method to determine and examine the inconsistency in pairwise comparison matrix given by the respondents. Saaty (1994) studies and sets a series of rules for acceptable

Table 6 Accuracy

Models	ARIMA	GM	ELM	Panel data	Priority vector
ARIMA	1	3/1	3/5	3/5	0.214
GM	1/3	1	1/5	1/5	0.072
ELM	5/3	5/1	1	5/5	0.357
Panel data	5/3	5/1	5/5	1	0.357

Table 7 Speed

Models	ARIMA	GM	ELM	Panel data	Priority vector
ARIMA	1	5/3	5/3	5/5	0.3125
GM	3/5	1	3/3	3/5	0.1875
ELM	3/5	3/3	1	3/5	0.1875
Panel data	5/5	5/3	5/3	1	0.3125

Table 8 DSR

Models	ARIMA	GM	ELM	Panel data	Priority vector
ARIMA	1	3/1	3/5	3/3	0.250
GM	1/3	1	1/5	1/3	0.083
ELM	5/3	5/1	1	5/3	0.417
Panel data	3/3	3/1	3/5	1	0.250

Table 9 Stability

Models	ARIMA	GM	ELM	Panel data	Priority vector
ARIMA	1	5/3	5/1	5/5	0.357
GM	3/5	1	3/1	3/5	0.214
ELM	1/5	1/3	1	1/5	0.072
Panel data	5/5	5/3	5/1	1	0.357

Table 10 Ease of use

Models	ARIMA	GM	ELM	Panel data	Priority vector
ARIMA	1	5/1	5/1	5/5	0.417
GM	1/5	1	1/1	1/5	0.083
ELM	1/5	1/1	1	1/5	0.083
Panel data	5/5	5/1	5/1	1	0.417

Table 11 Consistency checking results of judgment matrix

Criteria	λ_{max}	Consistency index	Consistency ratio	Consistent?
Accuracy	4.008	0.0027	0.030 (< 0.08)	Yes
Speed	3.873	−0.0423	−0.047 (< 0.08)	Yes
DSR	3.830	−0.0570	−0.063 (< 0.08)	Yes
Stability	3.863	−0.0456	−0.137 (< 0.08)	Yes
Ease of use	3.992	−0.0027	−0.003 (< 0.08)	Yes

CR values in which CR < 0.05 for 3×3 matrix; CR < 0.08 for 4×4 matrix and CR < 0.1 for much larger matrix. Table 11 summarizes the consistency checking results for each criterion. It is found that the judgment matrix of each criterion is consistent.

After obtaining the weight of each criterion in the 'criteria' level and the priority of each forecasting model in the 'alternative' level, we calculate the relative contribution of each forecasting model with respect to the perceived importance of the performance criteria form the perceptive of the supply chain practitioners. Combining the weighting in the 'criteria' level (in Table 3) and the priority in the 'alternative' level (in Table 12), the relative contribution of each model is obtained in Table 13. For different sorting groups, the calculating process is the same as above and the relative contribution of each forecasting model is shown in Table 14.

Table 12 Weights of the forecasting models

Criteria	ARIMA	GM	ELM	Panel data
Accuracy	0.2140	0.0720	0.3570	0.3570
Speed	0.3570	0.2140	0.0720	0.3570
DSR	0.2500	0.0830	0.4170	0.2500
Stability	0.3125	0.1875	0.1875	0.3125
Ease of use	0.4170	0.0830	0.0830	0.4170

Table 13 Relative contribution of each forecasting model

Category	ARIMA	GM	ELM	PPD
Overall	0.312	0.119	0.226	0.343

Table 14 Relative contribution of each forecasting model for different groups

Category	ARIMA	GM	ELM	PPD
Manager	0.3130	0.1195	0.2276	0.3399
Operator	0.3089	0.1186	0.2249	0.3476
Fashion	0.3106	0.1199	0.2266	0.3429
Basic	0.3098	0.1189	0.2295	0.3418
High-end market	0.3102	0.1197	0.2278	0.3423
Mass market	0.3108	0.1197	0.2273	0.3422

Table 13 shows that the PPD forecasting model has the highest contribution (with the consideration of the performance criteria of model's accuracy, speed, data sufficiency requirements, stability, and ease of use), followed by ARIMA, ELM, and GM. From Table 14, same finding is also observed when the forecasting tool is used by different position users (i.e., manager/operator), for predicting the demands of different kind of product features (i.e., fashionable/basic products) or for different targeted market (i.e., high-end/mass market). Therefore, by analyzing both the models' performances and the decision makers' preference, we find that PPD is the most promising and versatile one that can be used by different users, for various product features and in different targeted markets in the fashion industry.

4.2 Further analysis

After examining the relative contribution of each forecasting model, we further conduct a statistical test analysis using the Statistical Package for the Social Sciences (SPSS) software to study the relationships between the forecasting performance criteria and explore how decision makers evaluate these forecasting models.

4.2.1 Correlations of forecasting criteria

Table 15 summarizes the correlation test results. It indicates that when decision makers rank the importance of each forecasting criterion, there are significant correlations between different criteria. For example, there is a significant positive correlation between the perceived

Table 15 Correlation test results

	Accuracy	Speed	DSR	Stability	Ease of use
Accuracy	1	0.360**	0.415**	0.407**	0.167
Speed	0.360**	1	0.440**	0.495**	0.557**
DSR	0.415**	0.440**	1	0.481**	0.304**
Stability	0.407**	0.495**	0.481**	1	0.508**
Ease to use	0.167	0.557**	0.304**	0.508**	1

** Correlation is significant at the 0.01 level (2-tailed) importance of forecasting model's "accuracy" and "speed". In order words, decision makers desire to have a more accurate forecasting result together with a faster computation speed (i.e., without sacrificing the time for getting the forecasting result). However, such relationship is insignificant between the perceived importance of forecasting model's "accuracy" and "ease of use".

4.2.2 Comparison analysis

Next, we investigate whether there is any difference of the perceived importance of the performance criteria of each sorting groups (i.e., respondents' position, product feature and targeted market groups). We compare the average importance of each forecasting criterion graded by the respondents and the results are illustrated in Figs. 2, 3, and 4.

From Fig. 2, we find that for both the managers (senior position) and the operators (junior position) perceive the criterion "accuracy" as the most critical one among all five criteria. Interestingly, "speed" is treated as the least important one. From Fig. 3, "DSR" is revealed as the least important criterion for the practitioners working in the fashion companies selling highly fashionable items, whereas "speed" is treated as the least important criterion for the practitioners working in the fashion companies selling basic items. This difference can be explained by the fact that for the fashion companies selling highly fashionable items, they

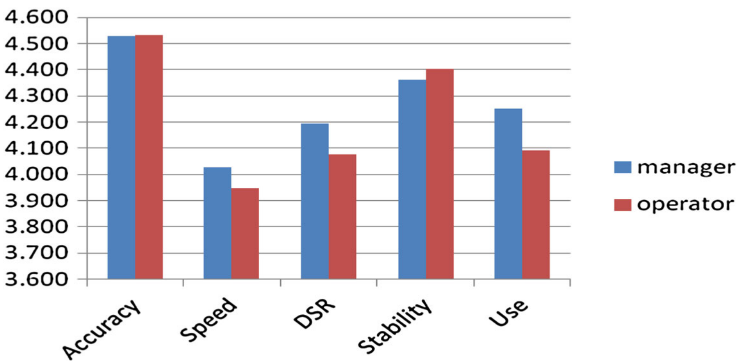

Fig. 2 Average importance of each criterion in respondents' position group

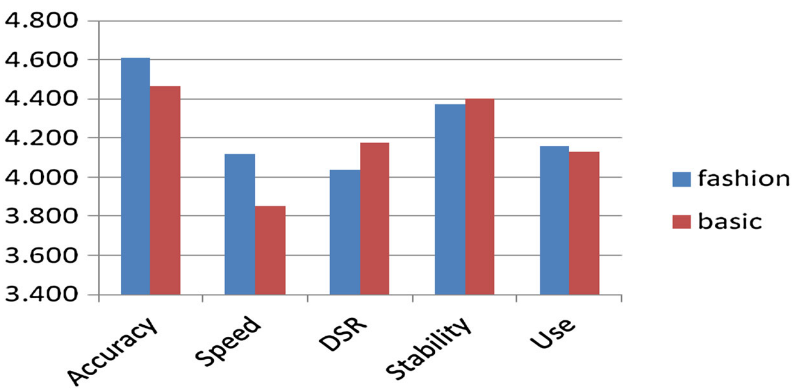

Fig. 3 Average importance of each criterion in product feature group

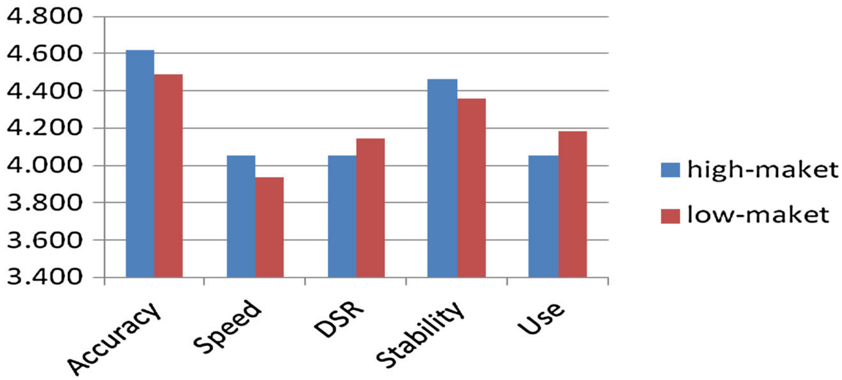

Fig. 4 Average importance of each criterion in targeted market group

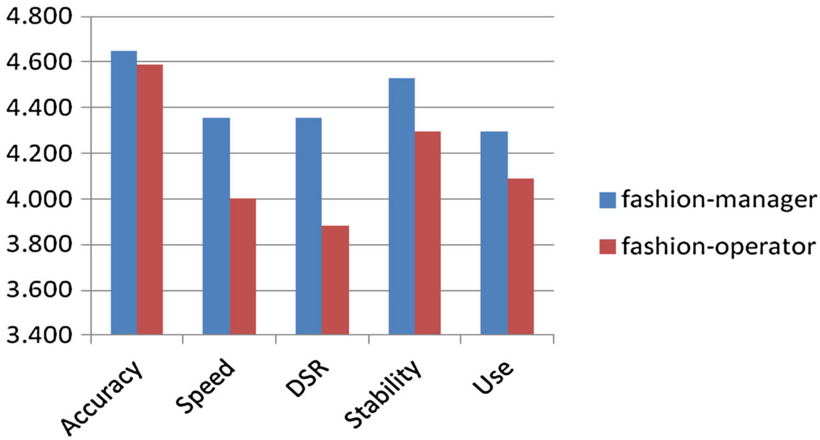

Fig. 5 Average importance of each criterion given by decision makers from fashion companies selling fashionable products

naturally have to forecast the demand in the absence of data as the fashionable products have very short product lives. Similar to the cases reported above, "accuracy" is still the most important criterion for both the "fashion" and "basic" groups of companies. It is interesting to note from Fig. 4 that the practitioners working in the high-end market fashion companies treat "DSR" and "speed" as the least important factors, whereas the practitioners working in the mass market fashion companies treat "speed" as the least important factor. Based on the above discussion, we find that "accuracy" is the most important criterion for demand forecasting from the practitioners' perspectives while "speed" and "DSR" are relatively unimportant.

As a remark, from Fig. 2, we also observe that the "priority sequence" of the perceived importance of the performance criteria from the manager's perspective is the same as those operator's (i.e., accuracy is the most important criterion, followed by stability, ease of use, data sufficiency requirements, and speed). We then proceed further and divide them with respect to the product features and yield Figs. 5 and 6.

Figure 6 indicates that the average importance scores towards each criterion for both the managers and the operators from the fashion companies selling basic products are very close. However, from Fig. 5, it is clear to observe that the average importance scores of each

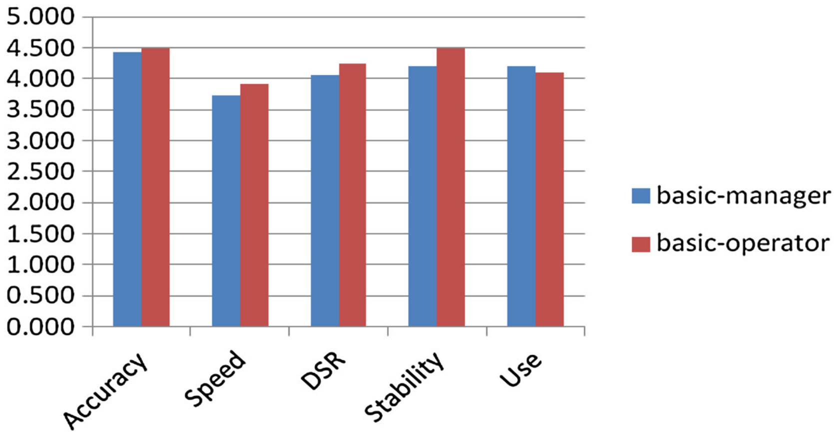

Fig. 6 Average importance of each criterion given by deicsion makers from fashion companies selling basic products

criterion are totally different between the managers and the operators, given that they work in the fashion companies selling highly fashionable products. To be specific, for the companies selling highly fashionable products, the operators perceive that the forecasting "speed" and "DSR" are not as important as the other criteria, while the managers concern more about these two criteria than operators when evaluating the performance of demand forecasting systems.

After comparing the preferences of managers and operators who work in the fashion companies selling different kinds of products, we further investigate the perceived performance of forecasting models by managers and operators from fashion companies with different target markets. The average importance given by managers and operators from the fashion companies targeting high-end market and mass market (i.e., low-end market) is illustrated in Figs. 7 and 8, respectively. Similar with companies selling fashion products, Fig. 7 indicates that managers and operators in high-end market companies have differently preference on 'speed' and 'DSR'. Specifically, managers concern more about these two factors than oper-

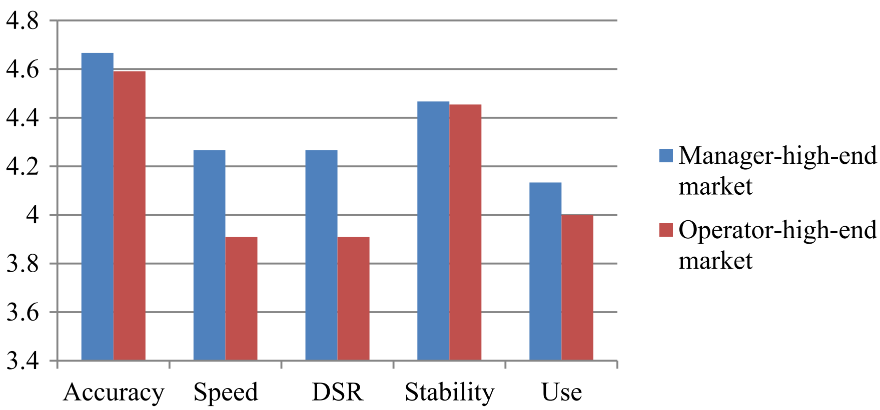

Fig. 7 Average importance of each criterion given by decision makers from fashion companies targeting at high-end market

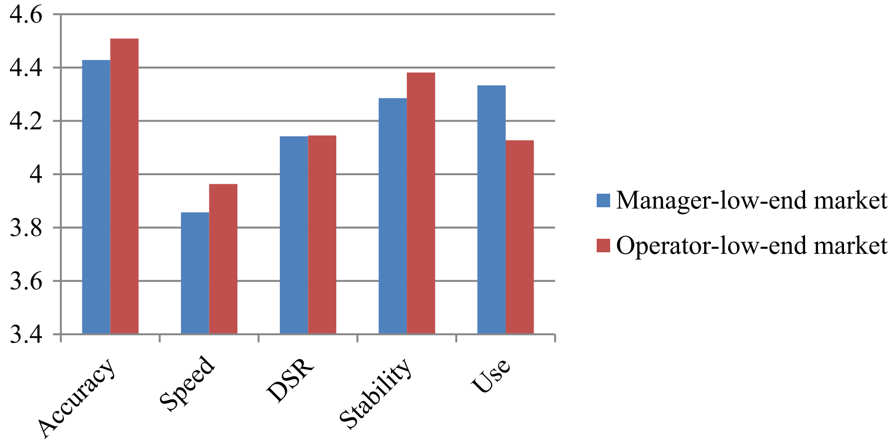

Fig. 8 Average importance of each criterion given by decision makers from fashion companies targeting at low-end market

ators when evaluating the forecasting performance of different methods. However, in mass market companies as demonstrated in Fig. 8, their preference almost shows no difference.

5 Concluding remarks, limitations and future research

In this study, we review a carefully selected set of computational models which can be applied for fast fashion demand forecasting, conduct a real sale data based computational analysis, and discuss the strengths and weaknesses of these versatile models. Followed by an industrial survey, we collect the perceived importance from industrialists towards different features of demand forecasting systems. Finally, we conduct an AHP analysis to provide the ranking of the fast fashion demand forecasting systems as well as reveal insights regarding the preferences of different groups of fashion industrialists. On the whole, we have the following findings:

(i) In general, “accuracy” is the most important criterion when employing a demand forecasting system and the pure panel-data (PPD) is the best system for forecasting the fast fashion products;
(ii) There is a significant positive correlation between the perceived importances of the performance criteria, however, such relationship is insignificant between the perceived importance of “accuracy” and “ease of use”;
(iii) The perceived importance of forecasting performance criteria is different between the managers and the operators for the companies selling highly fashionable or basic products. In particular, for the companies selling highly fashionable products, operators perceive that the forecasting “speed” and “data sufficiency requirements” are relatively less important, however, the managers value these two criteria much more when evaluating the performance of the demand forecasting system; and
(iv) The perceived importance of forecasting performance criteria shows a clear difference between the managers and the operators for the companies that target in the high-end markets. Specifically, managers perceive that ‘speed’ and ‘data sufficiency requirements’ are more important criteria than operators.

This study has some limitations. First, we review four analytical forecasting models only; namely, ARIMA, GM, ELM, and PPD. In addition to that, we evaluate the performance of the demand forecasting models based on five different factors, that is, accuracy, speed, data sufficiency requirements, stability, and ease of use. Finally, we conduct statistical tests with limited data in which a larger sample size is more preferable.

In the future, this study can be extended to explore the optimal decision for inventory management with dynamic demand forecasting. For instance, Lu et al. (2006) investigates a periodic review inventory model with the martingale model of forecast evolution while Iida and Zipkin (2006) study both additive and multiplicative forecast update. Besides, we can also consider developing optimization models for inventory distribution and allocation of a supply chain network with the application of the demand forecasting models to update the initial demand prediction. Caro and Gallien (2007) and Caro and Gallien (2010) provide an excellent reference on this topic. It is also interesting to investigate the value of information and the corresponding supply chain coordination achievement. For example, Li et al. (2014) find that supply chain coordination can be achieved with the help of a return policy under information asymmetry. Ai et al. (2012) consider two competing supply chains and the information can be shared through a revenue sharing contract to achieve supply chain coordination. Ryu et al. (2009) address the information sharing through the planned demand transferring method (PDTM), and the forecasted demand distributing method (FDDM). Even though the RFID technology can help to collect the demand information for improving the demand forecasting, however, limited studies analytically address this issue. For example, Chan et al. (2015) explore when RFID system outperforms the bar-coding system for inventory management and suggest implement it to improve the initial demand forecasting under the QRP with one ordering opportunity in their model. In the future, we can go deeper to investigate the dual-ordering supply chain setting. Last but not least, we can further explore a fashion supply chain with collaborative forecasting in which each supply chain member contributes to the demand forecast updating (such as Aviv 2001), and compare the supply chain performance among different forecasting models (Mostard et al. 2011). Ho and Choi (2014) also provide an excellent reference for collaborative planning and forecasting in fashion supply chain management.

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