Journal of Intelligent & Fuzzy Systems 31 (2016) 825–836
DOI:10.3233/JIFS-169014
IOS Press

Product life cycle based demand forecasting by using artificial bee colony algorithm optimized two-stage polynomial fitting

Liu Yue[a,*], Ju Wangwei[a], Zhao Jianguo[a], Gao Junjun[b], Zheng Jiazhou[b] and Jiang Aiping[b]
[a]*School of Computer Engineering & Science, Shanghai University, Baoshan District, Shanghai, China*
[b]*Sydney Institute of Language and Commerce, Shanghai University, Jiading District, Shanghai, China*

Abstract. Demand forecasting is one of the most essential components of supply chain management, which directly influences a company's overall performance and competitiveness. However, it is difficult to accurately forecast the demand of fashion products with short life cycle and high volatility characteristics such as footwear and apparel products. An integrated demand forecasting method named Improved ABC-PF is proposed in this paper based on Product Life Cycle (PLC) theory considering the characteristics of fashion products. First, a PLC model based on cubic polynomial which is divided into two stages by the best-selling point, is established instead of traditional PLC modeling methods. Second, an improved Artificial Bee Colony (ABC) algorithm is utilized to optimize the parameters of the two-stage PLC function, which is conducted by initial population selection, optimization function design and convergence rate improvement. After that, an inventory control strategy based on PLC analysis is studied and applied in the "Precise Order" mode. Finally, the proposed method is validated by real-world data from a Chinese footwear and apparel retailer. After being compared with the other demand forecasting methods such as Moving Average (MA), Support Vector Machine (SVM) and Radial Basis Function Neural Network (RBFNN), it is indicated that the proposed improved ABC-PF method can achieve higher prediction accuracy and lower safety inventory level, which improve the overall profitability of the company, therefore generate product demand management insights for footwear and apparel enterprises.

Keywords: Demand forecasting, product life cycle, artificial bee colony algorithm

1. Introduction

Demand forecasting is the basic component of supply chain management and product planning decision, which has a direct impact on companies' inventory level, profit ability and market competitiveness. Accurate demand forecasting is practical and necessary for real-world applications [1]. However, demand forecasting for fashion products such as shoes and clothing is very difficult due to their specific demand characteristics. Firstly, the life cycle of a footwear and apparel product usually lasts for only 2-3 months, which causes relative lower stability in demand sequence. Secondly, the fashion goods market may also be influenced by the market capacity since the popular trends always change very fast. Thirdly, the values of the fashion products have connections with some other random factors such as public events, seasons, holiday, and consumer preferences. Therefore, it is hard to perfectly match the supply-side with the demand-side. For those reasons, the suppliers and manufacturers are reluctant to bear the inventory risk which is caused by uncertainty demand fluctuations. Actually, from the perspective

*Corresponding author. L. Yue, School of Computer Engineering & Science, Shanghai University, 99 Shangda Road, Baoshan District, Shanghai 200444, China. Tel.: +86 138 1773 7563; E-mail: yliu@staff.shu.edu.cn.

of operation management, inventory overstocks and inaccurate replenishment can be seen as the major problems. The key of solving those bottleneck problems is accurate demand forecasting.

The traditional demand forecasting methods supposed that the product demand is stable and its historical experience is repeatable. However, the demands of footwear and apparel products are usually not stable which make the traditional methods encounter the problems of low accuracy and delay. Therefore, the demand forecasting for footwear and apparel products is mainly based on machine learning method, which can discover knowledge by analyzing data automatically to make predictions. Recently, a lot of works focus on developing novel demand forecasting models based on machine learning for footwear and apparel products. For example, Kin-Fan et al. [2] employed an evolutionary computation and neural network method to forecast the sales of an apparel store. Zhan-Li Sun et al. [3] used extreme learning machine to predict the demand of a fashion retailer. Ni et al. [4] proposed a two stage dynamic sales forecasting model based on neural network to conduct long-term and short-term predictions. Zhang et al. [5] processed the affecting factors such as season, climate conditions, price, gender etc. by using the fuzzy theory firstly and then proposed a LS-SVM dynamic demand forecasting model. Choi et al. [6] proposed a hybrid forecasting scheme which combines the classic SARIMA method and wavelet transform (SW). In summary, these researches mainly focus on applying or combining machine learning method with multiple technologies to demand forecasting. They usually build demand forecasting model based on historical sales data, and then use the obtained model to predict the future sales. However, these methods cannot be directly applied to the demand forecasting of fashion products. At first, the life cycle of footwear and apparel products is usually very short, and the sales are easily influenced by fashion, seasonal, consumer preferences and other random factors, which cause great variations on the sales data in different years. Secondly, the real-world data shows that different phases of Product Life Cycle (PLC) will affect the market demand of the product. However, the current demand forecasting methods based on machine learning for footwear & apparel products did not take the PLC characteristic into consideration.

PLC theory was proposed by Raymond Vernon in 1966 [7] and has been used as a strategic empirical model to guide the product market analysis and planning. Rink, David R. and J.E. Swan [8] listed 12 common types of PLC curves, such as wind, fashion and scallop type life cycle curves, these studies indicate that the PLC theory has entered into a quantitative research stage. Subsequently, Klepper [9] proposed the Klepper model which explained the regularities regarding the relationship within industries between firm size and firm innovative effort, innovative productivity, cost, and profitability. On the basis of the PLC theory, scholars have gradually applied the product life cycle characteristic for demand forecasting. PLC function is the core of demand forecasting, which mainly includes three types: logistic, bass and polynomial function. The logistic function is an econometric model, and is most widely used in PLC fitting. Ying et al. [10] analyzed the PLC fitted by a logistic model and pointed out that the environment constrains are the key influence factors. Accordingly, these solutions are aimed to seek opportunities and break up the market barrier by innovations. Bass function [11] is a diffusion model of integrated internal and external influences, which is based on the analysis of new product diffusion mechanism. Seol et al. [12] proposed a new approach based on bass model towards demand forecasting for new services such as Internet protocol TV (IPTV). In this method, historical data and competitive relationships with existing services are not necessary. Guo [13] synthesized the prevailing innovation diffusion and the NLBCU theory to provide a distinct, dynamic and endogenous perspective, which focus on consumer purchasing behavior across the entire PLC. Some literatures used polynomial function to fit the PLC curve for demand forecasting. Polynomial fitting (PF) is the process of constructing a curve based on polynomial which has the best fit goodness with the data point series. This model can fit the multiple nonlinear relationships between the value of $x_1, x_2, \ldots, x_n$ and the corresponding conditional mean of y by polynomial function. Moreover, PF is a common used method for regression analysis, which has been applied to describe nonlinear phenomena, such as the price of stock [14]. Comparing with the above three main life-cycle functions, polynomial has the best fitting accuracy for PLC modeling. Since the sales data of footwear or apparel products present a form of discrete nonlinear, it is suitable to use the PF method for these fashion products.

The major shortcoming of the PF method is that the model parameters are difficult to be determined. In some forecasting systems, the parameters are optimized by optimization algorithms such as

Genetic-Algorithm (GA) [15, 16], which can improve the prediction accuracy to a certain extent. Artificial Bee Colony (ABC) is a swarm based meta-heuristic algorithm proposed by Karaboga et al. [17]. It simulates the intelligent foraging behavior of the honey bees and has the advantages of simple operation, less control parameters, high search precision and strong robustness [18, 19]. The algorithm can also be used to identify a high quality optimal solution and find the balance between complexity and performance. Moreover, the ABC algorithm is usually used to optimize numerical problems and achieves better performance than the other algorithm such as genetic algorithm (GA), particle swarm optimization (PSO) algorithm and differential evolution (DE) algorithm. Feyza et al. [20] used ABC algorithm to predict the electricity energy consumption of Turkey and the obtained results were satisfactory. Hsieh et al. [21] proposed a new integrated prediction model which combined recurrent neural network with ABC algorithm for stock market forecasting and obtained a satisfactory predictive performance. In addition, Shah et al. [22] proved that ABC algorithm can improve the accuracy for earthquake prediction while using multilayer perceptron (MLP). Once ABC algorithm is applied to the regression model for optimizing curve fitting, it can further improve the accuracy of demand forecasting.

Our research group [23] approached the demand forecasting problem by using wavelet transform and ABC algorithm for optimized polynomial fitting, and proposed a demand forecasting method named ABC-PF for footwear and apparel products. However, the ABC-PF can be only used to predict the demand of the footwear or apparel product in the decline stage. In the real world, the footwear and apparel retailers prefer to know the exact demand of the products in all the stages of the life cycle. Therefore, this paper proposes a novel demand forecasting method based on PLC analysis by using ABC algorithm optimized two-stage polynomial fitting (named Improved ABC-PF) to predict the product demand in the whole PLC. First, a two-stage PLC model composed of two cubic polynomial functions is developed to simulate the PLC curves. Secondly, the ABC algorithm is optimized from three aspects including the selection of the initial population, the design of the optimization function, and the improvement of the convergence rate, and then utilized to optimize the parameters of the PLC functions. Furthermore, an inventory control strategy based on PLC analysis is studied and applied in the "Precise Order" mode. Finally, the real-world evaluation on a Chinese footwear and apparel retailer is executed.

The remainder of this paper is organized as follows: Section 2 describes the problem of demand forecasting and the basic assumptions. Section 3 introduces the main idea and technology of the Improved ABC-PF method. Section 4 presents the experiment results and compares the proposed method to previous approaches. Finally, conclusions are drawn in Section 5.

2. Problem description and basic assumptions

The product life cycle represents the period between the footwear or apparel product's first launch date into the market and its final withdrawal date. This cycle is split into four different stages which encompass the introduction stage, the growth stage, the maturity stage, and the decline stage [8], as is shown in Fig. 1.

The solid line and the dotted line respectively represent the total sales and profits. Four stages of the whole life cycle is a continuous process and display a single wave. The peak of the wave is called the best-selling point. The shape of the sales curve of a footwear or apparel product is very similar in adjacent years although the sales amounts may be different. Therefore, the curve fitting method is appropriate for simulating the whole sales curve of the footwear and apparel products. Then, we can predict the future sales and the sales in each stage according to the simulated sales curve. The predicted sales information will provide the manufacturers important tips about the operations, such as ordering, replenishment, inventory management and new product launch.

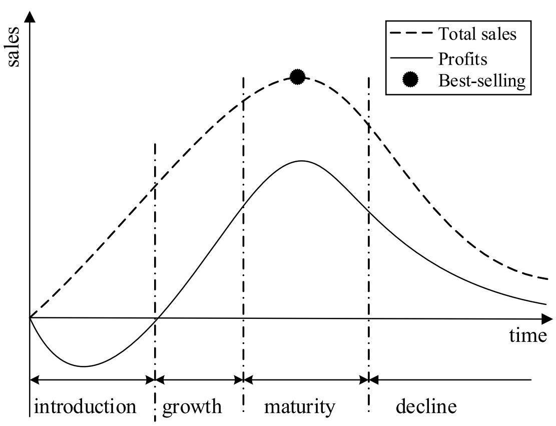

Fig. 1. The life cycle curve.

Before the further study, some assumptions should be proposed before using the Improved ABC-PF and it can be summarized as follows.

Assumption 1. Footwear and apparel products demand is uncertain and related to the PLC.

Assumption 2. The life cycle of a certain footwear or apparel product can be divided into four stages, the introduction stage, the growth stage, the maturity stage and the decline stage. The division of each stage is associated with demand growth.

Assumption 3. The basic unit cannot be subdivided as the footwear or apparel category is not a key variable.

Assumption 4. The length of sale season is T weeks.

3. Methodology

The demand forecasting method namely Improved ABC-PF has been proposed in this paper under the **Assumption** 1–4. It mainly includes four processes: (1) Modeling the whole PLC by the two-stage method which is based on cubic polynomial function; (2) Applying an improved ABC algorithm to optimize the demand learning model; (3) Forecasting sales by the Improved ABC-PF model; (4) Conducting inventory control via PLC analysis.

3.1. The two-stage PLC model based on cubic polynomial function

After comparing the features of PLC functions including logistic, bass and cubic polynomial, we can reach the following conclusions.

Logistic function can ideally fit the real data, especially in the case of the long-life-cycle product. Bass function takes the internal and external influences into consideration, which can be applied to more scenarios that of the logistic function. Comparing with the logistic and Bass, the cubic polynomial is more flexible, which can fit different kinds of PLC curve, and more suitable in the situation that the product has shorter life cycle. Since the demand of footwear and apparel products are not stable and usually with short life cycle character, cubic polynomial is chosen as the PLC function in this study, which is extended to, and a two-stage cubic polynomial model. In this model, the PLC function is divided into two stages by the best-selling point: the first stage is mainly used to fit the life cycle from the introduction stage to maturity stage, and the second stage works from the maturity stage to decline stage.

We assumes that the 2-tuple set (T_j, S_j) denotes the sales data of category j in store i, and then the two-stage PLC function is defined as Equation (1).

$$f(t) = \begin{cases} a_1 + b_1t^1 + c_1t^2 + d_1t^3 (1 \leq t \leq t^*) \\ a_2 + b_2t^1 + c_2t^2 + d_2t^3 (t^* < t \leq T) \end{cases} \tag{1}$$

where the vector $P_1 = [a_1, b_1, c_1, d_1]$ and $P_2 = [a_2, b_2, c_2, d_2]$ represent the cubic parameters of the first stage and the second stage, respectively. t^* is the intersections of the first stage and the second stage, which represents the local maxima in the maturity stage.

The PLC function is satisfied with the Equation (2) base on the theory of least square.

$$Q_{ij} = \min\left(\sum_{t=0}^{T_{ij}} [s_{ijt} - f_{ij}(t)]^2\right) \tag{2}$$

where Q_{ij} denotes the sum of squares errors between the sales of category i in shop j and the predicted sales.

3.2. The optimal demand learning model based on ABC algorithm

As it can be seen in Equation (1), there are several parameters need to be determined, which directly impact the performance of the demand learning model. In order to obtain the optimal model, an improved ABC algorithm is proposed to optimize the parameters of cubic polynomial. The improved ABC algorithm consists of three aspects: the initial population selection, the optimization function design, and the convergence rate improvement. The details of the Improved ABC algorithm are described in the following subsections.

3.2.1. The initialization of populations according to the parameters of the life cycle function

The population initialization is very important in ABC algorithm, which also affects the convergence rate and optimal results. Usually, the initialize populations are determined randomly if there is no useful priori information. Reasonable range of initial values will speed up the convergence and improve the stability. Although the PLCs of the same product category in different years are not strictly equal, they generally changes about 10 to 30 percent on the existing basis. Therefore, in order to reduce the optimum search space and promote the convergence rate, we set an updating fluctuation rate which has brief definitions as below.

Definition 1. The updating fluctuation rate r is a variable which is used to restraint the change range of parameters vector P. Given the initial values of the parameters vector P_0, the search space of the optimal values P will be reduced to the range of $[P_0 * (1 - r), P_0 * (1 + r)]$.

3.2.2. The designing of the optimization function

The optimization function is designed to estimate the state of each bee independently, so as to search for the optimal life cycle function parameters vector. The optimization function has a significant impact on building the life cycle learning model. The new optimal values of the parameters are close relative to the recent sales data which indicate the new change of the demand. Here, we define a new parameter to represent the impact of the recent sales data on the life cycle.

Definition 2. The recent sales width ω is the time interval between the current week and the former weeks, which related to the change of the product life cycles.

In ABC algorithm, the sum of square error between the prediction value and practical sales volumes is used as the optimizing object function Equation (3).

$$f(P) = \frac{1}{\omega} \sum_{t=0}^{\omega} \left| PX_{ijt} - s_{ijt} \right|^2 \tag{3}$$

where the PX_{ijt} denotes the predict sales, and S_{ijt} is the real sales.

3.2.3. The optimized ABC algorithm based on vector searching

Although the ABC algorithm has the better optimize performance compared with that of other optimal algorithms, but it usually has low convergent rate and is easily fall into “premature”. Several researchers have improved the ABC algorithm focus on the onlooker bee’s position updating. The updating strategy is shown in Equation (4).

$$x_{ij}(t+1) = \theta_{ij}(t) + \phi \left(\theta_{ij}(t) - \theta_{kj}(t) \right) \tag{4}$$

where x_i denotes the position of the onlooker bee, t is the iteration number. θ_k is the employed bee which is chosen randomly. j represents the dimension of the parameters vector. The function ϕ represents a series of random variable in the range –1 to 1, which has strong randomness. Although the function ϕ guarantees the diversity of swam, but it reduces the rate of convergence.

In order to improve the convergent rate and the stability of the ABC algorithm, this paper redefined the function ϕ to a vector, and divided the variable range into two parts as Equation (5).

$$\phi = \begin{cases} [-1, 0] & F(\theta_{ij}(t)) - F(\theta_{kj}(t)) > 0 \\ [0, 1] & \text{other} \end{cases} \tag{5}$$

And then a new strategy for the onlooker position updating of is defined as Equation (6).

$$x_{ij}(t+1) = \theta_{ij}(t) + \phi * \left| \theta_{ij}(t) - \theta_{kj}(t) \right| \tag{6}$$

The chosen neighborhood pollen source S_k is estimated at the first. If the fitness value $F(\theta(t)$ is greater than the current source of pollen S_k, then the onlooker bee moves to the source of pollen S_k according to the Equation (6); otherwise, it moves to the opposite direction.

3.2.4. Demand learning based on the optimized ABC algorithm

The core algorithm of the Improved ABC-PF algorithm applied for the demand learning method is to use the improved ABC algorithm optimize the parameters of the two-stage cubic polynomial model, and its detail steps are described as follows.

Step 1: Learn from the history sales data by the PLC function $Y = f(t, P)$, and obtain the PLC demand learning model, where t is the time series and P is the parameters vector.

Step 2: Forecast the demand from week 1 to ω by using the PLC model $Y_w = f(t, P)$.

Step 3: Repeat learning from week $w + 1$ to T by using the Improved ABC-PF algorithm. The detail of the Improved ABC-PF algorithm is described as follows.

Step 3.1: Initialize the populations according to the updating fluctuation rate r, where the populations belong to the rang of $[P(1 - r), P(1 + r)]$.
Step 3.2: The employed bees look for the pollen source, and record it when the fitness value is bigger than that of the current pollen. The fitness value is calculated by $f(P) = \frac{1}{\omega} \sum_{t=0}^{\omega} \left| PX_{ijt} - s_{ijt} \right|^2$.

Step 3.3: The onlooker bee selects the pollen according to $P_i = \frac{F(\theta_i)}{\sum_{k=1}^{S} F(\theta_k)}$, and updates the position by the improved strategy Equation (5).
Step 3.4: If the pollen reaches the iterate condition, the scout bee looks for the new pollen and records it.
Step 3.5: If the iteration times reach the limits, skip to Step 4; otherwise, skip to Step 3.2.

Step 4: If the product exits the market, end; otherwise, skip to the Step 3.

3.3. *The application of the improved ABC-PF method in the inventory control decision*

With the market competition and the electronic commerce network channels development, "precise order" is employed by more and more enterprises in recent years. In this study, we applied the Improved ABC-PF method to "precise order" pattern for demand forecasting and inventory control decision.

3.3.1. *The "precise order" pattern for footwear and apparel products*

"Precise order" refers to determine the purchase quantity considering store sales data, display space capacity, district characteristics, industry conditions and other factors. The research focus of the industry is to control the inventory from the starting point, reduce the risk of inventory, and promote the order fill rate.

In real world applications, the process of planning and production for the footwear and apparel products are illustrated in Fig. 2. The product planning should be done 9 to 10 months in advance before the sales season while the product design should be completed 8 to 9 months in advance. The order-placing meeting should be held 6 to 7 months in advance before production. The production should be finished 0–4 months ahead.

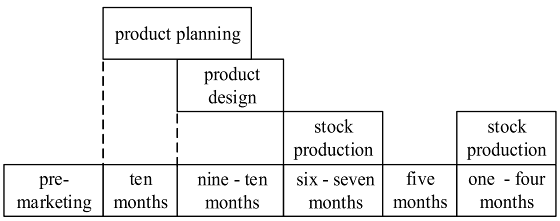

Fig. 2. The planning and production process of footwear and apparel products.

The general process of "Precise order" patterns can be described as follows. Firstly, people who in charge of selling would attend the meeting for the placement of orders before the sales season. Secondly, the order occupies 50% of the sales, and the remaining 50% orders will be completed in the following sales season. Lastly, the order in sales season is addressed by small batch replenishment, and each companies place orders every week. It may cost 14∼20 days to deliver the orders to retail stores. In this paper, we unified set that the delivery process costs 14 days.

3.3.2. *The steps of the application*

According to the general process of "Precise order" pattern, the application of the Improved ABC-PF demand forecasting method can be divided into 5 steps.

Step 1: Predict the sales of the product by using the two-stage cubic polynomial function before putting it to the market. The 50% of the predicted sales are pre-ordered and the rest can be purchased by small batch replenishment.

Step 2: Learn the demands from the recent sales data by using the Improved ABC-PF algorithm after the product being put to the market and predict the demands of the next three weeks.

Step 3: Determine to replenish or not. It depends on the comparison result between the predicted demand in step 2 and the current inventory level. If the inventory level is lower than the predicted demand, then an order will be placed and the quantity is the difference between the predicted demand and the current inventory.

Step 4: Calculate the current inventory level after the order arrives in two weeks later.

Step 5: Go to step 2 if the specific product's life cycle is not completed.

4. Experiments

4.1. *Experiment setup*

4.1.1. *The experimental dataset*

A footwear and apparels company headquartering in Quanzhou, Fujian, China, is taken as the empirical example. The company is a leading PRC-based fashion sportswear brand enterprise. It principally engages in the design, development, manufacture, distribution and marketing, as well as brand management of sports footwear, apparel and accessories products. The company has set up an extensive distribution network, which contains more than 7,000 retail outlets nationwide through exclusive distributors and their franchisees cover 31 provinces, autonomous regions and municipalities across the country.

In our experiments, a typical flagship store in Hangzhou city called JFL which occupies an area of 110 square meters is selected as the example store. The experimental data includes 7669 sales records of the cotton-padded clothes from 2010 to 2012. After analysis, the whole sales data showing a complete life cycle and it is suitable for building the demand forecasting model. For each method, we use the sales data in 2010 to 2011 as the training data for model building, and use the sales data in 2011 to 2012 as the testing data to evaluate the obtained model.

4.1.2. Traditional demand forecasting methods used for comparisons

In order to validate the effectiveness of the Improved ABC-PF, several traditional demand forecasting methods such as moving average (MA), support vector machine (SVM) and radial basis function neural net-work (RBFNN) are also used in this study.

Moving Average (MA). MA is a trend-following and lagging indicator because it is based on past prices. The two basic and commonly used MAs are the simple moving average (SMA) and the exponential moving average (EMA). The former is the simple average of a security over a defined number of time periods. The later gives bigger weight to more recent prices [24]. The most common application of MAs is to identify the following trend and determine support and resistance levels. MAs also form the basis for other indicators such as the Moving Average Convergence Divergence (MACD).

Support Vector Machine (SVM). SVM constructs a hyper plane or set of hyperplanes in a high or infinite dimensional space, which can be used for classification, regression, or other tasks [25]. Intuitively, a good separation is achieved by the hype plane which has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the margin is larger, the generalization error-rate of the classifier will be lower. Furthermore, the kernel technology let the SVM can be good to deal with the nonlinear dataset in the classification and regression problems.

Radial Basis Function Neural Network (RBFNN). The RBFNN is a forward network model with good performance and global approximation, and is free from the local minima problems [26]. It is a multi-input and single-output system, which consists an input layer, a hidden layer, and an output layer. During the data processing, the hidden layer performs nonlinear transforms for the feature extraction and the output layer produces a linear combination of output weights.

All these comparison algorithms are implemented by MATLAB R2009a. The cubic polynomial curve fitting functions POLYFIT and polynomial evaluation function POLYVAL in MATLAB toolbox are used in the two-stage PLC modeling. LibSVM toolkit is used for SVM, which is developed by Professor Lin [27]. RBFNN is provided by the Neural Network Toolbox for MATLAB. ABC algorithm is implemented by Karaboga [17]. The proposed algorithm, which contains vector search, the Improved ABC-PF algorithm, the calculation of error, safety stock and gross profit are implemented by author in this paper.

4.1.3. The evaluation metrics

The commonly used metrics for the demand forecasting methods evaluation are as follows: (1) Mean Absolute Deviation (MAD); (2) Root Mean Square Error (RMSE); (3) Mean Absolute Percentage Error (MAPE); (4) Absolute Percentage Error (APE). They are defined as Equations (7–10) respectively.

$$MAD = \frac{1}{T}\sum_{t=1}^{T}\left|y'_{ijt} - s_{ijt}\right| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(y'_{ijt} - s_{ijt}\right)^2} \tag{8}$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\frac{\left|y'_{ijt} - s_{ijt}\right|}{s_{ijt}} \tag{9}$$

$$APE = \frac{\left|y'_{ijt} - s_{ijt}\right|}{s_{ijt}} \tag{10}$$

In addition, the safety stock, the total inventory cost, and the total gross profit are also used as the evaluation indexes in order to demonstrate the effectiveness of the Improved ABC-PF in "Precise Order" pattern.

The safety stock of product j at moment t is defined as Equation (11).

$$ss_{jt} = k_j \cdot MAD_{jt} \tag{11}$$

where MAD_{jt} is the average absolute deviation of the demand forecasting of product j at first t cycles. It is shown in Equation (12).

$$MAD_{jt} = \frac{1}{t}\sum_{i=1}^{t}\left|y'_{ij} - s_{ij}\right| \tag{12}$$

where k_j is the safety stock factor of product j, S_{ij} is the whole demand in PLC and y'_{ij} is the predict value.

Combining economic order batch model with the "precise order" mode, the total inventory cost is formulated as Equation (13).

$$TIC = UC * Q + RC * N + HC * Q * T/2 \\ + UL * Q + UB * Q \tag{13}$$

where TIC is the total inventory cost, UC is the unit cost, RC is the reorder cost, N is the quantity of order, HC is the cost of carrying inventory, UL is the unit cost of shortage and UB is the unit cost of backlog.

Moreover, we formulate the total gross profit as Equation (14).

$$TGP = AS * AUP - TIC \tag{14}$$

where TGP denotes the total gross profit, AS presents the actual sales, AUP is the average unit price and TIC is the total inventory cost.

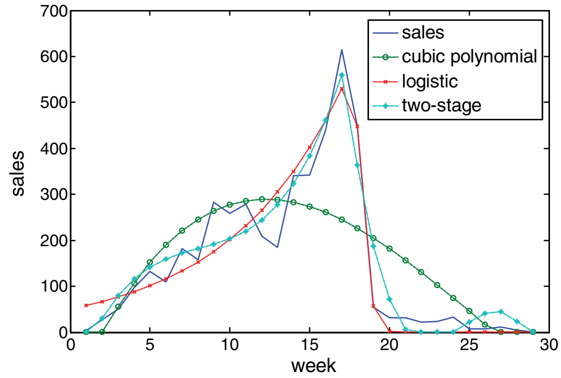

Fig. 3. The PLC curves fitted by the different methods.

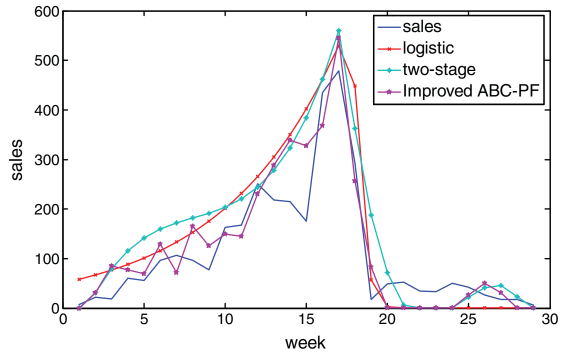

Fig. 4. The predicted demands by the different methods.

4.2. Experimental steps, results and analysis

4.2.1. Validation experiments on the improved ABC-PF model

Firstly, in order to validate the effectiveness of the two stage PLC function, a two-stage cubic polynomial model is built and compared with the other two kinds of PLC functions such as the cubic polynomial function and the logistic function. The experimental results are shown in Fig. 3.

Figure 3 shows that the cubic polynomial model got the worst result compared with the logistic function and the two-stage cubic polynomial. But it is obvious that the logistic function cannot depict the local peaks in the life cycle such as the peaks at the tenth and fifth week. The main reason is that logistic function is a fixed formula and lack of flexibility. The proposed two-stage cubic polynomial model can overcome the shortcomings of cubic polynomial and logistic function, which can reduce the sensitivity of the saw tooth data and handle the great variation of sales data. With the changes of the PLC curve, the curve of the two-stage cubic polynomial model is more close to the actual curve.

Secondly, the optimized ABC algorithm is employed to improve the performance of the two-stage cubic polynomial model. The parameters of the ABC algorithm are as follows, $\omega = 2$, $r = 0.2$. The experiment results are shown in Fig. 4. It can be found that the Improved ABC-PF capture the variations of the demand and fit the sales' curve perfectly. Especially, it can describe accurately the sales at the local peaks.

Thirdly, the two-stage cubic polynomial model and the Improved ABC-PF model are applied to the "precise order". The experiments are repeated ten times. Assuming that the retailer's target service level is 98%, the safety stock factor equals 2.56. The values of the other parameters are configured as: $UC = 100$, $RC = 300$, $HC = 0.4$, $UL = 50$, $UB = 12$, $T = 28$ while the average unit price is 180.

The results are listed in Table 1. The Improved ABC-PF has a higher prediction accuracy rate than that of the two-stage cubic polynomial model. In addition, the RMSE and MAPE of the Improved ABC-PF are reduced by 25.37%, 24.43% and

Table 1
The prediction results of the two-stage cubic polynomial model and the Improved ABC-PF model in "precise order" pattern

Method	Two-stage cubic polynomial model	Improved ABC-PF
Metric		
MAD	56.3	42.0
RMSE	73.4	55.5
MAPE	49.8%	37.1%
Safety Inventory	144	113
Order Number	3548	3394
Order Quantity	5	5
Inventory Level	1055	991
Stockout Quantity	0	0
Overstock Inventory	268	114
Total Inventory Cost	365427.1	347819.5
Real Sales	3280	3280
Total gross profit	224972.9	242580.6

25.38%, respectively. The safety stock and the total inventory cost reduced 31 and 17607.63, respectively, and the total gross margin increased 17607.63. With the comparison of the Improved ABC-PF model and the two-stage cubic polynomial model, the former can not only help the demand forecasting model make a progress in prediction accuracy but also decrease the inventory cost and improve the gross profit.

4.2.2. *Optimizing the parameters of the improved ABC-PF model*

As the prediction accuracy is affected by the recent sales width ω and the updating fluctuation rate r. The two-dimensional grid is used to select the best combination of ω and r. Set $\omega \in [1, 5]$ and $r \in [0.1, 0.5]$, the experimental results of error contour lines are shown in Fig. 5. It can be observed that the influence on the future sales by the former sales cannot be reflected when ω is too low. Meanwhile, the prediction accuracy is also impacted by the updating fluctuation rate r. When r is high, it is easy to deviate from the PLC curve; When r is low, the result is limited to the PLC curve. We found the forecasting results are relatively stable when ω belongs to [2, 4] with r in [0.2, 0.3].

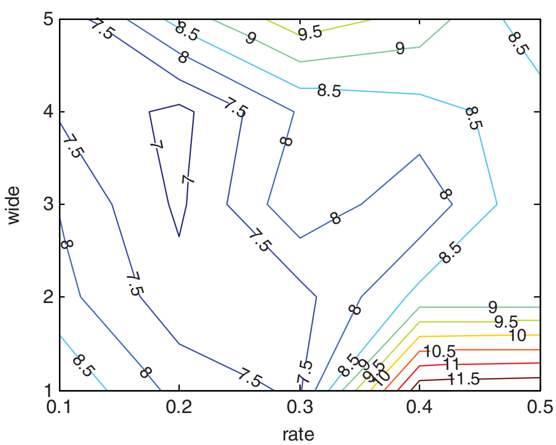

Fig. 5. The error contour lines of the Improved ABC-PF algorithm.

4.2.3. *Comparing the prediction results with the other demand forecasting methods*

In order to verify the effectiveness of the Improved ABC-PF method, we set up four groups of experiments and compare the prediction result of the Improved ABC-PF method with that of MA, SVM, and RBFNN.

After some trial and error experiments, the window width of MA is determined to 2, which is equal to the time window width of RBFNN. In all the four methods, the sales data from t to $(t + w)$ week is chosen as the training dataset to build the demand forecasting model. And then the sales data in $(t + w + 1)$ week is used for testing. The parameter settings detail of each method is provided in Table 2, where the kernel of SVM and RBFNN are all choose the radial basis kernel function and their parameters are determined by grid search method. After the parameters determined, four groups of experiments are carried out.

As it can be seen in Fig. 6, the Improved ABC-PF obtains the lowest MAD and RMSE than that of the other three methods. We also find that the Improved ABC-PF is superior to MA and SVM when MAPE is the evaluation index in Fig. 7, but the Improved ABC-PF doesn't work better than that of the RBFNN. The main reason is the Improved ABC-PF's poor performance in the introduction stage and the decline stage. Especially, the MAPE of SVM prediction result is apparently on the high side and even up to 129%.

Table 2
Parameter settings for each demand forecasting methods

Improved ABC-PF					MA	SVM			RBFNN	
PF	Improved ABC				Moving window	Penalty coefficient C	Kernel function	Gamma	Gamma	The number of nodes of the hidden layer
z	r	ω	Cycle times	Limit times						
3	0.2	2	1000	100	2	11.3	RBF	2	0.01	3

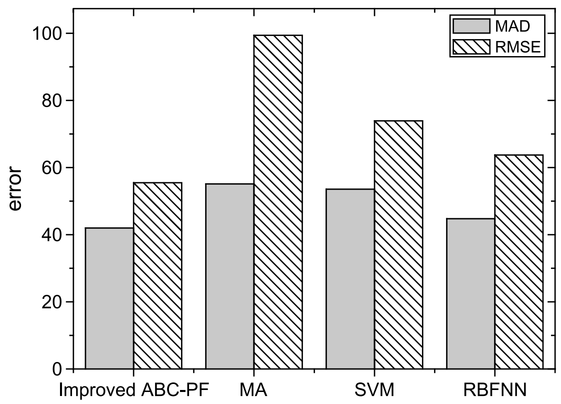

Fig. 6. The MAD and RMSE of the four different algorithms in demand forecasting.

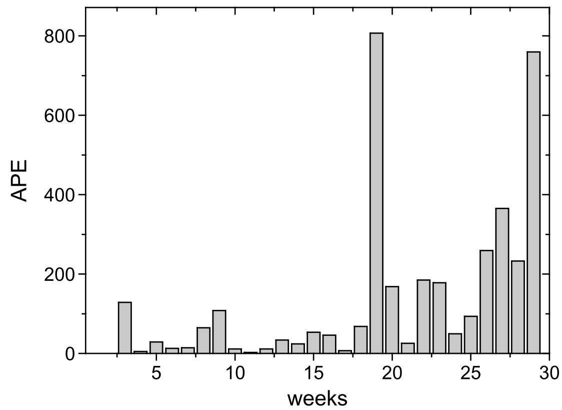

Fig. 8. The APE of each prediction points.

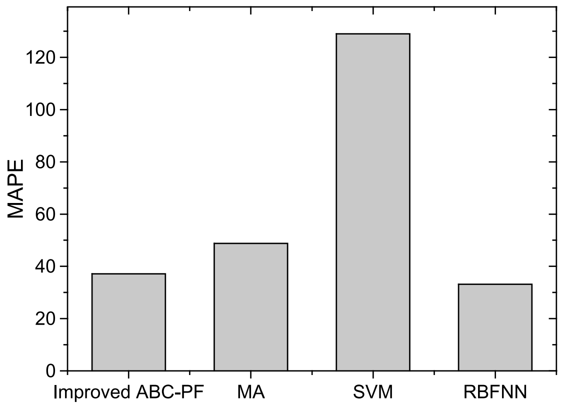

Fig. 7. The MAPE of the four different algorithms in demand forecasting.

Table 3
The prediction results of the improved ABC-PF and other compared methods in "precise order" pattern

Method	Improved ABC-PF	MA	SVM	RBFNN
Metrics				
Safety Inventory	113.25	141.82	137.2	131.51
Order Number	3394	3389	2873	3329
Order Quantity	5	4	8	8
Inventory Level	991.33	1273.9	1357.7	1026.7
Stockout Quantity	0	265.6	259.1	93
Overstock Inventory	114	311.9	135	85
Total Inventory Cost	347819.4	364257.3	311878.1	346719.7
Real Sales	3280	3014	3020.9	3187
Total Gross Profit	242580.5	178331.0	231883.8	226940.2

In order to find the reason of this phenomenon, we calculate the APE of each point in Fig. 8. It is obviously that the APE of the 19th and 29th prediction points even up to 700%, it is possibly caused by the underfitting problem which the SVM model can't learn the best-selling point. Generally, this kind of phenomenon does not appear in the Improved ABC model. It demonstrated that the SVM method has limitations in demand forecasting, and the outcome of the proposed method is more accurate.

Table 3 illustrates that the Improved ABC-PF performs best in the indicators such as the order number, inventory level, stockout quantity, safety inventory, real sales, and total gross profit. Although the total inventory cost and the overstock inventory is not the lowest, the stock out quantity of the Improved ABC-PF method is 0, which indicates that the proposed method can satisfy the demand perfectly. Compared to the MA, SVM and RBFNN, the safety inventory of the Improved ABC-PF are reduced by 20.14%, 17.45% and 13.88%, respectively, and the total gross profit are increased by 36.03%, 35.44% and 6.89%, respectively. These prediction results show that the Improved ABC-PF method is more suitable for footwear and apparel products' demand forecasting. Meanwhile, it also demonstrates that the Improved

ABC-PF method can be developed to a useful tool for the inventory control, and can help to handle the problems of high inventory and difficult replenishment in enterprise.

5. Conclusion and discussion

Demand forecasting accuracy directly affects the overall inventory cost and safety stock level, which is related to product gross margin and the market competitiveness, especially for those footwear and apparel enterprises. Since the demand management was successfully applied in many firms, such as ZARA and UNIQLO, more and more enterprises are realizing the importance of demand forecasting. Considering the fact that demands of footwear and apparel products are not stable and exist difference between each PLC stages, PLC is incorporated into the demand model building and safety inventory control. In this paper, a PLC based demand forecasting method called Improved ABC-PF is proposed, in which the two-stage polynomial fitting and optimized ABC algorithm are employed. Firstly, a two-stage life cycle function was constructed for footwear and apparel product. Secondly, in order to conquer the difference of life cycle between each year, an improved ABC algorithm was employed to optimize the demand learning model. Then, demand inventory control strategy based on PLC analysis is studied and applied in the "Precise Order" mode, and the Improved ABC-PF method also plays an important role in conducting safety inventory control. With the comparisons of the other demand forecasting methods such as MA, SVM and RBFNN, the Improved ABC-PF method shows the high accuracy superiority.

Although the Improved ABC-PF method has a satisfactory predictive performance, it still has some insufficiencies which should be enhanced. First, the demand of footwear and apparel products is affected by many other exogenous factors such as weather, holidays, and so on. These factors are not considered in the proposed method. Secondary, the experiential knowledge of the store managers and sales managers should also be taken into consideration in the process of demand modeling.

Acknowledgments

This research is supported by the National Natural Science Foundation of China (Grant No. 71302053), Shanghai Leading Academic Discipline Project (Grant No. J50103), and Shanghai University Innovation Foundation (Grant No. dcx2012058).

References

[1] C. Daganzo, Multinomial probit: The theory and its application to demand forecasting, 1979.

[2] K.-F. Au, T.-M. Choi and Y. Yu, Fashion retail forecasting by evolutionary neural networks, *Int J Production Economics* **114** (2008), 615–630.

[3] S.Z. Li, C.T. Ming, A.K. Fan and Y. Yong, Sales forecasting using extreme learning machine with applications in fashion retailing, *Decision Support Systems* **46** (2008), 411–419.

[4] Y. Ni and F. Fan, A two-stage dynamic sales forecasting model for the fashion retail, *Expert Systems with Applications* **38** (2011), 1529–1536.

[5] X. Zhang, Y. Sun and L. Guo, Forecasting model for apparel demand based on improved least squares support vector machine (LS-SVM) oriented to mass customization, *Journal of Textile Research* **5** (2010), 030.

[6] T.M. Choi, Y. Yu and K.F. Au, A hybrid SARIMA wavelet transform method for sales forecasting, *Decision Support Systems* **51** (2011), 130–140.

[7] R. Vernon, International investment and international trade in the product cycle, *International Executive* **8** (1966), 16.

[8] D.R. Rink and J.E. Swan, Product life cycle research: A literature review, *Journal of Business Research* **7** (1979), 219–242.

[9] S. Klepper, Entry, exit and innovation over the product life cycle, *American Economic Review* **86** (1996), 562–582.

[10] H. Ying H.E. Ping and L.I. Zhidong, Empirical study on product life cycle based on logistic model, *Journal of Jiangsu University of Science & Technology* **9** (2009), 51–54. (in Chinese)

[11] M.F. Bass, A new product growth for model consumer durables, *Management Science* **50** (1969), 215–227.

[12] S. Hyeonju, P. Gwangman, L. Hakyeon and Y. Byungun, Demand forecasting for new media services with consideration of competitive relationships using the competitive Bass model and the theory of the niche, *Technological Forecasting & Social Change* **79** (2012), 1217–1228.

[13] X. Guo, A novel Bass-type model for PLC quantification using aggregate market data, *International Journal of Production Economics* **158** (2014), 208–216.

[14] D. Shifei, H. Huajuan and N. Ru, Forecasting method of stock price based on polynomial smooth twin support vector regression, *Proceedings of the 9th International Conference on Intelligent Computing Theories 7995*, 2013, pp. 96–105.

[15] Y. Fang, K. Fataliyev, W. Lipo, F. Xiuju and W. Yaoli, Improving the genetic-algorithm-optimized wavelet neural network for stock market prediction, *Neural Networks (IJCNN), 2014 International Joint Conference on IEEE 10*, 2014, pp. 3038–3042.

[16] M. Zhu and L. Wang, Intelligent Trading Using Support Vector Regression And Multilayer Perceptrons Optimized With Genetic Algorithms, Neural Networks (IJCNN), *The 2010 International Joint Conference*, 54, 2010, pp. 1–5.

[17] D. Karaboga, B. Gorkemli, C. Ozturk and N. Karaboga, A comprehensive survey: Artificial bee colony (ABC) algorithm and applications, *Artificial Intelligence Review* **42** (2014), 21–57.

[18] D. Karaboga and B. Akay, A comparative study of artificial bee colony algorithm, *Applied Mathematics and Computation* **2** (2009), 108–132.

[19] D. Karaboga and B. Basturk, On the performance of artificial bee colony (ABC) algorithm, *Applied Soft Computing* **8** (2008), 687–697.

[20] F. Gurbuz, C. Ozturk and P. Pardalos, Prediction of electricity energy consumption of Turkey via artificial bee colony: A case study, *Energy Systems* **4** (2013), 289–3004.

[21] T.J. Hsieh, H.F. Hsiao and W.C. Yeh, Forecasting stock markets using wavelet transforms and recurrent neural networks: An integrated system based on artificial bee colony algorithm, *Applied Soft Computing* **11** (2011), 2510–2525.

[22] H. Shah, R. Ghazali and N.M. Nawi, Using artificial bee colony algorithm for MLP training on earthquake time series data prediction, *Journal of Computing* **3** (2011), 1112–4628.

[23] L. Yue, J. Wangwei, W. Kang and G. Junjun, Demand Forecasting for Footwear Products using Wavelet Transform and Artificial Bee Colony Algorithm Optimized Polynomial Fitting, *Accepted by the 11th International Conference on Natural Computation (ICNC'15)*, 2015.

[24] W.R. Thompson and C.S. Weil, On the construction of tables for moving-average interpolation, *Biometrics* **8** (1952), 51–54.

[25] V.N. Vapnik, The nature of statistical learning theory, *Neural Networks IEEE Transactions* **10** (1995), 988–999.

[26] T.S.S.V. Elanayar and Y.C. Shin, Radial basis function neural network for approximation and estimation of nonlinear stochastic dynamic systems, *Neural Networks IEEE Transactions on* **5** (1994), 594–603.

[27] C.C. Chang and C.J. Lin, LIBSVM: A library for support vector machines, *Acm Transactions on Intelligent Systems & Technology* **2** (2011), 389–396.