Neurocomputing 151 (2015) 342–353

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

A multiobjective optimization-based neural network model for short-term replenishment forecasting in fashion industry

Wei Du [a], Sunney Yung Sun Leung [a,*], Chun Kit Kwong [b]

[a] Institute of Textiles and Clothing, The Hong Kong Polytechnic University, Hong Kong, China
[b] Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong, China

ARTICLE INFO

Article history:
Received 10 June 2014
Received in revised form
21 August 2014
Accepted 15 September 2014
Communicated by Yang Tang
Available online 28 September 2014

Keywords:
Short-term replenishment forecasting
Fashion sales forecasting
Multiobjective optimization
Neural network

ABSTRACT

A multiobjective optimization-based neural network (MOONN) model is proposed to tackle the short-term replenishment forecasting problem in fashion industry. Our approach utilizes a new multiobjective evolutionary algorithm called nondominated sorting adaptive differential evolution algorithm (NSJADE) to optimize the weights of neural networks (NNs) for the short-term replenishment forecasting problem, acquiring the forecasting accuracy while alleviating the overfitting effect at the same time. The presented NSJADE also selects the appropriate number of hidden nodes for the NN according to different short-term replenishment forecasting problems. Extensive experiments based on real fashion industry data are performed to validate the effectiveness of the developed model. Experimental results reveal that the performance of the proposed model is superior than several popular models for the short-term replenishment forecasting problem.

1. Introduction

Sales forecasting estimates the future sales of a product based on the historical sales data, market trend, or other related factors. Under the circumstance of intensified global competition, sales forecasting is playing a more and more indispensable role in real-world industries, such as electronics [19], publishing [2], and apparel [27]. According to reliable sales forecasting methods, decision-makers can response quickly to market change, maintain the inventory in a relatively low level, and control the cost of production.

1.1. Fashion sales forecasting

In fashion industry, sales forecasting is a crucial part of apparel retailing and supply chain management [12]. Meanwhile, because of the particularities of fashion industry, like short product life cycles, uncertain customer demands, and massive product varieties [22], the forecasting process becomes very complicated. In order to solve the problem better, two main forecasting models are widely used: univariate forecasting model [27,1] and multivariate forecasting model [13,24]. In univariate forecasting models, researchers handle the sales forecasting problem relying on the historical sales data, which assumes that the underlying variation of data is constant. For instance, Wong and Guo [27] utilized one-step-ahead sales data to predict the sales of medium-priced fashion products in Mainland China. Au et al. [1] predicted the sales of T-shirt and jeans from several shops with the previous time series data. However, as mentioned above, the sales of fashion products are volatile, often influenced by fashion trends and weather conditions. So it is invalid to hypothesize that the trend of time series sales data is unchanged during the forecasting period. To cope with this, researchers integrate other influencing factors as the inputs of forecasting models besides the historical time series data, which is known as multivariate forecasting. Guo et al. [13] predicted the future sales for a large fashion retail company by considering product attributes, climate indices and economic indices. Sun et al. [24] achieved the forecasting according to the sales condition of a category of apparel with different sizes, colors and prices.

Replenishment is one of the most significant operations in the supply chain of fashion industry. Generally, the supply strategy of distributors or retailers is based on two steps: supply in a long-term horizon and replenishment in a short-term horizon [26]. The first step means distributing a certain number of products to the stores at the beginning of the sales season; the second step explains the replenishment for some fashion items during the sales season. Accurate long-term sales forecasting requires the company to be well-prepared before the selling season, which is basic for apparel companies; while successful short-term replenishment forecasting reflects the company's quick and efficient coping capacity. In addition, timely replenishment forecasting helps adjust the orders

* Corresponding author.
E-mail address: sunney.leung@polyu.edu.hk (S.Y.S. Leung).

http://dx.doi.org/10.1016/j.neucom.2014.09.030
0925-2312/

and deliveries for the stores, which keeps the right inventory level and makes the company more competitive as well.

To provide a more practical and robust forecasting methodology, this paper investigates a multivariate sales forecasting problem which facilitates short-term replenishment prediction for one of the largest retailers in fashion industry.

1.2. Techniques for sales forecasting

Varieties of forecasting techniques have been widely employed in sales forecasting. In general, there are two main categories of forecasting methods: linear and nonlinear. Linear methods apply a linear functional form for the problem to be predicted, such as exponential smoothing model [25,8] and autoregressive integrated moving average (ARIMA) model [9]. However, these two models fail to work when it comes to predict the fashion series featured by strong nonlinearity [20]. Therefore, a series of nonlinear models have been proposed, like expert systems [18], fuzzy systems [3] and neural network (NN) models [5,30]. Among them, NN models are mostly utilized owing to their satisfactory ability of detecting and extracting nonlinear relationships of the given information; furthermore, many literatures have shown that they exhibit much better performance than other traditional forecasting methods [27,1,5].

NN is a mathematical model consisting of a group of artificial neurons connecting with each other; the strength of a connection between two nodes is called "weight". Learning rules adjust the weights of the network to better fit the underlying relation of the given data. When NN was first introduced to the sales forecasting problems, back-propagation (BP) algorithm was employed as the learning rule for NN. However, BP is a gradient-based learning algorithm, which has been criticized for a long time because of its slow convergence speed. In recent years, a novel learning algorithm called extreme learning machine (ELM) has been presented [14], which tends to provide good generalization performance and fast learning speed at the same time. Thereafter, ELM was introduced to fashion sales forecasting by Sun et al. [24], whose experiments demonstrated that ELM-based NN had superior forecasting performance to BP-based NN. However, ELM may require far more hidden neurons due to the random determination of the input weights and hidden biases [33]. To handle this, Wong and Guo [27] optimized the input weights and hidden biases by integrating ELM with harmony search, which is a newly developed evolutionary algorithm. Their research in fashion sales forecasting exhibited the necessity of searching for the optimal values of input weights and hidden biases of ELM-based NN. In their research, training error was the only objective optimized by the evolutionary algorithm; the NN with the minimum training error was selected as the final network for the sales forecasting problem, which means the NN with the smallest training error is considered to have the best forecasting performance when it encounters the unseen data. Nevertheless, the features of the training samples do not represent the inherent underlying distribution of the new observations due to the existence of noise, which means the prediction effect of the "optimal" NN may be deteriorated by the overfitting phenomenon [17]. So it is not reasonable to merely minimize the training error of NN when executing the forecasting. While actually, for the forecasting problem solved by NN, there are other objectives that need to be optimized besides training error, like the number of hidden layer nodes or the sum of the absolute weights [10,16]. Therefore, optimizing more than one objective when settling the sales forecasting problem with NN comes to the first incentive of this paper. In this paper, multiobjective optimization (MOO) is introduced to optimize NN for solving the short-term replenishment forecasting problem, and to the best of our knowledge, it is the first paper that investigates the sales forecasting problems in *fashion* industry by using MOO-based model.

As we know, the number of hidden nodes influences the learning and generalization capability of NN. For the NN-based models that were utilized for the sales forecasting problem, the number of hidden nodes in NN was always fixed [24,2]. However, this operation is not reliable, because it is hard to determine how many hidden nodes are suitable for the problem beforehand. Recently, in order to reduce the randomness caused by the determination of the hidden node number, some researchers repeatedly run the NN-based models with a different number of the hidden nodes from 1 to N_{max} [13,27], which leads to the increasing of the forecasting model's computation complexity. Meanwhile, Choi et al. [4] proposed a searching mechanism to help find the suitable number of hidden nodes. This mechanism searches the optimal number of hidden nodes for the NN by gradually increasing the initial number of hidden nodes, where the search ends when the error begins to increase. However, there are two defects for this method: (1) forecasting error is the only indicator of the search; (2) the search is unidirectional, merely along the direction of increasing the hidden node number. Therefore, how to explore the hidden-node-number space comprehensively, as well as combining the information of optimizing NN's weights during the search, becomes the second incentive of this paper.

The third incentive of this paper comes from the difficulty that the short-term forecasting problem often faces [26] in fashion industry. In the clothing context, the sufficiency of historical sales data can be a very restrictive assumption in real-life situation [4]. And the lack of data is prone to causing the overfitting problem when NN is involved in the sales forecasting. Cross-validation [23] is a model validation technique mostly used when the training samples are not enough. In our paper, instead of the common training error, we set the average error of committing K-fold cross-validation (K-cv error) on the training samples as one of the objectives we intend to optimize. This operation effectively relieves the plight caused by the scarcity of the historical sales data (training data).

Motivated by the above discussion, in this research, a MOONN model is proposed to solve the short-term replenishment forecasting problem in fashion industry. The model utilizes a novel multiobjective evolutionary algorithm called nondominated sorting adaptive differential algorithm (NSJADE) to optimize NN for the forecasting problem. The main contributions of this paper are threefold: (1) MOO is introduced to optimize NN for the forecasting problem in fashion industry, where adaptive differential evolution (JADE) is elected as the search engine of NSJADE; (2) the proposed NSJADE is able to select the appropriate number of hidden nodes of the neural network according to different short-term replenishment forecasting problems; and K-cv error on the training samples is set as one of the objectives during the MOO process to relieve the side effects of insufficient historical data; (3) the results of extensive experiments obtained by our model are compared with two popular models [24,27] to show the advantages of this work.

The organization of this paper is as follows. Some preliminaries are given in Section 2. The proposed MOONN model for short-term fashion replenishment forecasting is illustrated in Section 3. In Section 4, the detailed experimental setup is introduced. In Section 5, extensive experiments are conducted to compare the forecasting performance of our model with that of several popular models, such as ELME and HI; meanwhile, experimental results and related analysis are provided. Finally, we conclude the whole paper in Section 6.

2. Preliminaries

This research utilizes a model called MOONN to solve a short-term fashion replenishment forecasting problem. The MOONN model is essentially based on a newly presented multiobjective