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A seasonal discrete grey forecasting model for fashion retailing

Min Xia [a,b], W.K. Wong [b,*]

[a] Department of Information and Communications Technologies, Nanjing University of Information Science and Technology, Nanjing, China
[b] Institute of Textiles and Clothing, The Hong Kong Polytechnic University, Hong Kong

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ABSTRACT

In the fashion retail industry, level of forecasting accuracy plays a crucial role in retailers' profit. In order to avoid stock-out and maintain a high inventory fill rate, fashion retailers require specific and accurate sales forecasting systems. One of the key factors of an effective forecasting system is the availability of long and comprehensive historical data. However, in the fashion retail industry, the sales data stored in the point-of-sales (POS) systems are always not comprehensive and scattered due to various reasons. This paper presents a new seasonal discrete grey forecasting model based on cycle truncation accumulation with amendable items to improve sales forecasting accuracy. The proposed forecasting model is to overcome two important problems: seasonality and limited data. Although there are several works suitable with one of them, there is no previous research effort that overcome both problems in the context of grey models. The proposed algorithms are validated using real POS data of three fashion retailers selling high-ended, medium and basic fashion items. It was found that the proposed model is practical for fashion retail sales forecasting with short historical data and outperforms other state-of-art forecasting techniques.

1. Introduction

In the fashion retail industry, fashion retailers need to provide right products at the right time while maintaining a good stock. To buffer against stock-out and maintain a high inventory level, fashion retailers usually keep large safety stocks. In order to keep down inventory levels, some retailers adopt a quick response policy [1] or improve their forecasting decisions by capturing updated market information and adjusting their forecasts in multiple stages [2,3]. An accurate prediction of customer demand is crucial to the profitability of retailers and allows upstream apparel manufacturers to increase or adjust their production which may finally influence the performance of the entire supply chain. In fashion retailing, demand uncertainty is notorious for creating many big challenges in logistics management [4–6]. The effectiveness of a supply chain depends primarily on precise forecasting of product sales [7], while the efficiency of the supply management optimisation relies on the forecast accuracy of the finished product sales [7–9].

Current forecasting techniques are generally divided into two groups: classical methods based on mathematical and statistical models (e.g. exponential smoothing, regression, Box–Jenkins autoregressive integrated moving average (*ARIMA*), generalised autoregressive conditionally heteroskedastic (*GARCH*) methods), and modern heuristic methods using artificial intelligence techniques including artificial neural networks (*ANN*) and evolutionary computation. In classical methods, the exponential smoothing, regression and *ARIMA* methods are based on the Box and Jenkins method and categorised as linear methods which employ a linear functional form for time-series modeling [10–12]. As these linear methods cannot capture features that commonly occur in actual time-series data like occasional outlying observations and asymmetric cycles, they may not be suitable for many real-world time series [13]. In addition, as the relationship between time-series data and the variables affecting sales performance is rather complex, sales performance cannot be determined only by high precision. The *GARCH* method is regarded as a nonlinear method which can characterise features in actual data. This is based on the assumption that the underlying data-generating process of the time series is constant. However, this assumption is not correct since shifting environmental conditions may cause the underlying data-generating process to change, particularly in a dynamic fashion business environment. The forecasting performance of such classical methods depends on the existence of reliable historical data for ensuring correct identification of model structures and efficient tuning of parameters. In modern heuristic methods, advanced artificial intelligence-based forecasting models have been developed. Modern heuristic methods include neural networks [14–16], fuzzy systems [17–20], and hybrid models [21,22]. These methods were developed to build nonlinear forecasting models. Generally, these models provide disparate results [23]. Indeed,

* Corresponding author. Tel.: +86 852 64306741.
E-mail address: calvin.wong@polyu.edu.hk (W.K. Wong).

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their performances essentially depend on the field of application, forecasting goal, user experience, and forecast horizon [24]. Furthermore, these methods also depend on the long historical data. The traditional models are thus generally inappropriate when using short historical data which are strongly perturbed by explanatory variables [23].

In fashion sales forecasting, forecasting apparel product sales is a challenging task and several forecasting models have been developed for fashion retailing [23,25–29]. However, insufficient historical data is still a limiting factor for these models. Frank et al. [30] investigated the forecasting of women's apparel sales by comparing the performance of statistical time series modeling and that of *ANN*. The results indicated that the *ANN* model performed better. Thomassey et al. [31] developed two complementary forecasting models for textile makers. The first model was used to obtain mean-term forecasting automatically by using fuzzy techniques to quantify the influence of explanatory variables. The second model using the neuro-fuzzy method performed short-term forecasting by re-adjusting mean-term model forecasts from actual sales. Paulo et al. [29] used an evolutionary neural network approach to searching for an ideal network structure for a forecasting system, and compared it with the traditional forecasting models. Indeed, a tremendous number of apparel product items exist and the historical sales data are thus often short and particularly perturbed by numerous factors, which are neither strictly controlled nor identified [28], such as weather, fashion trend, and economic environment. These data are not always available and have different levels of influences on sales [27]. In the previous efforts, there are few works suitable to deal with both seasonality and short historical data. Tseng et al. [32] and Wang et al. [33] proposed a hybrid grey model to forecast series with seasonality, applying the ratio-to-moving-average method in order to calculate the seasonal indexes and remove the seasonal factor. However, these works are not suitable for limited time series data. On the other hand, Tsaur [34] used a fuzzy grey regression for limited time series data, but this approach is not suitable for the seasonal time series data.

Recently, the grey forecasting model has been proposed as a promising alternative to time-series forecasting [35,36]. The grey forecasting model adopts the essential part of the grey system theory and has been successfully employed in various fields to demonstrate satisfactory results [37–46]. As it uses a first order differential equation to characterise a system, only a few discrete data are sufficient to characterise an unknown system. This makes the grey forecasting model suitable for conducting forecast in an environment where decision makers can reference only limited historical data [47]. This characteristic is very important for forecasting fashion sales. However, no application of the grey forecasting model was reported on time series forecasting for fashion retailing.

Obviously, the sales data of fashion retailing are with seasonality. However, it has been found that the grey forecasting model is inadequate in forecasting a time series with seasonality [48,49]. In order to solve the seasonality problem, we hence propose a seasonal discrete grey forecasting model (*SDGM*) for forecasting fashion retail sales. In this model, the accumulated generating operation (*AGO*) is improved by cycle truncation accumulated generating operation (*CTAGO*), and it generates a interesting results, the forecasting value $x(k+1)$ consists of two parts: $x(k+1-p)$ (p is the cycle) and a interpolation value. Thus, the seasonality characteristic from a seasonal time series of fashion retailing can be taken into account in the model. This study also extends the algorithms of the grey forecasting model with amendable items to increase forecasting accuracy. Thus, the forecasting model can deal with seasonality and limited data. Although there are several works suitable with one of them, there is no previous one can overcome both problems.

The remaining paper is organised as follows. In Section 2, traditional grey forecasting model is presented and discussed. A seasonal discrete grey forecasting model is proposed in Section 3. Section 4 presents the sales forecasting results for three fashion retail companies. Finally, Section 5 concludes this paper.

2. Grey forecasting model

In this section, the algorithms of grey forecasting model are introduced and discussed. The grey model, proposed by Deng [35,36], provided an effective means of predicting future data using only a small amount of past observed data. The raw time series output from an unknown system may be random; however, the degree of randomness of the raw time series may be reduced after repeated application of the accumulated generating operation (*AGO*). The grey forecasting model uses the operations of accumulated generation to build differential equations. Thus, it is sufficient for using ordinary differential equation to catch the regularity after one-time or two-time *AGO*.

The most commonly-used grey forecasting model is $GM(1,1)$, which indicates the model is constructed of a single variable. The description of the grey model is summarised as follows.

Let us assume the raw data series be $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$, where $x^{(0)}(j)$ is the datum at jth time and n is the total number of modeling data. The algorithm of $GM(1,1)$ is to forecast the value of $x^{(0)}(n+1)$.

Based on the initial sequence $X^{(0)}$, a new sequence $X^{(1)}$ is generated by the accumulated generating operation (AGO), where $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$, and $x^{(1)}(k)$ is derived as follows:

$$x^{(1)}(k) = AGO(x^{(0)}(k)) = \sum_{j=1}^{k} x^{(0)}(j), \quad k = 1, 2, \ldots, n. \tag{1}$$

A first-order differential equation is then fitted to the grey series, $x^{(1)}(t)$, and is written as

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b, \tag{2}$$

where the parameter a is called the developing coefficient and b is named the grey input. The whitening of grey derivatives and grey parameters is introduced for identification of Eq. (2). According to grey system theory, the whitening of grey derivatives for discrete data with unit time interval is given by

$$\left.\frac{dx^{(1)}(t)}{dt}\right|_{t=k} = x^{(1)}(k) - x^{(1)}(k-1) = x^{(0)}(k). \tag{3}$$

Defining a new variable $z^{(1)}(k)$, which is the whitening value of $x^{(1)}(t)|_{t=k}$. And $z^{(1)}(k)$ can be expressed as:

$$z^{(1)}(k) = \frac{1}{2}[x^{(1)}(k) + x^{(1)}(k-1)], \quad \forall k = 2, 3, \ldots, n. \tag{4}$$

By substituting Eq. (3) into Eq. (2)and using the whitening value, then writing the equation in a discrete differential form, we can get[40]:

$$x^{(0)}(k) + az^{(1)}(k) = b, \quad \forall k = 2, 3, \ldots, n. \tag{5}$$

The grey differential Eq. (5) is called the basic form of $GM(1,1)$ model, which gives that:

$$Y = B\theta + \varepsilon, \tag{6}$$

where θ is parameter vector; ε is model residual vector; and in which