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Managing return flow of end-of-life products for product recovery operations

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Abstract

Increased consciousness on environment and sustainability, leads companies to apply environmentally friendly strategies such as product recovery and product return management. These strategies are generally applied in reverse logistics concept. Implementing reverse logistics successfully becomes complicated for companies due to uncertain parameters of the system like quantity, quality and timing of returns. A forecasting methodology is required to overcome these uncertainties and manage product returns. Accurate forecasting of product return flows provides insights to managers of reverse logistics. This paper proposes a forecasting model based on grey modelling for managing end-of-life products' return flow. Grey models are capable for handling data sets characterized by uncertainty and small sized. The proposed model is applied to data set of a specific end-of-life product. Attained results show that the proposed forecasting model can be successfully used as a forecasting tool for product returns and a supportive guidance can be provided for future planning.

Keywords: end-of-life products, grey modelling, product return flow, product recovery.

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1. Introduction

In the industrialized world, environmentally sensitive business strategies provide several benefits to the companies, including increased ecological and economic value, declined negative impacts on the environment, enhanced corporate image etc. Managing return flow of products for recovery operations or product return planning is one of these strategies and disciplined by reverse logistics (Temur, Balcilar & Bolat, 2014). Reverse logistics is the process of accepting previously sent products from the point of consumption for possible, recycling, remanufacturing, reuse or disposal operations (Dowlatshahi, 2000). Implementing reverse logistics is a challenging issue due to unknown parameters of the system such as quantity, quality and timing of product returns (Temur et al., 2014). An important aspect of reverse logistics is to acquire a correct and timely forecasting for return quantities of products (Potdar & Rogers, 2012). Effective management of reverse logistics can be provided with accurate forecasting of product return flows.

This paper addresses the problem of forecasting return amount of end-of-life products. Forecasting a future development is a critical issue encountered in various research areas. A reliable prediction should provide the laws governing the phenomena of the system (Lin, Lee & Chang, 2009). Considering unknown parameters and few historical data in return flow of end-of-life products, in the scope of this paper, a forecasting model based on grey modelling is proposed for predicting end-of-life products' return flow amount. The forecasting model is applied to the different data sets of a certain product returned from consumers.

The remainder of this paper is structured as follows. Section 2 provides a review of the related literature. In Section 3, adopted forecasting methodology is presented. In Section 4, experimental results of the developed forecasting models are given and in Section 5 conclusions are summarized.

2. Literature review

A number of researchers investigated product return forecasting in literature. Some of these works are summarized as follows. Marx-Gomez, Rautenstrauch, Nurnberger and Kruse (2002) suggested a forecasting method to provide prognoses for the returns of scrapped products to recycling and remanufacturing. The methodology uses a simulation model for data generation, fuzzy inference system for forecasting in a determined period and neuro-fuzzy approach in forecasting multi-period. Xiaofeng and Tijun (2009) proposed a wave function based forecasting model, which considers periodic fluctuation, for returned products of reverse logistics. Yu, Williams, Ju and Yang (2010) studied the problem of forecasting global generation of obsolete computers employing a logistic model and material flow analysis. Chen and He (2010) proposed a composite forecast method combined with time series and the grey method. The method is implemented to the return data of household appliances. Potdar and Rogers (2012) proposed a reason code based forecasting model to forecast product returns. They employed the moving average and data envelopment analysis approaches to predict product returns by determined return reason. Krapp, Nebel and Sahamie (2013) formulated a forecasting methodology based on Bayesian estimation techniques for forecasting product returns in closed-loop supply chains. Ayvaz, Bolturk and Kactioglu (2014) developed a grey forecasting system to predict the return product in reverse logistics networks. Petridis, Stiakakis, Petridis and Dey (2016) studied estimation of global computer waste quantities using dynamic regressions, autoregressive models and trend model techniques.

As summarized above, different solution approaches are employed in various contributions of product return flow forecasting literature. Among these solution approaches not much study has been conducted on grey modelling based forecasting for returned end-of-life product quantities. Numerous studies employed grey modelling based forecasting system to varied fields. Such as; Huang and Lee (2011) applied grey modelling based forecasting system to tourism demand, Kumar and Jain (2010) proposed grey models to forecast energy consumption, Wang, Qi, Chen, Jingfan and Ming (2014) developed grey system theory based prediction model for topic trend on internet, and so on.

Considering successfully applications of grey forecasting models, this paper proposes grey modelling based forecasting models to predict returned end-of-life product quantities. Widely preferred grey forecasting model of GM (1,1) and improved GM(1,1) model with Fourier series are developed and applied to a certain end-of-life product's data sets .

3. Methodology

Grey system theory is an interdisciplinary theory and was proposed by Deng (1982). The theory was initially implemented to the field of control but then successfully applied to the various fields (Lee, Wu, & Tsai, 2014). Grey modelling based grey forecasting is one of the essential contents of grey system theory (Deng, 1989). Grey forecasting model is particularly effective in forecasting datasets that have unknown parameters and few data (Carmona Benitez, Paredes, Lodewijks & Nabais, 2013).

3.1. GM(1,1) model

The GM (1,1) model is a prediction model in grey theory with a first-order differential equation and one input variable to forecast future dynamics of a data sequence. Main advantage of the GM (1,1) modelling is that it requires small data samples and simple mathematical operations (Lee et al., 2014). The procedure of the GM (1,1) model is described in Equations (1)-(13) (Deng, 1989; Kayacan, Ulutas, & Kaynak, 2010; Hamzacebi & Es, 2014).

<u>Step 1:</u> Assume a time sequence $X^{(0)}$ that represents historical series of number of end-of-life products:

$$X^{(0)}=(x^{(0)}(1), x^{(0)}(2),\dots,x^{(0)}(n)) \quad n \geq 4 \tag{1}$$

Where n is sample size of the data series and $X^{(0)}$ is a nonnegative data sequence.

<u>Step 2:</u> Apply accumulated generation opereator to this sequence and generate a new data series $X^{(1)}$.

$$X^{(1)}=(x^{(1)}(1), x^{(1)}(2),\dots,x^{(1)}(n)) \quad n \geq 4 \tag{2}$$

Where $X^{(1)}$ is accumulated data sequence and $x^{(1)}(k)$ equals:

$$x^{(1)}(k)=\sum_{i=1}^{k} x^{(0)}(i) \tag{3}$$

<u>Step 3:</u> Constitute the GM(1,1) model equation as a first order grey diffential equation:

$$x^{(0)}(k)+az^{(1)}(k)=b \tag{4}$$

Where $z^{(1)}(k)$ denotes mean value of adjacent data and calculated as:

$$z^{(1)}(k)=0.5x^{(1)}(k)+0.5x^{(1)}(k-1) \quad k=2,3,\dots,n \tag{5}$$

$Z^{(1)}$ is the mean sequence of $X^{(1)}$ and defined as:

$$Z^{(1)}=(z^{(1)}(1), z^{(1)}(2),\dots,z^{(1)}(n)) \tag{6}$$

Step 4: Apply the whitenization process with whitening equation which is defined as:

$$\frac{dx^1(t)}{dt} + ax^{(1)}(t) = b \tag{7}$$

Where a is developing coefficient and b is grey input. These coefficients are estimated with applying least squares method and calculated as:

$$[a,b]^T = (B^T B)^{-1} B^T Y \tag{8}$$

Where B and Y are defined as:

$$Y = [x^{(0)}(2), x^{(0)}(3), \ldots\ldots, x^{(0)}(n)]^T \tag{9}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ . & . \\ . & . \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{10}$$

Step 5: Attain the prediction value of $x^{(1)}(t)$ at time k according to whitening equation as:

$$x_p^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} \tag{11}$$

Step 6: Obtain the prediction value of $x^{(0)}(t)$ at time (k+1) is with inverse accumulated generation operator as:

$$x_p^{(0)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak}(1-e^{a}) \tag{12}$$

The prediction value of $x^{(0)}(t)$ at time ($k+H$) is calculated as:

$$x_p^{(0)}(k+H) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-a(k+H-1)}(1-e^{a}) \tag{13}$$

While, the GM(1,1) model has been applied to the various forecasting problems with proven performances, its performance can still be improved with residual error modifications (Lin at al., 2009). Among the several approaches used in literature, Fourier series modification is adopted in this paper due to its capabilities.

3.2. Fourier series modification

Fourier series modification is employed in this paper to increase accuracy of prediction. The method provides filtering out noise and stochastic errors (Lin et al., 2009). Fourier series error residuals modification procedure is defined in Equations (14)-(21) (Lin et al., 2009; Hsu, Liu, Yeh, & Hung, 2009; Kayacan et al., 2010):

The residual series of the forecasting results can be obtained as:

$$\varepsilon^{(0)} = (\varepsilon^{(0)}(2), \varepsilon^{(0)}(3), \ldots, \varepsilon^{(0)}(n)) \tag{14}$$

Where $\varepsilon^{(0)}(k)$ can be calculated as:

$$\varepsilon^{(0)}(k) = x^{(0)}(k) - x_p^{(0)}(k) \quad k = 2,3,\ldots,n \tag{15}$$

Fourier series can approximate the residual series as:

$$\varepsilon^{(0)}(k) \cong \frac{1}{2}a_0 + \sum_{i=1}^{z}\left[a_i \cos\left(\frac{2\pi i}{T}k\right) + b_i \sin\left(\frac{2\pi i}{T}k\right)\right] \quad k = 2,3,\ldots,n \tag{16}$$

Where $T = n-1$ and indicates the length of the residual series (period). z defines the minimum deployment frequency of the Fourier series and calculated as $z = ((n-1)/2)-1$. Equation (16) can be rewritten as:

$$\varepsilon^{(0)} \cong PC \tag{17}$$

Where the P and C matrices are defined as:

$$P = \begin{bmatrix} 1/2 & \cos\left(2\frac{2\pi}{T}\right) & \sin\left(2\frac{2\pi}{T}\right) & \cos\left(2\frac{2\pi 2}{T}\right) & \sin\left(2\frac{2\pi 2}{T}\right) \ldots\ldots\ldots & \cos\left(2\frac{2\pi z}{T}\right) & \sin\left(2\frac{2\pi z}{T}\right) \\ 1/2 & \cos\left(3\frac{2\pi}{T}\right) & \sin\left(3\frac{2\pi}{T}\right) & \cos\left(3\frac{2\pi 2}{T}\right) & \sin\left(3\frac{2\pi 2}{T}\right) \ldots\ldots\ldots & \cos\left(3\frac{2\pi z}{T}\right) & \sin\left(3\frac{2\pi z}{T}\right) \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots\ldots & \ldots\ldots \quad \ldots\ldots & \ldots\ldots & \ldots\ldots \\ 1/2 & \cos\left(n\frac{2\pi}{T}\right) & \sin\left(n\frac{2\pi}{T}\right) & \cos\left(n\frac{2\pi 2}{T}\right) & \sin\left(n\frac{2\pi 2}{T}\right) \ldots\ldots\ldots & \cos\left(n\frac{2\pi z}{T}\right) & \sin\left(n\frac{2\pi z}{T}\right) \end{bmatrix} \tag{18}$$

$$C = [a_0 \; a_1 \; b_1 \; a_2 b_2 \ldots a_z \; b_z]^T \tag{19}$$

When Equation (17) is solved with the least-squares method, the coefficients matrix C can be derived as:

$$C \cong \left(P^T P\right)^{-1} P^T \varepsilon^{(0)} \tag{20}$$

$\varepsilon_p^{(0)}$ can be calculated by substituting the values of C into the Equation (16) and the prediction can be modified as:

$$x_{pf}^{(0)}(k) = x_p^{(0)}(k) + \varepsilon_p^{(0)}(k) \qquad k = 2,3,\ldots\ldots,n+1 \tag{21}$$

In the context of this paper, GM(1,1) model is modified with the above described Fourier series modification procedure and the improved model is called as Fourier-Grey Model (FGM).

4. Experimental results

In this paper, the proposed forecasting models, the GM and FGM models are applied to a certain end-of-life product's prediction and their performance is tested. Historical values of the end-of-life product are obtained from different collection centers belonging to different locations. A total of 15

locations' historical values including 6-year time interval is covered by the experimental study. Figure 1 shows actual values of the returned end-of-life products to the considered locations for product recovery. Data set refers number of returned end-of-life products to a location including a time series of 6-year.

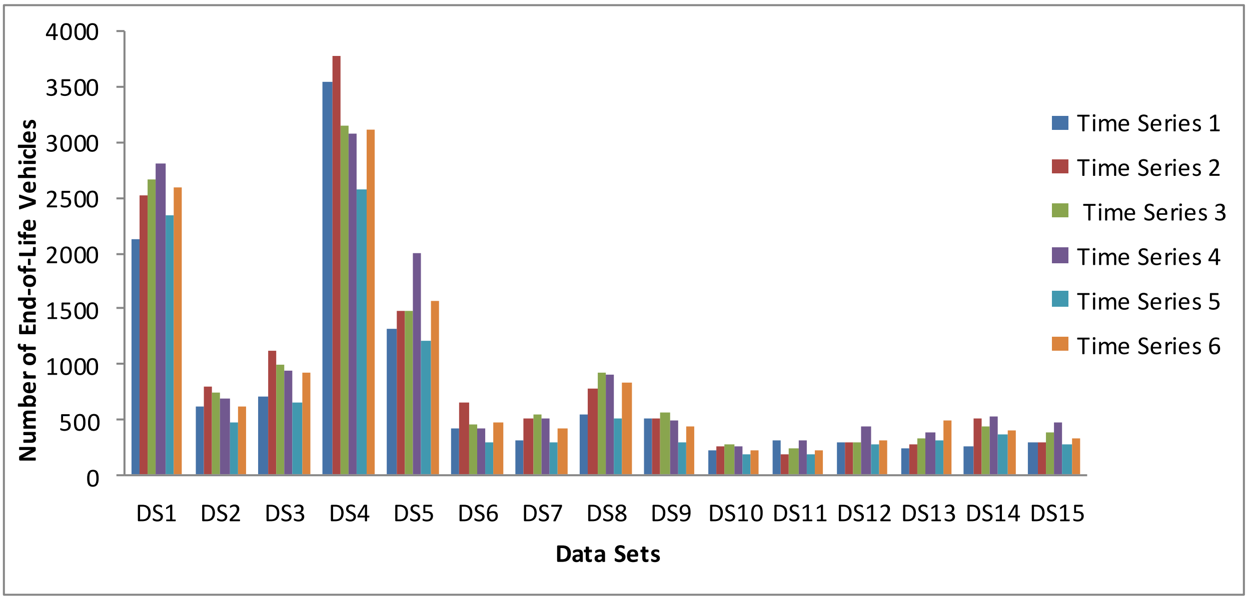

Figure 1. Actual values of data sets

To test the performance of the proposed forecasting models percentage relative error (RE %) and mean absolute percentage error (MAPE %) measures are adopted. These measures can be derived as:

$$RE\,\% = \frac{|x(k) - \hat{x}(k)|}{x(k)} \times \%100 \tag{22}$$

$$MAPE\ \% = \frac{1}{n}\sum_{k=1}^{n}\frac{|x(k) - \hat{x}(k)|}{x(k)} \times \%100 \tag{23}$$

Performance evaluation results of the proposed GM and FGM models for forecasting number of end-of-life products of 15 data sets are presented in Table 1 in terms of mean absolute percentage error. In data sets 1-4, data set 10 and data sets 13-14 both of the GM and the FGM models achieve prediction accuracy greater than 90 %. In data sets 7-9, data set 11 and data set 15, prediction accuracy greater than 90 % can be obtained with the FGM model. However, in data sets 5-6 and data set 12, prediction accuracy greater than 85 % can be provided. Additionally, within the fifteen data sets, in eleven data sets, the FGM model outperforms the GM model.

Table 1. Performance results of prediction models for data sets

Data Sets	MAPE % Values	
	GM	FGM
Data Set 1	4.47	3.32
Data Set 2	8.82	7.45
Data Set 3	9.53	8.83
Data Set 4	6.35	6.58
Data Set 5	11.13	12.38
Data Set 6	11.77	12.23
Data Set 7	14.33	7.74
Data Set 8	16.98	9.65
Data Set 9	14.38	6.73
Data Set 10	8.44	4.66
Data Set 11	14.24	9.89
Data Set 12	13.67	11.64
Data Set 13	9.89	8.22
Data Set 14	7.04	8.89
Data Set 15	15.06	8.51

For instance, the forecasting results of the data set 1 and data set 14 are presented in Tables 2 and 3, respectively. In data set 1, better MAPE value of 3.32 % is achieved with the FGM. So for future predictions of the relevant location, the FGM model can be employed. In data set 14, better MAPE value of 7.04 % is obtained with the GM model, so for this location future predictions can be provided with the GM model.

Table 2. Detailed results of data set 1

Time Series	Actual Value	GM		FGM	
		Model Result	RE %	Model Result	RE %
1	2120	2120	0.00	2120	0.00
2	2528	2645	4.63	2468	2.39
3	2667	2606	2.29	2728	2.27
4	2805	2567	8.48	2745	2.16
5	2346	2528	7.76	2407	2.58
6	2585	2491	3.64	2314	10.50
		MAPE %	4.47	MAPE %	3.32

Table 3. Detailed results of data set 14

Time Series	Actual Value	GM		FGM	
		Model Result	RE %	Model Result	RE %
1	251	251	0.00	251	0.00
2	514	514	0.00	470	8.56
3	438	479	9.36	482	10.05
4	535	447	16.45	491	8.22
5	370	417	12.70	414	11.89
6	404	389	3.71	345	14.60
		MAPE %	7.04	MAPE %	8.89

Among the proposed forecasting models, the proper model can be used for each location to obtain predicted values of future periods. Table 4 presents the future forecasted values of each location.

Table 4. Predicted numbers of end-of-life product for future periods

Locations	Future periods			
	1	2	3	4
Location 1	2575	2594	2260	2168
Location 2	447	401	265	217
Location 3	580	520	356	285
Location 4	2052	1822	1618	1437
Location 5	1447	1422	1397	1373
Location 6	188	148	116	92
Location 7	364	322	152	132
Location 8	706	663	344	300
Location 9	357	302	138	128
Location 10	207	193	136	124
Location 11	275	300	211	190
Location 12	376	433	348	308
Location 13	421	461	423	430
Location 14	363	339	316	295
Location 15	431	470	334	305

As a result of experimental studies, considering that real observations are used in forecasting, we can say that the proposed forecasting models achieve satisfactory accuracy results and the models can be used to analyze future developments of end-of-life products' return flow.

5. Conclusions

This paper investigates the issue of forecasting returned end-of-life products for managing product return flows in reverse logistics. A forecasting methodology based on grey modelling is proposed in the scope of this paper. The grey modelling is employed in the proposed forecasting model due to its capability for handling data sets which have uncertainty features and small sized. The basic GM model is modified with Fourier series correction to get improved forecasting accuracy. The proposed models are implemented to the data of a specific end-of-life product belonging to different locations. Attained results show that the proposed forecasting models can be successfully used as a forecasting tool for managing product returns and the proposed models can also guide the managers of the reverse logistics for future planning.

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