

A Grey System for the Forecasting of Return Product Quantity in Recycling Network

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Abstract— In recent years, Reverse Logistics (RL) activities has gained much attention in terms of economic, social and governmental reasons. For firms, it has become important to manage the reverse flow of products in an efficient way to obtain competitive advantage. However to design RL network is difficult because of some reasons. Especially, uncertain parameters related to return product quantity, quality and time are main characteristics of RL networks. One of the most important decisions of RL is to provide a correct and timely estimation of return waste product quantity, because it affects many decisions related to RL network design process directly. To predict return product in RL networks, intrinsic and extrinsic forecasting are some of the well-known and frequently used forecasting techniques. In this study, we proposed a grey forecasting system to forecast return product quantity in RL network. The contribution of this study is the first study that presented grey forecasting model for product return quantity in reverse logistics network design literature. Solutions showed that grey forecasting system is very efficient to predict return quantity.

Keywords— Reverse logistics, uncertainty, grey systems, return product forecasting, e-waste

1. Introduction

Recently, due to growing consumer awareness, green laws to collect and to recovery used products, economic reasons such as intending of manufacturers to reduce manufacturing costs and to sustain their competitive advantage, increasing use of reusable products, quality upgrading, popularity of re-manufacture, repair, recycle etc.

activities, reverse logistics has gain much attention for businesses.

In addition, because of increasing legislation and the realization that being 'green' can be profitable, sustainable operations has become an important issue in the field of operations [1].

RL has been defined as the movement of product or materials in the opposite direction for the purpose of creating or recapturing value, or proper disposal [2]. RL is practiced in many industries such as; computers, paper, producing steel, aircraft, automobiles, chemicals, electrical and electronics equipment, medical items. Reverse logistics activities has become profitable and sustainable business strategy for firms [3]. Therefore, nowadays manufacturers have integrated product recovery activities into their business processes [4]. Consequently, studies in the literature related to reverse logistics have been concluded on different aspects such as network design, return forecasting, economic and environmental performance, lot sizing, vehicle routing, etc. Design of reverse logistics network is one of the challenging reverse logistics problems. Facility location and allocation problem is important because of managing effectively transportation of used product from customers to recovery facilities, and supplying to market. These decisions need to be taken emphasize the importance of the issue of reverse logistics network design. Firms have to make large investments to adopt the reverse logistics activities. High installation costs make reverse logistics system design very important. The successful design of reverse logistics network helps firms to gain cost-effective recycling process, and competitive advantage. In brief, the accurate forecasting of product returns is important for procurement decisions, production planning, inventory and disposal management in such

remanufacturing operations [1]. However, Reverse Logistics Network Design (RLND) process is very difficult because of uncertainty.

Uncertainty is one of the main characteristics of RL networks. In particular, the strategic RLND has to take uncertainty into consideration. Especially, the time, quantity, and quality of returned products are main uncertain parameters. Therefore, the reverse logistics network should be designed in a way that it could cope with the uncertainty; otherwise the impact of uncertainty will be more than expected [5]. However, the most important uncertainty in reverse logistics network is return quantity because of the fact that it effects many critical decisions during network design. Better forecasting of the return product quantity could bring more profits, customer satisfaction and more efficient network design for companies [6]. In this paper, it is presented grey forecasting method to predict product return quantity in RLND. The contribution of study is that the first study that presented grey forecasting model for product return quantity in RLND literature by using real life data.

The remainder of this paper is organized as follows. In Section 2, it is reviewed grey forecasting and return quantity forecasting literature for reverse logistics network. In Section 3, it is explained grey forecasting method. In Section 4, it is developed grey forecasting model to predict e-waste return quantity and proposed model is applied to a reverse logistics firm in Turkey.

2. Literature Review

In this section, we made comprehensive literature review for grey forecasting systems and return product quantity forecasting in reverse logistics network.

Grey forecasting method used for many different area in literature. Yi [7] proposed a grey model to predict the number of talented persons. Xu and Wen [8] applied the grey forecasting model to forecast accurately the number of passengers on international air transportation. Chang et al. [9] presented grey systems to estimate performance of Diesel engine rely on a great deal of original data, and are not suitable for a few data. Lin and Yang [10] developed a grey forecasting model to predict the growth of Taiwan's opto-electronics industry. Akay and Atak [11] developed grey prediction with rolling mechanism approach to predict the the total and industrial electricity consumption of Turkey. Xie and Liu [12] introduced grey modelling to prediction of natural gas consumption. Andrawis et

al. [13] developed a forecasting model for inbound tourism demand for Egypt. Hsu [14] put forward an improved transformed grey model based on a genetic algorithm to forecast the output of opto-electronics industry. Lei and Feng [15] presented a novel grey model, PGM (1,2,a,b) for improving the forecasting performance for short-term electricity price efficiently and accurately. Hamzacebi and Es [16] used an optimized Grey Modeling (1,1) forecasting technique called Optimized Grey Modeling (1,1) to predict total electric energy demand of Turkey between 2013–2025. The Optimized Grey Modeling (1,1) technique is implemented both in direct and iterative manners. Mostafaei and Kordnoori [17] developed a grey GM (1, 1) model, using a technique that combines residual modification with Markov Chain model. They applied presented model energy consumption and supply of Iran to test the accuracy of model. Cui et al. [18] proposed a novel grey forecasting model in order to get a better forecasting model to increase the forecasting accuracy. Xie et al. [19] developed a new grey forecasting model based on non-homogeneous index sequence approximately, because of the fact that GM (1,1) and discrete grey model are constructed on the hypothesis that the original data sequence is in accord with homogeneous index trend. Samvedi and Jain [20] used grey prediction model in supply chain. They compared the model with moving average, weighted moving average methods and exponential smoothing during disruptions and stable situations in supply chain. Bahrami et al. [21] proposed a new model based on combination of the wavelet transform and grey model for short term electric load forecasting and is improved by particle swarm optimization algorithm. The model inputs are the weather data including mean temperature, mean relative humidity, mean wind speed, and previous days load data. To improve the accuracy of short term electric load forecasting, the generation coefficient of grey model is enhanced using particle swarm optimization algorithm. To verify its efficiency, the presented method is applied for New York's and Iran's load forecasting.

The second part of the literature review, we addressed the return forecast models in RLND problem. Design of RL networks involves generally high degree of uncertainty, in terms of time, quality and quantity of the returned products [22], [23]. However, the number of studies that handle uncertainties in literature is very low. Researchers usually used scenario based stochastic

programming techniques to cope with uncertainties [24], [25], [26], [27], [28], [5].

Although there are number of studies for forecasting in the forward supply chain, very few studies are available to predict product returns. Time series (intrinsic) and causal (extrinsic) methods that are applied for forecasting in forward logistics can be applied to predict return product quantity in reverse logistics [29].

Goh and Varaprasad [30] addressed the statistical way to predict return product quantity. They used the product life cycle parameters and basic time series techniques to forecast return product quantity for soft drinks reusable containers. Kelle and Silver [31] investigated forecasting return quantities problem of reusable containers to estimate demand. They estimated return ratio for forecasting the demand of reusable containers. Hess and Mayhew [32] presented a statistical model that direct marketing companies collect data from the return products and used it to predict the returns. The developed hazard rate model showed effect of product category, price etc. on product returns. In a simple linear regression method, they modelled 'time to return' based on the past returns and factors that affects these returns. There are various forecasting techniques used in the past. However, most studies were only based on time series. Marx-Gomez et al. [33] presented an extended forecasting method to predict waste product quantity and return time. They used neuro-fuzzy systems for forecasting process.

Toktay et al. [34] focused on return products forecasting at the operational level. The proposed model predicts quantity as a function of past sales data. Hanafi et al. [35] presented an integrated collection strategy which combines a fuzzy colored petri net forecasting method and collection network model to collect products. They applied presented method to a mobile phone collection in Australia. Xiaofeng and Tijun [6] presented a new model based on wave function to forecast return products of reverse logistics. Zhou et al. [36] developed a new approach to the forecasting of return product. This research established a model by adopting the Graphical Evaluation and Review Technique (GERT) network theory combined with Bill of Material (BOM) to forecast return quantity. Via presented model, the probability, the quantity and the expected timing of the returns are predicted. Potdar and Rogers [37] developed a methodology to forecast product returns for the consumer electronics industry using a combined approach of

data envelopment analysis /linear regression and a moving average.

Potdar and Rogers [29] presented a new forecasting technique based on reason codes for the consumer electronics industry to predict product returns. The methodology used namely central tendency approach and extreme point approaches. Clottey et al. [1] developed a generic forecasting approach to determine the distribution of the return products, as well as integrate it with an inventory model to enable production planning and control.

Also grey theory has been used with other methods in order to get better results. For instance, in 2014, Jiang et al. [57] use grey with support vector machine in rail demand. They combine ensemble empirical mode decomposition and grey support vector machine and they show the model is appropriate for short term high speed rail.

Although return product quantity prediction is very important issue for RLND, there is very limited study in literature. It is clear that there is a lack of literature. According to grey forecasting system literature review we saw that there is no any study that apply grey systems to reverse logistics area. In addition, literature associated with return product quantity forecasting in reverse logistics, grey systems is not used before. Therefore, in this study we developed grey forecasting method to predict return product quantity in RLND problem. The contribution of this study is to present grey forecasting systems to predict uncertainty related to quantity of return product. Literature review show that this is the first study to predict return quantity in e-waste reverse logistics network by using grey forecasting systems with real life application.

3. Grey Theory and Forecasting

A grey system, is developed by Julong Deng [38], is a system with characteristics between white and black ones. Grey System Theory (GST) has become an influential method of solving problems within environments with high uncertainty, under discrete small and incomplete data sets [39]. The Journal of Systems & Control Letters published the first article "The Control Problems of Grey Systems" about Grey Systems in 1982. In 1989, "The Journal of Grey System" is wound [40], [39]). From then on, the theory has been used in different areas with different aim (-one of them is forecasting). The model focuses on the study of problems that comprise of poor information and samples are formed small [39], [41]. The main

feature of grey theory is its capability of using as few as four data items to forecast the future data [11].

The systems with partially known and partially unknown information are named as grey systems. Grey System Theory (GST) is especially useful when the complete set of factors involved in the system's behavior is unknown or unclear, when the relationships of system factors to the system's behavior and inter-relationships among factors are uncertain, when the system behavior is too complex to determine completely or when only limited information on system behavior is available [42]. The application area of the system is wide such as engineering [43], chromatography [44], agriculture [45], health [46], meteorology [47], tourism [48], environment [49], [60], energy [50], machinery [51], finance [52], electricity [15], [58], [59], etc. Our desire on application is using the data in uncertain environment and because of that; we have to focus uncertain solution methods. Generally there are three methods which are used in uncertain systems [53]:

- Grey Systems
- Probability and Statistics
- Fuzzy Maths

Grey systems require poor information in forecasting. Data sequence does not significant but there has to be at least four data in order to forecast. But in probability and fuzzy maths there are some rules are nontrivial like data requirement should be fit any typical distribution in probability and statistics and has any known membership in fuzzy maths [53]. One advantage of GST over fuzzy approach is that GST fits better with multiple meanings (grey) environment [54]. This type of uncertainty is produced due to the lack of accurate values [55].

As we said, Grey Theory is applied in this paper for getting good forecasting outcome beside its simplicity. Grey systems theory has been applied in forecasting and five main categories of grey prediction are given as:

- Time series forecasting
- Calamity forecasting
- Seasonal calamity forecasting
- Topological forecasting
- Systematic forecasting

Typically, GM (1,1) (GM (1,1), i.e. first order grey model with one variable.) model is the main model of grey theory of prediction [12]. GM (1,1) has three basic operations: accumulated generating

operator (AGO), inverse accumulating operator (IAGO) and grey model (GM).

1st Operation: *Accumulated Generating Operator (AGO)*.

Original time series data with n samples is shown as:

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

AGO operator creates new time series sequence using the equation as below;

$$x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i) \quad (2)$$

From Eq. (2), a droningly series, $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n))$, is obtained. The second operation is creating the GM (1,1) by a first order grey differential equation.

$$x^{(0)}(k) + az^{(1)}(k) = b \quad (3)$$

In this Eq. (3), a, b and $z^{(1)}(k)$ are presented as follows;

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y \quad (4)$$

Where;

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \dots & \dots \\ -z^{(1)}(n) & 1 \end{bmatrix}, Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \dots \\ x^{(0)}(n) \end{bmatrix} \quad (5)$$

and,

$$z^{(1)}(k) = 0.5 (x^{(1)}(k) + x^{(1)}(k-1)) \quad (6)$$

$k = 2, 3, \dots, n$.

Here a is the development coefficient and b is driving coefficient.

2st operation: *Inverse Accumulating Operator (IAGO)*. Grey forecasting equation (Eq. (7)) is obtained by grey differential equation.

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} \quad (7)$$

$k = 1, 2, \dots, n$.

Here, $\hat{x}^{(1)}(k+1)$ shows the forecasting of x at the time $k+1$. The initial condition is;

$$x^{(1)}(0) = x^{(0)}(1) \quad (8)$$

3st operation: *GM (1,1)*

By applying the whole data in GM (1,1), the forecasting is fulfilled. Finally, in order to get the forecasted values, the final step is applied as follows;

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1 - e^a) \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-ak} \quad (9)$$

$k = 1, 2, \dots, n$.

3.1 Grey Prediction with Rolling Mechanism

Akay and Atak [11] issued Grey Prediction with Rolling Mechanism (GPRM) by using electricity consumption data. They showed that GPRM is better than Model of Analysis of the Energy Demand (MAED) is a kind of forecasting technique in energy.

In GPRM, $x^{(0)}(k+1)$ is forecasted by implementing GM (1,1) to the original time series $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n))$ under rule $k < n$ and $k \geq 4$. In this method, the model finds first value. After that, the first data, $x^{(0)}(1)$, is removed from old series and a new entry $x^{(0)}(k+1)$ is added to the end of the series.

3.2 Performance Measure Management

There are some forecasting methods and they have to be compared by some formulas called performance measures. There are four performance measures that used in this study. Here some notations are given;

E_t is the error term that means the difference between the forecasted and the actual value at the same time.

$$E_t = F_t - D_t \quad (10)$$

A_t is the absolute value of the error.

F_t is the Actual Value.

D_t is the Actual Value.

$Bias_t$ is the total Values of E_t .

Mean Squared Error (MSE): MSE expose the contribution of positive and negative errors to the lack of accuracy.

$$MSE_n = \frac{1}{n} \sum_{t=1}^n E_t^2 \quad (11)$$

Tracking Signal (TS_t): It is the ratio of bias and MAD. Bias is the total error [53].

$$TS_t = \frac{Bias_t}{MAD_t} \quad (12)$$

$$Bias_n = \sum_{t=1}^n E_t \quad (13)$$

If the TS_t values are between -6 and +6, the models are proper to forecast. If it is not, the forecasting method has to be changed [53].

4. Implementation

In this study, the goal is to predict the return quantity. The data comprise of 44 periods (see Table 2). To forecast the future data, three different levels of k are selected; k=4, 6, 8. The results and the actual values are shown in Fig.1, Fig.2, and Fig. 3.

Table 1. The actual and forecasted values of data

Actual	k=4	k=6	k=8
26,4			
34,45			
35,33			
61,62			
136,74	81,01		
154,24	234,18		
160,26	230,85	248	
173,23	175,08	242	
177,12	182,6	219	256
177,6	187,57	192	240
261,68	180,38	188	216
273,38	311,16	265	252
293	343,22	315	296
351,95	308,92	348	334
366,76	394,7	402	394
414,32	415,67	406	471
468,49	445,16	460	511
536,38	528,5	519	591
538,61	608,41	591	622
569,35	586,84	618	642
613	582,17	626	676
633,32	652,19	648	690
633,8	671,45	664	686
747,79	647,67	676	750
788,88	797,52	763	826
798,18	888,98	838	864
830,49	829,62	876	896
909,33	848,52	898	960
935,95	964,08	931	1001
1006,59	1001,26	982	1043
1038,48	1052,65	1064	1098
1144,32	1099,71	1107	1194
1182,64	1209,71	1192	1260
1254,8	1271,81	1264	1327
1358,24	1309,02	1330	1430
1372,74	1451,33	1437	1479
1554,66	1449,32	1463	1615
1998,73	1639,95	1625	1995
2063,74	2383,88	2111	2281
2360,22	2417,67	2379	2627
3060,12	2534,01	2720	3337
3698,41	3683,29	3435	4223
5167,4	4608,67	4291	5850
6066,91	6621,06	6297	7398

The results and the actual values are shown in Fig.1.

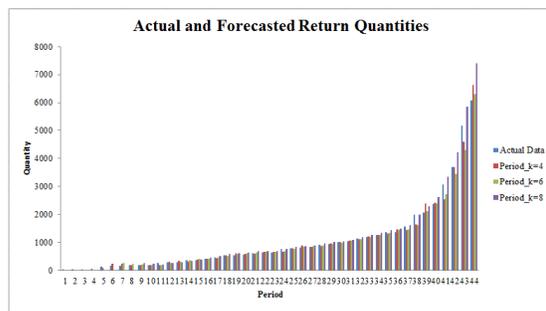


Figure 1. Actual and forecasted values under $k=4$, 6, 8.

The performance values of the forecasted values are given in the Table 3.

Table 2. The measures overall

Period	MSE	TSt
k=4	30322,0	-4,8
k=6	31647,6	-16,9
k=8	77980,1	34,7

It can be seen that, the TSt values of $k=6$ and $k=8$ are not appropriate for the raw data. Because the values are not between - 6 and + 6. As a result of that, $k=4$ is used for forecasting.

5. Conclusions

In recent years, because of economic, political, and environmental reasons more and more companies adopt reverse logistics activities in their business process. RL includes remanufacturing, repair, refurbishing, and recycling options. Reverse logistics is applied in many industries, such as; producing steel, aircraft, computers, automobiles, chemicals, appliances and medical items. Therefore reverse logistics has become increasingly important as a profitable and sustainable business strategy [3]. Designing of efficient RL network is one of the challenging reverse logistics problems. Reverse logistics network design is very difficult due to some critical parameters are uncertain. Especially, uncertainties in term of return product quantity, quality and time are the main characteristic of RL networks. The impact of uncertainty is more than expected [5]. Indeed, most important uncertainty of reverse logistics network is return quantity due to effect many variables in network. Better forecasting for the quantity of return products means efficient network, better customer satisfaction and better social picture for companies [6].

In this study, we developed grey forecasting method to predict product return quantity in reverse logistics network design. The theory of the Grey System was established during the 1980s by Prof. Deng Julong as a method for making quantitative predictions. In recent years, the system has been used in the calculation of organizational input and output values, as well as for agricultural, forestry, meteorological, and disaster predictions [56]. The contribution of this study is that the first study that presented grey forecasting model for product return quantity in reverse logistics network design literature. We applied presented model to forecast return quantity for third party e-waste firm at Turkey. Results show that grey forecasting method is very successful to predict return quantity. From this study, it is observed that forecasting the future values, with small k , gives better results in GPRM.

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