ARTICLE IN PRESS
TFS-18684; No of Pages 12
Technological Forecasting & Social Change xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

Grey modelling based forecasting system for return flow of end-of-life vehicles

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ARTICLE INFO

Article history:
Received 12 April 2016
Received in revised form 12 August 2016
Accepted 28 September 2016
Available online xxxx

Keywords:
End-of-life vehicles
Forecasting
Grey modelling
Product returns

ABSTRACT

Due to legislation and economic reasons, firms in most industries are forced to be responsible and manage their products at the end of their lives. Management of product returns is critical for the stability and profitability of a reverse supply chain. Forecasting the return amounts and timing is beneficial. The purpose of this paper is to develop a forecasting system for discarded end-of-life vehicles and to predict the number of end-of-life vehicles that will be generated in the future. To create the forecasting system, grey system theory, which uses a small amount of the most recent data, is employed. The accuracy of the grey model is improved with parameter optimization, Fourier series and Markov chain correction. The proposed models are applied to the case of Turkey and data sets of twelve regions in Turkey are considered. The obtained results show that the proposed forecasting system can successfully govern the phenomena of the data sets, and high accuracy can be provided for each region in Turkey. The proposed forecasting system can be used as a strategic tool in similar forecasting problems, and supportive guidance can be achieved.

1. Introduction

Growing interest in the reuse and recovery of products and materials has resulted from the scarcity of natural resources and raw materials, environmental reasons and governmental regulations about end-of-life products. Effective and efficient management of a series of activities required to retrieve a product from a customer and either recover value or dispose of it defines reverse supply chain management (Prahinski and Kocabasoglu, 2006). Managing product recovery operations efficiently is a challenging problem because of uncertainty in terms of the quantity, time and quality of the returned products. Return reasons of products can be classified as manufacturing-related returns, distribution-related returns and customer/user returns (De Brito and Dekker, 2002). For any type of return flow, assessment of the expected quantity, timing or location of return will provide insight to the managers of the reverse supply chain (Thierry et al., 1995).

Main theme of this paper is management of return flow of end-of-life products by providing a supportive forecasting tool. Forecasting the return flow of an end-of-life product is important for all decision levels of the reverse supply chain, including network design decisions at the strategic level, capacity planning decisions at the tactic level and production planning and inventory control decisions at the operational level (Toktay et al., 2003). Managing product return flows will be beneficial for the stability and profitability of a reverse supply chain.

The automotive industry is one of the largest industries in most countries because of its significant contributions to the economy. The increase in the production and sales of the automotive industry will also increase the number of end-of-life vehicles (Tian and Chen, 2014). Moreover, as reported by European Environment Agency (EEA) due to tighter environmental regulations, improvement in the environmental performance of new vehicles will result in rapid replacement of old vehicles with new ones (EEA, 2009). The European Automotive Manufacturers Association (ACEA) reported that, in 2014, 90.6 million motor vehicles were produced globally and 89.3 million vehicles were sold worldwide (ACEA, 2015).

Considering the perspective of Turkey, according to the Turkish Statistical Institute (TURKSTAT), the number of registered vehicles on the roads in Turkey increased 83.9% in the years 2004–2014 and reached nearly 19 million vehicles. The number of vehicles on the road increases by an average of 860,000 annually. In addition, in the years 2005–2014, 729,212 motor vehicles were scrapped in Turkey for recovery and recycling operations (TURKSTAT, 2015). Vehicles are strong pollutants during their useful life and at the end-of-life stage (Mahmoudzadeh et al., 2013), so a reverse supply chain should be formed to manage end-of-life vehicles' product recovery operations. In this context, forecasting the return flow of end-of-life vehicles is critical for constructing a reliable and profitable reverse supply chain (Govindan et al., 2015), and is main topic of this study. The topic is of interest to the managers and practitioners of the reverse supply chain or related economic operators.

There are important contributions in the product return flow forecasting literature. Within these contributions, several studies developed their models based on the sales data of the product, demographic information or product life cycle. Fuzzy systems, simulation models and probability and statistics techniques are commonly used as the solution

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http://dx.doi.org/10.1016/j.techfore.2016.09.030
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Please cite this article as: Ene, S., Öztürk, N., Grey modelling based forecasting system for return flow of end-of-life vehicles, Technol. Forecast. Soc. Change (2016), http://dx.doi.org/10.1016/j.techfore.2016.09.030

methodology. Some of the studies validated and applied their models using empirical data sets, and other studies used real data for validation and testing. Among the studies that used real data, generally the electrical and electronic equipment waste (e-waste) data are investigated for forecasting. To the best of the authors' knowledge, studies on the product return flow management of the automotive industry and model development for end-of-life vehicles return flow for recovery and recycling operations is lacking.

This paper investigates whether an efficient forecasting model can be designed for managing return flow of end-of-life vehicles with small amount of historical data. Determining the laws governing the phenomena of end-of-life vehicle return flows is an unaddressed issue. Considering there are a number of known factors, there are also some factors that may not be known or that have complex interrelations in return flow of end-of-life vehicles. In this paper, previous observations of the return flow system are analyzed to obtain meaningful phenomena for future prediction. Other than traditional statistical models, that require large samples, this paper will provide a better understanding in modelling small sized previous observations without any prior knowledge.

Under the scope of this paper, a forecasting system for the return flow of end-of-life vehicles is developed and the system is applied to the case of Turkish automotive industry. The proposed forecasting system is based on grey system theory, which handles data sets characterized by uncertainty and small size. Although there are important contributions in the literature on forecasting with grey modelling, not much research has been conducted on return flow forecasting based on grey modelling. This study contributes to the literature with a return flow forecasting system of end-of-life vehicles based on grey modelling. The rest of the paper is organized as follows: Section 2 presents a brief literature review of related works. Section 3 presents methodology and the proposed forecasting system for end-of-life vehicles in Turkey. The studied data characteristics and experimental results are provided in Section 4. Finally, conclusions are discussed in Section 5.

2. Literature review

In the literature, several researchers have studied forecasting the return amount of products for the management of product return flow. There are also various contributions about grey forecasting systems in literature in several fields. So, the literature can be reviewed in points of product return forecasting and grey forecasting under the scope of this paper. At first part of this section, existing papers about product return flow forecasting are presented. In some of the contributions regarding with return flow forecasting, fuzzy systems or neuro-fuzzy approaches are analyzed. Some researchers used probability and statistics techniques. Some papers studied system dynamics approach, wave function, logistic model and material flow analysis or graphical evaluation and review technique for return flow forecasting.

Among the prior studies that adopted fuzzy, fuzzy expert or neuro fuzzy systems to forecast product return flow; Marx-Gómez et al. (2002) presented a forecasting method based on a simulation model, fuzzy inference system and neuro-fuzzy approach to forecast the returns of scrapped products to recycling and remanufacturing. They employed a simulation model for data generation, a fuzzy system for one-period prognosis and a neuro-fuzzy approach for multi-period prognosis. Temur et al. (2014) developed a fuzzy expert system, including fuzzy systems and genetic algorithms, to forecast return quantity in a reverse logistics network. The proposed methodology was applied to a case study from the Turkish electrical and electronic equipment recycling sector.

Hanafi et al. (2008) studied the product collection strategy for waste electrical and electronic equipment that consists of two phases: the product return forecast and the collection network. The product return forecast phase of the proposed strategy is modeled by fuzzy-colored petri net forecasting that utilizes the demographic information, age and sales data of the product. The model was verified with a case study on mobile phones. Kumar et al. (2014) studied the closed-loop supply chain network design problem, and proposed a two-phase solution methodology: adaptive network-based fuzzy inference system for product return forecasting and a network optimization model. The proposed model was applied to an experimental study.

In order to apply fuzzy, fuzzy expert or neuro fuzzy systems to prediction of product return flow, influencing factors should be discovered properly in advance, and these techniques require expert knowledge. Besides, neural network based systems require large training and testing data sets for an accurate prediction. So applying these techniques to all type of product return flows or return flows with different sources may be challenging.

Considering the product return flow forecasting models with system dynamics approach, wave function, logistic model and material flow analysis or graphical evaluation and review technique, following works are encountered in literature. Srivastava and Srivastava (2006) developed a system dynamics model that associates product returns with the number of products in use, estimated demand, product life cycle and environmental impact policies for modelling a reverse logistics network. Kumar and Yamaoka (2007) presented a system dynamics model for the Japanese automotive industry to examine the relationships between reduce, reuse and disposal using motor vehicle consumption data and motor vehicle consumption forecast data. They used Holt's linear exponential smoothing technique for forecasting. Xiaofeng and Tijun (2009) developed a forecasting model for returned products of reverse logistics based on a wave function considering periodic fluctuation.

Yu et al. (2010) addressed the problem of forecasting global e-waste (obsolete computers) generation. They used a logistic model and material flow analysis for the solution. To address the lack of lifespan data, they developed a method to determine lifespan based on stock and sales data. Agrawal et al. (2014) proposed a forecasting model based on a graphical evaluation and review technique to predict the percentage and timing of product returns. The proposed model was validated through a case study of a mobile phone manufacturing company in India.

System dynamics models or different models used in product return forecasting may require estimation of some input parameters or interviews with related stakeholders.

Among the prior works about probability and statistical models employed in product return flow prediction; Potdar and Rogers (2012) presented a forecasting methodology based on reason codes for the consumer electronics industry to forecast product returns. In their model, the return data pattern is analyzed for each return reason, and the moving average and data envelopment analysis methods are used for forecasting product returns by determined return reason. Clottey et al. (2012) developed a forecasting model to determine the distribution of the returns of used products, and integrated the forecasting model with an inventory model. They applied the proposed model to the remanufacturing operations of an electronics original equipment manufacturer. Benedito and Corominas (2013) formulated a Markov decision model to obtain an optimal manufacturing policy. The quantity of products returned is modeled as a stochastic process, where the returns in a period depend on the quantity of products sold in the preceding periods.

Krapp et al. (2013) proposed a forecasting approach based on Bayesian estimation techniques to predict the returns of a product in closed-loop supply chains. Petridis et al. (2016) developed a framework for the estimation of the global e-waste (obsolete computers) generation. In their work, different lifespan distribution types were considered for the regions, and the expected e-waste quantities were customized using the sales and lifespan data. Dynamic regressions, autoregressive models and trend models were used in the forecasting framework.

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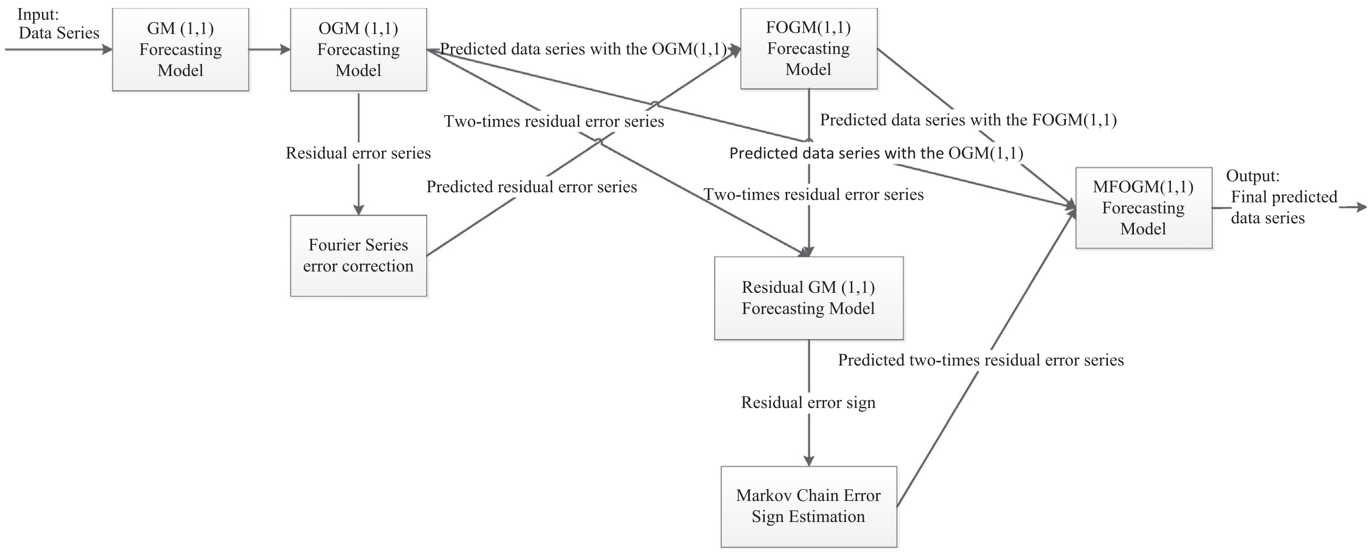

Fig. 1. Framework of the proposed forecasting system.

Probability and statistical models which applied to the product return flow management require large sample data sets and prior knowledge, such as the probability distribution of the input data. So, one can face obstacles while studying these approaches in product return forecasting, especially with real data instead of simulation input.

Only limited number of papers studied grey theory based forecasting system to product return flow management. Ayvaz et al. (2014) formulated a grey forecasting method to predict the return quantity in a reverse logistics network design and applied their model to e-waste return quantity forecasting in Turkey. Chen and He (2010) developed a composite forecast method based on time series and the grey method. They applied the model to the return data of household appliances.

Forecasting end-of-life vehicle return is a challenging task in terms of determining the laws governing the phenomena of the system. Even though there are a number of known factors, there are also some factors that may not be known or that have complex interrelations between them. In this respect, analyzing previous observations of the system to obtain meaningful phenomena for future prediction is a more practical alternative (Lin et al., 2009). Several forecasting models, such as regression models and neural networks, are traditionally applied to varied fields, but these techniques require large observed data sets for high accuracy (Lee and Tong, 2011). By focusing on small and uncertain data, the grey system theory differs from probability and statistical models, which investigate large samples, and fuzzy theory, which addresses cognitive uncertainty (Lee et al., 2014). Moreover, the model does not require any prior knowledge, such as the probability distribution of the input data (Hamzacebi and Es, 2014).

The main contribution of this paper is the development of a forecasting system for the return flow of end-of-life vehicles. The proposed forecasting system is based on grey system theory and improvements by parameter optimization, Fourier series and Markov chain correction.

In second part of the literature review section, prior works about grey forecasting is presented. The grey theory, which is an interdisciplinary scientific research, has been widely and successfully applied to various systems, such as social, economic, industrial, transportation and ecological. There are important contributions in the grey system theory literature. For example; Zhou et al. (2006) applied grey modelling based prediction approach to forecasting electricity demand, Kayacan et al. (2010) applied their grey theory based models to the prediction of foreign currency exchange rate, Lin et al. and Cui et al., 2013 applied their grey forecasting models to the illustrative example data sets, Nguyen et al. (2013) predicted tourism demand in Vietnam grey forecasting models, Wang et al. (2014) implemented their grey modelling based prediction for topic trend on Internet, Hamzacebi and Es (2014) forecasted annual electricity consumption in Turkey.

In grey forecasting literature, some of the researchers applied grey theory with improvements by parameter optimization, Fourier series or Markov chain correction to increase accuracy. Hamzacebi and Es (2014) and Lee et al. (2014) improved their forecasting models' accuracy by optimizing adjustment coefficient (α). Lin et al. (2009), Kayacan et al. (2010), Huang and Lee (2011) and Nguyen et al. (2013) applied Fourier series correction to their grey models and obtained better results in terms of the mean absolute percentage error. Several studies improved the performance of grey forecasting models by modelling residual errors by Markov chain theory (e.g., Hsu, 2003; Kumar and

Input : $X^{(0)}$ data series (Equation 1)
Step 1: Generate $X^{(1)}$ with accumulating generation operator (Equation 2-3)
Step 2: Generate background sequence $Z^{(1)}$ (Equation 4-6)
Step 3: Define GM(1,1) model equation (Equation 7), calculate a and b coefficients (Equation 8-11)
Step 4: Generate $x_p^{(1)}(k+1)$ (Equation 13)
Step 5: Generate $x_p^{(0)}(k+1)$ by applying inverse accumulating generation operator (Equation 14)
Output: Predicted data series $X_p^{(0)}$

Fig. 2. Procedure of the GM(1,1) algorithm.

Input: Data Series
Step 1: Generate GM (1,1) model considering α=0.1
Step 2: Calculate mean absolute percentage error (MAPE) of GM (1,1) with α=0.1
Step 3: If $\alpha<0.9$ then $\alpha^{new}=\alpha+0.1$ go to step 4; else determine best value of α that gives minimum MAPE and stop
Step 4: Calculate MAPE′ for α^{new} with GM (1,1)
Step 5: If MAPE′ < MAPE then MAPE = MAPE′; else MAPE= MAPE go to step 3
Output: OGM model with best value of α and predicted data series with OGM

Fig. 3. Procedure of the OGM algorithm.

Jain, 2010; Lee et al., 2004; Li et al., 2007; Wang and Meng, 2008). Moreover, Lin et al. (2001), Lin and Lee (2007), Hsu et al. (2009) and Lin et al. (2009) adopted both Fourier series and Markov chain theory to fit residual errors obtained from a grey forecasting model.

However, despite its successful applications in varied fields, the grey theory has been studied in limited number of papers for return flow prediction (Ayvaz et al., 2014; Chen and He, 2010). Considering the advantages of grey models for small and uncertain data sets, differently from previous studies, in this paper, a grey modelling based forecasting system is designed for end-of-life vehicle return flow prediction, and the proposed system is applied to the case of Turkey.

3. Methodology

As stated in Section 2, predicting product returns for the effective planning of recovery and recycling operations of end-of-life products is a challenging task due to the uncertainty in the factors that govern the phenomena of the system. Moreover, generally not much observation can be obtained for previous periods. Considering these characteristics of the return flow and the advantages of grey system theory, a forecasting system based on grey modelling (GM) is designed for predicting end-of-life vehicle returns. The forecasting system includes following sub-models; basic GM(1,1) model, optimized grey model (OGM), grey model with parameter optimization and Fourier series modification (FOGM) and the improved form of the OGM and FOGM models with Markov chain theory (MFOGM). Foundations of grey system theory, parameter optimization, Fourier series modification and Markov chain theory modification are provided in Appendix A.

The framework of the forecasting system is shown in Fig. 1, including the inputs and outputs for each forecasting sub-model. Despite the complex illustration, the proposed system is capable of obtaining forecasting results with good accuracy for data sets with different characteristics.

An overview of the GM(1,1) algorithm used in the forecasting system is shown in Fig. 2. To improve the performance of GM(1,1), model parameter optimization of adjustment coefficient α is integrated into the algorithm and the OGM model (parameter optimized grey model) is developed. The procedure of the OGM is presented in Fig. 3.

The residual error series obtained from the OGM model are used in the Fourier series correction for the proposed forecasting system, and by adding the predicted error residuals to the OGM results, the modified prediction values are produced. The FOGM model (grey forecasting model with parameter optimization and Fourier series modification) is then developed. The procedure of the FOGM algorithm is shown in Fig. 4.

For the two-times residual error correction on the FOGM or OGM models, the residual GM(1,1) model is established. Then, to estimate the sign of the two-times errors, Markov chain theory is adopted. Consequently, the improved form of the OGM and FOGM models is developed with Markov chain theory (MFOGM). The procedure of the MFOGM model is presented in Fig. 5.

An overview of the proposed forecasting system for predicting the return flow of end-of-life vehicles is presented in Fig. 6. The proposed system starts by generating a basic GM(1,1) model; then, the OGM is developed. Error correction is performed with Fourier series using the results of the OGM model, and the FOGM model is generated. Then, the system checks the MAPE of the OGM and FOGM models. If the MAPE values are <10%, the system uses one of the model with the lower MAPE for the studied data set. If the MAPE values are >10%, the system generates the MFOGM model with the OGM or FOGM model according to their MAPE values. Briefly, the system uses OGM, FOGM and MFOGM sub-models and obtains prediction values from one of these models for the studied data sets with the best accuracy.

4. Experimental results

In this paper, the proposed forecasting system is applied to the end-of-life vehicle return flow prediction in Turkey. Historical data sets for discarded end-of-life vehicles are provided from TURKSTAT for each region in Turkey. Eighty-one cities in Turkey are partitioned into 12 geographic regions. The regions in Turkey and the included cities are shown in Table 1. Future predictions of Turkey's end-of-life vehicle return flow are performed for each region in this study.

In the scope of this study, only the number of discarded cars are considered and modeled for future prediction. It should be noted that, end-

Input: $\varepsilon^{(0)}$ Residual error series of the OGM model
$X_{po}^{(0)}$ Predicted data series obtained from the OGM model
Step 1: Generate Fourier data matrix **F** (Equation 20) to obtain predicted error residuals with Fourier series equation (Equation 18)
Step 2: Generate coefficients matrix **C** with equation (22) by applying least square method to equation (19)
Step 3: Obtain $\varepsilon_p^{(0)}$ predicted residual errors, by substituting coefficients matrix values obtained from equation (22) to equation (18)
Step 4: Obtain predicted data series modified by Fourier series with Equation (23)
Output: Predicted data series with Fourier series modification $X_{pf}^{(0)}$

Fig. 4. Procedure of the FOGM algorithm.

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Fig. 5. Procedure of the MFOGM algorithm.

of-life vehicle term includes vehicles returned from the end user and full-damaged vehicles came from insurance companies. In Fig. 7, the number of end-of-life vehicles returned for recovery or disposal in the 12 regions in Turkey between the years 2008 to 2013 is presented graphically.

The data sets of the 12 regions have different characteristics and trends. For the regions which have low population density or low economic strength, as well as in relation with total number of registered vehicles in the region, the number of end-of-life vehicles is at low levels. Similarly, in the regions which have high population density or high economic strength and high number of total registered vehicles, the number of end-of-life vehicles is at high levels. Although each data set has different trend, we can see from the Fig. 7 that, in the years 2009 and 2010 there is an increase in the number of end-of-life vehicles. This increase can be a result of tax discounts or other contributions for purchasing new vehicles. End-of-Life Vehicle directive in Turkey is published in 2009 (December 30th) and the directive is started to be applied in 2011 (January 1st). It can also be interpreted from the Fig. 7 that, the directive does not have a significant effect on the number of end-of-life vehicles for each region as an increasing trend.

Figs. 8 and 9 presents total number of vehicles (car) and number of yearly new registered vehicles (car) in each region of Turkey which are obtained from TURKSTAT.

It is clear from the Fig. 8 that, total numbers of registered vehicles are increasing every year in each region of Turkey and maximum number of vehicles belongs to İstanbul. Similarly new vehicle registration in İstanbul is more than the other regions (Fig. 9). However, considering Figs. 7 and 9, it is observed that numbers of discarded vehicles are considerably less than numbers of new registered vehicles for each region. This results increase in total number of vehicles and shows that the vehicles are also active in secondary market.

Average age of the vehicles (car) and range of the vehicle's (car) age in 2013 for each region are obtained from TURKSTAT and shown in Fig. 10. We can see that average age of vehicles is commonly between 11 and

Input: Data series
Step 1: Generate GM (1,1) model considering α=0.5 and calculate MAPE of the GM(1,1) model
Step 2: Determine best value of α and generate the OGM model
  Step 2.1: Calculate MAPE of the GM (1,1) with α=0.1
  Step 2.2: If $\alpha<0.9$ then $\alpha^{new}=\alpha+0.1$; else determine best value of α that gives minimum MAPE and go to Step 3
  Step 2.3: Calculate MAPE′ for α^{new} with the GM (1,1)
  Step 2.4: If MAPE′ < MAPE then MAPE = MAPE′; else MAPE = MAPE go to Step 2.2
Step 3: Modify the OGM model with Fourier series, generate the FOGM model and calculate MAPE of the FOGM
Step 4: If $FOGM_{MAPE} < OGM_{MAPE}$ then use the FOGM model for the data set Else use the OGM model
Step 5: If $FOGM_{MAPE}$ and OGM_{MAPE}>% 10 generate the MFOGM model with the model have lower MAPE and calculate the MAPE of the MFOGM model
Output: Predicted data series obtained from the model with minimum MAPE

Fig. 6. Overview of the proposed forecasting system.

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Table 1
Regions in Turkey.

Regions	Including cities
West Anatolia	Ankara, Konya, Karaman
East Marmara	Bursa, Kocaeli, Eskişehir, Sakarya, Bolu, Düzce, Bilecik, Yalova
Aegean	İzmir, Manisa, Muğla, Aydın, Denizli, Afyonkarahisar, Kütahya, Uşak
East Black Sea	Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane
Mediterranean	Antalya, Adana, Mersin, Hatay, Kahramanmaraş, Isparta, Osmaniye, Burdur
Central Anatolia	Kayseri, Sivas, Nevşehir, Aksaray, Yozgat, Niğde, Kırıkkale, Kırşehir
West Marmara	Balıkesir, Tekirdağ, Çanakkale, Edirne, Kırklareli
West Black Sea	Samsun, Çorum, Tokat, Zonguldak, Kastamonu, Amasya, Karabük, Sinop, Bartın, Çankırı
North East Anatolia	Erzurum, Erzincan, Kars, Ağrı, Iğdır, Ardahan, Bayburt
Central East Anatolia	Malatya, Elazığ, Van, Muş, Bitlis, Bingöl, Hakkari, Tunceli
South East Anatolia	Gaziantep, Şanlıurfa, Diyarbakır, Adıyaman, Mardin, Batman, Kilis, Şırnak, Siirt
İstanbul	İstanbul

14 years for each region, except for İstanbul. In İstanbul, average age of vehicles is about 7 years. Similarly, number of vehicles which are older than 10 years is generally >50% of total vehicles in each region, except for İstanbul. Number of vehicles which are older than 10 years is about 28% percent of total vehicles in İstanbul. However, there isn't a marked connection between average age of vehicles and number of discarded vehicles in the regions.

Considering these issues and data, developing a forecasting model that covers all of the regions' data sets is a complex problem. The proposed forecasting system can be implemented to enable the selection of the best-fitted model from the sub-models for each data set.

In the literature, different performance measures are adopted by researchers. To determine the accuracy of the forecasting models, two performance measures are utilized in this study: percentage relative error (RE) and mean absolute percentage error (MAPE) as presented in Appendix B.

Lewis (1982) proposed a MAPE classification to determine the forecasting accuracy level. According to this classification, the forecasting accuracy is considered high for MAPE values less than or equal to 10%. The remaining reference values are shown in Table 2.

The proposed forecasting system is applied to the data sets of the 12 regions. The most recently observed data from 2008 to 2013 are used in the development and testing of the GM(1,1) model. Performance evaluation in terms of the MAPE % for each sub-model is obtained as in Table 3. For all regions, in curve fitting, the forecasting system provides accuracy >90%, and in eight regions, 95% accuracy is achieved.

In West Anatolia, the best MAPE value is obtained by the OGM model (4.62%), and this sub-model can be used in the future prediction of this region. For the regions of the East Marmara, Aegean, Mediterranean, Central Anatolia, West Marmara, North East Anatolia, South East Anatolia and İstanbul, the FOGM model provides the best MAPE values of 3.89%, 3.11%, 6.98%, 1.98%, 9.20%, 5.94%, 4.17% and 4.43%, respectively. The FOGM model can be used in the future predictions for these regions. According to the forecasting system, as summarized in Fig. 5, the MFOGM model is only applied to the regions of the East Black Sea, West Black Sea and Central East Anatolia, which have MAPE values >10% for the GM, OGM or FOGM models; with the MFOGM model, the MAPE values for these regions are decreased to 2.19%, 1.87% and 6.78%, respectively. For these regions, the MFOGM model can be used for future predictions.

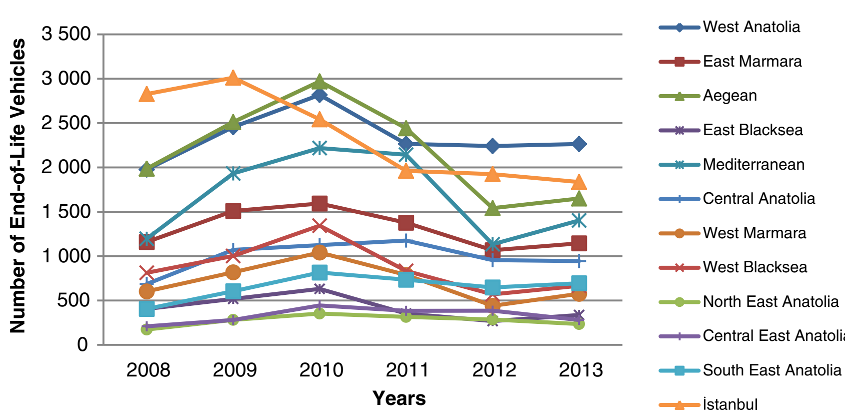

Fig. 7. Characteristics of the data sets for each region in Turkey.

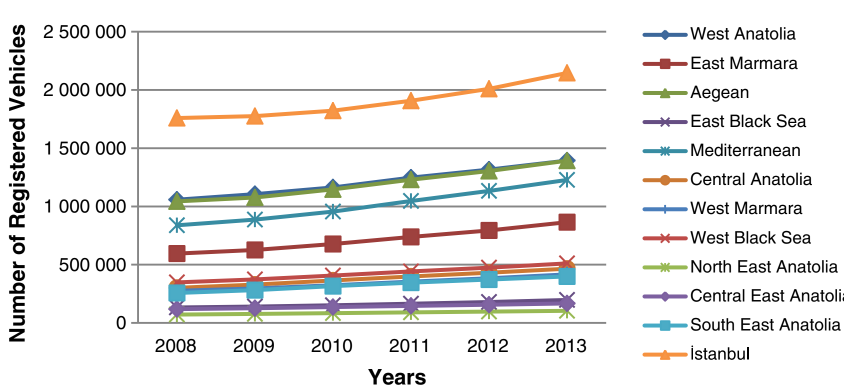

Fig. 8. Total number of registered vehicles for each region in Turkey.

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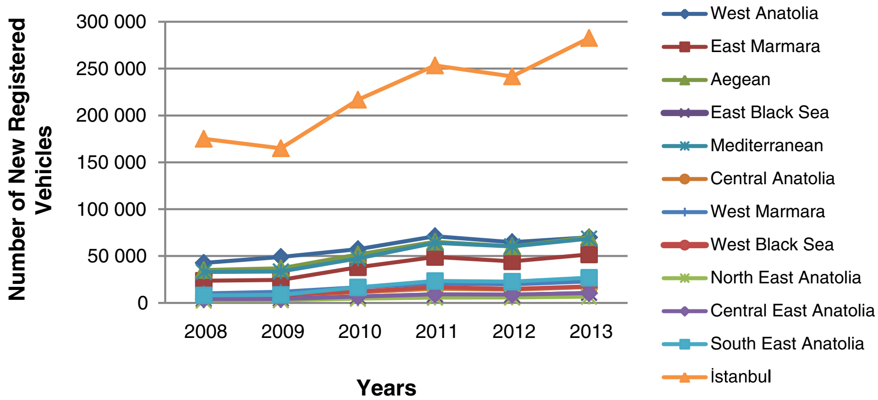

Fig. 9. Number of yearly new registered vehicles for each region in Turkey.

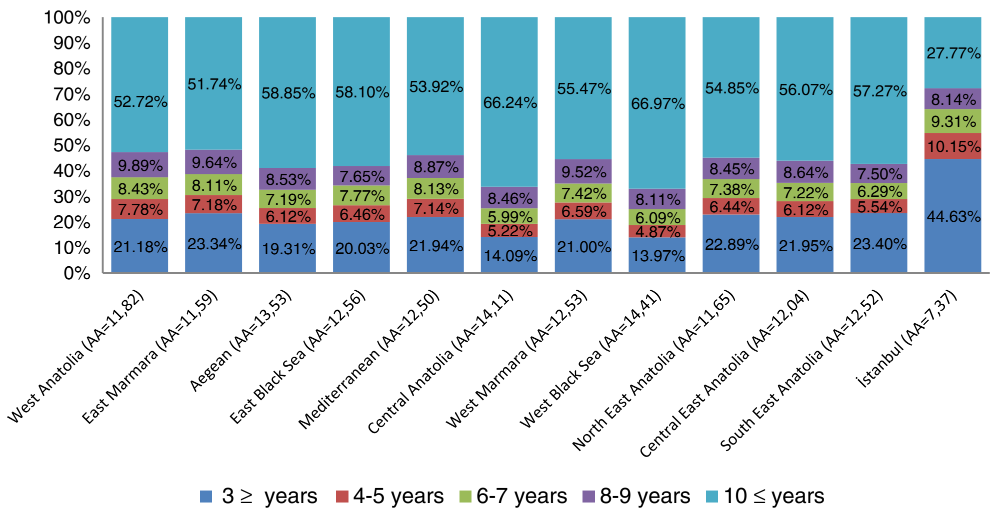

Fig. 10. Average age (AA) of vehicles and range of vehicles' age in 2013 for each region in Turkey.

To observe the detailed results of the forecasting system and the OGM, FOGM and MFOGM sub-models, three examples of regions and their curve fitting results that provide the best accuracy with the OGM, FOGM and MFOGM models are presented in Tables 4, 5 and 6, respectively.

In curve fitting of the end-of-life vehicle flow of the West Anatolia, the GM (1,1) model is first developed, and the RE and MAPE values for the curve fitting results are obtained. Then, the α parameter that gives the minimum MAPE is determined, and the OGM model is established. The FOGM model is developed from a modification of the OGM with Fourier series. Among the accuracy results of the GM, OGM and FOGM, the OGM model, which gives best MAPE value (4.62%), is selected for future predictions of the West Anatolia.

Similarly, the forecasting system is implemented for the curve fitting of Central Anatolia. In this case, the minimum MAPE value is obtained with the FOGM model (1.98%), and the FOGM model is selected for future predictions of the Central Anatolia. In both the West Anatolia and Central Anatolia, the MFOGM model is not applied because the accuracy results are >90% according to the OGM and the FOGM, respectively.

For curve fitting of the end-of-life vehicles in the West Black Sea, all sub-models are developed because the MAPE values for the GM, OGM and FOGM models are >10%. With the two-times error residuals sign estimation using residual GM and Markov chain, the MAPE is decreased to 1.87%. Therefore, because it has the best accuracy, the MFOGM model can be used for the future predictions in the West Black Sea.

Table 2
MAPE reference values for forecasting accuracy (Lewis, 1982).

Range of MAPE	Forecasting accuracy
≤10%	High
10–20%	Good
20–50%	Feasible
≥50%	Low

Table 3
Performance evaluation of the forecasting models for curve fitting.

		GM	OGM	FOGM	MFOGM
	Regions	% MAPE	% MAPE	% MAPE	% MAPE
1	West Anatolia	4.83	4.62	4.79	
2	East Marmara	6.44	6.18	3.89	
3	Aegean	11.20	10.51	3.11	
4	East Black Sea	15.00	13.24	11.75	2.19
5	Mediterranean	13.77	13.69	6.98	
6	Central Anatolia	5.48	5.20	1.98	
7	West Marmara	16.04	15.86	9.20	
8	West Black Sea	13.43	13.06	10.49	1.87
9	North East Anatolia	10.16	9.99	5.94	
10	Central East Anatolia	17.05	16.09	13.12	6.78
11	South East Anatolia	7.55	7.39	4.17	
12	İstanbul	5.72	5.45	4.43	

Please cite this article as: Ene, S., Öztürk, N., Grey modelling based forecasting system for return flow of end-of-life vehicles, Technol. Forecast. Soc. Change (2016), http://dx.doi.org/10.1016/j.techfore.2016.09.030

Table 4
Forecasting system curve fitting results of the West Anatolia.

Years	Observed data (NUMBER of End-of-Life Vehicles)	GM (1,1) Result	% RE	**OGM (1,1) Result**	**% RE**	FOGM (1,1) Result	% RE
2008	1977	1977	0	**1977**	**0**	1977	0
2009	2455	2621	6.76	**2578**	**5.01**	2676	5.79
2010	2818	2500	11.28	**2457**	**12.81**	2409	5.05
2011	2266	2384	5.21	**2341**	**3.31**	2099	6.28
2012	2241	2274	1.47	**2231**	**0.45**	2146	6.35
2013	2265	2169	4.24	**2126**	**6.14**	2598	5.29
% MAPE			4.83		**4.62**		4.79

Table 5
Forecasting system curve fitting results of the Central Anatolia.

Years	Observed data (Number of End-of-Life Vehicles)	GM (1,1) Result	% RE	OGM (1,1) Result	% RE	**FOGM (1,1) Result**	**% RE**
2008	687	687	0	687	0	**687**	**0**
2009	1071	1124	4.95	1114	4.01	**1044**	**2.57**
2010	1124	1095	2.58	1084	3.56	**1152**	**2.45**
2011	1176	1067	9.27	1055	10.29	**1149**	**2.34**
2012	955	1040	8.90	1027	7.54	**983**	**2.88**
2013	945	1013	7.20	1000	5.82	**930**	**1.64**
% MAPE			5.48		5.20		**1.98**

The end-of-life vehicle return flow forecast results of the 12 regions in Turkey and the observed data for 2014 and 2015 are represented graphically in Figs. 11 and 12, respectively. For 2015, the observed data from TURKSTAT contains only the first 10 months of the year. Therefore, the data were spread to the 12 months proportionally.

The curve fitting and forecast results are capable of managing the phenomena of the data. Although in some regions the accuracy of the models can be improved, the models provide good results, with the worst accuracy of 90.8%, considering the models are used on real data not empirical or simulation data.

To provide guidance in the management and planning of the recovery and recycling operations of discarded vehicles, the return flow of end-of-life vehicles in Turkey is predicted with the proposed forecasting system, as in Table 7, for each region and for a five-year period. According to the Liu and Lin (2010), making long, mid or short term prediction with grey modelling depends on the value of developing coefficient (a). When $-a \leq 0.3$, GM(1,1) can be applied to make mid-term to long-term predictions. The value of developing coefficient obtained in our models fits this case. So, we can say that, making a prediction for a five-year period is acceptable in our case study. Besides, projected data for number of end-of-life vehicles for future periods with acceptable

Table 6
Forecasting system curve fitting results of the West Black Sea.

Years	Observed data (Number of End-of-Life Vehicles)	GM (1,1) Result	% RE	OGM (1,1) Result	% RE	FOGM (1,1) Result	% RE	**MFOGM (1,1) Result**	**% RE**
2008	813	813	0	813	0	813	0	**813**	**0**
2009	1003	1189	18.54	1131	12.76	1097	9.40	**1021**	**1.80**
2010	1344	1005	25.22	955	28.94	1250	7.01	**1363**	**1.40**
2011	835	849	1.68	807	3.35	929	11.29	**820**	**1.82**
2012	569	717	26.01	681	19.68	475	16.56	**548**	**3.76**
2013	667	606	9.15	576	13.64	542	18.70	**651**	**2.45**
% MAPE			13.43		13.06		10.49		**1.87**

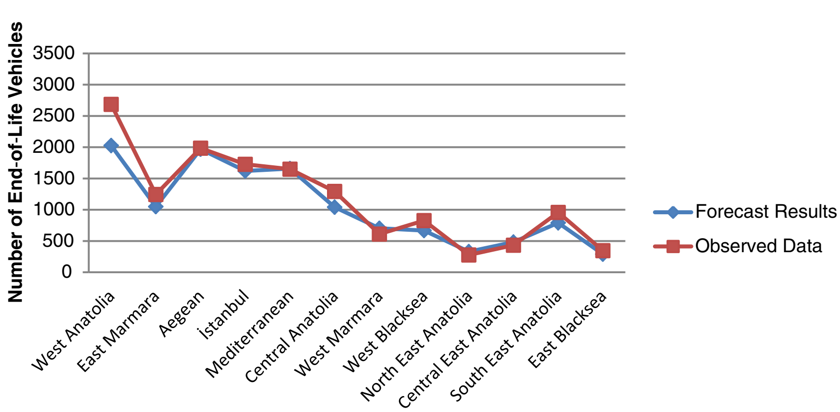

Fig. 11. Forecast results and observed data of 2014 for each region in Turkey.

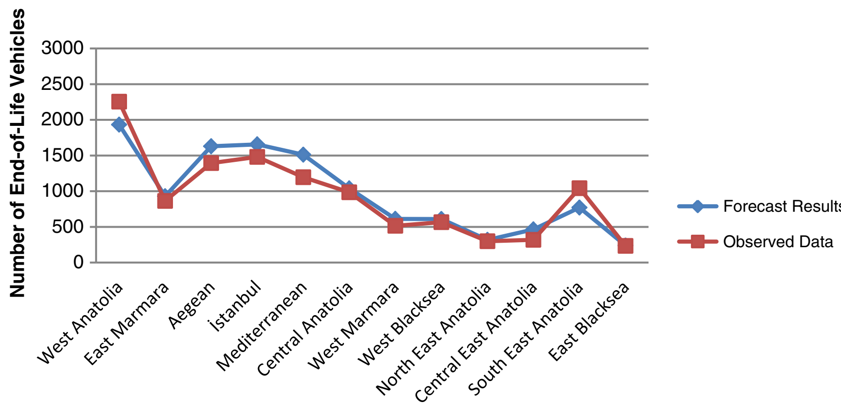

Fig. 12. Forecast results and observed data of 2015 for each region in Turkey.

forecast errors will be quite beneficial to the practitioners or economic operators in the management and planning of the recovery and recycling operations.

5. Conclusions

Forecasting the return flow of end-of-life products is a complicated problem that includes a number of known and unknown parameters that affect the return of products. Although several researchers have investigated product return forecasting, the return flow of end-of-life vehicles has rarely been studied.

In this paper, a forecasting system based on grey system theory is designed and return flow of end-of-life vehicles in Turkey is predicted. The proposed forecasting system is composed of sub-models based on grey modelling and improvements by parameter optimization, Fourier series and Markov chain correction. In the experimental results, the original data of discarded vehicles of the different regions in Turkey are obtained from TURKSTAT. The results of the forecasting sub-models are compared for each region, and the performance of the models differed for each region due to the characteristics of the related data sets. The proposed forecasting system achieved high accuracy for all regions in Turkey. The results of the future predictions provide guidance to the managers and practitioners of recovery and recycling systems.

There are multiple contributions of this paper. This paper contributes to the literature with a model for end-of-life vehicles return flow forecasting. To the best of the authors' knowledge, minimal study has been conducted on return flow forecasting based on grey modelling, and not much study has investigated combination of parameter optimization, Fourier series and Markov chain improvements on grey modelling. This paper demonstrates that grey modelling can be successfully applied to product return flow forecasting. Moreover, the proposed forecasting system can be used as a strategic tool for any product return flow forecasting under uncertainty with a small amount of recent data.

For future research, different methods can be investigated for end-of-life vehicle return flow forecasting, and the performance of the methods can be compared. Additionally, the forecasting models can be integrated into recovery network decisions, and a decision support system can be established for the management of end-of life vehicle returns.

Table 7
Forecasting results in Turkey up to 2020 in terms of number of end-of-life vehicles.

Regions	2016	2017	2018	2019	2020
West Anatolia	1841	1754	1672	1593	1519
East Marmara	981	988	1164	1102	871
Aegean	1068	1088	1593	1370	680
İstanbul	1625	1555	1452	1394	1374
Mediterranean	771	837	1363	1118	827
Central Anatolia	1073	1098	1418	1466	1222
West Marmara	358	384	545	462	248
West Black Sea	547	703	926	771	579
North East Anatolia	212	189	211	201	165
Central East Anatolia	517	244	610	162	751
South East Anatolia	623	646	797	776	628
East Black Sea	286	350	360	386	339

Appendix A. Foundations of grey system theory

Grey system theory was first introduced by Deng in early 1980s. The theory is an interdisciplinary scientific theory and has been widely applied to various systems. Grey models predict the future values of a time series based on a set of the most recent data (Kayacan et al., 2010). Grey system theory is one of the most common methods used for studying data sets characterized by uncertainty and small size (Wang et al., 2014). In grey theory, GM(η,m) characterizes a grey model, where η is the order of the difference equation, and m is the number of variables. Because of the computational efficiency of GM(1,1), the first order one variable grey model is common among researchers (Kayacan et al., 2010).

A.1. GM(1,1) model

The GM(1,1) model can only be used in positive data sequences and requires at least four observations. To smooth the randomness of the primitive data, an accumulating generation operator is applied to the data and the differential equation is solved to obtain the predicted value of the system. To obtain the predicted value of the original data, the inverse accumulating generation operator is applied. The formulation of the GM(1,1) model is constructed as follows in Eqs. (1)–(15) (Deng, 1989; Hui et al., 2009; Kayacan et al., 2010; Kumar and Jain, 2010; Wang et al., 2013).

Consider $X^{(0)}$ as a time sequence:

$$X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \ldots., x^{(0)}(n)\right) \quad n \geq 4 \tag{1}$$

This time sequence is subjected to the accumulating generation operator, and $X^{(1)}$ is obtained.

$$X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \ldots., x^{(1)}(n)\right) n \geq 4 \tag{2}$$

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \qquad k = 1, 2, \ldots., n \tag{3}$$

The background sequence of $X^{(1)}$ is defined as $Z^{(1)}$:

$$Z^{(1)} = \left(z^{(1)}(1), z^{(1)}(2), \ldots, z^{(1)}(n)\right) \tag{4}$$

$z^{(1)}(k)$ is obtained by applying the mean operation to the adjacent data of $x^{(1)}$and is derived as:

$$z^{(1)}(k) = \alpha x^{(1)}(k) + (1-\alpha)x^{(1)}(k-1) \quad k = 2, 3, \ldots, n \quad \alpha \in [0, 1] \tag{5}$$

The horizontal adjustment coefficient (α) used in the formulation of $z^{(1)}(k)$ is commonly assumed as 0.5, and Eq. (5) is converted into Eq. (6) as:

$$z^{(1)}(k) = 0,5x^{(1)}(k) + (1-0,5)x^{(1)}(k-1) \quad k = 2, 3, \ldots, n \tag{6}$$

The basic form of the GM(1,1) model can be defined as:

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{7}$$

where a and b are coefficients. a is the developing coefficient, and b is the grey input. Writing Eq. (7) in matrix form results in Eq. (8):

$$\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ . \\ . \\ x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ . & . \\ . & . \\ -z^{(1)}(n) & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} \tag{8}$$

Coefficients a and b are obtained by the least-squares method as:

$$[a, b]^T = \left(\mathbf{B}^T\mathbf{B}\right)^{-1}\mathbf{B}^T\mathbf{Y} \tag{9}$$

where $\mathbf{B}$ and $\mathbf{Y}$ are data matrices which are formulated as:

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

$$\mathbf{Y} = \left[x^{(0)}(2) \;\; x^{(0)}(3) \;\; \ldots\ldots \;\; x^{(0)}(n)\right]^T \tag{11}$$

The whitening equation is defined as:

$$\frac{dx^1(t)}{dt} + ax^{(1)}(t) = b \tag{12}$$

According to the whitening equation, with $x^{(1)}(1) = x^{(0)}(1)$, $x_p^{(1)}(k+1)$ is obtained as:

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

To obtain the predicted value of the primitive data at time $(k + 1)$, the inverse accumulating generation operation $(x^{(0)}(k+1) = x^{(1)}(k+1) - x^{(1)}(k))$ is applied as:

$$x_p^{(0)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right]e^{-ak}(1-e^a) \tag{14}$$

The predicted value of the primitive data at time $(k + H)$ is calculated as:

$$x_p^{(0)}(k+H) = \left[x^{(0)}(1) - \frac{b}{a}\right]e^{-a(k+H-1)}(1-e^a) \tag{15}$$

Despite the satisfactory performance of grey modelling in small data sets, the forecasting accuracy of the grey models can be improved by modelling residuals. Several methods have been proposed in the literature for modelling residuals, such as Fourier series, Markov chain, neural networks, parameter optimization and genetic programming. In this paper, considering their successful implementations and improvements, parameter optimization, Fourier series and Markov chain methods are investigated.

A.2. Parameter optimization in grey modelling

The horizontal adjustment coefficient (α) used in the derivation of the background sequence of the data ($Z^{(1)}$) affects the forecasting performance of grey models. The best value of this coefficient can be obtained by experiments (Hamzacebi and Es, 2014). α is commonly assumed to be 0.5 in the literature.

A.3. Fourier series correction

The basis of using Fourier series in forecasting techniques is to transform the one-time residual series into frequency spectra and to select the low frequency terms. Fourier series can be adopted by the grey forecasting model to filter out the noise of the high frequency modes and randomness (Lin et al., 2009).

Considering the forecasting results, the residual series can be defined as:

$$\varepsilon^{(0)} = \left(\varepsilon^{(0)}(2), \varepsilon^{(0)}(3), \ldots, \varepsilon^{(0)}(n)\right) \tag{16}$$

The residual error at time k $\varepsilon^{(0)}(k)$can be derived as:

$$\varepsilon^{(0)}(k) = x^{(0)}(k) - x_p^{(0)}(k) \quad k = 2, 3, \ldots, n \tag{17}$$

The residual series can be modeled by a Fourier series as:

$$\varepsilon^{(0)}(k) \cong \frac{1}{2}af_0 + \sum_{i=1}^{z}\left[af_i \cos\left(\frac{2\pi i}{U}k\right) + bf_i \sin\left(\frac{2\pi i}{U}k\right)\right] \quad k = 2, 3, \ldots, n \tag{18}$$

In Eq. (18), U, where $U = n-1$, denotes the length of the period, and z indicates the minimum deployment frequency of the Fourier series, where $z = \left(\frac{n-1}{2}\right) - 1$. Eq. (18) can be converted into the form as follows:

$$\varepsilon^{(0)} \cong \mathbf{F}\,\mathbf{C} \tag{19}$$

where the $\mathbf{F}$ and $\mathbf{C}$ matrices are defined as:

$$\mathbf{F} = \begin{bmatrix} 1/2 & \cos\left(2\frac{2\pi}{U}\right) & \sin\left(2\frac{2\pi}{U}\right) & \cos\left(2\frac{2\pi 2}{U}\right) & \sin\left(2\frac{2\pi 2}{U}\right) \ldots\ldots & \cos\left(2\frac{2\pi z}{U}\right) & \sin\left(2\frac{2\pi z}{U}\right) \\ 1/2 & \cos\left(3\frac{2\pi}{U}\right) & \sin\left(3\frac{2\pi}{U}\right) & \cos\left(3\frac{2\pi 2}{U}\right) & \sin\left(3\frac{2\pi 2}{U}\right) \ldots\ldots & \cos\left(3\frac{2\pi z}{U}\right) & \sin\left(3\frac{2\pi z}{U}\right) \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \quad \ldots\ldots & \ldots\ldots & \ldots\ldots \\ 1/2 & \cos\left(n\frac{2\pi}{U}\right) & \sin\left(n\frac{2\pi}{U}\right) & \cos\left(n\frac{2\pi 2}{U}\right) & \sin\left(n\frac{2\pi 2}{U}\right) \ldots\ldots & \cos\left(n\frac{2\pi z}{U}\right) & \sin\left(n\frac{2\pi z}{U}\right) \end{bmatrix} \tag{20}$$

$$\mathbf{C} = [a_0 \; a_1 \; b_1 \; a_2 \; b_2 \; \ldots \; a_z \; b_z]^T \tag{21}$$

By applying the least-squares approach to Eq. (19), the coefficients matrix $\mathbf{C}$ can be derived as:

$$\mathbf{C} \cong \left(\mathbf{F}^T\mathbf{F}\right)^{-1}\mathbf{F}^T\varepsilon^{(0)} \tag{22}$$

By substituting the coefficient matrix values obtained from Equation (22) into Eq. (18), the estimated residual error series $\varepsilon_p^{(0)}$can be obtained. Fourier series correction can be modeled as (Kayacan et al., 2010; Lin et al., 2009):

$$x_{pf}^{(0)}(k) = x_p^{(0)}(k) + \varepsilon_p^{(0)}(k) \qquad k = 2, 3, \ldots\ldots, n+1 \tag{23}$$

A.4. Markov chain theory

Markov chain is a particular type of stochastic process and is widely used in various research fields, such as engineering, physics and biology, to generate stochastic models. Considering stochastic process X, the random variables of this process are referred as $X(t)$, and the process can be defined as $X = \{X(t), t \in TK\}$. The Markov property must be satisfied in a Markov chain such that the future evolution of the conditional probability depends only on the current state of the system and not on the sequence of events that preceded it. Due to this feature, the Markov chain can be used as a forecasting method for these events (Hsu et al., 2009).

Considering S as the state space of the Markov chain $\{X_m\}$, the transition probability from the current state i to the next state j can be defined as:

$$P_{ij} = \mathrm{Prob}\{X_{m+1} = j | X_m = i\} \qquad i, j \in S, m \in \{0, 1, 2, \ldots.\} \tag{24}$$

The transition probability matrix $\mathbf{P}$, including P_{ij} for all i and j, can be formed as:

$$\mathbf{P} = \begin{bmatrix} P_{11} & P_{12} & \ldots & P_{1k} \\ P_{21} & P_{22} & \ldots & P_{2k} \\ \ldots & \ldots & & \ldots \\ P_{k1} & P_{k2} & \ldots & P_{kk} \end{bmatrix} \qquad S = 1, 2, \ldots.k \tag{25}$$

The elements of matrix $\mathbf{P}$ must ensure the following features (Hsu et al., 2009):

1) $P_{ij} \geq 0 \qquad \forall i, j \in S$
2) $\sum_{j \in S} P_{ij} = 1 \qquad \forall i \in S$

Markov chain can be used to improve the accuracy of GM(1,1) models for forecasting systems that have large random fluctuations (Kumar and Jain, 2010). In the literature, two approaches have been used to improve the performance of grey forecasting models by Markov chains: forecasting residual errors and forecasting the sign of the residual errors. To forecast the residual errors with Markov chains, the residual error series are partitioned into equal intervals called states in the range of the maximum and minimum residual errors, and the probability of a certain error state in the next step is defined by a transition probability matrix. To forecast the sign of the residual errors, two states are described to address the positive and negative sign of the error, and transition probabilities are calculated according to the transition frequency between the defined states.

Appendix B. Performance measures used for accuracy of forecasting results

$x\,(k)$: original observed data at time k.
$\hat{x}\,(k)$: predicted value for time k.
n: number of data points used in the prediction.

$$\%\quad RE = \frac{|x\,(k) - \hat{x}\,(k)|}{x\,(k)} \times \%100 \tag{26}$$

$$\%\quad MAPE = \frac{1}{n} \sum_{k=1}^{n} \frac{|x\,(k) - \hat{x}\,(k)|}{x\,(k)} \times \%100 \tag{27}$$

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Please cite this article as: Ene, S., Öztürk, N., Grey modelling based forecasting system for return flow of end-of-life vehicles, Technol. Forecast. Soc. Change (2016), http://dx.doi.org/10.1016/j.techfore.2016.09.030

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Please cite this article as: Ene, S., Öztürk, N., Grey modelling based forecasting system for return flow of end-of-life vehicles, Technol. Forecast. Soc. Change (2016), http://dx.doi.org/10.1016/j.techfore.2016.09.030