End-of-life Vehicle Amount Forecasting based on an Improved GM (1, 1) Model

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***Abstract*—With a rapidly increasing of vehicle production and powerful purchasing capability of Chinese consumers, the automobile ownership will keep a raising tendency in Chinese market. End-of-life vehicle (ELV) recycling contributes to sustainability achievement of the automobile supply chain, as well as the improvement of resource utilization. To provide more evidence on strategic plan of ELV recycling industry and renewable sector with precise ELV amounts, a modified GM (1, 1) model is improved to make the predication in terms of ELV recycling. Specifically, the residual error and time response function are developed to improve the accuracy of forecasting model. Taking ELV recycling amounts from 2015 to 2018 as experimental samples, numerical results show that the ELV recycling amount in 2019 is about 2.2 million. In addition, the modified GM (1, 1) model demonstrates a better performance and superior availability comparing with the traditional GM (1, 1) model and regression forecasting models.**

***Index Terms*—End-of-life vehicle (ELV); recycling amount; improved GM (1, 1); forecasting; residual error amendment**

I. Introduction

WITH booming development of domestic automobile industry, China has become a country with the most production and sales volume all over the world since 2009. In addition, an increasingly purchasing power of potential vehicle consumers contributes to booming of the automobile industry. Both two drivers motivate soaring of the vehicle ownership in Chinese market [1]. With development of vehicle industry, business activities of after-market have been focused by academic researchers and industrial practitioners, for instance, car maintenance, insurance, car beauty and recycling business [2-4]. Driven by the requirement of sustainable philosophy and circular economy, recycling operations of end-of-life vehicles (ELVs) are adopted to improve the resources utilization.

Due to late start of Chinese vehicle industry and production driven strategy, Chinese ELV recycling industry is still at its infancy [3]. Firstly, unbalanced development in different regions leads to used cars flowing into the black market, and it is very common in western areas. Secondly, the recycling rate is not particularly satisfactory as supposed comparing with developed nations due to lack of disassembly techniques and recycling technologies. Last but not least, there are litter legislated regulations and standard procedures to regulate renewable organizations regarding ELV recycling activities.

There are different kinds of recycling channels based on their degradation degree of EOL parts after the complete dismantling [3, 5]. It is effective for the automobile industry to achieve sustainability and resource re-utilization by EOL product recycling. According to degradation degree of ELVs, a 4R-oriented recycling procedure including reusing, recovery, remanufacturing and recycling, is proposed and designed to improve recycling efficiency [5]. These diverse recycling channels contribute to efficiency improvement of ELV parts re-utilization. In practical, the most cost-effective is reuse and recovery activity, especially for those redundant ELV parts with higher residual value. Re-manufacturing is also considered to be an alternative way to perform ELV recycling business. For other ELV parts, material-recycling and energy-recycling activities are carried out to realize material recycling and energy re-utilization. Renewable resources recovered mainly contain metal, iron, steel, plastic and other valuable material, depicted in Figure 1 [3].

ELV recycling industry will motivate development of material and renewable resource industries. From Figure 1, we find many kinds of material can be recycled from ELVs. With development of dismantling and grinding techniques, more fruitful kinds of recyclable metals will be collected, contributing to the sustainability of vehicle supply chain.

The mathematical models are typically used to analyze diverse organization modes of ELV recycling. It has grown up to be a theoretical foundation for the rational choice of components organization mode of the vehicle closed-loop supply chain. It is effective to achieve a circular economy by ELV recycling operations. Recently, ELV recycling studies mostly focus on disassembly, recycling channels, regional recycling policy and economic mechanism. ELV recycling, regarding as a crucial industrial activity of end of vehicle supply chain, assists sustainability achievement by resources and energy recovery. Chen developed a dynamical model to investigate how governmental policies influenced ELV recycling industry, assisting governmental officers to curb the black-market situations and promote corresponding legislations on disassembly and recycling business [6]. Zhou proposed a 4R-oriented recycling channel to improve the ELV recycling efficiency [5]. The disassembly effort index (DEI) was proposed and formulated to represent economic analysis of ELV disassembly business, facilitating to derive an estimation of disassembly cost and return on investment [7]. Rosa formulated a system dynamics (SD) model to elaborate the real-time scenarios in terms of ELV recycling operations, assisting recycling efficiency improvement by strategic management and industrial implementations [8].

Numerous related researches in terms of ELV recycling

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industry are studied from above-mentioned segments. However, there is little attention on the ELV recycling quantity forecasting study. The precise predication on ELV recycling amount not only assists sustainable achievement of the ELV industry, but also contributes to the industry deployment and planning of renewable resources. Therefore, this research aims at developing a forecasting model on ELV recycling, facilitating the sustainability achievement of the automobile industry.

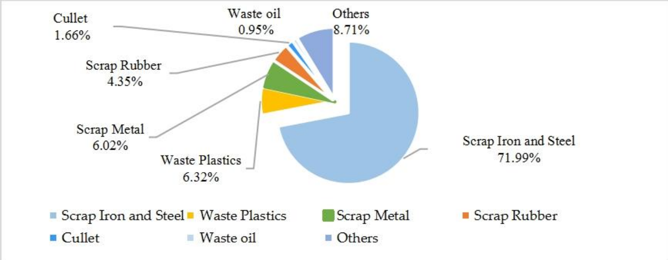

Figure. 1 Renewable resources distribution of ELV recycling

There are numerous forecasting methods applied in different scenarios, for instance, time series forecasting, regression analysis, neural network, grey system and data-driven machine learning techniques etc. [9-13]. Saad presented the comparison analysis by two forecasting models to predict the research output of four sample countries (USA, China, India and Pakistan), that is, the GM (1, 1) model and nonhomogeneous discrete grey model (NDGM) [14]. Experimental results demonstrated that the NDGM showed a better performance on research output forecasting than the traditional GM (1, 1) model. Kumar presented comparisons among different forecasting models regarding energy demand predication, and forecasting methods with a decreasing sequence based on the fitting accuracy were listed as follows: artificial neural network (ANN), support vector machine (SVM), autoregressive integrated moving average (ARIMA), fuzzy logic (FL), regression modelling (RM), genetic algorithm (GA), particle swarm optimization (PSO), grey prediction (GM) and autoregressive moving average (ARMA) [15]. In addition, big-data analytics techniques were developed and employed to deal with forecasting problems considering non-structure data mining techniques [16-18]. The appropriate selection of a forecasting model in terms of certain scenario is not just based on fitting accuracy of the predication model, but also specific application scenario employed. It is very common that the same forecasting model will show a different performance in diverse industrial scenarios. Meer studied electricity consumption prediction by setting different probabilistic forecasting models, and forecasting accuracy was discussed by probabilistic forecasting of solar power and load forecasting [19]. With development of information technology and computer science, artificial-based machine learning methods have advantages comparing to traditional forecasting models and algorithms. In the electricity price forecasting model, Jesus made a comparison between machine learning approaches and traditional empirical models, and results showed that the formulated machine learning method outperformed state-of-the-art techniques with a higher accuracy [20].

On the premise of sample benefits, grey methods have been widely studied and used in different industrial sectors. GM (1, 1) model is extensively applied to sales volume prediction of various sectors on account of its unique superiority in definite sample quantity. Li had reviewed the optimization algorithm implemented to solve an optimal sequence of coefficients of background value and optimum translation of the Quasi-smooth series [21]. On the base of this study, Wang formulated a forecasting model to predict human resources requirements by combining BP neural network and GM (1,1) model, and results demonstrated that the hybrid model showed a better performance than GM (1,1) or BP neural networks with less deviations and superior simulation results [22]. According to Meer's study [19], there was no single preferred forecasting model that can be employed in any circumstance, and we should develop the forecasting model based on characteristics of sample data sets, industrial context and the issue we addressed.

Since the vital significance of ELV recycling predication on the industry deployment and planning, this paper attempts to formulate a forecasting model to predict the ELV recycling in the Chinese market due to the advantage of grey method with little data samples [11]. Both ARIMA and BP neural network prediction models show a good forecasting performance. However, the prerequisite of these applications is large number of experimental samples. Since the ELV industry is at its infancy and the lack of standard regulations, there are limited samples for ELV recycling forecasting. Therefore, the grey theory will be employed to predict ELV recycling amount.

The reminder of this paper is organized as following. The traditional GM (1, 1) model is described in Section 2. Subsequently, the modified GM (1, 1) forecasting model is improved and presented. Section 4 illustrates a numerical case in terms of ELV recycling amount forecasting. Finally, we put an end to this paper with some conclusions.

II. GM (1, 1) FORECASTING MODEL

The grey system, proposed by Prof. Julong Deng from the Huazhong University of Science and Technology in 1982, has become one of the essential methods that can be applied to forecast systematically analysis as well as modeling in the fields of economic social and science areas. In terms of the development status of ELV recycling industry and the feature of small sample size, we make full use of GM (1, 1) model to predict the total amount of ELV recycling amount.

A. GM (1, 1) model predication

Suppose original data is $x^{(0)}=\left(x^{(0)}(1),x^{(0)}(2),\dots,x^{(0)}(n)\right)$, and the primitive data can be used for modeling if it falls in the admissible coverage range. The original data sequence can be transferred to $x^{(1)}=\left(x^{(1)}(1),x^{(1)}(2),\dots,x^{(1)}(n)\right)$.

Consider $z^{(1)}(k)$ is the neighbour value generated by the data sequence of $x^{(1)}$ by the following Eq. (1).

$$z^{(1)}(k)=\alpha x^{(1)}(k)-(1-\alpha)x^{(1)}(k-1) \tag{1}$$

Then GM (1, 1) model is defined by a grey differential equation in the following Eq. (2).

$$x^{(0)}(k)+\alpha z^{(1)}(k)=b \tag{2}$$

The two parameters α and b can be estimated by least square technique found in Eq. (3) - (5).

$$(\alpha b)^T = (B^T B) B Y_N \tag{3}$$

$$B = \begin{pmatrix} -z^{(1)}(2), & -z^{(1)}(3), & ..., & -z^{(1)}(n) \\ 1, & 1, & ..., & 1 \end{pmatrix} \tag{4}$$

$$Y_N = \left(x^{(0)}(2), x^{(0)}(3), ..., x^{(0)}(n)\right)^T \tag{5}$$

Suppose the differential equation of GM (1, 1) model is found in the following Eq. (6).

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{6}$$

The solution of the differential equation of GM (1, 1) model is also called the time response function, and it is found by the following equation:

$$\hat{x}^{(1)}(t) = \left(x^{(1)}(0) - \frac{b}{a}\right)e^{-at} + \frac{b}{a} \tag{7}$$

And then, the equation of time response sequence is depicted in Eq. (8).

$$\hat{x}^{(1)}(k+1) = \left(x^{(1)}(0) - \frac{b}{a}\right)e^{-at} + \frac{b}{a} \tag{8}$$

Suppose $x^{(1)}(0) = x^{(0)}(1), k = 1, 2, ..., n-1$, and forecasting equation is generated by accumulative reduction operation found in Eq. (9).

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

B. Parameter estimation

Parameters in the grey differential equation play a significant role on the GM (1, 1) forecasting model, where α reflects the development tendency of grey system [10, 23]. When $-\alpha < 0.3$, the GM (1, 1) model can be employed for the mid-long-term predication. When $0.3 < -\alpha < 0.5$, the model can be used for the short-term forecasting. When $0.5 < -\alpha < 1$, the traditional GM (1, 1) model should be modified to improve the forecasting accuracy. When $-\alpha > 1$, it may be inappropriate to adopt the GM (1, 1) model for specific predication. The parameter b calling grey action, reflecting the fluctuation of data variation. Both two parameters can be calculated by the least square technique.

C. Model validation

To validate the effectiveness and accuracy of the GM (1, 1) forecasting model, three indicators are employed including residual error, relatiative error and small error probability P [24, 25].

The residual error is obtained by the following Eq. (10).

$$\varepsilon^0(k) = x^{(0)}(k) - \hat{x}^{(0)}(k) \tag{10}$$

And the relative error is found in Eq. (11).

$$\gamma(k) = \frac{q(k)}{x^{(0)}(k)} \times 100\% = \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \tag{11}$$

Suppose the average and variance of $X^{(0)}$ is $\bar{x}$ and S_1^2, and they are calculated by Eq. (12). The average value and the variance of $\varepsilon^{(0)}$ can be found in Eq. (13).

$$\bar{x} = \frac{1}{n}\sum_{k=1}^{n} x^{(0)}(k), S_1^2 = \frac{1}{n}\sum_{k=1}^{n}\left(x^{(0)}(k) - \bar{x}\right)^2 \tag{12}$$

$$\bar{\varepsilon} = \frac{1}{n}\sum_{k=1}^{n} \varepsilon^{(0)}(k), S_2^2 = \frac{1}{n}\sum_{k=1}^{n}\left(\varepsilon^{(0)}(k) - \bar{\varepsilon}\right)^2 \tag{13}$$

The ratio of mean variance is calculated by Eq. (14).

$$C = \frac{S_2}{S_1} \tag{14}$$

While the smaller the C value, the better performance the forecasting model shows.

The small error probability P is obtained by the Eq. (15).

$$p = P\left(\left|\varepsilon^0(k) - \varepsilon^0\right| < 0.6745 S_1\right) \tag{15}$$

Specifically, when the accuracy of fitting value is more than 90%, the forecasting model can be regarded as a better accuracy requirement [24, 26, 27].

III. The Improved GM (1, 1) Model

To improve the forecasting accuracy of the GM (1, 1) model, many improved GM (1, 1) applications are employed in different industrial sectors. In this study, the residual error is embedded into the traditional GM (1, 1) forecasting model.

Suppose the residual error between predication value and actual value is $\varepsilon^0(k) = x^{(0)}(k) - \hat{x}^{(0)}(k)$, $k = k_0, k_0+1, ..., n$. The used data of residual error sequences is $\varepsilon^{(0)} = \left(\varepsilon^{(0)}(k_0), \varepsilon^{(0)}(k_0+1), ..., \varepsilon^{(0)}(n)\right)$. And then, the absolute value of residual sequence is obtained in the following Eq. (16).

$$|\varepsilon|^{(0)} = \left(\left|\varepsilon^{(0)}(k_0)\right|, \left|\varepsilon^{(0)}(k_0+1)\right|, ..., \left|\varepsilon^{(0)}(n)\right|\right) \tag{16}$$

The new time response function is generated by modeling the residual error $\varepsilon^{(0)}$, formulated in Eq. (17).

$$\hat{\varepsilon}^{(1)}(k+1) = \left[\varepsilon^{(1)}(1) - \frac{b'}{a'}\right]\varepsilon^{-a'k} + \frac{b'}{a'}, k = k_0, k_0+1, ..., n \tag{17}$$

The same parameter estimation method is employed similar to the traditional GM (1, 1) forecasting model. The previous $\hat{x}^{(0)}$ is replaced by the $\hat{\varepsilon}^{(0)}$, and the improved GM (1, 1) model is formulated by the following Eq. (18).

$$\hat{x}_{\varepsilon}^{(0)}(k+1) = \hat{x}^{(0)}(k+1) \pm \hat{\varepsilon}^{(0)}(k+1) \tag{18}$$

Note that the polarity of the residual correction value is consistent with the $\varepsilon^{(0)}$.

IV. Numerical Case of ELV Recycling Forecasting

The improved GM (1, 1) model is developed and employed to forecast the ELV recycling amount. To verify the effectiveness and accuracy of the proposed model, the comparison analysis is implemented in this section as well.

A. Results by traditional GM (1, 1) model

ELV recycling amount data are collected from the statistical handbook in terms of automobile industry from the association of renewable resources and re-utilization in China. Since the ELV recycling industry is in infancy, the statistical data in the beginning periods may not reflect the increasing tendency. Therefore, recent smaple data from 2015 to 2018 are collected and used in this study. The original data sequence is found in Eq. (19).

$$x^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), x^{(0)}(4)\right) = (187.4,\ 179.8,\ 174.1,\ 199.1) \tag{19}$$

The time response sequence obtained by the GM (1, 1) model is found in Eq. (20).

$$\hat{x}^{(1)} = (187.4,\ 370.3275,\ 565.9386,\ 774.7702) \tag{20}$$

The cumulative reduction operation is implemented to derive the fitting value of ELV recycling amount, illustrated in Eq. (21)

$$\hat{x}^{(0)} = (187.4,\ 182.9275,\ 195.6111,\ 208.8316) \tag{21}$$

The preication accuracy by the traditional GM (1, 1) model is presented in Tabel 1.

Table 1 Predication results

Year	Actual Value	Fitting Value	Residual Error	Stepwise Ratio	Predication Accuracy
2015	187.4	187.4	0	/	94%
2016	179.8	182.9	-0.0172	-0.1128	
2017	174.1	195.6	-0.1235	-0.1025	
2018	199.1	208.8	-0.0487	-0.0487	

B. Results by the improved GM (1, 1) model

Similar steps are implemented as above-mentioned described, and the residual error sequence is presented in Eq. (22) – (23).

$$\varepsilon^{(0)}(k) = x^{(1)}(k) - \hat{x}^{(1)}(k) \tag{22}$$

$$\varepsilon^{(0)} = \left(\varepsilon^{(0)}(k_0), \varepsilon^{(0)}(k_0+1), \ldots, \varepsilon^{(0)}(n)\right) \tag{23}$$

The orginal sequence is generated by taking from k_0 to n, and $\varepsilon^{(0)}(k)$ is the absolute value. The improved GM (1,1) model is modified by modeling the corrected residual error, found in Eq. (24).

$$\hat{\varepsilon}^{(1)}(k+1) = \left[\varepsilon^{(0)}(k_0) - \frac{b^{'}}{a^{'}}\right] \varepsilon^{-a^{'}(k-k_0)} + \frac{b^{'}}{a^{'}} \tag{24}$$

Parameters are estimated by the above-mentioned steps. And the improved GM (1,1) model revised by $\hat{\varepsilon}^{(0)}$ is presented in Eq. (25).

$$\hat{x}_{\varepsilon}^{(0)}(k+1) = \hat{x}^{(0)}(k+1) \pm \hat{\varepsilon}^{(0)}(k+1) \tag{25}$$

The fitting value by the improved GM (1, 1) model is calculated in Table 2.

As shown in Table 1 and Table 2, the accuracy of the traditional GM (1, 1) model is 94%, while the predication accuracy of the improved GM (1, 1) model achieves to 98%, demonstrating the better performance of the modified GM (1,1) model than typical one. Therefore, the improved GM (1, 1) model can be used to forecast the ELV recycling amount in 2019, and the specific calculation of ELV recycling in 2019 is 2.2077 million.

Table 2. Fitting results by the improved GM (1, 1) model

Year	Actual Value	Revised Value	Revised Residual Error	Relative Error	Predication Accuracy
2015	187.4	187.4	0	0	98%
2016	179.8	179.8	0	0	
2017	174.1	167.2139	6.8861	0.0396	
2018	199.1	205.5032	-6.4032	0.0322	

Note: the actual data comes from the Chinese association of renewable resources and re-utilization, and C=0.5, P=1.

C. Comparison analysis

To testify the efficiency and advantage of the improved GM (1, 1) model, the experimental analysis is implemented by comparing with other forecasting techniques. According to the observation of the scatter plot mapped by the actual data, the quadratic curve of non-linear regression model is introduced to forecast the ELV recycling amount. The quadratic non-linear regression model is presented in Eq. (26).

$$y_i = \beta_1 + \beta_2 x_i + \beta_3 x_i^2 + \varepsilon_i \tag{26}$$

Suppose the residual error of between an observed value and the estimated value of the regression model is E, and the parameter estimation formula is presented in Eq. (27) - (29).

$$E = Y - \hat{Y} \tag{27}$$

$$\hat{Y} = XB \tag{28}$$

$$E^T E = (Y - \hat{Y})^T (Y - \hat{Y}) \tag{29}$$

According to the extremum principle, the regression coefficient matrix B in the non-linear regression model can be estimated in Eq. (30) – (31).

$$\begin{aligned} \frac{\partial E^T E}{\partial B} &= \frac{\partial (Y - \hat{Y})^T (Y - \hat{Y})}{\partial B} \\ &= \frac{\partial (Y^T Y - 2\hat{Y} X B + B^T X^T X B)}{\partial B} \\ &= -2(Y^T X)^T + 2(X^T X)B = 0 \end{aligned} \tag{30}$$

$$\hat{B} = (X^T X)^{-1} (X^T Y) \tag{31}$$

The relative coefficient R is calculated by inputting the estimated parameters, and the non-linear regression model is formulated, which can be used to forecast the ELV recycling under the condition that the R value satisfies the fitting requirement. The accuracy of the regression model is tested by the standard variation presented in the following Eq. (32).

$$S = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n-3}} \tag{32}$$

The sample data is input into the regression model $y_i = \beta_1 + \beta_2 x_i + \beta_3 x_i^2 + \varepsilon_i$, and the parameters are estimated by least square method, whose results are presented in the following Tabel 3.

Table 3. Results calculated by the nonlinear regression model

Year	Practical Value	Fitting Value	Relaitve Error	*R*	*S*
2015	187.4	188.84	-0.0076	0.9995	6.4399
2016	179.8	175.48	0.024		
2017	174.1	178.42	-0.0248		
2018	199.1	197.66	0.0072		

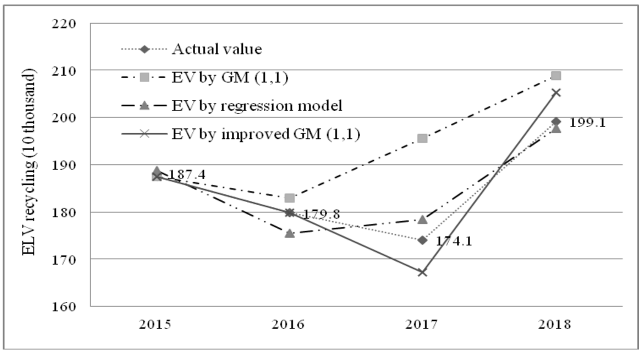

Figure 2. Comparison analysis among different forecasting results

As can be observed in the Table 3, the quadratic non-linear regression model shows a good performance on ELV recycling forecasting, and the predication value in 2019 is 2.332 million.

The actual data and estimated values of the ELV recycling amount by different forecasting models are presented in the Figure 2, and the gap between practical value and estimated value among different techniques is depicted.

From Figure 2, both the improved GM (1, 1) model and non-linear regression model show superior performance on forecasting. To verify the proposed improved GM (1, 1) model, the comparison analysis is performed compared with non-linear regression model, and the estimated value of ELV recycling amount is presented in the following Table 4, as well as the relative error.

As we can see from Table 4, the average relative error of the improved GM (1, 1) model is about 0.0904, and the quadratic non-linear regression model 0.0159. Results derived from the above tables show that there exists positive deviation for improved GM (1, 1) model, while most of the estimated is smaller than the actual value of sample data for the regression model. However, both of the two models have a satisfactory performance, whose deviation degree does not exceed 5%. From Table 4, we found that forecasting results by improved GM (1, 1) model outperformed than nonlinear regression model with less average deviation.

Due to limitation of sample data for ELV recycling industry in China, the GM (1, 1) model shows a better feasibility than regression models due to its grey characteristics. From the comparison analysis, the feasibility and effectiveness of the improved GM (1, 1) model is verified, and it caters to the ELV recycling forecasting.

Table 4. Comparison results among different forecasting models

Year	Actual Value	Estimated Value by Forecasting Models		Relative Error	
		Improved GM (1,1) Model	Quadratic Non-linear Regression Model	Improv -ed GM (1,1) Model	Quadratic Non-linear Regression Model
2015	187.4	187.4	188.84	0	-0.0076
2016	179.8	179.8	175.48	0	0.024
2017	174.1	167.2139	178.42	0.0396	-0.0248
2018	199.1	205.5032	197.66	0.0322	0.0072

D. Discussion

ELV recycling, as a new industry in Chinese market, has been motivated by an increasing of vehicle ownership and environmental sustainability requirement [3]. Since ELV recycling industry is in its infancy, there is not much sample data for accurate predication. Considering the unique advantage of grey predication modelling with limited testing data set. The grey forecasting method is employed to assist industrial managers to predicate ELV recycling. To improve the predication accuracy of the model, an extended GM (1,1) model is developed in our research.

This study offers theoretical contributions for forecasting techniques and applications. The modified GM (1, 1) forecasting model is developed to improve the predication efficiency and the accuracy by defining the residual error variables. The improved ELV recycling forecasting model shows a better performance than traditional GM (1,1) predication model. Also, it outperforms other forecasting models with less predication error, such as linear regression and non-linear regression models. From the numercial case and comparison analysis, the proposed novel GM (1, 1) forecasting model fits the ELV recycling sector.

In addition, this research provides practical implications for industrial management of ELV recycling sector. The developed forecasting model has been utilized to predicate ELV recycling amount, assisting automobile sector to perform extended producer responsibility (EPR) and scientific layout of the ELV recycling industry. Also, the scientific predication on ELV recycling amount will assist to achieve sustainability of vehicle supply chain by resource allocation and regional industry deployment. This ELV recycling forecasting technique and its industrial application contributes to the development of EOL industry and sustainability achievement of automobile industry.

V. Conclusion

In this study, the residual error is developed to modify the traditional GM (1, 1) model, and an improved GM (1, 1) model is formulated to achieve ELV recycling forecasting. A numerical case is implemented to validate the feasibility of the formulated predication model. Besides, experimental analysis is conducted to verify the performance of the proposed forecasting model comparing with quadratic regression model and traditional GM (1, 1) model.

This paper also carries some limitations. Due to un-standard regulations of the ELV recycling industry in China, there is not much sample data for predication. The lack of awareness and regulated legislation cause the slow development of the ELV recycling sector, also the extreme unbalance of regional discrepancy contributes to second-car flowing into black-market. With development of ELV recycling industry, other regression models and artificial intelligence-based approaches can be developed in this industrial sector under the condition of much more sample data. From viewpoint of the vehicle industry, the theoretical forecasting in terms of ELV recycling amount can only make guidance theoretically, and how to make some constructive guidance for industrial deployment and improvement of recycling utilization, also relies on the positive involvement from different stakeholders, for instance the renewable organizations, OEMs, and the individual vehicle consumers.

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References

[1] Zhou Fuli, Wang Xu, and Samvedi Avinash, “Quality Improvement Pilot program selection based on dynamic hybrid MCDM approach,”

Industrial Management & Data Systems, vol. 118, no. 1, pp 144-162, 2018.

[2] Guajardo, Jose A., Morris A. Cohen, and Serguei Netessine, "Service Competition and Product Quality in the US Automobile Industry," Management Science, vol. 62, no. 7, pp 1860-1877, 2015.

[3] Zhou Fuli, Lim Ming Kim, He Yandong, Lin Yun, and Chen Shan, "End-of-life Vehicle (ELV) Recycling Management: Improving Performance using an ISM Approach," Journal of Cleaner Production, vol. 228, pp 231-243, 2019.

[4] Ye Zhenggeng, Cai Zhiqiang, Zhou Fuli, Zhao Jiangbin, and Zhang Pan, "Reliability Analysis for Series Manufacturing System with Imperfect Inspection considering the Interaction between Quality and Degradation," Reliability Engineering & System Safety, vol 189, pp 345-356, 2019.

[5] Zhou Fuli, Wang Xu, Goh Mark, Zhou Lin, and He Yandong, "Supplier portfolio of key outsourcing parts selection using a two-stage decision making framework for Chinese domestic auto-maker," Computers & Industrial Engineering, vol. 128, pp 559-575, 2019.

[6] Chen Zhiguo, Chen Dingjiang, Wang Tao, and Hu Shanying, "Policies on End-of-life Passenger Cars in China: Dynamic Modeling and Cost-benefit Analysis," Journal of Cleaner Production, vol. 108, pp 1140-1148, 2015.

[7] Das, Sanchoy K., Pradeep Yedlarajiah, and Raj Narendra, "An Approach for Estimating the End-of-life Product Disassembly Effort and Cost," International Journal of Production Research, vol. 38, no.3, pp 657-673, 2000.

[8] Rosa, Paolo, and Sergio Terzi, "Improving End-of-life Vehicle's Management Practices: An Economic Assessment through System Dynamics," Journal of Cleaner Production, vol. 184, pp 520-536, 2018.

[9] Suganthi L., and Anand A. Samuel, "Energy models for demand forecasting—A review," Renewable and Sustainable Energy Reviews, vol. 16, no. 2, pp 1223-1240, 2012.

[10] Hao Quan, Dipti Srinivasan, and Abbas Khosravi, "Short-Term Load and Wind Power Forecasting Using Neural Network-Based Prediction Intervals," IEEE Transactions on Neural Networks & Learning Systems, vol. 25, no. 2, pp 303-315, 2017.

[11] Wang Zhengxin, Li Qin, and Pei Lingling, "A seasonal GM (1, 1) Model for Forecasting the Electricity Consumption of the Primary Economic Sectors," Energy, vol. 154, pp 522-534, 2018.

[12] Sobri, Sobrina, Sam Koohi-Kamali, and Nasrudin Abd Rahim, "Solar Photovoltaic Generation Forecasting Methods: A Review," Energy Conversion and Management, vol. 156, pp 459-497, 2018.

[13] Hofmann, Erik, and Emanuel Rutschmann, "Big Data Analytics and Demand Forecasting in Supply Chains: a Conceptual Analysis," International Journal of Logistics Management, vol. 29, no. 2, pp 739-766, 2018.

[14] Javed, Saad Ahmed, and Sifeng Liu, "Predicting the Research Output/growth of Selected Countries: Application of Even GM (1, 1) and NDGM Models," Scientometrics, vol. 115, no.1, pp 395-413, 2018.

[15] Debnath, Kumar Biswajit, and Monjur Mourshed, "Forecasting Methods in Energy Planning Models," Renewable and Sustainable Energy Reviews, vol. 88, pp 297-325, 2018.

[16] Al-Jallad, Nashat T., Xu Ning, and Mergani A. Khairalla, "An Interpretable Predictive Framework for Students' Withdrawal Problem using Multiple Classifiers," Engineering Letters, vol. 27, no. 1, pp. 1-8, 2019.

[17] Chen Rung-Ching, "Using Deep Learning to Predict User Rating on Imbalance Classification Data," International Journal of Computer Science, vol. 46, no. 1, pp 109-117, 2019.

[18] Ouyang Xinyu, Zhao Nannan, Gao Chuang, and Wang Lidong, "An Efficient Twin Projection Support Vector Machine for Regression," Engineering Letters, vol. 27, no. 1, pp 103-107, 2019.

[19] Van der Meer, Dennis W., Joakim Widén, and Joakim Munkhammar, "Review on Probabilistic Forecasting of Photovoltaic Power Production and Electricity Consumption," Renewable and Sustainable Energy Reviews, vol. 81, pp 1484-1512, 2018.

[20] Lago Jesus, Fjo De Ridder, and Bart De Schutter, "Forecasting Spot Electricity Prices: Deep Learning Approaches and Empirical Comparison of Traditional Algorithms," Applied Energy, vol. 221, pp 386-405, 2018.

[21] Li Li, and Li Xican, "Optimization Algorithm and its Application of the GM (1, 1) Model," Statistics & Decision, vol. 35, no. 13, pp 77-81, 2019.

[22] Wang Baoxian, and Liu Yi, "Human Resource Demand Forecasting Method Based on Grey BP Neural Network Model," *Statistics & Decision*, vol. 34, no. 16, pp 181-184, 2018.

[23] Zhou Fuli, Wang Xu, and Goh Mark, "Fuzzy Extended VIKOR-based Mobile Robot Selection Model for Hospital Pharmacy," International Journal of Advanced Robotic Systems, vol. 15, no. 4, pp. 1-11, 2018.

[24] Prabowo, Hendro E., and Tohari Ahmad, "Improving Prediction Error Expansion based Data Hiding Method for Securing Confidential Data," International Journal of Computer Science, vol. 45, no. 4, pp 540-551, 2018.

[25] Zhou Fuli, He Yandong, and Zhou Lin, "Last Mile Delivery with Stochastic Travel Times considering Dual Services," IEEE Access, vol. 7, pp 159013-159021, 2019.

[26] Zhou Fuli, Lim Ming Kim, He Yandong, and Pratap Saurabh, "What attracts vehicle consumers' buying: A Saaty scale-based VIKOR (SSC-VIKOR) approach from after-sales textual perspective?" Industrial Management & Data Systems, vol. 120, no. 1, pp 57-78, 2020.

[27] Zhou Fuli, Wang Xu, He Yandong, and Goh Mark, "Production Lot-sizing Decision-Making considering Bottleneck Drift in Multi-stage Manufacturing System," Advances in Production Engineering & Management, vol. 12, no.3, pp 213-220, 2017.