Application of Grey Linear Regression Combined Model in Predicting the Motor Oil Wear Particles for Passenger Cars

Chunjiang Bao[1, a, *], Zhikuan Wang[1, b], Lipeng Xu[1, c]
[1]College of Mechanical and Automotive Engineering, Liaocheng University, Liaocheng Shandong, China

Keywords: Passenger car, engine oil, particle content, grey linear regression combination model.

Abstract: A new model is established by combining the grey model and the linear regression model to synthesize the advantages of the two models, and then the number of oil wear particles in passenger cars is predicted. The three models are used to predict and compare the particle content of different levels of passenger car oil. The prediction results of wear particles in the SJ oil for No.1 passenger car show that the prediction accuracy of the grey linear regression combined model are higher than the linear regression model (1.85%) and the grey model (0.29%), and for the SL oil are 1.34% and 0.45%, respectively. For No.2 passenger car, the prediction accuracy is increased by 2.86% in SJ oil and 1.28% in SL oil for the linear regression model, and 0.12% in SJ oil and 2.62% in SL oil for the grey model. The results indicated that the combined model has better prediction effect, and it can be applied to the prediction of oil wear particles in passenger cars. Through the prediction of combined model and the judgment of cleanliness grade, it can provide the basis for automobile to replacement oil by quality.

1 INTRODUCTION

As a result of the relative movement between the friction pairs during operation, the oxidation products produced by oil oxidation and the entry of external gravel will accelerate the wear of the engine, resulting in an increase in the number of wear particles in the oil, which will accelerate the deterioration of oil quality. In addition, oil replacement prematurely will cause oil waste, and oil replacement too late will make the number of wear particles in the oil exceeding the standard, accelerating the deterioration of oil quality. The deterioration of oil has a great harm to the engine of passenger cars, and the use of degraded oil for a long time will accelerate the corrosion and wear of engine parts, leading to serious mechanical faults, so the problem of oil replacement according to the quality has been widely concerned by people.

At present, there are many models currently used for prediction, mainly including grey models, linear regression models, time series models, and various combined models. (Y. Wang, et al, 2013) adopted the combined models based on the variance reciprocal and the optimal weighting are applied to optimize the forecasting model. The accuracy of forecast models on passenger and freight traffic volume has been improved, which provides a reasonable basis for the planning and development of the transportation system. (S.Z. Chen, et al, 2019). Unbiased model and sliding GM (1, 1) model were combined with BP neural network optimized by genetic algorithm (GA), and a combined forecasting model of GA-grey neural network was obtained, which took into account the advantages of grey theory, genetic algorithm and BP neural network. Finally, the effectiveness of the proposed combination model was verified with specific examples. (H. Hao, et al, 2018). Presented a combined prediction model consisting of a grey model, exponential smoothing and an artificial neural network optimized by the particle swarm optimization (PSO) algorithm. The prediction of the number of end-of-life vehicles to be recycled in this paper will support the end-of-life vehicle recycling industry in terms of recycling management and investment decision-making and provide a reference for the formulation and implementation of policies relating to end-of-life vehicles. (Tobita, Mikio, et al, 2016)l combined the logarithmic and exponential decay functions and developed methods for obtaining global solutions using nonlinear least squares calculations for such complex functions.

Bao, C., Wang, Z. and Xu, L.
Application of Grey Linear Regression Combined Model in Predicting the Motor Oil Wear Particles for Passenger Cars.
DOI: 10.5220/0008850800380049
In *Proceedings of 5th International Conference on Vehicle, Mechanical and Electrical Engineering (ICVMEE 2019)*, pages 38-49
ISBN: 978-989-758-412-1

Their models significantly improved the fitting performance of the postseismic time series and the prediction performance of the evolution of postseismic deformation. (F.L. Ren, et al, 2018) adopted the optimized multiple linear regression model and grey GM(1,1)model to forecast the power demands of Shaanxi Province in recent years and obvioused that the prediction model has the high accuracy. To improve the prediction accuracy of bridge structure deformation. (J.Z. Xin, et al, 2018) based on data mining and to accurately evaluate the time-varying characteristics of bridge structure performance evolution, this paper proposes a new method for bridge structure deformation prediction, which integrates the Kalman filter, Autoregressive Integrated Moving Average Model (ARIMA), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). Finally, this paper provides a new way for structural behavior prediction based on data processing, which can lay a foundation for the early warning of bridge health monitoring system based on sensor data using sensing technology. (Y. Han, 2016) used grey prediction theory to construct the grey model GM (1, 1) and linear regression weighted combination model, used to predict the settlement of subgrade. The studies show that the model has a certain practical application value and provides a new way for the study of subgrade settlement prediction. (D. Liang, et.al, 2014) verified the feasibility of this combination model is verified through the example. It can obtain higher prediction accuracy by collecting relative little data. The combination model has a lot of advantages in the machine tool sales forecast. (K.P. Bi, et al, 2016) verified the gray-linear regression combined model is proved to be valid and more accurate forecasting method compare with single forecasting model through practical example. (B. Zeng, et al, 2013) used the inverse accumulation generator of the original sequence, the non-homogeneous exponential incremental sequence is transformed into homogeneous exponential incremental sequence, and then a DGM (1, 1) model is established using the new sequence. Finally, two examples are given to illustrate the simplicity, practicability and operability of the model. (N. Tian, Y. Wei. 2018) Based on the direct modeling of the approximate non-homogeneous exponential discrete grey model, this paper constructs a new grey forecasting model, which not only improves the modeling accuracy of approximate non-homogeneous exponential sequences, but also extends the application scope to such cases as the combination of the increasing-decreasing sequence. Finally, examples are employed to verify the effectiveness and feasibility of the proposed method. (Y.X. Jiang, Q.S. Zhang, 2015) Based on the recursive solution to unbiased GM (1, 1) model, proposed the method of time series piecewise representation. The results show that the recursive model has higher fitting precision, and also verify the effectiveness and the practicability of the representation method of time series based on the grey forecasting model. (H.R.Zhao, X.Y.Han, S.Guo, 2018) presented a hybrid annual peak load forecasting model (MVO-DGM (1, 1). The model uses the latest optimization algorithm MVO (multi verse optimizer) to determine the two parameters of DGM (1, 1) model, and then uses the optimized DGM (1, 1) model to predict the annual peak load. Taking the annual peak load of Shandong Province from 2005 to 2014 as an example, the analysis results show that the DGM (1, 1) model parameter determination method based on MVO algorithm has significant advantages over the least square estimation method, particle swarm optimization and Drosophila optimization algorithm.

In this paper, the CSI 5200 Three Vector Oil Analyzer is used to detect and analyze the oil of passenger cars of different grades, and the number of wear particles in the oil is obtained, and then the degree of deterioration of engine oil quality and the wear condition of the engine are judged according to the cleanliness grade. Because the analysis cost of deterioration degree of passenger locomotive oil is higher, the analysis period is longer, and the data obtained is relatively less, the grey model is selected to predict the deterioration degree of passenger locomotive oil. The grey model is suitable for data prediction in exponential form, which is not consistent with the linear rule of actual data. Therefore, this paper chooses the combination of grey model and linear regression model to form a new combination model for forecasting and analysis, which can not only make up for the lack of linear law in grey model, but also give full play to the advantages of grey model, thus improving the limitations of single model and improving the accuracy of forecasting (J.F. Jing, K.C. Li, F.K. Deng, et al, 2015). Due to the different temperatures, loads and rotational speeds, the chemical composition of the wear particles is likely to be not the same, which also has an impact on the number of wear particles. In this paper, the prediction of wear particles is carried out under the same wear mechanism.

2 EXPERIMENTAL METHOD

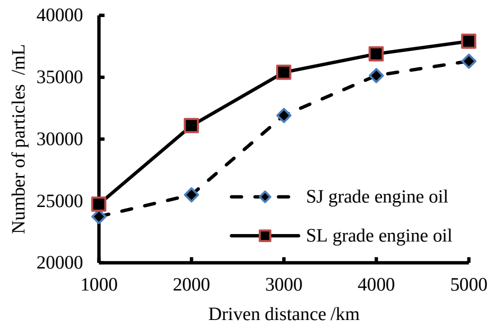
2.1 Experimental Materials and Instruments

The three vector oil analyzer (CSI 5200) is used to detect and analyze the SVW71612BS type Shanghai Volkswagen new santana sedan, which can quickly obtain the number of wear particles in the oil. CSI 5200 three vector oil analyzer can carry out viscosity measurement, dielectric constant measurement, moisture measurement and particle count. Two passenger cars (No.1 and No.2) equipped with CPD engines are selected, and the oil selected by the engines of the two passenger cars is the oil with a viscosity rating of SAE 15W/40, a performance rating of API SJ, a viscosity rating of SAE 10W/40, and a performance rating of API SL. Two passenger cars are in good condition and the road conditions are flat. As the passenger cars used to take on the driving training task, so the engine working conditions are relatively bad. Typically, drivers of passenger cars replace oil when their passenger car mileage reaches about 5000 km. The passenger car uses a special sampler to extract oil once per 1000 km of travel, and adds the same amount of new oil to the same model. During the experiment, the oil is heated to 40 ℃ and the number of particles in the oil is measured using the CSI 5200 three vector oil analyzer.

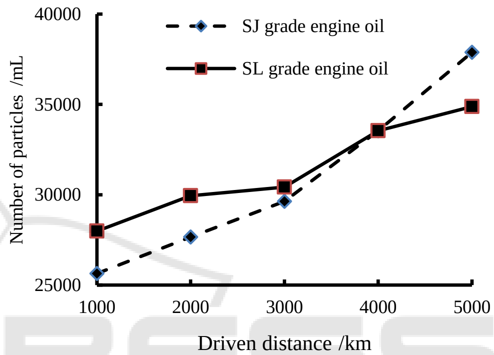
2.2 Selection of Experimental Data

The trend of change in the number of 5~15μm wear particles per milliliter in the oil of the No.1 and No.2 passenger cars measured by the experiment is shown in Figure1.

In the process of oil circulation, large wear particles will be filtered out by the oil filter, and small particles will continue to flow with the oil, when the number of particles increased to a certain extent, it is necessary to replace the oil, otherwise the oil passage will be blocked, leading to serious accidents. As can be seen from Figure1a and Figure1b, the change in the number of 5~15μm wear particles per milliliter in No.1 and No.2 passenger cars is more obvious, to some extent, which can reflect the degree of deterioration of the engine oil quality and the condition of engine wear. Therefore, taking the number of 5~15μm wear particles per milliliter in passenger car oil of two different grades, SJ Grade and SL Grade as an example, the grey linear regression combined model is used to predict the deterioration degree of the engine oil quality.



(a) Passenger car No.1



(b) Passenger car No.2

Figure 1. Number of particles 5~15μm per milliliter in different grades of engine oil.

2.3 Oil Cleanliness Analysis

Clean lubricating oil can extend the service life of mechanical equipment, improve the operating efficiency of equipment, different equipment have different requirements on the cleaning degree of lubricating oil, steam turbines and hydraulic systems require high cleanliness of lubricants, while the internal Combustion engines require relatively low requirements. The relationship between the degree of lubricating oil cleanliness required by different equipment and the ISO 4406 cleanliness level is shown in Table 1 (B. Chen, J.G. Wang , 2012;X. Xiao, H. Guo, S. Mao, 2014). As the mileage of passenger cars increases, changes in the ISO 4406 cleanliness level for No.1 and No.2 passenger cars oil are shown in Table 2 and Table 3.

Table 1. Relationship between the cleaning degree of lubricating oil required by different equipment and the ISO 4406 cleanliness level.

Oil product	Turbine oil	Hydraulic oil	Gear oil	Internal combustion engine oil
12/9	very clean	very clean	-	-
14/11	very clean	very clean	very clean	-
16/13	clean	clean	very clean	very clean
18/15	dirty	dirty	very clean	very clean
20/17	dirty	dirty	dirty	clean
22/19	dirty	dirty	dirty	dirty
24/21	dirty	dirty	dirty	dirty

Note: 22/19 means that if the number of particles larger than 5 μm is within 20000~40000 per milliliter of oil, the grade is 22; more than 15μm. If the number is within 2500~5000, the rating is 19

Table 2. ISO 4406 cleanliness level for different grade passenger car oils for passenger car No.1.

Grade	Driven distance /km					
	0	1000	2000	3000	4000	5000
SJ grade	19/16	22/16	22/16	22/15	22/15	22/16
SL grade	18/15	22/15	22/15	22/15	22/15	22/15

Table 3. ISO 4406 cleanliness level for different grade passenger car oils for passenger car No.2

Grade	Driven distance/km					
	0	1000	2000	3000	4000	5000
SJ grade	19/16	22/16	22/16	22/15	22/15	22/16
SL grade	19/15	22/15	22/15	22/15	22/16	22/16

As can be seen from Table 2 and Table 3, the cleanliness level of the new oil is between 18/15~20/17, indicating that the new oil is clean. With the increase in mileage of No. 1 and No. 2 passenger cars, the ISO 4406 grade of two grades of passenger car oil is between 18/15~22/19, and according to the cleanliness level required by the internal combustion engine, it is indicated that no replacement oil is required when the passenger car mileage reaches 5000km. According to Tables 1, 2 and 3, as well as the cleanliness grade, two different grades of oil contain a large amount of wear particles of about 5μm, which easily lead to engine lubrication system blockage and siltation. This means that when the oil flows through the oil filter, some of the large particles will be filtered out and the small particles will flow with the oil. When the cleaning level of oil reaches 22/19, the oil should be replaced in time.

3 GREY LINEAR REGRESSION COMBIMATION MODEL

In 1982, Professor Deng proposed a new system theory method for studying the problem of less data and uncertainty of poor information, which is the grey system theory (J.S. Wang, 2015). The core of Grey system theory is grey model, and the grey model is suitable for the prediction of the development trend of the original series with exponential growth, without considering the actual situation with linear law, the prediction effect is often poor. Linear regression model is only a linear description of the future development trend, for the change of large data prediction results are quite different. The new model, which combines the grey model with the linear regression model, is called the grey linear regression combined model (Y.B. Zhou, L.F. Jiao, 2008). The linear regression model is combined with the grey model to avoid the disadvantage of a single model and to draw on each other's strengths, which can improve the prediction accuracy of the model.

3.1 Model Establishment

The process of establishing a grey linear regression combination model is as follows:

The original number be listed as:

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)) \tag{1}$$

Perform an accumulation of the original series $X^{(0)}$ to get a new series:

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)) \tag{2}$$

Wherein: $X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i), (k = 1,2,\cdots,n)$,

Finding the first-order differential equation for the new series:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{3}$$

Among them, a is he development coefficient, which b is the amount of grey action. When t represents the unit time, the differential form of the differential equation is equal to the differential form, that is:

$$\frac{dx^{(1)}}{dt} = x^{(1)}(t+1) - x^{(1)}(t) = x^{(0)}(t) \tag{4}$$

Therefore, the differential equation of the $GM(1,1)$ model can be expressed as:

$$x^{(0)}(t) + ax^{(1)}(t) = b \tag{5}$$

The formula (5) is called the original form of the $GM(1,1)$ model.

Find the solution of (3):

$$x^{(1)}(t) = (x^{(1)}(1) - \frac{b}{a})e^{-at} + \frac{b}{a} \tag{6}$$

For convenience, record as:

$$\hat{x}^{(1)}(t+1) = c_1 e^{\lambda t} + c_2 \tag{7}$$

Linear regression equations such as $y = ax + b$ and exponential equations such as $y = ce^x$ are used to fit the cumulative sequence $X^{(1)}(t)$, thus, a new model sequence is generated, and seek its undetermined coefficients. The new sequence is:

$$\hat{x}^{(1)}(t) = c_1 e^{\lambda t} + c_2 t + c_3 \tag{8}$$

Wherein, c1, c2, c3 is the undetermined coefficient. In order to obtain the parameters, the sequence of parameters is:

$$\begin{aligned} Z(t) = X^{(1)}(t+1) - X^{(1)}(t) &= c_1 e^{\lambda(t+1)} + c_2(t+1) + c_3 - c_1 e\lambda t - c_2 t - c_3 \\ &= c_1 e^{\lambda t}(e^{\lambda} - 1) + c_2 \end{aligned} \tag{9}$$

Wherein: $t = 1,2,\cdots,n-1$.And assume that:

$$\begin{aligned} X_m = Z(t+m) - Z(t) &= \hat{X}^{(1)}(t+m+1) - \hat{X}^{(1)}(t+m) - X^{(1)}(t+1) + X^{(1)}(t) \\ &= c_1 e^{\lambda t}(e^{\lambda m} - 1)(e^{\lambda} - 1) \end{aligned} \tag{10}$$

Transform equation (10):

$$\frac{X_m(t+1)}{X_m(t)} = \frac{c_1 e^{\lambda(t+1)}(e^{\lambda m} - 1)(e^{\lambda} - 1)}{c_1 e^{\lambda t}(e^{\lambda m} - 1)(e^{\lambda} - 1)} = e^{\lambda} \tag{11}$$

In order to obtain the solution λ, the two sides are derived:

$$\lambda = \ln \frac{X_m(t+1)}{X_m(t)} \tag{12}$$

When m takes different values, the corresponding λ value will be obtained, find the average value of $\bar{\lambda}$ of λ, and use $\bar{\lambda}$ as the estimated value of λ, thereby improving the precision of λ. The steps are as follows:

$$X_1(1) = Z(2) - Z(1) = X^{(1)}(3) - 2X^{(1)}(2) + X^{(1)}(1)$$
$$X_1(2) = Z(3) - Z(2) = X^{(1)}(4) - 2X^{(1)}(3) + X^{(1)}(2)$$
$$\Downarrow$$
$$X_1(m) = Z(m+1) - Z(m) = X^{(1)}(m+2) - 2X^{(1)}(m+1) + X^{(1)}(m)$$

Determined by (12):

$$\lambda_{(1)}(1)\cdots\lambda_{(1)}(m-1)$$
$$\lambda_{(2)}(1)\cdots\lambda_{(2)}(m-2)$$
$$\lambda_{(3)}(1)\cdots\lambda_{(3)}(m-3)$$
$$\Downarrow$$
$$\lambda_{(m-1)}(1)$$

The average value is obtained:

$$\bar{\lambda} = \frac{2\sum_{i=1}^{m-1}\sum_{j}^{m-i}\lambda_{(i)}(j)}{m(m-1)} \tag{13}$$

Wherein: m=n-2. If $L_t = \exp(\bar{\lambda} t)$, the equation (8) can be transformed:

$$\hat{X}^{(1)} = c_1 L_t + c_2 t + c_3 \tag{14}$$

Using the least squares method, the estimated values of c_1, c_2, c_3 are obtained.

$$X^{(1)} = \begin{bmatrix} x^{(1)}(1) \\ x^{(1)}(2) \\ \vdots \\ x^{(1)}(n) \end{bmatrix}, C = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix}, A = \begin{bmatrix} L(1) & 1 & 1 \\ L(2) & 2 & 1 \\ \vdots & \vdots & \vdots \\ L(n) & n & 1 \end{bmatrix} \tag{15}$$

Then $X^{(1)} = AC$, the values of c1, c2, c3 are obtained using the least squares method. Bring it into equation (8) and get the prediction formula for the combined model:

$$\bar{X}^{(1)}(t) = c_1 e^{\bar{\lambda} t} + c_2 t + c_3 \tag{16}$$

Wherein, c1, c2, c3 are the undetermined coefficients.

3.2 Model Test

The combined model residuals is:

$$q(i) = x^{(0)}(i) - \hat{x}^{(1)}(i) \tag{17}$$

The Relative error is:

$$\varepsilon(i) = \frac{q(i)}{x^{(0)}(i)} \tag{18}$$

The average relative error is:

$$\varepsilon(avg) = \frac{1}{n-1}\sum_{i=2}^{n}|\varepsilon(i)| \tag{19}$$

The model accuracy is:

$$p = (1-\varepsilon(avg)) \times 100\% \tag{20}$$

It is generally believed that when $p \geq 90\%$, the accuracy is acceptable, that is, the model can be used. The accuracy level is shown in Table 4 (Y Zhou, Y Luo, SM Jia, et al, 2014).

Table 4. Predictive model accuracy division.

Predictive model accuracy level	P value
First grade	≥99%
Two grade	95%≤p<99%
Three grade	90%≤p<95%
Four grade	<90%

4 APPLICATION OF GREY LINEAR REGRESSION COMBIMED MODEL

4.1 Linear Regression Model Prediction

The linear regression model is an equation of the form $y = ax + b$. From the experimental data, the prediction equations for the number of wear particles of 5~15μm per milliliter in the different grades of the No.1 passenger cars are:

$$y_{SJ}^{1} = 3.77444x + 19193.08 \tag{21}$$

$$y_{SL}^{1} = 2.8827x + 24540 \tag{22}$$

Similarly, the prediction equations for the number of 5~15μm wear particles per milliliter in different grades of the No.2 passenger car are:

$$y_{SJ}^{2} = 0.9811x + 2499.60 \tag{23}$$

$$y_{SL}^{2} = 0.4288x + 20496.19 \tag{24}$$

The results of predicting the number of 5~15μm particles per milliliter in different grades of oil through the above equations are shown in Tables 5 and 6.

Table 5. Number of particles 5~15μm per milliliter in different grades of motor oil on the 1st passenger car (pieces).

Grade	Driven distance /km				
	1000	2000	3000	4000	5000
SJ grade	22968	26742	30516	34291	38065
SL grade	27422	30305	33188	36071	38954

Table 6. Number of particles 5~15μm per milliliter in different grades of motor oil on the 2nd passenger car (pieces).

Grade	Driven distance /km				
	1000	2000	3000	4000	5000
SJ grade	25640	27655	29631	31572	35408
SL grade	27988	30740	32344	34408	36719

4.2 Grey Model Prediction

The equation of the form $y = ae^{x} + b$ is the grey model equation. Using MATLAB for data fitting, the prediction equations of the number of 5~15μm wear particles per milliliter in different grades of oil in No.1 passenger car are:

$$y_{SJ}^{1} = 58374.5645e^{-0.875t} - 35142.4821 \tag{25}$$

$$y_{SL}^{1} = 45862.8695e^{-0.684t} - 19849.2547 \tag{26}$$

Similarly, the prediction equations for the number of wear particles per milliliter of 5~15μm in the different grades of the No.2 passenger car are:

$$y_{SJ}^{2} = 42178.75e^{-0.578t} - 17298.215 \quad (27)$$

$$y_{SL}^{2} = 53117.296e^{-0.854t} - 28832.795 \quad (28)$$

Through the above formula, the number of particles of 5~15μm per milliliter in different grades of oil is predicted, and the results are shown in Table 7 and Table 8.

Table 7. Number of particles 5~15μm per milliliter in different grades of motor oil on the 1st passenger car (pieces).

Grade	Driven distance /km				
	1000	2000	3000	4000	5000
SJ grade	23227	27008	30453	33561	36333
SL grade	26991	29723	32858	36274	39042

Table 8. Number of particles 5~15μm per milliliter in different grades of motor oil on the 1st passenger car (pieces).

Grade	Driven distance /km				
	1000	2000	3000	4000	5000
SJ grade	25740	27685	30421	32894	36841
SL grade	25482	28156	31856	34258	38563

4.3 Combined Model Prediction

(1) Model establishment

The grey linear regression combined model is established by using the number of 5~15μm particles per milliliter in the SJ grade oil of No. 1 passenger car as the original series:

$$X^{(0)} = \{23742 \quad 25493 \quad 31911 \quad 35132 \quad 36304\}$$

After a cumulative increase:

$$X^{(1)} = \{23742 \quad 49235 \quad 81146 \quad 116278 \quad 152582\}$$

When $m = 1$:

$$X_{(1)}(1) = Z(2) - Z(1) = 6418$$

$$X_{(1)}(2) = Z(3) - Z(2) = 3221$$

$$X_{(1)}(3) = Z(4) - Z(3) = 1172$$

The solution: $\lambda_1(1) = -0.69, \lambda_1(2) = -1.01$.

When $m = 2$, Similarly, it can be obtained that: $X_{(2)}(1) = 3221, X_{(2)}(2) = 1172$. From the formula, it can be obtained that: $\lambda_2 = -0.69$. It can be obtained that $\bar{\lambda} = -0.9$. From MATLAB, it can be obtained that: $C = [-27521.28 \quad 2015.86 \quad 30754.89]$

The prediction formula for the number of 5~15μm particles per milliliter in the SJ grade oil of No.1 passenger car can be obtained:

$$\bar{X}_{SJ}{}^{1}(t) = -27521.28e^{-0.9t} + 2015.86t + 30754.89 \quad (29)$$

Similarly, the prediction formula for the number of 5~15μm particles per milliliter in SL grade Oil of No. 1 passenger car is:

$$\bar{X}_{SL}{}^{1}(t) = -18963.41e^{-0.6035t} + 5241.25t + 28756.95 \quad (30)$$

According to the derivation of the above formula, the prediction formulas for the number of particles of 5~15 μm per milliliter in the different grades of the passenger car of No. 2 passenger car are:

$$\bar{X}_{SJ}{}^{2}(t) = -35274.52e^{-0.75t} + 4625t + 15247.12 \quad (31)$$

$$\bar{X}_{SL}{}^{2}(t) = -25874e^{-0.81t} + 3589t + 8952.86 \quad (32)$$

From the prediction formulas (29),(30) and formulas (31), (31), the number of particles of 5~15 μm per milliliter in different grades of oil can be obtained. The results are shown in Table 9 and Table 10.

Table 9. Number of particles 5~15 μm per milliliter in different grades of motor oil on the 1st passenger car (pieces).

Grade	Driven distance /km				
	1000	2000	3000	4000	5000
SJ grade	23576	26788	30942	34789	36567
SL grade	25785	28952	32245	35365	37154

Table10. Number of particles 5~15 μm per milliliter in different grades of motor oil on the 1st passenger car (pieces).

Grade	Driven distance /km				
	1000	2000	3000	4000	5000
SJ grade	25425	27523	30425	33986	37425
SL grade	26895	28452	30487	33721	35154

(2) Model test

According to Table 9 and Table 10 and formulas (17) and (18), the residuals and relative errors of the 5~15μm particles per milliliter and the predicted values of the grey linear regression combination model are obtained. The results are shown in Table 11 and Table 12.

From the data in equations (19), (20) and Table 11 and Table 12, the average errors of the grey linear regression combined model of No.1 passenger car are 2.1% and 4.61% respectively, and the accuracy are 97.99%, 95.38%. The average errors of the grey linear regression combined model of No.2 passenger car are 1.3%, 2.08% respectively, and the accuracy is 98.7%, 97.92%, respectively. According to the classification of prediction accuracy in Table 3, the prediction accuracy level of the number of 5~15μm particles per milliliter in different grades of oil using the combined model is level-2. The grey linear regression combined model can be applied to the prediction of oil wear particles in passenger cars.

4.4 Model Comparison

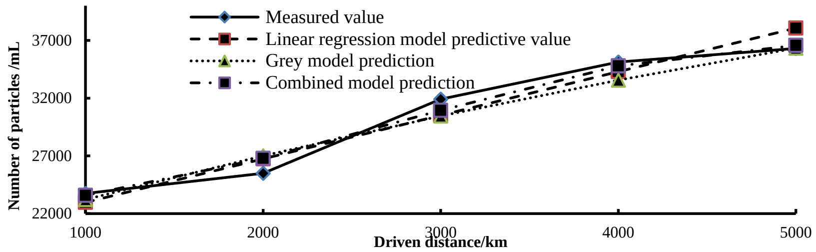
Through the prediction of three models, it can be found that the prediction value of 5~15μm particles per milliliter of different grades in passenger car oil is obtained. Compared with the measured values, the trend of the number of 5~15μm particles per milliliter of different grades in No.1 and No.2 passenger cars is obtained, which is shown in Figure 2 and Figure 3.

Table 11. Residual and relative error of predicted values of passenger car combination model No.1.

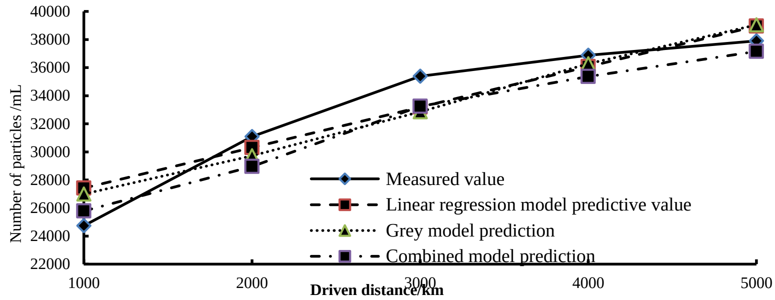
Driven distance /km		1000	2000	3000	4000	5000
SJ grade	Measured value	23742	25493	31911	31911	31911
	Predictive value	23576	26788	30942	34789	36567
	Residual	166	-1295	969	343	-263
	Eerror/%	0.7	-5.08	3.04	0.98	-0.72
SL grade	Measured value	24739	31084	35391	36882	37910
	Predictive value	25785	28952	33245	35365	37154
	Residual	-1000	2132	3146	1517	756
	Error/%	-4.04	6.86	6.06	4.11	1.99

Table 12. Residual and relative error of predicted values of passenger car combination model No.2.

Driven distance /km		1000	2000	3000	4000	5000
SJ grade	Measured value	25640	27655	29632	33542	37879
	Predictive value	25425	27523	30425	33986	37425
	Residual	215	132	-793	-444	454
	Error/%	0.84	0.48	-2.68	-1.32	1.20
SL grade	Measured value	27988	29940	30424	33542	34879
	Predictive value	26895	28452	30487	33721	35154
	Residual	1093	1488	-63	-179	-275
	Error/%	3.91	4.97	-0.21	-0.53	0.79

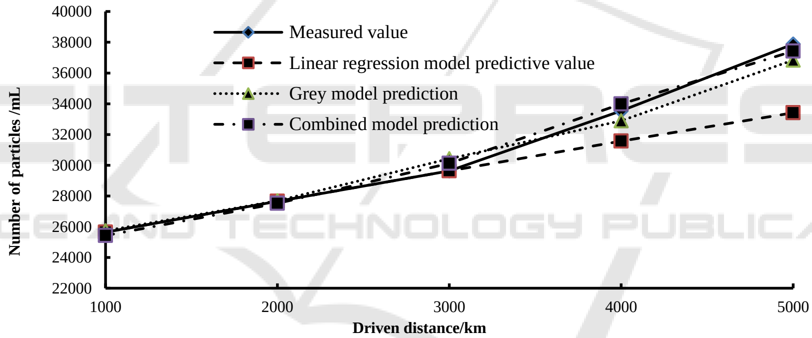


(a) SJ grade engine oil

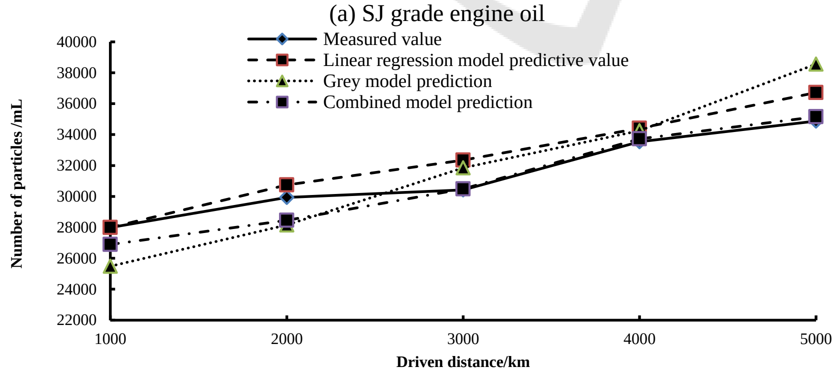


(b) SJ grade engine oil

Figure 2. Comparison of predicted values of 5~15μm particles per milliliter in different grades of passenger car No.1.



(a) SJ grade engine oil

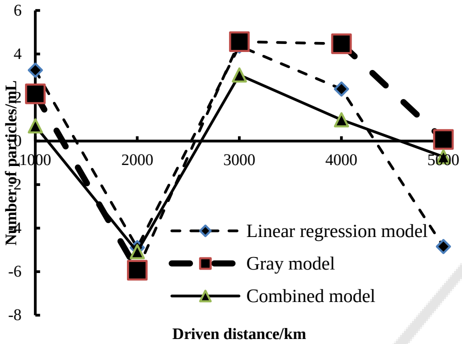


(b) SL grade engine oil

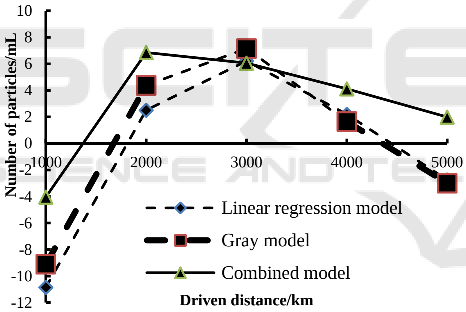
Figure 3. Comparison of predicted values of 5~15μm particles per milliliter in different grades of passenger car.

According to the prediction results and the cleanliness grade analysis of the combined model, the number of 5~15μm particles per milliliter of different grades in passenger car oil does not exceed 40000. At this time the oil is clean and does not need to be replaced. While if the number of 5~15μm particles per milliliter in the oil exceeds 40000, the oil cleanliness has exceeded the passenger car engine requirements of the cleaning degree of oil. There are too many impurities in the oil, and it can not continue to use. Otherwise, it will accelerate the deterioration of oil quality, resulting in engine wear failure, and the oil should be replaced in time.

According to the experimental data and the predicted values of three prediction models, the relative error and average error of the predicted value of 5~15μm particles per milliliter in different grades of oil are obtained and shown in Table 8. The changing trends of different relative errors are shown in Figure 4 and Figure 5.

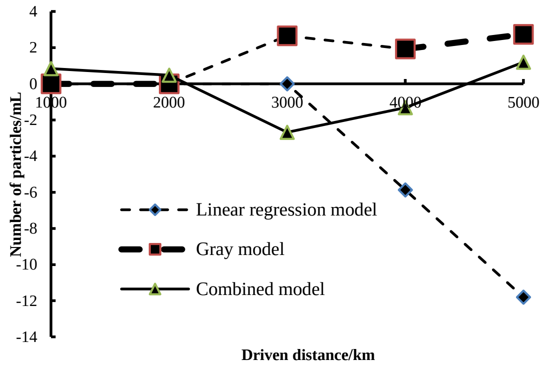


(a) SJ grade engine oil

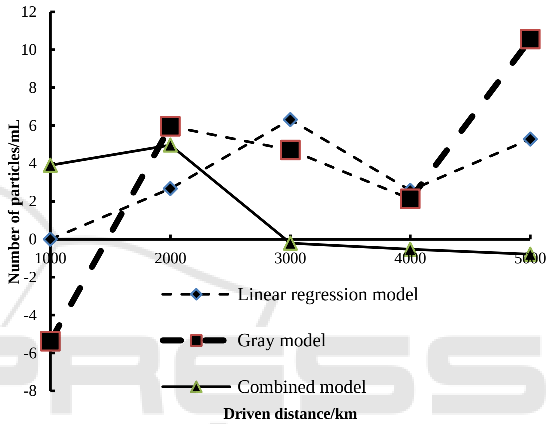


(b) SL grade engine oil

Figure 4. Comparison of relative errors of predicted values of 5~15 μm particles per millet in different grades of motor oil of No.1 passenger car.



(a) SJ grade engine oil



(b)SL grade engine oil

Figure 5. Comparison of relative errors of predicted values of 5~15μm particles per millet in different grades of motor oil of No.2 passenger car.

Table 13. Relative error analysis of predicted values of 5~15μm particles per milliliter in different grades of passenger car No.1.

Driven distance /km	SJ grade relative error/%			SL grade relative error/%		
	Linear	Grey	Combined	Linear	Grey	Combined
1000	3.26	2.17	0.70	-10.85	-9.10	-4.04
2000	-4.90	-5.94	-5.08	2.51	4.38	6.86
3000	4.37	4.57	3.04	6.22	7.16	6.06
4000	2.39	4.47	0.98	2.20	1.65	4.11
5000	-4.85	0.07	-0.72	-2.75	-2.99	1.99
Error/%	3.95	3.44	2.10	4.90	5.06	4.61

Table 14. Relative error analysis of predicted values of 5~15 μm particles per milliliter in different grades of passenger car No.2.

Driven distance /km	SJ grade relative error/%			SL grade relative error/%		
	Linear	Grey	Combined	Linear	Grey	Combined
1000	0	0	0.84	0	-5.38	3.91
2000	0	0	0.48	2.67	5.96	4.97
3000	0	2.66	-2.68	6.31	4.71	-0.21
4000	-5.87	1.93	-1.32	2.58	2.13	-0.53
5000	-11.80	2.74	1.20	5.28	10.56	-0.79
Error/%	4.16	1.42	1.30	3.36	4.80	2.08

According to Table 13 and Table 14, it can be found that the wear particles in the SJ oil for No.1 passenger car show that the prediction accuracy of the grey linear regression combined model are higher than the linear regression model (1.85 %) and the grey model (0.29 %), and for the SL oil are 1.34 % and 0.45%, respectively. For No.2 passenger car, the prediction accuracy is increased by 2.86% in SJ oil and 1.28% in SL oil for the linear regression model, and 0.12% in SJ oil and 2.62% in SL oil for the grey model. According to the relative error changes of the predicted values of each model, the relative error of the predicted values of the combined model are much smaller than those of the grey model and the linear regression model. This shows that the grey linear regression combined model is better than the grey model and the linear regression model. The grey linear regression combined model can be applied to the prediction of passenger car oil wear particles. According to Table 8 and the prediction of the grey linear regression combination model, when the mileage of the passenger car reaches 5000km, the number of 5~15μm particles per milliliter in the SJ grade and SL grade oil does not exceed 40000, indicating that the oil is clean at this time. The drivers of the passenger cars generally perform oil replacement when the passenger car's mileage reaches 5000km. Combined with the predicted results, the oil is replaced prematurely and the oil is still in a clean state, resulting in a waste of oil. It is suggested that when changing oil, the degree of deterioration of oil quality should be considered, extend the oil replacement period appropriately, realize the replacement of oil according to quality, avoid the waste of oil, and save the cost of use.

5 CONCLUSIONS

(1) With the increase of mileage in passenger cars, the content of particles in oil also increases slowly. The change trend of particle content of 5~15μm is obvious and regular, which can be used as the main index to monitor engine wear. If the cleanliness of the oil reaches 22/19, the oil should be replaced.

(2) The grey linear regression combined model is established by combining the grey model with the linear regression model, which makes up for the deficiency of the single model and improves the prediction accuracy.

(3) The example shows that the prediction accuracy of the grey linear regression combined model is higher than the linear regression model and the grey model. It indicated that the combined model can be applied to the prediction of oil wear particles in passenger cars.

(4) According to the cleanliness level, when the mileage of passenger cars reaches 5000km, the oil replacement is too early at this time and the oil is still in a clean state. The oil replacement period should be extended appropriately, and realizing the replacement of oil according to quality.

ACKNOWLEDGEMENTS

This work was financially supported by the Funding of National Science and Technology Support Program (2015BAG02B01).

REFERENCES

B. Chen, J.G. Wang. Research on grey linear regression combined model algorithm, Journal of Xi\'an University of Arts and Science (Natural Science Edition), 2012, 15(1): 82-85.

B. Zeng, S.F. Liu. Unbiased direct DGM (1, 1) model of non-homogeneous exponential sequence and its application in electric load forecasting. Statistics & Information Forum, 2013,732-733.

D. Liang, Y.F. Hu, L.F. Ma, et al. Forecasting for Machine Tool Sales Based on Grey Linear Regression Model. Advanced Materials Research, 2014, 945: 2935-2938.

F.L. Ren, W.B. Li, T. He. Linear regression and grey theory's application in the Power prediction, 2018.

H. Hao, Q. Zhang, Z.G. Wang, Forecasting the number of end-of-life vehicles using a hybrid model based on grey model and artificial neural network, Journal of Cleaner Production, 2018, (202): 684-696.

H.R.Zhao, X.Y.Han, S.Guo. DGM (1, 1) model optimized by MVO (multi-verse optimizer) for annual peak load forecasting. Neural Computing and Applications, 2018, 30(6):1811–1825.

J.F. Jing, K.C. Li, F.K. Deng, et al. Grey line of corrosion of oil and gas pipelines, Sexual regression combined prediction model. Oil & Gas Storage and Transportation, 2015, 34(12):1300-1304.

J.S. Wang. Standard of lubricating oil cleanliness and detection of particulate pollution, Measurement and testing technology, 2015, 42(5): 21-22.

J.Z. Xin, J.T. Zhou, S.X. Yang, Bridge structure deformation prediction based on GNSS data using Kalman-ARIMA-GARCH model, Sensors, 2018, 18(1) 298: 1-6.

K.P. Bi, G.H. Yan, H. Y. Zhang, et al, Research on equipment failure rate forecasting based on gray-linear regression combined model. 2016 Prognostics and System Health Management Conference, 2016, 19-21.

N. Tian, Y. Wei Application Scope and extension of approximate non-homogeneous exponential discrete grey model. Statistics & Decision, 2018, 8: 126-132.

S.Z. Chen, S. Li, F. Xiao, Forecasting of asphalt pavement performance based on GA-Grey neural network, Journal of Chongqing Jiaotong University (Natural Science), 2019, 159-164.

Tobita, Mikio. Combined logarithmic and exponential function model for fitting postseismic GNSS time series after 2011 Tohoku-Oki earthquake, Tobita Earth, Planets and Space, 2016 68(41):1-12.

X. Xiao, H. Guo, S. Mao. The modeling mechanism extension and optimization of grey GM (1, 1) model, Applied Mathematical Modelling, 2014, 38(5): 1896-1910.

Y.B. Zhou, L.F. Jiao. Standards and test methods of oil cleanliness, Lubricating Oil, 2008, 23(1): 63-64.

Y. Han, Weighted grey linear regression combined model and its application based on wavelet pretreatment, Industrial Instrumentation & Automation, 2016, (06): 152-158.

Y. Wang, X.M. Chen, Y.H. Han. Forecast of passenger and freight traffic volume based on elasticity coefficient method and grey model, Procedia-Social and Behavioral Sciences, 2013, (96): 136-147.

Y.X. Jiang, Q.S. Zhang. Recursive solution to approximate non-homogeneous unbiased GM (1, 1) model and its application. Control and Decision, 2015, 30(12):524-554.

Y Zhou, Y Luo, SM Jia, et al. Grey-linear regression combination model for ritting and predicting layered land subsidence in Beijing, Urban Geology, 2014, 9(4): 52-56.