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General Regression Neural Network and Artificial-Bee-Colony Based General Regression Neural Network Approaches to the Number of End-of-Life Vehicles in China

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ABSTRACT Establishing the number of vehicles that will reach the end of their useful lives in the coming years will substantially affect recycling management and recycling policy. Thus, how to construct a reasonable, accurate model to forecast a product's end of life is important for recycling management. To improve forecast accuracy for vehicle end of life, this paper proposes two approaches: a general regression neural network (GRNN) and an optimized GRNN based on an artificial bee colony. These approaches are applied to forecast the number of end-of-life vehicles (ELVs) in China. In addition, the proposed models are used to predict the number of ELVs that will appear in China from 2016 to 2020 by combining the forecasting data for the main factors that influence the number of such vehicles. Theoretical and simulation results indicate that the described approaches are effective and feasible. This paper provides practical data support and a better theoretical model for researchers, government managers, and industrial engineers faced with the problems posed by ELVs.

INDEX TERMS Data processing, end-of-life vehicles, intelligent optimization, modeling and simulation.

I. INTRODUCTION

Today, increasing public awareness of end-of-life products is causing a dramatic expansion of the disassembly and remanufacturing industries [1]–[3]. In China, the Traffic Management Bureau of the Public Security Ministry estimated that by 2020, the number of vehicles will increase to 280 million [4]. Obviously, there will be a large number of end-of-life vehicles (ELVs) in the coming decades. With the appearance of large numbers of ELVs, prediction models have been introduced [5]. Effective prediction of the number of ELVs can not only contribute to the reuse of such vehicles but also guide the formulation of policies and regulations. Conventionally, the number of ELVs is forecast by an empire multiply factor of 5%-8% of the total number of vehicles; this method has low accuracy [6].

Recently, because of their good prediction accuracy, a number of concepts based on gray theory, fuzzy systems and neuro-fuzzy approaches and used in several industry forecasting fields have been applied to the ELV problem [7]–[9]. For example, in [10], a Weibull distribution model with two parameters based on vehicle production year has been employed to predict the number of end-of-life vehicles. In [11], a gray forecasting system for the number of end-of-life products based on local vehicle market data is proposed. The model's accuracy is optimized with Markov chain correction and Fourier series. In [12], an electrical-waste product return amount is forecast using a gray forecasting model for a reverse logistics network in Turkey. The fuzzy expert system is also applied to predict the number of obsolete products in reverse logistics networks in [13]. The described forecasting method is applied to a case study on the electrical and electronic equipment recycling industry in Turkey. In [14], a forecasting model for product return is established using an adaptive network-based fuzzy inference system and applied in an experimental study. This approach was proposed to forecast the number of end-of-life products

TABLE 1. Historical data for ELVs and their influencing factors (1995-2015).

Year	Production number (Ten thousand vehicles)	Sales number (Ten thousand vehicles)	Vehicle population (Ten thousand vehicles)	Highway freight turnover (Billion tons per km)	Passenger turnover (Billion persons per km)	GDP (Billion Yuan)	Income of per urban resident (Yuan)	Number of ELVs (Ten thousand vehicles)
1995	145.27	144.18	1040.02	4694.9	4603.1	60793.73	4283	36
1996	147.49	145.87	1100.08	5011.2	4908.8	71176.59	4838.9	39
1997	158.26	156.59	1219.09	5271.5	5541.4	78973.03	5160.3	43
1998	162.78	160.31	1319.3	5483.38	5942.8	84402.28	5425.1	46
1999	183.16	183.3	1452.94	5724.3	6199.2	89677.05	5854	50
2000	206.82	207.84	1608.94	6129.4	6657.4	99214.55	6280	55
2001	234.15	237.11	1802.04	6330.4	7207.1	109655.17	6859.6	64
2002	325.12	325.05	2053.2	6782.5	7805.8	120332.7	7702.8	71
2003	444.37	439.08	2382.93	7099.5	7695.6	135822.8	8472.2	85
2004	507.05	507.11	2693.71	7840.9	8748.4	159878.3	9421.6	93
2005	570.77	575.82	3160	8693.2	9292.1	184937.4	10493	109
2006	727.97	721.6	4985	9754.2	10130.85	216314.4	11759	145
2007	888.24	879.15	5099.61	11354.7	11506.8	265810.3	13786	175
2008	934.51	938.05	5696.78	32868.2	12476.1	314045.4	15781	220
2009	1379.1	1364.48	6539	37188.8	13511.4	340902	17175	270
2010	1826.47	1806.19	7185.7	43389.7	15020.8	401202	19109	290
2011	1841.89	1850.51	10578	51374.7	16732.6	471564	23979	410
2012	1927.18	1930.64	11400	59992	18468.4	519322	24565	440
2013	2201.8	2223.5	13784	70542	20615	582420	28091	523
2014	2344.2	2386.3	16408	79245	22943	642624	31157	607
2015	2428.9	2499.7	19487	86798	25533	700950	34350	700

for recycling and remanufacturing through a data generation simulation model [15].

Although several methods have been applied to forecast the number of the end-of-life vehicles (ELVs) (e.g., approximate assessment and multiple linear regression), they were executed using inaccurate data and models. I.e., these methods were not sufficiently intelligent. To improve forecasting accuracy and productivity, the development of intelligent forecasting approaches that consider multiple factors is important. To this end, this study proposes two novel intelligent forecasting approaches for Chinese end-of-life vehicles: a general regression neural network (GRNN) and an optimized GRNN based on an artificial bee colony (ABC), termed ABC-GRNN.

Our paper makes several important contributions. (1) To improve forecasting accuracy and productivity, we propose an intelligent forecasting concept to predict the number of ELVs. (2) GRNN and ABC-GRNN are applied to forecast the number of ELVs. The former makes full use of its good forecasting performance when a sample size is small. The latter makes full use of the optimization ability of ABC to improve forecasting accuracy. In addition, through simulation experiments, we test the effectiveness and feasibility of the presented approaches in forecasting the number of ELVs. (3) By combining the proposed models with the polynomial fitting method, the future number of end-of-life vehicles for 2016 to 2020 in China is obtained.

The remainder of the paper is organized as follows. Section II describes the factors that influence the number of the end-of-life vehicles. In Section III, the construction of GRNN and ABC-GRNN models for forecasting the number of ELVs is described. Section IV presents the forecasting analysis results. Finally, Section V concludes our paper and describes future research directions.

II. INFLUENCING FACTOR ANALYSIS

A large array of political and economic factors have a substantial impact on the number of end-of-life vehicles. In this study, 7 such factors are considered: vehicle production number, vehicle sales number, vehicle population, highway freight turnover, passenger turnover, GDP and income per urban resident. The historical data (1995-2015) for these factors are surveyed for China (Table 1). Most of the relevant data were found in [16].

III. FORECASTING MODELS

The data for the 7 influencing factors are regarded as the input variables in forecasting, while the number of ELVs is termed the output. The forecasting models are described as follows.

Taking the forceful and nonlinear connection between the forecasting objective and its influencing factors into account, the following three methods are used to construct forecasting models: a general regression neural network (GRNN), an artificial bee colony (ABC) and an optimized GRNN based on ABC (ABC-GRNN).

A. GRNN

A GRNN is a branch of RBF-NNs and a radial learning NN. It is superior to traditional RBF-NNs in approximation ability and learning speed. In particular, when a sample size is small, a GRNN can maintain a good forecasting performance. Thus, we adopt it to forecast number of end-of-life vehicles [17]–[23].

Essentially, a GRNN is a form of nonlinear regression analysis. Its forecasting result can be expressed as follows:

$$E[\mathbf{Y}|\mathbf{X}] = \frac{\int_{-\infty}^{\infty} \mathbf{Y} f(\mathbf{X}, \mathbf{Y}) d\mathbf{X}}{\int_{-\infty}^{\infty} f(\mathbf{X}, Y) d\mathbf{X}} \tag{1}$$

where $\boldsymbol{X}$ is an r-dimensional input variable, $\boldsymbol{X} = [x_1, x_2, \ldots, x_r]^{\mathrm{T}}$, and $\boldsymbol{Y}$ is a k-dimensional output variable, $\boldsymbol{Y} = [y_1, y_2, \ldots, y_k]^{\mathrm{T}}$. The output result of GRNN is $f(\mathbf{X}, \mathbf{Y})$, which is a joint probability density function of $\boldsymbol{X}$ and $\boldsymbol{Y}$. $E[\mathbf{Y}|\mathbf{X}]$ is an expected value of $\boldsymbol{Y}$ under the special condition of $\boldsymbol{X}$.

A GRNN structure is shown in Fig. 1. It consists of four layers: input, pattern, summation and output.

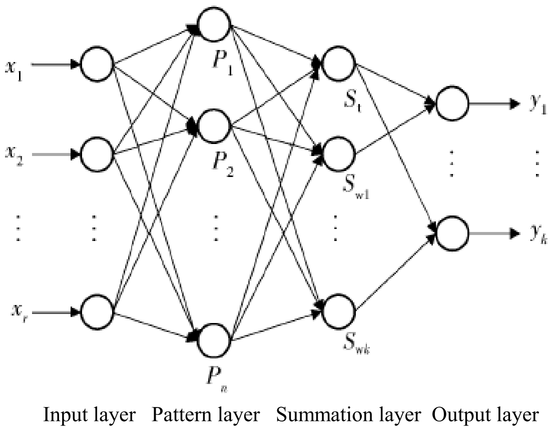

FIGURE 1. GRNN structure graph.

(1) The input layer: the number of input neurons r in a GRNN equals the number of input variables in earning samples in an input layer. In this paper, it is 7.

(2) The pattern layer: the number of neurons in a pattern layer equals sample size n. The transfer function of each neuron is expressed as follows:

$$P_i = \exp\left[-\frac{(\mathbf{X}-\mathbf{X}_i)^T(\mathbf{X}-\mathbf{X}_i)}{2\sigma^2}\right], \quad i = 1, 2, \ldots, n \tag{2}$$

where $\mathbf{X}_i$ is ith neuron of its corresponding learning sample, and σ is a smoothing factor. In this paper, n is set to be 20.

(3) The summation layer: the summation layer typically uses two approaches. The first method is the sum of the neurons of all pattern layers, and its transfer function is as follows:

$$S_t = \sum_{i=1}^{n} P_i \tag{3}$$

The second approach is the weighted sum of the neurons of all pattern layers. It is expressed as follows:

$$S_{wj} = \sum_{i=1}^{n} y_{ij} P_i, \quad j = 1, 2, \ldots, k. \tag{4}$$

where k is the number of dimensions of output layers.

To improve computing efficiency, the first method is applied in this paper.

(4) The output layer: the number of input neurons of output layers equals the number of dimensions of output variable k, and the ith element of the corresponding forecasting result of the output result of the jth neuron is as follows:

$$\mathrm{y}_j = \frac{S_{wj}}{S_t}, \quad j = 1, 2, \ldots, k. \tag{5}$$

As can be observed from equations 1-5, the smoothing factor σ has a large impact on the forecasting result. Thus, its determination method is important for the forecasting calculation. In this paper, it is determined by minimizing the mean square value of the error between its output and the actual output.

Based on the preceding description, the GRNN has the following steps:

1) Initialize the input data, i.e., the data for the 7 factors that influence the number of end-of-life vehicles listed in TABLE 1.

2) Construct a GRNN structure by using the command *newgrnn* in Matlab software.

B. ABC

Because of its good nonlinear complex optimization capabilities, an ABC is a warm intelligence algorithm that is applied in many contexts, for example, disassembly, transportation and structural engineering [24]–[30].

An ABC is an optimum algorithm that functions by imitating the behavior of a bee swarm seeking food sources. In an ABC, the location of food sources is the solution of the optimization problem. By using the ABC, the corresponding fitness value can be calculated. The employed bee corresponds to food sources in the ABC and shares information with other bees to produce a new feasible food source. The onlooker bee selects the food source that is shared by the employed bees. Typically, food sources with larger fitness values have a higher probability of being selected. Then, employed and onlooker bees seek food sources in their current location if the fitness value of new food sources is larger than the fitness value of the original food sources. Otherwise, the original food sources are maintained. If the food sources do not change when the search reaches a given time.

In an ABC, the probability of an onlooker bee seeking food sources is calculated as follows:

$$\mathrm{P}_i = \frac{f_i}{\sum_{i=1}^{N} f_i} \tag{6}$$

where N is the number of food sources and f_i is fitness value of the ith food source.

The food source locations are updated by the following formulation:

$$v_i^j = x_i^j + \varphi_i^j (x_i^j - x_k^j) \tag{7}$$

where v_i^j is the location of a new food source and x_i^j is the position of the original food source, $k \neq i$.

Based on the preceding description, the ABC has the following steps:

Step 1. Initialize the corresponding parameters of ABC and the number of simulation cycles;
Step 2. Update the food source through the employed bee.
Step 3. Compute the objective function value and fitness of all chromosomes;
Step 4. Search new food source through the scout bee phase.
Step 5. Repeat Steps 2-4 for a predefined number of iterations; and
Step 6. Report the best individual as the optimal solution.

C. ABC-GRNN

According to the preceding discussion, the hybrid foresting algorithm ABC-GRNN, which consists of an ABC and a GRNN, has the following steps. Note that the ABC's optimization aim is to obtain the best smoothing factor σ by minimizing the mean square value of the error between its output and the actual output.

Step 1: Initialize parameters of the GRNN and construct a GRNN structure.

Step 2: Determine the parameters of the ABC.

Step 3: Initialize the food sources of the ABC. I.e., the smoothing factor in the GRNN is regarded as food source and initialized.

Step 4: Update the food source (the smoothing factor in the GRNN) via the employed bee.

Step 5: Compute the objective function value and fitness of all chromosomes by reading the GRNN data;

Step 6. Find new food source through the scout bee phase.

Step 7. Repeat Steps 3-6 for a predefined number of iterations; and

Step 8. Regard the best individual as the best smoothing factor σ (optimal solution).

Step 9. Based on the best σ in Step 8, construct a GRNN, and use it to train and forecast the number of end-of-life vehicles.

By analyzing the preceding Steps, the ABC-GRNN can be described by the following flowchart (Fig. 2).

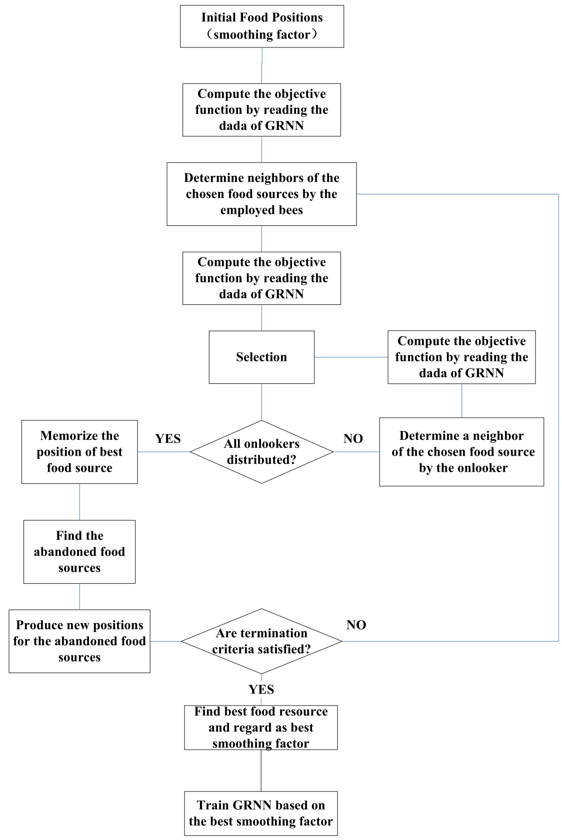

FIGURE 2. ABC-GRNN algorithm outline.

IV. FORECASTING RESULTS AND ANALYSIS

According to the described enumeration approaches, the forecast and its results for the number of Chinese end-of-life vehicles are obtained in this section.

A. FORECASTING RESULT

1) By using the GRNN algorithm, the forecasting results for the number of Chinese end-of-life vehicles are presented (TABLE 2).

2) Similarly, by using the ABC-GRNN algorithm, the forecasting results for the number of Chinese end-of-life vehicles are presented (TABLE 2).

In addition, the forecasting results and errors of both algorithms are presented in Figs. 3 and 4.

B. FORECASTING PERFORMANCE ASSESSMENT

To compare the forecasting results of the two approaches, three performance parameters are applied: the mean value of absolute error (M_v), the standard deviation of absolute error (S_d) and the correlation coefficient (R^2) between the actual value and the forecast one [31]. The mathematical expressions of these parameters are presented as follows. In addition, the obtained parameters for the two forecasting approaches are listed in TABLE 3.

$$M_v = \frac{1}{n}\sum_{i=1}^{n}\left|x_0 - y_f\right| \tag{8}$$

$$S_d = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_0 - y_f)^2} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_0 - y_f)^2}{\sum_{i=1}^{n}(x_0 - \bar{x}_0)^2} \tag{10}$$

where x_0 is the actual value of the number of Chinese end-of-life vehicles, $\bar{x}_0$ is the average value of actual data for the number of Chinese end-of-life vehicles and y_f is the forecasting value.

TABLE 2. Forecasting results of GRNN and ABC-GRNN models.

Year	Actual value	GRNN		ABC-NN	
		Forecast value	Error	Forecast value	Error
1995	36	39.2105	-3.2105	36.5648	-0.5648
1996	39	33.0077	5.9923	37.6221	1.3779
1997	43	48.7869	-5.7869	41.2554	1.7446
1998	46	41.268	4.732	44.0124	1.9876
1999	50	55.2231	-5.2231	51.6872	-1.6872
2000	55	50.3224	4.6776	54.2209	0.7791
2001	64	67.1509	-3.1509	65.1003	-1.1003
2002	71	68.0054	2.9946	71.2546	-0.2546
2003	85	80.2681	4.7319	85.6352	-0.6352
2004	93	96.2651	-3.2651	102.9009	-9.9009
2005	109	112.2521	-3.2521	107.5694	1.4306
2006	145	140.2259	4.7741	144.3642	0.6358
2007	175	170.9986	4.0014	174.2581	0.7419
2008	220	222.1564	-2.1564	220.3678	-0.3678
2009	270	285.6875	-15.6875	271.9659	-1.9659
2010	290	285.9958	4.0042	291.0365	-1.0365
2011	410	407.6354	2.3646	408.6531	1.3469
2012	440	445.1003	-5.1003	439.0258	0.9742
2013	523	519.1039	3.8961	522.6489	0.3511
2014	607	604.2254	2.7746	608.4635	-1.4635
2015	700	695.1258	4.8742	699.0121	0.9879

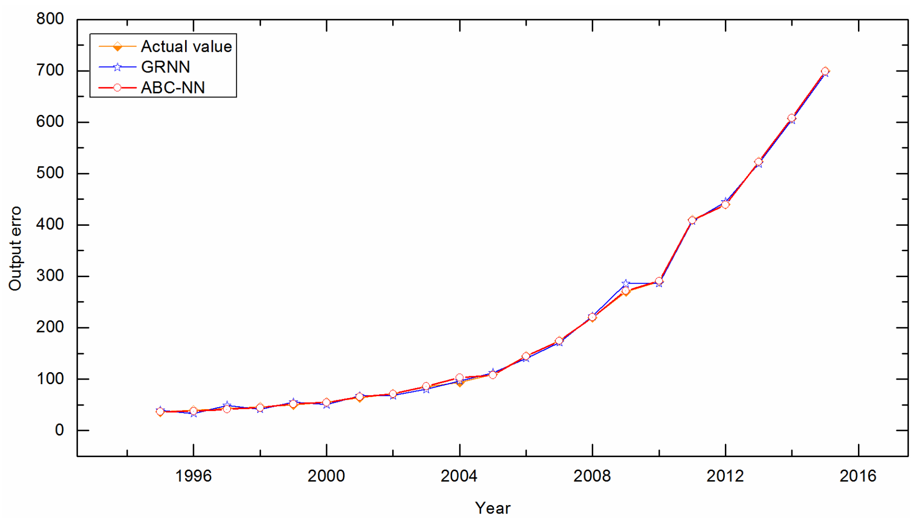

FIGURE 3. Prediction results of GRNN and ABC-NN models.

TABLE 3. Performance comparison for the two prediction models.

Assessment parameter	Prediction model	
	GRNN	ABC-GRNN
Mean value (M_v)	4.6024	1.4921
Standard deviation (S_d)	5.3345	2.4539
Correlation coefficient (R^2)	0.9992	0.9998

As shown in Table 3, the following instructive conclusions can be obtained:

1) For both forecasting models, the correlation coefficient is greater than 0.99. These results indicate that the GRNN and ABC-GRNN are highly feasible when applied to forecast the number of Chinese end-of-life vehicles.

2) The three assessment parameters of the ABC-GRNN are better than those of the GRNN. Thus, the ABC-GRNN possesses better forecasting ability than the GRNN. That is, the ABC has a better optimization ability than the GRNN.

V. FUTURE TREND OF THE NUMBER OF ELVS IN CHINA

A. OBTAINING FUTURE FACTOR DATA

To forecast future ELV numbers in China, it is essential to obtain future data for the relevant factors. In this study, we adopt a polynomial fitting method. This method

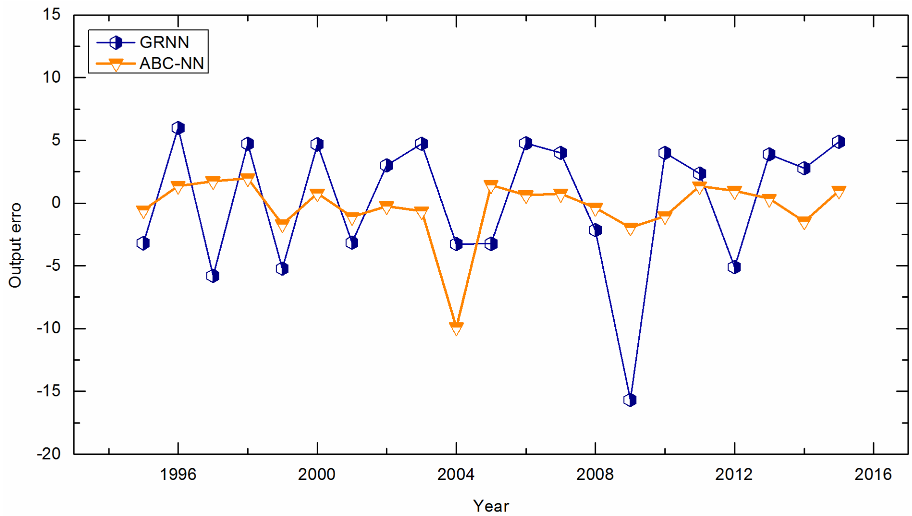

FIGURE 4. Output errors of GRNN and ABC-NN models.

has been used to successfully address many industrial problems [31]–[32].

In addition, it should be noted that a different order m would result in a different fitting formula for the related factor. However, if m is too small, estimation accuracy is low. If m is too large, calculation is difficult. Thus, there is a reasonable value for m, and its fitting formula can accurately describe the actual condition. In this paper, m is set to be 2, 3 and 4. When applying historical data for each factor to fit its approximate formula, the different fitting formula can be obtained under a different order m. To quantitatively evaluate the fitted formula, the correlation coefficient (R^2) is used. Typically, the larger that the value of R^2 is, the better the fitting. Thus, we can obtain the optimal fitting formula of each relevant factor by comparing R^2 values. In the next section, the fitting result of each factor is presented using this method.

1) FITTING RESULT FOR PRODUCTION NUMBER

By comparing fitting results for production number under different m values, when $m = 4$, the fitting result is the best, and its corresponding correlation coefficient R^2 is 0.9814. Finally, the fitting formula of production number PV is obtained:

$$PV = -0.0713y^4 + 2.8459y^3 - 28.251y^2 + 112.95y + 26.227 \quad (11)$$

where $y = Y - 1995$, and Y is the Year.

2) FITTING RESULT FOR SALES NUMBER

Similarly, when $m = 4$, the fitting result for sales number is the best, and its corresponding correlation coefficient R^2 is 0.9829. Its fitting formula SV is as follows:

$$SV = -0.0659y^4 + 2.6645y^3 - 26.353y^2 + 106.22y + 31.123 \quad (12)$$

TABLE 4. Obtained data for factors influencing the ELV number.

Year	GRNN	ABC-GRNN	Mean/actual value
2016	799.5	802.8	801.1
2017	913.9	911.1	912.5
2018	1034.9	1027.0	1030.9
2019	1149.1	1156.0	1152.5
2020	1487.6	1484.6	1486.1

3) FITTING RESULT FOR VEHICLE POPULATION

Similarly, when $m = 4$, the fitting result for vehicle population is the best, and its corresponding correlation coefficient R^2 is 0.9838. Its fitting formula VP is as follows:

$$VP = 0.1634y^4 - 3.6287y^3 + 53.213y^2 - 160.86y + 1225.6 \quad (13)$$

4) FITTING RESULT FOR PASSENGER TURNOVER

Similarly, when $m = 4$, the fitting result for passenger turnover is the best, and its corresponding correlation coefficient R^2 is 0.9709. Its fitting formula PT is as follows:

$$PT = -2.824y^4 + 130.48y^3 - 1623.7y^2 + 6963.4y - 2542.8 \quad (14)$$

5) FITTING RESULT FOR TURNOVER OF HIGHWAY FREIGHT

Similarly, when $m = 3$, the fitting result for turnover of highway freight is the best, and its corresponding correlation coefficient R^2 is 0.9985. Its fitting formula HFT is as follows:

$$HFT = 2.7818y^3 - 35.61y^2 + 542.69y + 4078.3 \quad (15)$$

6) FITTING RESULT FOR GDP

Similarly, when $m = 4$, the fitting result for GDP is the best, and its corresponding correlation coefficient R^2 is 0.9838. Its

TABLE 5. Predicted future numbers of ELVs (2016-2020).

Year	Production number (Ten thousand vehicles)	Sales number (Ten thousand vehicles)	Vehicle population (Ten thousand vehicles)	Highway freight turnover (Billion tons per km)	Passenger turnover (Billion persons per km)	GDP (BillionYuan)	Income of per urban resident (Yuan)
2016	2438.3	2547.2	23081	92593	28403	755530	37637
2017	2352.7	2510.9	27251	95957	31569	804330	40980
2018	2150.5	2371.1	32065	96148	35047	845060	44335
2019	1808.7	2106.6	37592	92355	38855	875270	47655
2020	1302.4	1649.7	43807	83701	43009	89229	50888

fitting formula GDP is as follows:

$$GDP = 0.1634y^4 - 3.6287y^3 + 53.213y^2 - 160.86y + 1225. \quad (16)$$

7) FITTING RESULT FOR INCOME PER URBAN RESIDENT

Similarly, when $m = 4$, the fitting result for income per urban resident is the best, and its corresponding correlation coefficient R^2 is 0.9948. Its fitting formula $PURI$ is as follows:

$$PURI = -0.1971y^4 + 10.607y^3 - 99.712y^2 + 702.15y + 3679 \quad (17)$$

Based on obtained the fitting formula of each factor, the future data for these factors is obtained for different years (TABLE 4).

B. OBTAINING THE NUMBER OF ELVS IN CHINA AND ITS TREND

According to the results of Section V, the performance of the two models is highly satisfactory when used to forecast the number of ELVs in China. Thus, we adopt these models to forecast future ELV numbers in China. The detailed results are presented as follows.

1) FORECAST FUTURE NUMBER OF ELVS VIA GRNN

We use the obtained future data for the seven factors shown in Table 4 and obtain the number of ELVs via a fitting method as the output data of GRNN prediction. These data are introduced into the GRNN trained using historical data to obtain the future number of ELVs, as listed in the third column of Table 5.

2) PREDICTED FUTURE NUMBER OF ELVS VIA ABC-GRNN

We use obtained future data for the seven factors shown in Table 4 and obtain the number of ELVs via a fitting method as the output data of ANC-GRNN prediction. These data are introduced into the ABC-GRNN trained by historical data to obtain the future number of ELVs, as listed in the fourth column of Table 5.

From Table 5, the forecast results of the models are nearly consistent. This outcome indicates that the prediction result is correct. To reduce the error, we regard the mean value of these models as the actual result for the future number of ELVs in China.

Based on the results, the ELV number in China will continue to rapidly increase in the coming few years and exceed 1400 ten thousand. Therefore, China must enhance vehicle recovery and management and promote the sustainable development of China automotive industry.

VI. CONCLUSIONS

The number of Chinese end-of-life vehicles has a large impact on scrapped vehicle recycling management and the formulation of related recycling policies. To resolve this difficult problem, this study proposed a novel application of a general regression neural network (GRNN) and an optimized GRNN based on an artificial bee colony (ABC) to forecast the number of Chinese end-of-life vehicles. The simulation results indicate that both the GRNN and the ABC-GRNN can effectively forecast the number of Chinese end-of-life vehicles. The ABC-GRNN has higher fitting accuracy and stronger generalization ability and produces fewer forecasting errors than the GRNN. These results indicate that when our method is applied to forecast the number of Chinese end-of-life vehicles, the forecast result will have high reliability. In addition, the proposed models are combined to forecast the number of end-of-life vehicles in China for 2016 to 2020 by using the main factors that influence the number of such vehicles. The described research provides practical data support and a better theoretical model for researchers, government managers and industrial engineers faced with the problem of end-of-life vehicles.

A variety of uncertain factors have an important influence on the number of end-of-life vehicles. How to consider these uncertain factors represents an interesting research direction for future study on forecasting the number of end-of-life vehicles [34], [35].

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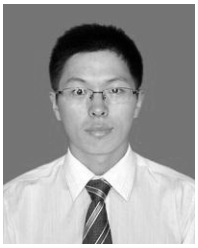

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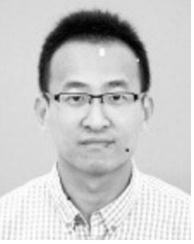

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