Research on Industrial Hazardous Waste Generation in China Based on Combination Forecasting Model

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Abstract. As the largest developing country, with the rapid development of society and economy, China's industrial hazardous waste generation is constantly increasing. In order to promote the scientific and effective management of industrial hazardous wastes, it is necessary to carry out reliable prediction research on industrial hazardous wastes generation. In view of the analysis of existing studies, firstly, this article considers the trend model, gray model, support vector machine model, and ARIMA model based on the sample data amount and the applicability of the prediction method to predict the hazardous waste production data separately; Then, the entropy weight method is used to evaluate independent models through multiple error indicators to determine the combined weight of each independent model; Finally, a combination forecasting model was established to study the production of industrial hazardous waste, and the application of the combination forecasting model to the forecast of industrial hazardous waste production in China was explored.

1. Introduction
The World Health Organization (WHO) defines hazardous waste as: "Hazardous waste is the waste with physical, chemical, or biological characteristics that requires special management and disposal processes to avoid causing health hazards or other harmful environmental effects". Hazardous wastes are usually highly toxic, explosive, flammable, and even radioactive [1]. If they are not properly managed, they will pose a threat to the environment [2] and the health of people [3]. In order to develop effective collection, treatment and disposal strategies, stakeholders and waste management service companies must make reliable predictions of waste generation [4]. Failure to make accurate predictions of the amount of waste generated may lead to failure of management policies in waste management and environmental governance, expansion of environmental pollution and insufficient or excessive waste disposal capacity [5]. Facing the huge threat caused by hazardous waste, how to effectively predict the waste generation has become a topic of great concern for the national government and many scholars. Based on the analysis of the preliminary research results, this paper constructs a combined forecasting model based on the entropy weight method. According to the practicability of forecasting methods and the characteristics of forecasting data in the study, an independent model suitable for combination is selected, and the entropy weight method is used to determine the weight when the independent models are combined. A combined forecasting model is established to predict the generation of industrial hazardous waste.

2. Research methods

2.1. Literature review based on relevant forecasting theory of waste generation
In recent years, academia has carried out extensive research on the prediction of waste generation. Detailed discussions have been studied in many aspects makes the prediction more accurate, such as: the geographical distribution of waste [6], waste components [7], waste generation factors [8,9] etc. Petridis et al. used Trend, ARMA, and Exponential Smoothing models to predict e-waste production in 25 countries in Western Europe, Eastern Europe, Asia Pacific, Australia, North America, and Southeast America. The results show that the monotonically increasing time series data makes the ARMA model prediction more accurate [4]. Karpušenkaitė and others conducted a prediction study on medical hazardous waste in Lithuania and found that Smoothing splines and Kernel regression methods performed very well in both regional and long-term data [10]. In the case of Iasi Romania, Ghinea et al. investigated the generation and composition of municipal solid waste and found that the curve trend model is most suitable for the prediction of municipal solid waste [7]. Denafas et al. used time series models to assess the amount and composition of municipal solid waste production in four Eastern European cities. The results show that the Seansen Exponential Smoothing and Winters Additive methods show higher prediction accuracy [11]. Intharathirat et al. carried out a long-term prediction of urban solid waste production in Thailand through a multivariable gray model, and pointed out that when using the gray model for prediction, a small number of outliers in the data can be accepted, which is an advantage of the gray model [9]. In a study of factors and yield predictions of Chinese municipal solid waste, Chhay et al. compared with multiple methods, and found that the artificial neural network (ANN) prediction results are consistent with the actual data trend [12]. Abbasi et al. used four intelligence models to predict the municipal solid waste production to test the performance of the different models. The results show that the intelligence models have good prediction performance and can be successfully used as municipal solid waste prediction [13]. According to the review of the above literature, it can be found that scholars have conducted extensive research on the prediction of various types of waste generation, but there are still some shortcomings. First of all, from the perspective of research objects, most scholars’ research mainly focuses on the generation prediction of municipal solid waste, medical waste, and electronic waste, and there are relatively few studies on the generation prediction of industrial hazardous waste; Secondly, in terms of research methods, many scholars use one or more of the time series analysis methods, causal analysis methods, and intelligent methods to predict waste production at the same time. Due to the different principles and starting points of various prediction methods, the focus of the impact factors considered in a single model is different, and most of them lack universal applicability. Combined forecasting is an important research branch in the field of prediction, Bates and Granger in 1969 for the first time put forward the "combined forecasting" idea, that is in the process of combination forecast, the research on a problem uses two or more than single prediction methods, and endows different independent prediction methods of effective information with the appropriate weights, thus higher forecast precision is obtained by combination [14]. Compared with single-item forecasting models, combination forecasting models can usually contain more comprehensive forecasting information, which can reduce forecasting errors caused by incorrect parameter or model application [15]. For example, Karpušenkaitė et al. developed a combination forecasting models by randomly determining the weights of the two models, which can effectively improve the accuracy of the total output prediction of automobile waste and medical waste [16]. Rimaitytė et al. used non-parametric seasonal exponential smoothing, autoregressive moving average, and a combination of the two models to predict the generation of municipal solid waste in Lithuania. The results show that the combination model using linear regression to determine independent model weights is the most accurate [17]. In addition, Hibon also proved that combination prediction can reduce the risk of prediction while ensuring the accuracy of prediction [18].

2.2. The structure of the technology acceptance model

2.2.1. General description of mathematical combination prediction model. Let the actual value of the prediction object be \( y(t), t = 1, 2, ..., n \), there are \( m \) models whose prediction value of the prediction object at time \( t \) be \( \hat{y}_i(t), t = 1, 2, ..., n \), \( i = 1, 2, ..., m \). \( w_i \) is the weight of prediction model \( i \) in the
combination prediction model, and \( \hat{y}(t) \) is the combination prediction value at time \( t \), then the combination prediction model can be described as:

\[
\hat{y}(t) = \sum_{i=1}^{m} w_i \hat{y}_i(t), t = 1,2, ..., n
\]

s.t. \( \sum_{i=1}^{m} w_i = 1, w_i \geq 0 (i = 1,2, ..., m) \)  (1)

From equation (1), it is known that determining the weight coefficient \( w_i \) of each independent model is the key to combination prediction model.

2.2.2. Introduction of model prediction performance evaluation indicators. The model predictive evaluation indicators used in this paper mainly include the following:

(1) Sum of Squared Error (SSE)

\[
\text{SSE} = \sum_{t=1}^{n} (y_t - \hat{y}_t)^2
\]

Where \( y_t \) is the actual value, \( \hat{y}_t \) is the predicted value, the same as below.

(2) Mean of absolute Error (MAE)

\[
\text{MAE} = \frac{1}{n} \sum_{t=1}^{n} |y_t - \hat{y}_t|
\]

(3) Mean-Square Error(MSE)

\[
\text{MSE} = \frac{1}{n} \left( \sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \right)^{\frac{1}{2}}
\]

(4) Mean Absolute Percentage Error (MAPE)

\[
\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \frac{|y_t - \hat{y}_t|}{y_t}
\]

(5) Mean Square Percent Error (MSPE)

\[
\text{MSPE} = \frac{1}{n} \left( \sum_{t=1}^{n} \left( \frac{y_t - \hat{y}_t}{y_t} \right)^2 \right)^{\frac{1}{2}}
\]

2.2.3. Entropy weight method to determine combination model weights. The basic idea of the entropy weight method is to quantify the information contained in the various errors of each independent prediction model according to the concept and characteristic of information entropy, and use this information to determine the weight of each independent model, as much as possible eliminate the influence of subjective factors [19]. In this paper, the steps to determine the combined weight of each independent model using the entropy weight method are as follows:

(1) Building the initial indicator matrix

With \( m \) independent models and \( n \) error indicators, the corresponding index value is \( a_{ij} \), where \( i = 1,2, ..., m, j = 1,2, ..., n \), then the initial index matrix \( A = (a_{ij})_{m \times n} \) is as follows:

\[
A_{m \times n} = \begin{bmatrix}
    a_{11} & a_{12} & \cdots & a_{1n} \\
    a_{21} & a_{22} & \cdots & a_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    a_{m1} & a_{m2} & \cdots & a_{mn}
\end{bmatrix} \quad (i = 1,2, \cdots, m, j = 1,2, \cdots, n)
\]

(2) Evaluation index conversion

There are three types of indicators in common evaluation systems: cost indicators, benefit indicators, and fixed indicators. The error indicator used in this paper is the cost indicators. The following method can be used to convert the cost indicators into the benefit indicators:

\[
\hat{c}_{ij} = \frac{a_{ij}^*}{a_{ij}} = \frac{\min_j[a_{ij}]}{a_{ij}}
\]

Where \( \min_j[a_{ij}] \) represents the smallest index value among the \( j \) index. Thus, the transformation matrix \( C = (c_{ij})_{m \times n} \) is obtained as follows:

\[
C_{m \times n} = \begin{bmatrix}
    c_{11} & c_{12} & \cdots & c_{1n} \\
    c_{21} & c_{22} & \cdots & c_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    c_{m1} & c_{m2} & \cdots & c_{mn}
\end{bmatrix} \quad (i = 1,2, \cdots, m, j = 1,2, \cdots, n)
\]

(3) Normalize the transformation matrix using standardized processing methods
\[ z_{ij} = \frac{c_{ij}}{c_j} (i = 1, 2, \ldots, n; j = 1, 2, \ldots, m) \]  

(8)

The standardized evaluation matrix \( Z = (z_{ij})_{m \times n} \) is obtained as follows:

\[
Z_{m \times n} = \begin{bmatrix}
Z_{11} & Z_{12} & \cdots & Z_{1n} \\
Z_{21} & Z_{22} & \cdots & Z_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
Z_{m1} & Z_{m2} & \cdots & Z_{mn}
\end{bmatrix} (i = 1, 2, \ldots, m, j = 1, 2, \ldots, n)
\]  

(4)

(4) Determine the entropy value and entropy weight of each attribute index

According to the definition of entropy, the entropy value \( e_j \) and entropy weight \( \theta_j \) of the \( j \) attribute index are:

\[
e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} \frac{c_{ij}}{c_j} \ln \frac{c_{ij}}{c_j}
\]  

(9)

\[
\theta_j = \frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)}
\]  

(10)

(5) Calculate the weight of each independent model

\[
w_i = \frac{\sum_{j=1}^{n} (\theta_j z_{ij})}{\sum_{i=1}^{m} \sum_{j=1}^{n} (\theta_j z_{ij})}
\]  

(11)

Where \( w_i \) is the combined weight of the independent prediction model \( i \).

2.2.4. The structure of the combined forecasting model. The original data of this research will be divided into two groups (training group and testing group) for prediction research. Four kinds of independent forecasting methods (curve trend model, gray model, support vector machines model, ARIMA model) are selected for model training, and five inspection error indicators are selected for forecasting model performance evaluation. Then, on the basis of introducing the entropy weight method, different independent models are endowed different combined weights according to the performance in forecasting. Finally the combined model is built based on entropy weight method, the model structure as shown in figure 1.

![Figure 1. The structure of the combined forecasting model.](image-url)

3. Results and discussion

3.1. Data sources
As the largest developing country in China, with the rapid development of the economy, the amount of hazardous industrial waste is increasing year by year. According to 2006-2018 data from the China Bureau of Statistics[20], China’s annual industrial hazardous waste generation was 69.37 million tons in 2017, which is about 5 times the industrial hazardous waste output in 2005, with an average annual growth rate of 41.43%, especially, showing rapid growth trend in 2013. As shown in Figure 2.

This paper takes China as the research object, the data used in this paper comes from China Statistics Bureau, including the national industrial hazardous waste output, industrial GDP, population, urbanization rate and general public expenditure from 2005-2017. For better model performance, the data from 2005 to 2014 accounting for 80% of the total are used as training data set and the rest from 2015 to 2017 as testing data set.

3.2. Prediction generation of industrial hazardous wastes in training group

3.2.1. Performance of different methods. In view of the existing researches, four independent models are selected in this paper based on the sample data and the applicability of the prediction method -- trend model, gray model, SVM and ARIMA model. Then we use the training data to fit the parameters of each model.

(1) Curve trend model

As shown in Figure 1, China's industrial hazardous waste production shows a curve increasing trend from 2005 to 2014. According to the data characteristics, power model, exponential model, growth model and other prediction methods were selected for further analysis. Using IBM SPSS Statistics 22, the results show that the goodness of fit $R^2$ of growth model is 0.852, signifying that the coefficient of this model is significant, namely the best prediction effect.

(2) Gray model

GM (1,1) model is used to fit the training data through Python 3.7, and the results show that model accuracy grade of the posteriori ratio difference $C = 0.15$ ($\leq 0.35$) is at a high precision level. It is worth mentioning that the development coefficient $a = -0.1460$, the grey action amount $b = 927.838$, and the goodness of fit $R^2$ is 0.8322.

(3) Support vector machines model

SVM (linear), SVM (RBF), SVM (poly) and SVM (sigmoid) kernel function support vector machine models were selected to fit the training data through Python 3.7. According to the results, SVM (poly) whose goodness of fit $R^2$ is 0.8266 shows the best performance, while the other three have relatively poor prediction accuracy due to the small amount of data.

(4) Arima model
It can be seen in Figure 1 that the training group data is non stationary time series. Thus, the training data were preprocessed by 2-medium difference, and then we tested its stability through Python 3.7. As a result, the P value is 0.04 (< 0.05), which means the data can be considered as a stationary time series at 95% confidence. According to the calculation of Akaike information criterion (AIC), the AIC index of ARIMA(0,2,1) model is the lowest, and the goodness of fit of this model is 0.7734, denoting that the model is suitable.

After model comparison and verification, four independent prediction models are finally selected, and their training prediction results are shown in Table 1.

| Year | Act. V al. | Growth model | GM(1,1) | SVM(Poly) | ARIMA(0,2,1) |
|------|-----------|--------------|---------|-----------|--------------|
|      | Pre.va l. | Error | Pre.va l. | Error | Pre.va l. | Error | Pre.va l. | Error |
| 2005 | 1161.     | 0.21   | 930.1    | 0.20   | 1338.   | -0.15 | —        | —     |
|      | 57        | 3      | 55       | 5      | 905.7   | 0.16  | —        | —     |
| 2006 | 1076.     | 0.01   | 1094.4   | -0.01  | 1288.   | -0.19 | 1255.    | -0.16 |
|      | 11        | 95     | 5        | 5      | 963.6   | 0.11  | —        | —     |
| 2007 | 1079.     | -0.17  | 1288.    | -0.19  | 1255.   | -0.16 | 1255.    | -0.16 |
|      | 35        | 98     | 89       | 7      | 1003.   | 0.26  | —        | —     |
| 2008 | 1483.     | -0.09  | 1517.    | -0.12  | 1179.   | 0.13  | 1030.    | 0.26  |
|      | 17        | 38     | 45       | 52     | 1416.   | 0.01  | —        | —     |
| 2009 | 1741.     | -0.22  | 1786.    | -0.25  | 1607.   | -0.12 | 1416.    | 0.01  |
|      | 23        | 26     | 23       | 49     | —       | —     | —        | —     |
| 2010 | 2044.     | -0.29  | 2102.    | -0.32  | 2806.   | -0.77 | 1539.    | 0.03  |
|      | 20        | 79     | 37       | 95     | —       | —     | —        | —     |
| 2011 | 2399.     | 0.30   | 2475.    | 0.28   | 3000.   | 0.13  | 1785.    | 0.48  |
|      | 89        | 40     | 55       | 79     | —       | —     | —        | —     |
| 2012 | 2817.     | 0.19   | 2914.    | 0.16   | 3135.   | 0.10  | 4009.    | -0.16 |
|      | 47        | 40     | 08       | 26     | —       | —     | —        | —     |
| 2013 | 3307.     | -0.05  | 3430.    | -0.09  | 3386.   | -0.07 | 4102.    | -0.30 |
|      | 70        | 41     | 35       | 49     | —       | —     | —        | —     |
| 2014 | 3883.     | -0.07  | 4038.    | -0.11  | 3457.   | 0.05  | 3842.    | -0.06 |
|      | 23        | 28     | 59       | 80     | —       | —     | —        | —     |

3.2.2. Performance of combination forecasting. The entropy weight method is used to evaluate the independent model by multiple error indexes, and the combined weight of each independent model is determined. The combination forecasting model is established to predict the output of industrial hazardous waste, exploring the applications in the production prediction of industrial hazardous waste in China.

Step 1: According to formula (2) ~ formula (6), we calculated the prediction error index value of training group of each independent model, and built the initial evaluation matrix, shown in Table 2.
Table 2. Initial value table of independent model training error index

| Model          | SSE (198239.6660) | MAE (340.9421) | MSE (140.7975) | MAPE (0.1590) | MSPE (0.0587) |
|----------------|--------------------|----------------|-----------------|---------------|--------------|
| Growth model   | 198239.6660        | 340.9421       | 140.7975        | 0.1590        | 0.0587       |
| GM(1,1)        | 1970447.9136       | 366.8094       | 140.3726        | 0.1730        | 0.0617       |
| SVM(Poly)      | 2017410.9453       | 327.0511       | 142.0356        | 0.1844        | 0.0854       |
| ARIMA(0,2,1)   | 4082161.5606       | 484.4604       | 252.5545        | 0.2265        | 0.1181       |

Table 3. Standardization of independent model training error index

| Model          | SSE   | MAE   | MSE   | MAPE  | MSPE  |
|----------------|-------|-------|-------|-------|-------|
| Growth model   | 0.2878| 0.2721| 0.2815| 0.2871| 0.3191|
| GM(1,1)        | 0.2896| 0.2529| 0.2824| 0.2638| 0.3032|
| SVM(Poly)      | 0.2828| 0.2836| 0.2791| 0.2476| 0.2192|
| ARIMA(0,2,1)   | 0.1398| 0.1915| 0.1570| 0.2015| 0.1585|

Table 4. Entropy value and entropy weight of each training error index of independent models

| Model          | SSE   | MAE   | MSE   | MAPE  | MSPE  | θj   |
|----------------|-------|-------|-------|-------|-------|------|
| Growth model   | 0.9735| 0.9924| 0.9816| 0.9942| 0.9745| 0.3160|
| GM(1,1)        | 0.9924| 0.9816| 0.9745| 0.9942| 0.9735| 0.0911|
| SVM(Poly)      | 0.9745| 0.9924| 0.9816| 0.9942| 0.9924| 0.2197|
| ARIMA(0,2,1)   | 0.9942| 0.9745| 0.9735| 0.9924| 0.9924| 0.0692|

Table 5. Training error prediction value and error of the combination forecasting model

| Year | 2005  | 2006  | 2007  | 2008  | 2009  | 2010  | 2011  | 2012  | 2013  | 2014  |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Act. | 1161. | 1084. | 1079. | 1357. | 1430. | 1589. | 3431. | 3465. | 3156. | 3633. |
| Val. | 57    | 00    | 00    | 00    | 00    | 22    | 24    | 89    | 52    |       |
| Act. | 1221. | 1338. | 1667. | 2179. | 2480. | 3116. | 3489. | 3810. |       |       |
| Val. | 35    | 03    | 89    | 63    | 75    | 44    | 15    | 54    |       |       |
| Error| 0.131 | 0.014 | 0.166 | 0.371 | 0.277 | 0.100 | 0.105 | 0.048 |       |       |
3.2.3. Analysis of Performance of Prediction Models in Training Group. By comparing the prediction results of the combined model (Table 6) with those of the independent models (Table 1), it can be found that the error fluctuation of the growth model and the combination forecasting model is smaller and the prediction performance is better among the five prediction models. Furthermore, the combination forecasting model improves all kinds of prediction accuracy in terms of error indexes compared with other independent models. Specifically, the combined model is the best for SSE and MAPE, next to growth model in MAE, ranking second in MSPE, while there is a poor performance in MSE. See Table 6 for the comparison results of error indexes of each model.

| Models            | SSE    | MAE    | MSE    | MAPE  | MSPE  |
|-------------------|--------|--------|--------|-------|-------|
| Growth model      | 1982393.6660 | 340.9421 | 140.7975 | 0.1590 | 0.0587 |
| GM(1,1)           | 1970447.9136 | 366.8094 | 140.3726 | 0.1730 | 0.0617 |
| SVM(Poly)         | 2017410.9453 | 327.0511 | 142.0356 | 0.1844 | 0.0854 |
| ARIMA(0,2,1)      | 4082161.5606 | 484.4604 | 252.5545 | 0.2265 | 0.1181 |
| Combination model | 1592840.9021 | 349.7975 | 157.7598 | 0.1519 | 0.0666 |

Next, five prediction error indexes weights (SSE, MAE, MSE, MAPE, MSPE) are used to calculate the prediction performance scores of each prediction model quantitatively through equation (12). The predicted performance score is \( S_i \).

\[
S_i = \sum_{j=1}^{n} (\theta_j z_{ij})
\]  

Compared with growth model, GM (1, 1), SVM (poly) and ARIMA (0, 2, 1), the comprehensive prediction performance of combination model is improved by 1.00%, 3.66%, 14.38% and 87.60% respectively. The comprehensive scores of predicted performance of each model are shown in Table 7.

| Models            | Predictive Performance Comprehensive Score | Rank | Combination model performance improvement ratio |
|-------------------|--------------------------------------------|------|------------------------------------------------|
| Growth model      | 0.2270                                     | 2    | 1.00%                                           |
| GM(1,1)           | 0.2211                                     | 3    | 3.66%                                           |
| SVM(Poly)         | 0.2004                                     | 4    | 14.38%                                          |
| ARIMA(0,2,1)      | 0.1222                                     | 5    | 87.60%                                          |
| Combination model | 0.2292                                     | 1    | ——                                              |

3.3. Prediction generation of industrial hazardous wastes in test group

3.3.1. Performance of prediction models. From the above training results, it can be seen that the combination forecasting model performs well in the prediction of industrial hazardous waste production in China. Next, through the test group data to test each prediction model, to explore the effectiveness of the model in China's industrial hazardous waste production prediction. According to the prediction of industrial hazardous waste production in China from 2015 to 2017, as shown in Table 8, we get the prediction values and errors of each prediction model through the above calculation formulas.
Table 8. Predicted values and errors of each prediction model in the testing set

| Year | Act. Val. | Act. Val. | Error | Pre. Val. | Error | Pre. Val. | Error | Pre. Val. | Error | Pre. Val. | Error |
|------|-----------|-----------|-------|-----------|-------|-----------|-------|-----------|-------|-----------|-------|
| 2015 | 397       | 453       | 6.11  | 475       | 5.90  | 3.90      | 19    | 532       | 5.34 | 8.59      | 02    |
| 2016 | 534       | 532       | 0.00  | 559       | -     | 0.19      | 56    | 573       | -    | 6.24      | 07    |
| 2017 | 693       | 624       | 0.09  | 658       | 0.05  | 0.04      | 65    | 725       | 0.04 | 8.76      | 64    |

3.3.2. Analysis of performance of prediction models in test group. According to the prediction data in Table 1 and table 8, draw the line chart of predicted value and actual value of each model, as shown in Figure 3. It can be seen that the prediction results of each model are consistent with the actual value trend, the error fluctuation of growth model, GM (1, 1) and combination model is small, and the prediction value is relatively stable. Because SVM (poly) and ARIMA (0, 2, 1) model will change according to the fluctuation of the actual value in the prediction process, it has a great influence on the prediction error.

The final score of prediction performance of each prediction model is calculated quantitatively by equation (12) using the weight of five prediction error indexes, and the results are shown in table 9.
Table 9. Final comprehensive scores of model training results

| Models           | Predictive Performance | Rank | Combination model performance improvement ratio |
|------------------|------------------------|------|-----------------------------------------------|
| Growth model     | 0.231601               | 2    | 0.83%                                         |
| GM(1,1)          | 0.224564               | 3    | 3.99%                                         |
| SVM(Poly)        | 0.168712               | 4    | 38.41%                                        |
| ARIMA(0,2,1)     | 0.141608               | 5    | 64.90%                                        |
| Combination model| 0.233515               | 1    | —                                             |

The calculation results show that with the increase of prediction data, the prediction performance of growth model, GM (1,1), ARIMA (0,2,1) model are improved with high prediction accuracy, which implies that these three models are more suitable for short period data prediction. We also find that the final score of SVM (poly) decreases, which shows that the prediction effect of this model for short period data is not as good as the first three models, and the prediction result is greatly affected by the fluctuation of original data. In addition, the comprehensive prediction performance of combination model is still the best. Compared with growth model, GM (1,1), SVM (poly), ARIMA (0,2,1) and other models, the comprehensive prediction performance of combination model improves by 0.83%, 3.99%, 38.41% and 64.90% respectively. However, we find that the prediction effect of this model is affected by SVM (poly) model, and the improvement of prediction performance is lower than that of training set prediction, denoting that the prediction performance of this model will be affected by the prediction effect of independent model.

4. Conclusions

In this paper, four independent models and a combination forecasting model based on entropy weight method are used to study the production of industrial hazardous waste in China from 2005 to 2017. Some conclusions are drawn as follows.

(1) With the rapid development of social economy in China, the generation of industrial hazardous waste has been increasing, especially in recent years.

(2) For short period data prediction, the applicability of different models is different. Among them, trend model, gray model [21] and ARIMA model [4] have better performance in short-term data prediction. Due to the poor training data, SVM model is not good in short-term data prediction [10].

(3) The combination model, to some extent, can improve the prediction performance [22], but it will be affected by the independent model. When there is an unsuitable independent model, the prediction performance of the combined model will be affected [23]. In general, the combined model based on entropy weight method proposed in this paper can make full use of the information contained in each independent model, which has strong practicability and stability. The empirical analysis shows the effectiveness of the model and it can be widely used to predict hazardous waste output in China.

5. References

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