Combined weight-varying model for production prediction of residential solid waste: a case study of Xiamen

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Abstract. The problem of residential solid waste (RSW) has drawn increasing attention. It is important to accurately predict the amount of RSW for planning solid waste management. In this research, a combined weight-varying model was presented based on logarithm fit, linear fit, exponential smoothing, and grey prediction GM(1, 1). The optimal weights in combined weight-varying model were determined in accordance with the amount of RSW in Xiamen City from 2009 to 2014 and the production from 2015 to 2024 had been predicted. The results showed that combined weight-varying model performed very well at prediction precision and the amount of RSW in Xiamen City would likely be 2.40 to 2.90 million tons..

1 Introduction

Residential solid waste (RSW) is generally produced by activities and services in daily life, such as the cleaning, cooking, packaging, huge use of plastic bags. The problem of RSW is attracting increasing attention of the people as the improper handling and management of RSW from households is causing threat to the land, the environment as well as endangering public health [1, 2]. With the rapid development of Chinese society and economy, the rapid urbanization and the improvement of living standard, RSW generated in the process is also increasing rapidly [3].

But simultaneously, what you can see in this picture is the relative underperformance of the classification, recycling and processing of garbage [4]. RSW has become a major factor affecting municipal construction, living and sustainable development. The planning of an optimal regional or national waste-management strategy requires a reliable tool for predicting accurately the output of RSW. It is the key step for selection of solid waste collection, transportation, treatment, and facilities construction.

In recent years, a lot of methodologies have been put forward on predicting the output of solid waste [5, 6, 7, 8]. These models have their own advantages in the accuracy and the calculation process, and they have been widely used in practice. In this article, a combined weight-varying model was presented and applied to predicting the amount of RSW in Xiamen City which is based on logarithm fit, linear fit, exponential smoothing, and grey prediction GM(1, 1). The results will provide reference and advices for the development of RSW disposal project construction and urban planning..

2 Methodology

2.1 Combined weight-varying model

If there are m kinds of prediction methods for the same forecasting problem, the predicted value at t-th period in combined weight-varying model can be represented as

$$f(t) = \sum_{i=1}^{m} w_i(t) f_i(t) \tag{1}$$

where $f_i(t)$ is the predicted value at t-th period of i-th prediction method, $w_i(t)$ is the weight at t-th period of i-th prediction method, and

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

in which t=1, 2, 3, ⋯, n. n is the quantity of forecasting periods. m, n, i, t∈**N**.

2.2 The determination of the optimum weights

Based on least square criterion, the optimum weight $w_i(t)$ at t-th period shall meet the following limit,

$$\min\ J(t) = \sum_{i=1}^{m} w_i(t) \cdot |F(t) - f_i(t)| \tag{3}$$

where $F(t)$ is the actual value at t-th period.

According to linear programming, the solutions [9, 10] are

(1) ∀ i, $F(t)$-$f_i(t)$≥0, and |$F(t)$-$f_p(t)$| is minimum, $1 \leq p \leq m$, p∈**N**, then

$$\begin{cases} w_p(t) = 1 \\ w_i(t) = 0,\ i \neq p \end{cases} \tag{4}$$

(2) For i, a few are $F(t)$-$f_i(t) \geq 0$, and |$F(t)$-$f_p(t)$| is minimum; others are $F(t)$-$f_i(t) \leq 0$, and |$F(t)$-$f_q(t)$| is minimum, then

$$\begin{cases} w_p(t) = \dfrac{|F(t) - f_q(t)|}{|F(t) - f_p(t)| + |F(t) - f_q(t)|} \\ w_q(t) = \dfrac{|F(t) - f_p(t)|}{|F(t) - f_p(t)| + |F(t) - f_q(t)|} \end{cases} \tag{5}$$

2.3 The determination of weights at later periods

Based on the formula (3) and (4), the weight at (n+j)-th period is

$$w_i(n+j) = \frac{1}{n} \sum_{t=j}^{n+j-1} w_i(t) \tag{6}$$

where j = 1, 2, 3, ⋯. j∈**N**.

3 The production prediction of RSW in Xiamen

3.1 Data

According to Fujian Statistical Yearbook, the output of RSW in Xiamen from 2009 to 2014 is shown in the second column inTable 1. The production of RSW in Xiamen from 2015 to 2024 will be predicted on the basis of this and the combined weight-varying model.

Table 1 The production and errors of predicted production of RSW in Xiamen from 2009 to 2014

year	production/ $\times 10^4$ tons	LF1	LF2	ES	GM(1, 1)	VW
2009 (1)	87.42	8.3426	4.2338	-1.4092	0.0000	0.0000
2010 (2)	94.45	-4.5809	0.2809	2.4439	2.5454	-0.0001
2011 (3)	95.87	-14.8329	-9.282	1.0475	-6.4115	0.0002
2012 (4)	120.97	1.9856	4.8351	6.4460	7.1398	1.9856
2013 (5)	123	-2.4080	-4.1178	-3.0469	-3.6827	-2.4080
2014 (6)	142.15	11.4936	4.0493	-2.8902	1.1635	0.0001

3.2 The component of combined weight-varying model

Logarithm fit (LF1), linear fit (LF2), exponential smoothing (ES), and grey prediction GM(1, 1) are selected as components of combined weight-varying model (VW). Matlab is used for data processing to get estimated values of corresponding parameter of the four prediction methods where years from 2009 to 2014 are simplified to 1～6. Based on parameter estimated values, the predicted production from 2009 to 2014 are then calculated and the prediction errors are presented in the third to the sixth column in Table 1.

The prediction errors at t-th period of i-th prediction method are calculated by

$$E_i(t) = F(t) - f_i(t) \tag{7}$$

The quadratic sum of errors of i-th prediction method is calculated by

$$S_i = \sum_{t=1}^{n} [F(t) - f_i(t)]^2 \tag{8}$$

According to section 1.2, the optimal weights in combined weight-varying model are determined by formula (4) and (5). Weights from 2015 to 2024 are calculated by formula (6) as shown in Table 2. Then, the predicted production from 2009 to 2014 based on combined weight-varying model is obtained by formula (1) and their prediction errors are showed in the seventh column in Table 1.

The smaller the quadratic sum of errors, the better the prediction precision. Among the five methods, combined weight-varying model has the smallest one, 9.7410. So its prediction precision is the best and it can be used for predicting production from 2015 to 2024.

Table 2 Weights in combined weight-varying model

year	LF1	LF2	ES	GM(1, 1)
2009	0.0000	0.0000	0.0000	1.0000
2010	0.0578	0.9422	0.0000	0.0000
2011	0.0000	0.0000	0.8596	0.1404
2012	1.0000	0.0000	0.0000	0.0000
2013	1.0000	0.0000	0.0000	0.0000
2014	0.0000	0.0000	0.2870	0.7130
2015	0.3430	0.1570	0.1911	0.3089
2016	0.4001	0.1832	0.2230	0.1937
2017	0.4572	0.0567	0.2601	0.2260
2018	0.5334	0.0662	0.1602	0.2403
2019	0.4556	0.0772	0.1869	0.2803
2020	0.3649	0.0900	0.2180	0.3270
2021	0.4257	0.1051	0.2065	0.2627
2022	0.4395	0.0964	0.2091	0.2550
2023	0.4460	0.0819	0.2068	0.2652
2024	0.4442	0.0861	0.1979	0.2718

3.3 The production prediction of RSW in Xiamen from 2015 to 2024

The production of RSW in Xiamen from 2015 to 2024 is predicted in terms of estimated values of parameters obtained in section 2.2 where years from 2015 to 2024 are simplified to 7～16. Accordingly, the production predicted by combined weight-varying model is calculated through formula (1) as shown in Table 3.

Table 3 The production prediction of RSW in Xiamen from 2015 to 2024 / $\times 10^4$ tons

year	LF1	LF2	ES	GM(1, 1)	VW
2015 (7)	135.0939	149.0836	155.7187	156.9053	147.9697
2016 (8)	138.9379	160.0665	167.1803	174.6215	156.0179
2017 (9)	142.3285	171.0494	179.4251	194.3381	165.3606
2018 (10)	145.3615	182.0323	192.4531	216.2808	172.3711
2019 (11)	148.1051	193.0152	206.2643	240.7011	188.397
2020 (12)	150.6099	203.9981	220.8587	267.8787	209.0854
2021 (13)	152.9141	214.981	236.2363	298.1250	214.7924
2022 (14)	155.0474	225.9639	252.3971	331.7863	227.3109
2023 (15)	157.0335	236.9468	269.3411	369.2483	243.0916
2024 (16)	158.8914	247.9297	287.0683	410.9402	260.4273

In Table 3, the production of RSW by 2024 in Xiamen can be divided into three intervals: less than 2 million tons, 2.40 to 2.90 million tons, more than 4 million tons. LF2, ES and VW have the similar estimated production. Based on the above conclusion—The performance from 2009 to 2014 of combined weight-varying model is better—It is almost inevitably the case that the production of RSW in Xiamen by 2024 will be 2.40 to 2.90 million tons. This data can be used as a reference for the RSW management plan of Xiamen City.

4 Conclusions

(1) A combined weight-varying model was presented based on logarithm fit, linear fit, exponential smoothing, and grey prediction GM(1, 1).

(2) The production of RSW from 2009 to 2024 was predicted using five models above in which the combined weight-varying model showed the highest precision and it could be applied to forecasting production of RSW.

(3) It was most likely the case that the production of RSW in Xiamen by 2024 will be 2.40 to 2.90 million tons. It provided the fundamental data for the urban planning and solid waste management.

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