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A Method of Garbage Quantity Prediction based on Population Change

Qiumei YU^{1,2}, Hongjie WAN^{1,2}, Junchen MA^{1,2}, Huakang LI³, Guozi SUN^{1,2,*}

¹ Key Laboratory of Urban Land Resources Monitoring and Simulation, MNR, Shenzhen

² School of Computer Science, NUPT, Nanjing, China

³ School of Artificial Intelligence and Advanced Computing, XJTLU, Suzhou, China

² Springer Heidelberg, Tiergartenstr. 17, 69121 Heidelberg, Germany

sun@njupt.edu.cn; y0zzzhy@qq.com

Abstract. Aiming at the problem that the amount of urban waste changes due to population changes and is difficult to predict, a method for predicting the amount of waste based on urban population changes is proposed. After analyzing the correlation between the urban population data of Shanghai and the annual output of garbage from 2000 to 2019, the correlation coefficient and strong correlation data items are calculated. On this basis, judge whether the original population data items meet the conditions of the grey prediction model, and determine whether it can be modeled according to the grey model. Based on the grey theory, this paper analyzes the basic situation of population changes and future population growth trend in Shanghai. Finally, the annual production of municipal solid waste in Shanghai from 2020 to 2025 is predicted based on multiple linear regression analysis. The results show that the waste production of Shanghai has shown a slow growth trend since 2019, and will not increase significantly in the natural state in recent years, which provides a reference basis for subsequent research and analysis.

Keywords: Population Changes, Waste Production, Correlation Analysis, Grey Prediction Model, Multiple Linear Regression.

1 Introduction

The research report issued by the Health and Family Planning Commission shows that during the 12th Five Year Plan period, the national migrant population will increase by about 8 million every year, and more than 253 million by the end of 2014. This large-scale population flow is bound to have a major impact on the population distribution and structure, national economic and industrial layout, economic, social and cultural environment of large and medium-sized cities in China, and even make great changes in the regional urban and rural population structure and sociology-economic layout^[1]. As one of the key elements of urban productivity, with the high-speed flow of population between urban nodes across the country, it is bound to lead

to the reconfiguration and integration of other elements, which may have a significant inactive influence on the entire urban network^[4].

2 Background

2.1 A Subsection Sample

The report of the 19th CPC National Congress clearly pointed out that "*Promote Green Development and Strive To Solve Outstanding Environmental Problems*", which further highlighted the importance of cooperation between green development and environmental protection^[5]. Many researchers in China have also analyzed the impact causes and prediction results of waste production. It is generally believed that the impact of population on waste production accounts for the majority^[6]. H. H. Huangfu used grey absolute correlation analysis and concluded that population index is one of the main factors affecting municipal solid waste^[7]. W. Cao estimated and analyzed the per capita domestic waste production coefficient in Jinan in view of the large selection range and uncertainty of the per capita domestic waste production coefficient^[9].

Some researchers have also investigated other reasons that can affect waste production. It still shows that the increase of urban domestic waste is related to the population. Z. Zeng^[10] based on the statistical data of the total domestic waste removal and transportation in Anhui Province from 2009 to 2016, using the method of mathematical statistical analysis^[11], analyzed the changes and influencing factors of the total domestic waste removal and transportation in Anhui Province. The conclusion is that the most direct reason for the change of the total amount of domestic waste treatment in Anhui Province is the change of the total urban population.

Therefore, understanding the distribution law of urban floating population and analyzing the relationship between population flow and domestic waste are of great significance to promote the construction of "landscape city, green city".

The goal of this paper is to predict the output of municipal solid waste by analyzing the population flow. Firstly, the correlation between population flow and waste production is analyzed^[12], and then the development trend of population flow is predicted and analyzed through the grey prediction model. Finally, the output of urban domestic waste is predicted according to the population flow.

3 Model

In order to predict the annual output of municipal household waste more scientifically and rationally, the correlation between population data and waste yield needs to be analyzed and the data characteristics with strong correlation should be preserved before the model can be established. Then the annual output of garbage is predicted and analyzed using population data. The technical road-map for the experiment is shown in Fig. 1.

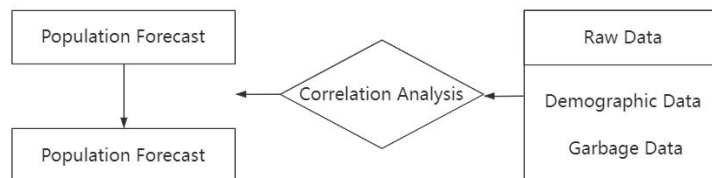


Fig. 1. The chart of experimental technology route.

This section only describes urban population forecasting models and garbage yield forecasting models, and details such as correlation analysis will be covered in more detail in the next section.

3.1 Construct Urban Population Prediction Model

First of all, the method of grey theoretical system is used to analyze and calculate the population-related data, and then the grey prediction model is used for prediction analysis.

Among them, the grey prediction model is to judge the similarity of the development trend between various factors in the system, process the original data with representative characteristics in the system accordingly, find the law of data change, and then predict the future development trend through differential equations.

In the grey prediction model, the GM(1,1) model is a first-order model, which is more suitable for population growth models with stable growth rates.

1) The Class-compare Verification

In order to make the grey prediction model more reliable in predicting urban population mobility, it is necessary to check the level ratio of the original data series before establishing the model to judge whether it meets the accuracy requirements of the grey model.

Assume $x^{(0)} = (X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n))$ (n is the number of data) is the accumulated original data sequence and all are non-negative numbers.

Formula for calculating the level ratio of data series:

$$\rho(k) = \frac{x^{(0)}(k)}{x^{(0)}(k+1)} \quad (1)$$

Among, $\rho(k)$ is stepwise ratio, $x^{(0)}(k)$ and $x^{(0)}(k+1)$ are adjacent means.

If all $\rho(k)$ falls within the interval $(e^{\frac{-2}{n+1}}, e^{\frac{2}{n+2}})$, the original data sequence can be modeled by GM(1,1); On the contrary, the data sequence needs to be translated. Therefore, the class-compare verification can be used to verify whether the grey model is suitable for data prediction.

2) Grey Prediction Model

The grey prediction model generates a new number column by adding up, then establishes a first-order single-variable differential equation, and then predicts the data using the fitting function. The specific implementation steps are as follows:

a) The original data series for an element is known to be:

$$x^{(0)} = (X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n)) \quad (2)$$

Accumulate $X^{(0)}$ once to generate a new sequence $X^{(1)}$:

$$x^{(1)} = (X^{(1)}(1), X^{(1)}(2), \dots, X^{(1)}(n)) \quad (3)$$

Among,

$$x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i), k = 1, \dots, n$$

Compared with the original sequence, the randomness of this new sequence is greatly and the stability is greatly increased.

b) Make $Z^{(1)}$ the nearest mean generation sequence of $X^{(1)}$:

$$Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)) \quad (4)$$

Among,

$$z^{(1)}(k) = \frac{1}{2}x^{(1)}(k) + \frac{1}{2}x^{(1)}(k-1)$$

c) The grey differential equation model for GM (1,1) is:

$$u = X^{(0)}(k) + az^{(1)}(k) \quad (5)$$

Among, a is the development factor and u is the amount of ash.

d) By fitting the least squares to solve parameters a 、 u . The formula is calculated as follows:

$$\begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T Y_n \quad (6)$$

Where B is the data matrix,

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}$$

Where Y_n is column vector,

$$Y_n = [x^0(2), x^0(3), x^0(4), \dots, x^0(n)]^T$$

- e) The trend of change in the new series is approximately described by differential equations.

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \quad (7)$$

The model's time response function is:

$$\hat{x}(t) = \left[x^{(1)}(0) - \frac{u}{a} \right] e^{-at} + \frac{u}{a} \quad (8)$$

The corresponding grey differential equation time response sequence is:

$$\hat{x}(k+1) = \left[x^{(1)}(0) - \frac{u}{a} \right] e^{-at} + \frac{u}{a}, \quad k = 1, \dots, n \quad (9)$$

Assume $x^{(1)}(0) = x^{(0)}(1)$, so

$$\hat{x}(k+1) = \left[x^{(1)}(1) - \frac{u}{a} \right] e^{-at} + \frac{u}{a}, \quad k = 1, \dots, n \quad (10)$$

Then do the tired and sub-tractable grey prediction equation:

$$\begin{aligned} & \hat{x}^{(0)}(k+1) \\ &= \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \\ &= \left[x^{(0)}(1) - \frac{u}{a} \right] (1 - e^{-a}) e^{-ak} + \frac{u}{a} \\ & \quad (k = 1, 2, \dots, n-1) \end{aligned} \quad (11)$$

Finally, the model can be tested by residual test and correlation test.

3.2 Multiple Linear Regression Models

In this paper, the regression model is used to predict the output of urban household waste by analyzing the population flow. Linear Regression assumes that there is a linear relationship between the features and the results in the dataset, and thus the desired results are obtained. Its expression is:

$$Y = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n + b \quad (12)$$

Where Y is the result set, x_i constitutes the feature set, a_i is the regression coefficient, b is the random error and follows the normal distribution $N(0, \sigma^2)$.

Assuming that a and β are the optimal solutions, the regression equation is $a * X + \beta^T$. At this time, Y is obtained through the assumed optimal solution. There is a certain error between this and the actual results, which is optimized by the least square method.

The main idea of least squares optimization is to select unknown parameters to minimize the sum of residuals between theoretical values and observed values. The expression of objective function is:

$$\min f(x) = \sum_{i=1}^n l_i^2(x) = \sum_{i=1}^n [y_i - f(x_i, a_i)]^2 \quad (13)$$

Among, $l_i(x)(i = 1, 2, \dots, n)$ is the residual function.

4 Analysis of Correlation

Before predicting the annual output of MSW, it is necessary to analyze the correction between urban population and MSW output.

4.1 The Source of Data

Table 1. Relevant data 2015-2019.

X_0	2015	2016	2017	2018	2019
X_1	2415.27	2419.7	2418.33	2423.78	2428.14
X_2	3809	3816	3814	3823	3830
X_3	536.76	541.62	564.13	551.95	556.23
X_4	2.69	2.68	2.66	2.65	2.64
X_5	1442.97	1450	1455.13	1462.38	1469.3
X_6	10.59	13.07	11.77	9.84	9.14
X_7	12.42	12.35	12.64	12.57	12.52
X_8	11.61	11.2	11.85	13.75	13.69
X_9	5.32	4.64	4.17	3.92	3.41
Y	790	880	900	984	1038

The statistical data of Shanghai were mainly obtained from The Shanghai Statistical Yearbook and the database of the National Bureau of Statistics. The data related to population flow in Shanghai from 1978 to 2018 and the original data of municipal

solid waste production were obtained. Table 1 shows the data related to population mobility and the amount of urban domestic waste in Shanghai from 2015 to 2019.

In Table 1, the data are as follows:

X_0 : year

X_1 : permanent resident population (10000 persons)

X_2 : population density (person / km²)

X_3 : total households (10000 households)

X_4 : average population per household (person)

X_5 : births (10000 persons)

X_6 : deaths (10000 persons)

X_7 : immigrant population (10000 persons)

X_8 : emigration population (10000 persons)

Y : Domestic waste (10000 tons)

4.2 Data Analysis

The output of municipal solid waste is of great significance for waste treatment in the later stage. This paper mainly starts from the direction of population flow. On the analysis of influencing factors of waste production, in addition to selecting factors through theory and establishing model analysis, finally, on the basis of analysis conclusion, combined with the current objective conditions and policy factors, the future output of municipal solid waste in Shanghai is predicted.

Fig. 2 and Fig. 3 show a graph of changes in population-related data for 2000-2019.

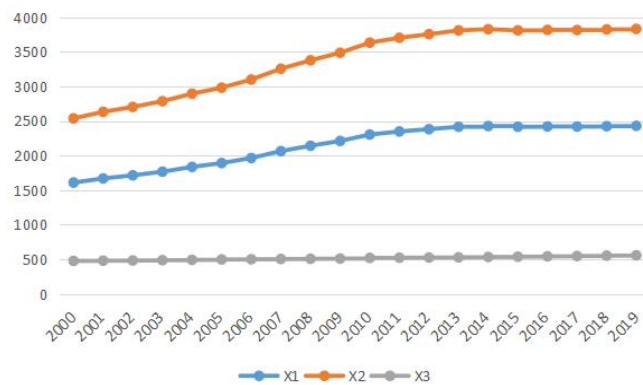


Fig. 2. X_1 - X_3 related data change.

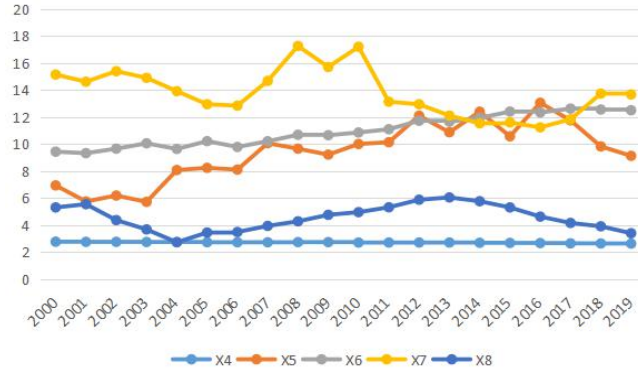


Fig. 3. X_4 - X_8 related data change.

Since 2000, the number of permanent residents in Shanghai has increased year by year, and the growth rate has increased significantly around 2010; The number of registered residence population and total number of households increased at the end of the year. The fluctuation of immigration and emigration rate also increased around 2010.

Fig. 4 shows the curve of annual output of domestic waste in Shanghai from 2000 to 2019.

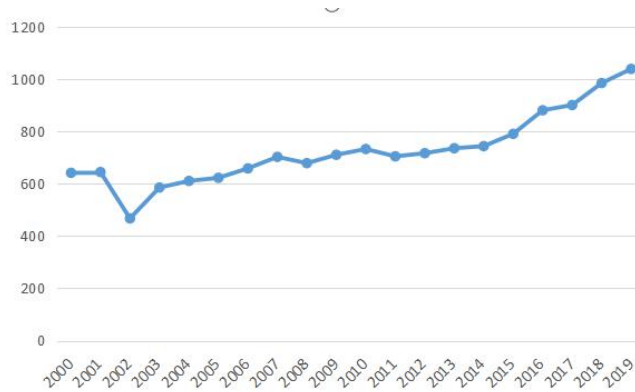


Fig. 4. Chart of annual output of garbage.

Comparing the quantity change curve of annual waste output in Figure II, the output increased sharply after 2010, and increased to 17 times the original in just four years by 2014.

The correlation between population mobility and the generation of waste must be positively correlated. When the population flow tends to be stable, coupled with the new methods of waste treatment, the waste output basically tends to be stable. Without special circumstances, the annual waste output should not increase significantly around 2010.

4.3 The Analysis of Correlation

The analysis of correlation refers to the analysis of more than two characteristic elements with correlation, so as to evaluate the degree of correlation between the two features. Correlation analysis can be carried out only when there is a certain connection or probability between the two features.

The commonly used Pearson product moment correlation coefficient is used to analyze the correlation between two continuous variables. It is a linear correlation coefficient, and the formula is:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (14)$$

The value range of correlation coefficient r is $[-1, 1]$, when r is greater than 0, the correlation is positive. And when r is less than 0, the correlation is negative.

- When r satisfies $|r| \geq 0.8$, the two variables are highly correlated.
- When r satisfies $0.5 \leq |r| < 0.8$, there is a moderate correlation between the two variables.
- When r satisfies $0.3 \leq |r| < 0.5$, there is a low correlation between the two variables.
- The correlation is weak when it is less than 0.3.

Each data (X_0 - X_8) in Fig. 2 and Fig. 3 were used as x variables respectively, and the data (Y) in Fig. 4 was used as y variables to conduct correlation analysis. The correlation analysis results are as follows:

Table 2. Table captions should be placed above the tables.

(x, y)	r
(X_0, Y)	0.983
(X_1, Y)	0.953
(X_2, Y)	0.950
(X_3, Y)	0.947
(X_4, Y)	-0.870
(X_5, Y)	0.587
(X_6, Y)	0.852
(X_7, Y)	-0.382
(X_8, Y)	-0.322

It can be seen from Table II that X_4 , X_7 and X_8 data features are negatively correlated with Y , while other data features are positively correlated.

The absolute value of correlation coefficient between X_5 , X_7 , X_8 and garbage yield Y is less than 0.85, so these three data are not used as reference for garbage yield prediction, and the final selection result is: X_0 , X_1 , X_2 , X_3 , X_4 and X_6 are closely related data items.

5 Prediction of Urban Population Flow

In order to ensure the feasibility of the grey prediction model, this section first performs a hierarchical test on the distribution of the original data series (X_0 , X_1 , X_2 , X_3 , X_4 , X_6), and then establishes the model for population prediction, and objectively and effectively evaluates the accuracy of the model.

5.1 Check Data

The original data column (data are X_1 , X_2 , X_3 , X_4 , X_6 , each item has 20 data from 2000 to 2019) is $X^{(0)}$, then $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(20)\}$,

Calculate the stage ratio according to the formula:

$$\rho(k) = \frac{x^{(0)}(k)}{x^{(0)}(k+1)}, \quad k = 1, \dots, n-1 \quad (15)$$

The calculation results of stage ratio inspection are spread in table 3. According to the results in Table 3, it can be concluded that the level ratios of data series are all within the range $(e^{\frac{-2}{n+1}}, e^{\frac{2}{n+2}})$.

All the levels are in $0.909 \leq \rho(k) \leq 1.095$, Therefore, the grey prediction conditions can be met and modeling can be carried out.

Table 3. Data level comparison result.

X	$\min \rho(k)$	$\max \rho(k)$
X_0	1.00	1.00
X_1	0.95	1.00
X_2	0.95	1.00
X_3	0.98	1.00
X_4	1.00	1.01
X_5	0.71	1.21
X_6	0.94	1.04
X_7	0.85	1.31
X_8	0.79	1.35

5.2 Forecast urban population related data

Table 4. Parameter calculation result.

X	a	u
X_1	-0.021	1735.853
X_2	-0.021	2737.710
X_3	-0.008	472.907
X_4	0.002	2.792
X_6	-0.018	9.125

- 1) Calculate the coefficient a, u according to the formula:

$$\begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T Y_n \quad (16)$$

The results are shown in Table 4.

If a is positive, the development trend is decreasing. Otherwise, it increases.

- 2) According to the obtained parameters, determine the grey prediction model,

$$\hat{x}^{(0)}(k+1) = \left[x^{(0)}(1) - \frac{u}{a} \right] (1 - e^{-a}) e^{-ak} + \frac{u}{a} \quad (17)$$

The superscript $\hat{}$ indicates the predicted value. Put $\hat{x}^{(0)}(k+1)$ into $X^{(0)}$, and delete $x^{(0)}(1)$, the first field of $X^{(0)}$. Then get a new sequence:

$$X_1^{(0)} = \{x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n), \hat{x}^{(0)}(k+1)\} \quad (18)$$

Construct the model of GM(1,1) again, generate a new equation of prediction, etc. Until the completion of the prediction task and get a higher prediction result.

- 3) Putting the coefficient a, u into the model, and predicting the urban population data of Shanghai from 2020 to 2025.

The results are shown in Table 5:

Table 5. Prediction result of GM (1,1).

X_0	2020	2021	2022	2023	2024	2025
X_1	2430.19	2435.11	2438.33	2441.83	2445.91	2449.29
X_2	3833.52	3841.54	3846.83	3852.62	3859.3	3864.86
X_3	561.50	566.66	571.55	576.87	582.01	587.22
X_4	2.63	2.62	2.60	2.59	2.58	2.57
X_6	12.63	12.57	12.6	12.62	12.61	12.64

It can be seen from Table 5 that in the following years, the data of population flow in Shanghai do not change much, which was in line with the change trend described above.

6 Prediction of Municipal Solid Waste Output

According to what has been mentioned above, there is a close correlation between the output of municipal solid waste (MSW) and population flow, so it is feasible to make use of the development situation of urban population flow in Shanghai to forecast MSW.

In this section, the result set of the above predicted data items is used as the dependent variable x , and multiple linear regression is used to predict the output of MSW, and gradient improvement is used to reduce the error in the regression analysis.

6.1 Multiple Linear Regression

In regression analysis, if there are two or more independent variables, it is called multiple regression. Actually, a phenomenon is usually contacted with multiple factors. Using the optimal combination of multiple features to predict or evaluate dependent variables is more effective and practical than using only one feature.

Multiple linear regression calculation formula:

$$\hat{y} = w_1 * x_1 + w_2 * x_2 + \dots + w_n * x_n + b \quad (19)$$

Among,

x : Influencing factors; w : Influencing weight;

n : the number of x ; \hat{y} : the prediction output.

6.2 Experimental results

Multiple linear regression was used to forecast and compare the waste yield, The results are shown in Table 6:

Table 6. Actual and predicted value of domestic waste in 2015-2019.

X_0	Actual value	Predicted value	loss
2015	790	834.34	5.61
2016	880	879.38	0.07
2017	900	915.19	1.69
2018	984	959.42	2.50
2019	1038	1004.09	3.27%

Multiple regression analysis was conducted on the annual MSW output of Shanghai and the six factors of X_0 , X_1 , X_2 , X_3 , X_4 and X_6 .

The model parameter is $b = -101254.17$, $w = [50.74, 0.56, -0.63, -0.12, 456.09, -19.95]$.

The accuracy of the above prediction model can reach 94.29%, and the annual output of municipal solid waste from 2020 to 2025 can be predicted by using this model. The results are shown in Table 7.

Table 7. Annual waste production forecast of Shanghai from 2020 to 2025.

X_0	2020	2021	2022	2023	2024	2025
Y	1046.37	1090.80	1129.69	1173.13	1216.95	1260.28

The experimental results show that by 2025, the annual output of domestic garbage in Shanghai will be 12.6028 million tons, an increase of nearly 2.22 million tons compared with 2019, an increase of about 21.41%.

7 Conclusion

From the data correlation analysis, the average household population is negatively correlated with waste production. The grey prediction model is more applicable in population prediction and can be used to predict the short-term growth trend.

From the prediction results, the growth rate of waste production in Shanghai has decreased since 2019, but by 2025, the output is expected to reach 12.6028 million tons, an increase of about 21.41% compared with 2019. Waste treatment is still a major problem we have to face.

In the research of this paper, due to the periodic changes of the data, the prediction result may be the change result of a certain period. If it is necessary to predict more long-term data, these are far from enough and need to be further studied.

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