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Prediction of Municipal Mortality in Housing Based on Dual Gray-Markov Model

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Based on the gray-Markov model, a gray-Verhulst prediction model is proposed to further fit, and constructing a double-gray-Markov model to solve the problem evident in the oscillating development sequence or the saturated curve sequence in data from 2006 to 2018 for the toll of safety-related accidental deaths. This model is intended to achieve better prediction of the death toll caused by safety issues in housing and municipal accidents. The forecast results show that the hitherto increasing numbers of such accidents are slowing decreasing although the death toll is still high, indicating that the management of housing and municipal safety needs to be more efficient and effective.

Keywords: housing city security, double-gray-Markov, predict, analysis

1. INTRODUCTION

Municipal housing engineering is characterized by one-off, complex construction operations, multi-work cross-construction, and many safety-influencing factors. This accounts for the numerous safety-related accidents and the large number of deaths (Wang et al., 2016; Adam, 2020). Facing increasingly complicated construction conditions and various external environmental factors, accurately predicting the number of deaths in municipal housing safety-related accidents, and scientifically assessing the effectiveness of municipal housing safety management, are issues to be resolved by on-site safety management. The formulation of policies by relevant government departments and the on-site safety management by the respective enterprises have important practical significance in terms of providing valuable safety guidelines.

In 1906, the Russian mathematician Markov, first proved that under the independence of random variables, Markov Chain does not belong to the weak condition of the law of large numbers and the central limit theorem (Cao et al., 2019). The stochastic process is called Markov chain (Garcia-Ferrer et al., 2006; Moreno, 2020). Scholars from various countries have conducted research to improve the gray-Markov model and its application to predict the number of deaths likely to occur in municipal housing projects. In 2010, other researchers first established and applied the gray-Markov model to predict the number of safety-related deaths on building sites, based on the applicable scope and limitations of the gray system and the Markov chain (Yin et al., 2010). In 2016, other pioneers established a modified gray Markov model (MMSGM), which utilizes Markov cycle chain conversion technology and a capture mechanism to reduce the prediction error of samples (Edema et al., 2016; Shi et al., 2017). Compared with gray model and gray Markov model, the accuracy was improved by 85% and 70%, respectively.

In this paper, data is collected showing the number of deaths resulting from housing safety-related accidents in China from 2006 to 2018, The concatenated data has the problem of late sliding development sequence or saturated curve sequence, that cause inaccurate gray-Markov model predictions. The application of a gray Verhulst prediction model fitting can

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better solve this problem, and more accurately predict the number of accidental deaths likely to occur in municipal buildings(Lihong Sui, 2021).

2. DOUBLE GRAY-MARKOV PREDICTION MODEL

2.1 Establishment of GM (1, 1) Gray Model

The establishment of the model involves several steps. (1) Select the GM (1, 1) model. The causes of housing municipal security accidents are complex and difficult to express, unable to summarize objective laws. Therefore, the problem of safety-related accidents in municipal housing projects can be regarded as a gray system (Yang et al., 2011). The number of deaths from accidents in different years is regarded as the gray quantity; according to the number of fatal accidents, establish the GM (1, 1) gray prediction model.

(2) Optimize the data for deaths resulting from construction accidents. Assume $\{x^{(0)}(k)|k = 1, 2\cdots, n\}$ for optimized non-negative data sequence, One-time accumulation sequence $\{x^{(1)}(k)|k = 1, 2\cdots, n\}$, among $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(k)$, $k = 1, 2\cdots, n$ average value generates sequence, in $z^{(1)}(k) = 0.5[x^{(1)}(k) + x^{(1)}(k-1)]$, $k = 1, 2\cdots, n$

Establish gray differential equations: $x^{(0)}(k) + az^{(1)}(k) = b$, $k = 1, 2\cdots, n$

The relative albino differential equation is: $\frac{dx^{(1)}}{dt} + ax^{(1)}(t) = b$, a and b are parameters, and t is time.

Assume $u = [a, b]^T$, $Y = [x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)]^T$., $B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}$ though least square method, obtain: $J(u) = (Y - Bu)^T(Y - Bu)$ The highest estimate is obtained with:

$$\hat{u} = [\hat{a},\ \hat{b}]^T = (B^T BY)$$

Determine the gray GM (1, 1) prediction with this equation:

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right)?e^{(-\hat{a}k)} + \frac{\hat{b}}{\hat{a}},\ k = 1, 2\cdots, n,$$

and $\hat{Q}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$

In the above formula, $\hat{a}$ is the development coefficient, reflecting the growth rate of the data series $x^{(0)}$; $\hat{b}$ is an endogenous variable; $\hat{Q}(k+1)$ based on GM (1, 1) model point trend values k, reveal the overall development trend of the system.

2.2 Establishment of Gray Verhulst Forecast Mode

The GM (1, 1) model has too major requirements according to the optimized non-negative data sequence index rules. The uncertainty pertaining to the number of deaths resulting from safety-related accidents in municipal housing projects, poses a big problem. In order to solve the wobble development sequence or the saturated curve sequence in the data for the later period, gray Verhulst prediction model is used to predict the later data (Deng et al., 2019; Khan et al., 2020).

Establish gray Verhulst model: $x^{(0)} + az^{(1)} = b(z^{(1)})^2$, a, b are parameters.

The whitening equation of the relative gray Verhulst model is: $\frac{dx^{(1)}}{dt} + ax^{(1)}(t) = b(x^{(1)})^2$. it is time. The formula is as follows:

$$u = [a, b]^T,\ Y = [x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)]^T,$$

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

Then the least square method estimates the relationship between time and death toll: And the solution of the whitening equation is:

$$\hat{x}^{(1)}(t) = \frac{a\overset{\wedge}{x^{(0)}}(1)}{\hat{b}x^{(0)}(1) + \left[\hat{a} - \hat{b}x^{(0)}(1)\right]e^{\hat{a}t}}$$

The time response sequence of the gray Verhulst model is:

$$\hat{x}^{(1)}(k+1) = \frac{ax^{(\hat{0})}(1)}{\hat{b}x^{(0)}(1) + \left[\hat{a} - \hat{b}x^{(0)}(1)\right]e^{\hat{a}k}}$$

The cumulative reduction formula is:

$$\hat{C}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$$

The formula above obtains the growth rate of the data sequence $\hat{C}(k+1)$; based on the gray Verhulst model trend values at time k, the system reveals the overall trend.

By further fitting the gray model, the “gray double intersection” fitting model has both a near-trend trend and saturation in the later period.

The formula of the “gray double intersection” fitting model is:

$$y\hat{u}ce(k) = A_1\hat{C}(k) + A_2\hat{Q}(k)\ (A_1 + A_2 = 1)$$

and A_1, A_2 are gray double-intersection fitting weights

2.3 Precision of Markov Prediction Results

(1) State division (Li et al., 2016). The number of deaths from safety-related accidents is very different each year, with the data for 2006–2018 showing neither an upward nor downward trend. Because the boundaries and effects in different years are different, it is necessary to combine the basic time series change trend of the data and determine the state division criteria. Additionally, the state of the data sequence is divided by the relative value standard, it is written as $E_1, E_2, \cdots E_n, (E_i \in [\otimes_{1i}, \otimes_{2i}], i = 1, 2, \cdots m)$. The gray element $\otimes_{1est}$ and $\otimes_{2est}$ are seen as the upper and lower bounds of the optimal state E_{est}. The relative value is the actual value of the data series divided by the gray predicted trend value.

Table 1 Data optimization table of deaths from housing and municipal safety accidents in China from 2006 to 2018.

Year series	1	2	3	4	5	6	7	8	9	10	11	12	13
Years	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Death toll	1048	1012	921	802	772	738	624	674	648	554	735	807	840
Optimization	9.542	9.881	10.858	12.469	12.953	13.55	16.026	14.837	15.432	18.051	13.605	12.392	11.905

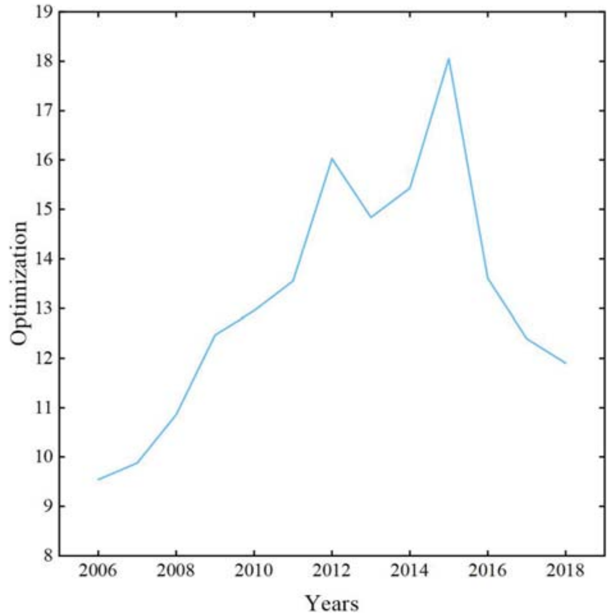

Figure 1 Trend chart of optimized data for municipal and housing deaths in China from 2006 to 2018.

(2) Based on the state change, a transition probability matrix is constructed (Yan et al., 2014). The probability of transition from step-m state E_i to state E_j is called step-m state transition probability, its formula is $P_{ij}^{(m)} = \frac{n_{ij}^{(m)}}{N_j}$, $n_{ij}^{(m)}$ is the number of times the state E_i transitions to the state E_j in step-m; E_i is the frequency of state E_i. The transfer matrix is as follows:

$$p^{(m)} = \begin{bmatrix} p_{11}^{(m)} & p_{12}^{(m)} & \cdots & p_{1n}^{(m)} \\ p_{21}^{(m)} & p_{22}^{(m)} & \cdots & p_{2n}^{(m)} \\ \vdots & \cdots & \ddots & \vdots \\ p_{n1}^{(m)} & p_{n2}^{(m)} & \cdots & p_{nn}^{(m)} \end{bmatrix}$$

(3) Determine the state turn of adjacent time. Select k times adjacent to the predicted time. According to the distance between this state and other states, choose a different number of transfer steps. Assuming that the prediction target is in the E_i state, Check line i of the state transition probability matrix $p^{(k)}$, if $max(p_j^{(k)}) = p_{ij}^{(k)}$, then the maximum probability of state E_i becomes E_{i+n}.

(4) Determine the predicted value. In general, $p^{(m)}$ is ergodic in actual overall prediction, when $m \to \infty$, $p^{(m)} \to \pi_j$ (Not dependent on i). This shows that with reference to the long-term trend, the number of deaths due to security accidents in year n will basically be fixed and fluctuate in an optimal state E_{est}. By including the gray predicted value $y\hat{u}ce(k)$ in the following formula, the fluctuation range of the predicted value can be predicted.

$$(y\hat{u}ce_1(k),\ y\hat{u}ce_2(k)) = (\otimes_{1est},\ \otimes_{2est})y\hat{u}ce(k)$$

3. PREDICTIVE ANALYSIS OF DEATH TOLLS IN SECURITY ACCIDENTS

3.1 Data Optimization

The number of deaths resulting from safety-related housing accidents nationwide from 2006 to 2018 was obtained from the official website of the Ministry of Urban Housing and Rural Development, and a double gray-Markov model is established to predict the death toll trend.

According to the data, the overall trend indicates a decrease in the number of deaths caused by safety-related accidents at municipal housing sites, which does not meet the basic pattern of the gray model index (Zhou et al., 2019). Therefore, the original data is optimized by the gray system. The optimization formula is: $x_0 = \frac{10000}{x_{original}}$. The data then aligns with the basic form of the gray system. The results shown in Table 1 and Figure 1 are obtained after optimization.

3.2 Preliminary Forecast of Death Toll

Gray prediction analysis of optimized data is conducted through MATLAB. The results are shown in Table 2 and Table 3.

Table 2 Data table of gray GM (1,1) prediction.

Year	$x^{(0)}$	$x^{(1)}$	Gray GM (1, 1) prediction				
			$\hat{x}_1^{(1)}$	$\hat{x}_1^{(0)}$	$\hat{e}_1^{(0)}$	$\hat{d}_1^{(0)}$	$\hat{r}_1^{(0)}$
2006	9.542	9.542	9.542	9.542	0	0	\
2007	9.881	19.423	21.807	12.265	−2.384	0.241	0.026
2008	10.858	30.281	34.285	12.478	−1.620	0.149	0.082
2009	12.469	42.750	46.978	12.693	−0.225	0.018	0.122
2010	12.953	55.703	59.891	12.913	0.040	0.003	0.029
2011	13.550	69.254	73.028	13.136	0.414	0.031	0.036
2012	16.026	85.279	86.391	13.364	2.662	0.166	0.147
2013	14.837	100.116	99.986	13.595	1.242	0.084	−0.089
2014	15.432	115.548	113.816	13.830	1.602	0.104	0.030
2015	18.051	133.599	127.885	14.069	3.981	0.221	0.138
2016	13.605	147.204	142.198	14.313	-0.707	0.052	-0.338
2017	12.392	159.596	156.758	14.560	-2.169	0.175	-0.107
2018	11.905	171.500	171.570	14.812	-2.907	0.244	-0.050

Table 3 Data table of gray Verhulst prediction.

Year	$x^{(0)}$	$x^{(1)}$	Gray Verhulst prediction			
			$\hat{x}_2^{(1)}$	$\hat{x}_2^{(0)}$	$\hat{e}_2^{(0)}$	$\hat{d}_2^{(0)}$
2006	9.542	9.542	9.542	9.542	0	0
2007	9.881	19.423	13.201	3.659	6.222	0.630
2008	10.858	30.281	18.131	4.930	5.928	0.546
2009	12.469	42.750	24.662	6.531	5.938	0.476
2010	12.953	55.703	33.120	8.459	4.495	0.347
2011	13.550	69.254	43.764	10.644	2.906	0.214
2012	16.026	85.279	56.680	12.916	3.110	0.194
2013	14.837	100.116	71.679	14.999	−0.163	0.011
2014	15.432	115.548	88.236	16.557	−1.125	0.073
2015	18.051	133.599	105.519	17.283	0.768	0.043
2016	13.605	147.204	122.537	17.018	−3.413	0.251
2017	12.392	159.596	138.360	15.823	−3.431	0.277
2018	11.905	171.500	152.305	13.945	−2.040	0.171

Because of data fluctuations, the gray GM (1, 1) model can fit the number of accident fatalities from 2006 to 2011; however, it is predicted that the saturation or S-shaped fluctuation data after 2012 will not be accurate. The gray Verhulst forecast is relatively consistent with the fluctuation trend of accidental deaths after 2012 (Gong et al., 2017). As shown in Figure 2, with further fitting of the gray model, the "gray double intersection" fitting model will have trend characteristics, and later there will be fluctuation saturation.

The formula of the "gray double intersection" fitting model is as follows:

$$y\hat{uce}(k) = A_1\hat{C}(k) + A_2\hat{Q}(k)$$

By analysing death data for the last two years, estimating the parameters A_1 and A_2 for 2019, and obtaining $A_1 = A_2 = 0.5$, it can be preliminarily predicted that the trend value of the number of accidental deaths in 2019 is about 854.

As can be seen from Figure 2, the double-gray fitting model is closer to the actual data than the gray GM (1, 1) and gray Verhulst models. It can be concluded that the accuracy of the double-gray fitting model is superior to that of the gray GM (1, 1) model and the gray Verhulst model in predicting the number of deaths in the construction of municipal housing.

3.3 Markov Accurate Prediction

(1) Reasonable division of status. With the double-gray model, the predicted value of the number of deaths per year is obtained; then the actual value is divided by the most realistic value predicted by the double-gray model to obtain the corresponding relative value, as shown in Table 4.

(2) The relative value is obtained based on Table 5, and combined with the actual accident death status. Then, it is divided into four different levels of status according to the status of the effect: the relative value is 80% to 90%, which is state 1 (the number of deaths is greatly decreased); the relative value is 90% 100%, which is state 2 (weak falling state); The relative value is 100% ∼ 110%, which is state 3 (weak rising state); the relative value is 110% ∼ 130%, which is state 4 (strong rising state). This is shown in Table 5 below.

Establish the state transition probability matrix of the death toll. Based on the status divided above and the status transition table for each year, the available matrix $\hat{P}^{(1)}$ is:

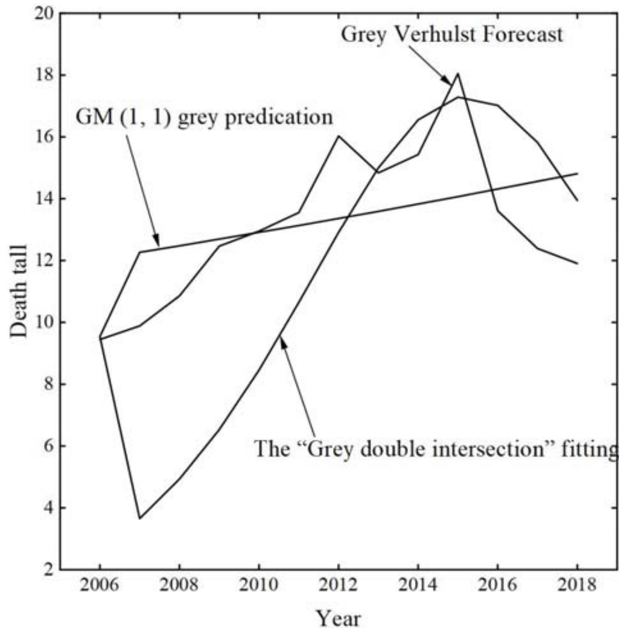

Figure 2 Double-gray fitting prediction chart.

Table 4 Relative number of accidental deaths.

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Percent (%)	1.000	1.241	1.149	1.018	0.997	0.969	0.834	0.916	1.073	0.957	1.251	1.277	1.171

Table 5 Trend table of death status transition, 2006–2018.

Number	Year	State	Transition trend
1	2006	2	Initial value
2	2007	4	$2 \to 4$
3	2008	3	$4 \to 3$
4	2009	3	$3 \to 3$
5	2010	2	$3 \to 2$
6	2011	2	$2 \to 2$
7	2012	1	$2 \to 1$
8	2013	2	$1 \to 2$
9	2014	3	$2 \to 3$
10	2015	2	$3 \to 2$
11	2016	4	$2 \to 4$
12	2017	4	$4 \to 4$
13	2018	4	$4 \to 4$

$$\hat{P}^{(1)} = \begin{bmatrix} 0\frac{1}{12}00 \\ \frac{1}{12}\frac{1}{12}\frac{1}{12}\frac{1}{12} \\ 0\frac{1}{6}\frac{1}{12}0 \\ 0\frac{1}{12}\frac{1}{12}\frac{1}{6} \end{bmatrix}$$

According to $\hat{P}^{(n)} = (\hat{P}^{(1)})^n \ (n = 1, 2, 3 \ldots\ldots)$ MATLAB calculates step 13 and the transition matrix for ∞.

The calculation results show that State 2 is about 37%, both State 3 and State 4 are about 26%, and the upper section of State 2 is the most suitable state E_{est}. $\otimes_{1k} = 95\%$, $\otimes_{2k} = 100\%$, the predicted value of the number of fatal accidents in 2019 predicted by the "gray double intersection" fitting model is about 854, which is included in the Markov prediction model, and the prediction range can be obtained:

$$2019\text{: } (y\hat{u}ce_1(k),\ y\hat{u}ce_2(k)) = (\otimes_{1est},\ \otimes_{2est})y\hat{u}ce(k) = (811,\ 854)$$

Finally, the comprehensive "double gray-Markov" model can accurately predict the fluctuation range of accidental death toll in 2019, which is (811, 854).

4. CONCLUSIONS

The prediction result obtained by the double-gray-Markov model indicates the trend of the death toll. Judging from the predicted value, the death toll resulting from safety-related accidents in municipal housing projects has decreased, although the death toll is still high, indicating that the management of safety on municipal housing sites is still facing tremendous challenges. According to public opinion, the safety of construction personnel should be *s* priority. Due to the proliferation of social media and the development of sophisticated channels of communication, the issue of safety in the workplace and the number of deaths resulting from inadequate safety measures on municipal construction sites, will attract an increasing amount of public attention. (Wang, 2019) It is recommended that: relevant government departments amend the current laws and regulations; engineering enterprises and employees increase safety awareness; and safety management and the overall safety standards of the industry be improved. This can only be achieved through reforms introduced by government departments and company managers.

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