Ekoloji 26(101): 17-23 (2017)

Prediction of the Death Toll of Environmental Pollution in China's Coal Mine Based on Metabolism-GM (1, n) Markov Model

Song Jiang [1], Minjie Lian [1,2], CaiWu Lu [1*], Qinghua Gu [1], Hai Zhao [1]

[1] School of Management, Xi'an University of Architecture and Technology, Shaanxi, 710055, PR CHINA

[2] Sinosteel Mining Co., Ltd, Beijing, 100080, CHINA

[*] Corresponding author: 604869605@qq.com

Abstract

The data of death toll in China's coal mine cuased by environmental pollution is very difficult to predict because of its characteristics of small data volume, strong discreteness and non-linearity. In order to accurately predict the death toll in coal mine caused by environmental pollution, and take effective preventive measures to reduce casualties, in this paper, the grey GM (1, n) forecast model, Markov Theory and metabolic thought are combined. With the calculation of weight of grey Markov model by order relation analysis method, the predictive model is constructed, and a method which is suitable for predicting the death toll of environmental pollution in coal mineis proposed. Based on the death toll of coal mine traffic accidents from 2001 to 2013, the above model is used to predict the death toll of coal mine environmental pollution in 2014, and the result is compared with the actual data. The result shows that the relative error of the prediction on the death cuased by environmental pollution in China's coal mine based on metabolism-GM (1, n) Markov model is 32.73% less than that of grey GM (1, n) prediction model. It can be seen that the proposed grey Markov model has high prediction accuracy and meets the actual demand. It is an effective method to predict the death of China's coal mine generated by environmental pollution.

Keywords: metabolism, Markov model, Gray model, environmental pollution

Jiang S, Lian M, Lu C, Gu Q, Zhao H (2017) Prediction of the Death Toll of Environmental Pollution in China's Coal Mine Based on Metabolism-GM (1, n) Markov Model. Ekoloji 26(101): 17-23.

INTRODUCTION

As one of China's main energy sources, coal has made a great contribution to economic growth. Although China is already the world's largest consumer of coal, it is not a coal-mining power. According to statistics, China produces one third of the world's coal. But due to the backward technology and equipment, and the lack of personnel quality and management tool in the process of coal mining, the death toll of environmental pollution in coal mine of China occupies 80% of the world's coal mine death toll (Yin et al. 2017). Accurate prediction of death caused by environmental pollution in coal mine can provide technical support and theoretical basis for ensuring safe production in mines, finding out the causes of accidents in time, preventing accidents and making emergency decisions after disasters. The environmental pollution in coal mines has the characteristics of complexity and various non-linearity. Guo X used GM (1,1) model to predict the trend of injury rate per 1000 population in environmental pollution of coal mine (Guo et al. 2014). Todd A J et al. adopted the grey system model to collect the data of million tons of death rate in coal mine from 2003 to 2008, and predicted the data of 2009 and 2010, which achieved relatively good results (Todd et al. 2009). In order to accurately predict the general trend of safe production in coal industry, Wang X established the modified residual error GM (1,1) model in the prediction of million tons of death rate in coal industry by using the grey system, and accurately predicted million tons of death rate in China's coal industry. He X introduced the statistical analysis of environmental pollution in China's coal mine in recent years, and predicted the coal mine risk with the view of technology and economy (He and Song 2012). JY Lan used the grey system model to predict million tons of death rate that generated by environmental pollution in coal mine from 1990 to 2010. The model overcomes the random fluctuation generated from the influence of data accuracy (Lan and Zhou 2014). From the above researches, it can be known that the grey system prediction can be well applied to the prediction of the

 Received: 21 Jan 2017 / Accepted: 12 May 2017

death toll of environmental pollution in China's coal mine.

Markov model refers to a sequence of random variables, which corresponds to the state of a system, and the state of the system at a certain moment only depends on the state at the previous moment. This model is a mathematical method to predict the development and change of a system by the transition probability between states. It is suitable for forecasting problems with large random fluctuation, and is highly scientific and applicable (Lisnianski et al. 2017). Zhang W used the grey Markov model to predict the injury rate per 1000 population and number of deaths and injuries in China's coal mines. However, the principle of new information priority is not fully considered in the model, so the prediction accuracy is not high. Because of the particularity of the prediction of the injury rate per 1000 population and number of deaths and injuries in coal mine, especially it is influenced by many factors, the dynamic of its own change is strong, and the law of relevant influence factors is difficult to express accurately, so it is still difficult for the existing research methods to reach the higher prediction accuracy.

Because the accuracy of the conventional grey prediction model is low, and the environmental pollution of coal in China have the characteristics of small data volume, strong discreteness and non-linearity, it is necessary to improve the grey Markov model. In this paper, the grey theory GM (1, n) model is used to predict death toll in coal mines, and the residual error of the prediction is corrected. On this basis, Markov theory is further used to construct state transition probability matrices. And then metabolism thought is integrated. The old or less valuable information is deleted according to the time series, and the obtained prediction results are added as a new predictive data source. And then the next moment is predicted to improve the accuracy of the model prediction. Finally, the death toll in coal mines of 2014 is predicted on the basis of simulation research on the data from 2001 to 2013. The prediction results show that this combined model has higher prediction accuracy than the traditional GM (1,1), so it has higher practical application value.

THE CHARACTERISTICS OF COAL MINE PREDICTION SYSTEM

The coal mine production system can be regarded as a complicated systems engineering of man-machine-material-environment interaction. Any factor in the system may cause an accident, and some of the factors are uncertain, which belongs to typical grey system model (Gong et al. 2014).

Table 1. Death toll of environmental pollution in China's coal mine from 2001 to 2014

Year	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Death toll	5670	6995	6702	6027	5491	4746	3758
Year	2008	2009	2010	2011	2012	2013	2014
Death toll	3216	2630	2433	1973	1384	1067	931

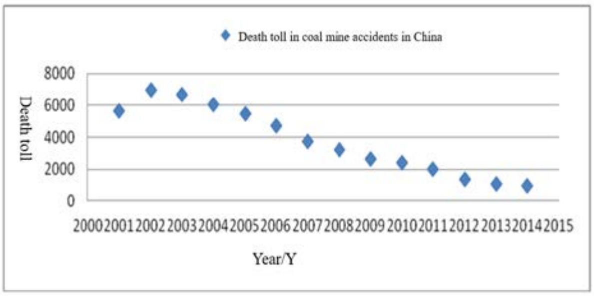

Fig. 1. Trend chart of death toll in coal mines in China

According to the overall data collected from the website of the State Administration of Work Safety, the data of the death toll cused by environmental pollution in coal mine in China since 2001 are showed in **Table 1**.

In order to directly reflect the death toll of environmental pollution in coal mine in China, the data is introduced into the scatter plot to form **Fig. 1**.

It can be seen from **Fig. 1** that the death toll of China's coal mine resulting from environmental pollution has the characteristics of small data volume, strong discreteness and non-linearity, which just satisfies the condition of uncertainty of grey system research (Chuang et al. 2017).

GREY MARKOV PREDICTION MODEL AND ITS IMPROVEMENT

GM (1, n) is a prediction model representing n variables and first order differential in the grey theory proposed by Chinese scholar Deng Julong in 1982. It is mainly suitable for short-term prediction with small data volume and little state fluctuation. It is the most basic one of prediction models in agriculture, economy, transportation and logistics. The principle is that by Accumulated Generating Operation, a set of originally disordered sequence is generated into a sequence presenting exponential growth variation, thereby weakening the randomness and volatility of the original data. It is regarded as a function regarding time based on the original sequence to establish the GM (1,1) model, that is, n is 1, and a linear first-order differential equation is established, and the differential equation is solved to obtain the gray prediction value of the accumulated sequence. Finally, the prediction value of the original sequence is obtained by reduction operation.

Grey Prediction Model GM (1, n)

Assume that $X^{(0)}$ is the original data sequence corresponding to the time series, one can obtain ${X_i}^{(0)} = [{x_i}^{(0)}(1), {x_i}^{(0)}(2), \cdots, {x_i}^{(0)}(n)]$ $i = 1,2,\cdots,n$ After accumulation on ${X_i}^{(0)}$, a sub cumulative generating sequence is obtained, i.e., ${X_i}^{(1)} = [{x_i}^{(1)}(1), {x_i}^{(2)}(2), \cdots, {x_i}^{(3)}(n)]$ $i = 1,2,\cdots,n$

Where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$ $(k = 1,2,\cdots,n)$.

Mean generation with consecutive neighbors is made on $X_i^{(1)}$, one can obtain

$Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \cdots, z^{(1)}(n))$, $Z^{(1)}(k) = \frac{1}{2}(x^{(1)}(k) + x^{(1)}(k-1))k = 2,3,\cdots,n$

Finally, the $GM(1, n)$ grey differential equation regarding $X_i^{(1)}$ is constructed,

$$X_1^{(0)}(k) + \alpha Z_1^{(0)}(k) = \sum_{i=2}^{n} \beta_i X_i^{(0)}(k) \quad (2)$$

Regarding Sequence $X_i^{(1)}$ as Function $X_i^{(1)} = X_i^{(1)}$ (t) regarding time (i.e., t) based on original sequence, one can obtain $GM(1, n)$ albinism differential equation,

$$\frac{d{X_1}^{(1)}}{dt} + \alpha {X_1}^{(1)} = \beta_2 {X_2}^{(1)} + \beta_3 {X_3}^{(1)} + \cdots + \beta_n {X_n}^{(1)} \quad (3)$$

Where $\alpha, \beta_1, \beta_2, \cdots, \beta_n$ are all parameters.

Assume that Sequence $Y_n = \left[{x_i}^{(0)}(1), {x_i}^{(0)}(2), \cdots, {x_i}^{(0)}(n)\right]^T$, permanent list $\hat{\alpha} = (\alpha, \beta_1, \beta_2, \cdots, \beta_n)^T$, one can obtain

$$Y_n = B\hat{\alpha} \quad (4)$$

It can be solved as follows:

$$\hat{\alpha} = (B^T B)^{-1} B^T Y \quad (5)$$

Where

$$B = \begin{pmatrix} -z^{(1)}(2) & {x_2}^{(1)}(2) & \cdots & {x_n}^{(1)}(2) \\ -z^{(1)}(3) & {x_2}^{(1)}(3) & \cdots & {x_n}^{(1)}(3) \\ \vdots & \vdots & & \vdots \\ -z^{(1)}(n) & {x_2}^{(1)}(n) & \cdots & {x_n}^{(1)}(n) \end{pmatrix}$$

By substituting Parameter $\hat{\alpha}$ into Equation (3), one can obtain

$$\hat{x}_1^{(1)}(k+1) = \left[x_1^{(0)}(1) - \frac{1}{\alpha}\sum_{i=2}^{n} \beta_i x_i^{(1)}(k+1)\right] e^{-\alpha k} + \frac{1}{\alpha}\sum_{i=2}^{n} \beta_i x_i^{(1)}(k+1) \quad (6)$$

The solution obtained by Equation (6) is the predictive value of $X_i^{(0)}$, i.e., the sequence after Accumulated Generating Operation on the original sequence, so the predictive value of the original sequence in $GM(1, n)$ model can be obtained by the reduction operation:

$$\hat{x}_1^{(0)}(k) = \hat{x}_1^{(1)}(k) - \hat{x}_1^{(1)}(k-1) \quad (7)$$

To sum up, $\hat{x}_1^{(0)}(k)$ is the predictive value of the original sequence in $GM(1, n)$ prediction model.

Residual can be calculated according to

$$\varepsilon^0(k) = x_1^{(1)}(k) - \hat{x}_1^{(1)}(k) \quad (8)$$

The residual represents the degree of deviation between the original data and the prediction data (Liu et al. 2017). The smaller the residual, the smaller the degree of deviation, and the better the prediction accuracy.

Let $\varepsilon^0 = (\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_n)$denote the generated original residual, where ε^0 is the residual sequence of $X_1^{(0)}$. $GM(1,1)$ model is established for the residual sequence to obtain its parameter $P = [\alpha_\varepsilon, \beta_\varepsilon]^T$. The simulation value of $\hat{\varepsilon}^0(k+1)$ is calculated according to Equation (8).

$$\hat{\varepsilon}^0(k+1) = (-\alpha_\varepsilon)(\varepsilon^0(k_0) - \frac{\beta_\varepsilon}{\alpha_\varepsilon}) e^{-\alpha_\varepsilon(k-k_0)} \quad (9)$$

Then the Equation (6) in this paper is modified to

$$\hat{x}_1^{(1)}(k+1) = \begin{cases} \left[x_1^{(0)}(1) - \frac{1}{\alpha}\sum_{i=2}^{n} \beta_i x_i^{(1)}(k+1)\right] e^{-\alpha k} + \frac{1}{\alpha}\sum_{i=2}^{n} \beta_i x_i^{(1)}(k+1), k < k_0 \\ \left[x_1^{(0)}(1) - \frac{1}{\alpha}\sum_{i=2}^{n} \beta_i x_i^{(1)}(k+1)\right] e^{-\alpha k} + \frac{1}{\alpha}\sum_{i=2}^{n} \beta_i x_i^{(1)}(k+1) \pm \hat{\varepsilon}^0(k+1), k > k_0 \end{cases} \quad (10)$$

The symbol of $\hat{\varepsilon}^0(k+1)$ is consistent with that of residual ε^0.

Improved Grey Markov Prediction Model

In the above prediction model, the original data is accumulated into a quasi-exponential sequence, and the potential laws of the sequence are analyzed so as to obtain the predictive value. It is usually only suitable for the change of the original data that is close to the exponential change. The method of Markov model state division is based on grey $GM(1, n)$. The method of state division in Markov model based on grey $GM(1, n)$ is as follows. According to the relative error distribution of prediction results of $GM(1, n)$ model, the corresponding scatter plot and n x axis-paralleled straight lines are made. The region between each two adjacent straight lines can be regarded as one state, which is denoted as state Ei.

The number of dividing state interval generally depends on the capacity of the original data (Fu and Liu 2017). When the capacity of original data is small, the total number of state transitions is relatively small. So, in order to more objectively reflect the transition of original data between states, the number of divisions should be less. On the contrary, when the capacity of original data is large, in order to mine more information from the state transition probability matrices to improve the prediction accuracy, the number of divisions should be more. The number of transitions from State E_i to State E_j is $n_{i\to j}$, and the number of transitions from State E_i to another state is N_i, then the probability that the state Ei transfers to the state Ej is

$$P_{i\to j} = \begin{cases} \dfrac{n_{i\to j}}{N_i} & , N_i > 0 \\ 0 & , N_i = 0 \end{cases} \tag{11}$$

The state transition probability matrix can be calculated according to Equation (11) as

$$P = \begin{pmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{pmatrix} \tag{12}$$

In Equation (12), $P_{n1} + P_{n2} + \cdots + P_{nn} = 1$.

When the state transition probability matrix P is established, we assume that the object at Time n is in State Ei. If the kth row satisfies $\max P_{ij} = P_{kl}$, it is considered that at Time n+1 (predictive time) State Ei is most likely to transfer to State Ej, so that the change interval $[E_{1i}, E_{2i}]$ of the predictive value is determined, and the median of this interval is the predictive value at Time n+1.

$$\hat{y}(n+1) = \frac{1}{2}(E_{1i}, E_{2i}) \tag{13}$$

The relative difference is

$$\Delta\varepsilon = \frac{|\varepsilon(n)|}{x^{(0)}(n)} \tag{14}$$

In general, when $GM(1, n)$ prediction model is combined with Markov model for prediction, the data source for calculating state transition probability matrix is fixed, that is, the model cannot provide a new information source for predicting the applied data sequence and add latest prediction result to the data sequence. When this kind of fixed data source is used to predict the time far from now, great errors will be generated in the results of prediction.

Therefore, in this paper, in the process of modeling, the idea of metabolism is integrated, that is, when the predictive value at Time n+2 is predicted, the predicted data is added as new information, and then the earliest data information is deleted to improve the general $GM(1, n)$ Markov model. The specific process is as follows:

In that original data sequence $X_i{}^{(0)} = [x_i{}^{(0)}(2), x_i{}^{(0)}(3), \cdots, x_i{}^{(0)}(n)]\ i = 1,2,\cdots,n$, predicted data $\hat{Y}(n+1)$ is added as new information, and then the earliest data information is deleted, so that the new data sequence can be obtained as:

$X_i{}^{(0)} = [x_i{}^{(0)}(2), x_i{}^{(0)}(3), \cdots, x_i{}^{(0)}(n), \hat{Y}(n+1)]i = 1,2,\cdots,n,$

With this data sequence, a new one-step state transition probability matrix is constructed to predicted at Time n+1. So that this prediction model becomes a closed loop and a series of predicted data can be obtained.

PREDICTION RESULTS OF THE GREY MARKOV MODEL IMPROVED

Based on the data of death toll caused by environmental pollution in China's coal mine, Accumulated Generating Operation was carried out:

$X^{(1)}(k)$={5670,12665,19367,25394,30885,35631,39389,42604,45234,47667,49640,51024,52091}

The solution obtained through the Equation (6) is the predictive value of sequence $X_i^{(0)}$ which is generated by Accumulated Generating Operation on the original sequence, so the predictive value of the original sequence in $GM(1, n)$ model can be obtained by the reduction operation:

$$x^{(0)}\ (k) = 8855.7532e^{-0.1452\ (k-1)}$$

Mean relative error is 7.3506%. The prediction result is showed in **Table 2**.

Table 2. Prediction result of accidents from 2001 to 2014

Year	Predicted death toll	Year	Predicted death toll
2001	5670	2008	3204.85
2002	7658.89	2009	2771.71
2003	6623.78	2010	2397.11
2004	5728.57	2011	2073.14
2005	4954.35	2012	1792.95
2006	4284.77	2013	1550.63
2007	3705.68	2014	1341.15

Table 3. Corrected predicted result of accidents from 2001 to 2014

Year	Predicted death toll	Absolute error	Year	Predicted death toll	Absolute error
2001	5670	0	2008	3352.52	-136.52
2002	7038.90	-43.9	2009	2798.03	-168.03
2003	6416.25	285.75	2010	2333.86	99.14
2004	5836.00	191	2011	1797.24	175.76
2005	5303.65	187.35	2012	1383.93	0.07
2006	4820.55	-74.55	2013	1065.71	1.29
2007	4018.20	-260.2	2014	821.95	110.28

According to the principle of new information priority, it is believed that there is ordered relation in$\{X^{(0)}(1), X^{(0)}(2) \cdots X^{(0)}(14)\}$ which is $X^{(0)}(14)X^{(0)}(13)X^{(0)}(12)X^{(0)}(11) > X^{(0)}(10) > X^{(0)}(9) > X^{(0)}(8) > X^{(0)}(7) > X^{(0)}(6) > X^{(0)}(5) > X^{(0)}(4) > X^{(0)}(3) > X^{(0)}(2) > X^{(0)}(1) \Rightarrow X^{*}(1) > X^{*}(2) > X^{*}(3) > X^{*}(4) > X^{*}(5) > X^{*}(6) > X^{*}(7) > X^{*}(8) > X^{*}(9) > X^{*}(10) > X^{*}(11) > X^{*}(12) > X^{*}(13) > X^{*}(14)$. And following equations are given:

$$r_2 = \frac{\omega_1^*}{\omega_2^*} = 1.3, r_3 = \frac{\omega_2^*}{\omega_3^*} = 1.3, r_4 = \frac{\omega_3^*}{\omega_4^*} = 1.3$$

$$r_5 = \frac{\omega_4^*}{\omega_5^*} = 1.3\ , r_6 = \frac{\omega_5^*}{\omega_6^*} = 1.2\ , r_7 = \frac{\omega_6^*}{\omega_7^*} = 1.2$$

$$r_8 = \frac{\omega_7^*}{\omega_8^*} = 1.2,\ r_9 = \frac{\omega_8^*}{\omega_{10}^*} = 1.2,\ r_{10}\frac{\omega_9^*}{\omega_{11}^*} = 1.1$$

$$r_{11} = \frac{\omega_{10}^*}{\omega_{11}^*} = 1.1, r_{12} = \frac{\omega_{11}^*}{\omega_{12}^*} = 1.1,$$

$$r_{13} = \frac{\omega_{12}^*}{\omega_{13}^*} = 1.1, r_{14} = \frac{\omega_{13}^*}{\omega_{14}^*} = 1$$

One can obtain the solutions: $\omega_1 = 0.2123, \omega_2 = 0.1633, \omega_3 = 0.1256, \omega_4 = 0.0966, \omega_5 = 0.0743, \omega_6 = 0.0619, \omega_7 = 0.0516, \omega_8 = 0.0430, \omega_9 = 0.0358, \omega_{10} = 0.0325, \omega_{11} = 0.0295, \omega_{12} = 0.0268, \omega_{13} = 0.0244, \omega_{14} = 0.0244$

Substituting the weight coefficient into the original sequence, one can obtain the equation: $X' = \{138.35, 170.68, 179.61, 177.8, 178.46, 169.91, 161.59, 165.95, 162.95, 162.8, 180.77, 190.59, 173.83, 174.24\}$. It can be predicted by GM (1,1) that

$$x^{(0)}(k) = \frac{171.5434e^{0.0012(k-1)}}{\omega_k}(k > 1)$$

Table 4. State division

State	State description	m
E_1	Extremely overvalued	0.93～0.97
E_2	Overvalued	0.97～1.01
E_3	Normal	1.01～1.05
E_4	Undervalued	1.05～1.09
E_5	Extremely undervalued	1.09～1.13

Note: $m = \frac{\text{Actual value}}{\text{Predictive value}}$

Table 5. Markov state transition of grey prediction result of death in coal minecaused by environmental pollution

Year	m	State	Year	m	State
2001	1	E_2	2008	0.95	E_1
2002	0.99	E_2	2009	0.93	E_1
2003	1.04	E_3	2010	1.04	E_3
2004	1.03	E_3	2011	1.09	E_5
2005	1.03	E_3	2012	1.00	E_2
2006	0.98	E_2	2013	1.00	E_2
2007	0.93	E_1			

It is predicted that the death toll in 2014 is $174.5/0.2123 = 821.95$. Mean relative error is 3.8416%. The predicted result is shown in **Table 3**.

The number of state division is related to the number of samples and the fitting error range. If the number of state division is large, more samples will be needed. If it is small, the difference of states is not obvious, and the significance of fluctuation adjustment is lost (Ruan et al. 2017). In general, 3 to 5 states are preferable. State division is showed in **Table 4**.

From **Table 3** and **Table 4**, state transitions of death in coal mine cause by environmental pollution from 2001 to 2013 can be found, as showed in **Table 5**.

According to the definition of state transition probability and the representation of the state transition probability matrix, five state transition conditions are statistically analyzed. By substituting the statistical result into Equation (14), one can obtain the state transition probability matrix.

$$p(1) = \begin{bmatrix} 2/3 & 0 & 1/3 & 0 & 0 \\ 1/4 & 1/2 & 1/4 & 0 & 0 \\ 0 & 1/3 & 2/3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

According to the principle of Markov prediction model, the prediction of the state after the original data can be obtained. It can be obtained that the state of 2013 is E_2, that is, the state probability vector is (1 / 41 / 21 / 400). It can be seen that the state of 2014 is most likely to transfer to E_2. Then the predictive result of accidents in 2014 is:

Table 6. Prediction of death toll in coal mines in 2014

Year	Actual value	Grey prediction		Weighted grey Markov prediction	
		Predictive value	Relative error	Predictive value	Relative error
2014	931	1341	44.03%	826	11.3%

CONCLUSION AND SUGGESTIONS

According to the data characteristics of the death toll in coal mine cuased by environmental pollution, the grey Markov prediction model is established by integrating the grey system theory and the Markov principle. With the calculation of weight of grey Markov model by order relation analysis method, a weighted grey Markov prediction model is proposed, which is not only in conformity with the principle of new information priority, but also improves the flexibility and the value of practical application. Comparing the predictive value and actual value of death toll of environmental pollution in China's coal mine in 2014, we can conclude the following results:

(1) Prediction of death toll in coal mines is of great significance to coal mine safety management. At the same time, the conditions that affect the change of death toll in coal mines are complex. The prediction has the characteristics of obvious random fluctuation and the ambiguity of available information. It is a typical grey system.

(2) The relative error of death toll in coal mine cuased by environmental pollution in 2014 predicted by traditional grey system model is 44.03%, while the relative error predicted by the improved grey Markov model is 11.3%. It can be concluded that prediction method for predicting the death toll in coal mines based on grey Markov can reflect the variation and is of strong practicality.

(3) In order to predict more accurately the death toll in coal mine caused by environmental pollution in further study and to make up defects of the prediction model, the qualitative analysis of external factors such as numbers of new mines, changes of environmental protection policies, is needed to added in the analysis of data and other related factors.

ACKNOWLEDGEMENTS

This work was supported by 51774228 (Natural Science Foundation of China which title is “Study on Metallurgical 5D Production Schedule Modeling and Collaborative Optimization for Metallic Open-pit Mine under Grade-Price-Cost Constraints”) , 2017JM7005 (Natural Science Foundation of Shaanxi Province which title is “Intelligent fusion and early warning of multi-source heterogeneous flow data based on rock failure”) and 2017G-B1-0519(Key technology projects of safety prevention and control of major accidents in State Administration of work safety which title is “Research on safety monitoring and warning system of ultra deep shaft surrounding rock based on multi-source heterogeneous information fusion”).

REFERENCES

Chuang LI, Yuan M, Wang Y, et al. (2017) Prediction of Coal Mine Safety Accidents Fatalities Based on Grey Markov Model(GMM). Industrial Safety & Environmental Protection.

Fu H, Liu X (2017) Research on the Phenomenon of Chinese Residents' Spiritual Contagion for the Reuse of Recycled Water Based on SC-IAT. Water, 9(11).

Gong Z, Chen C, Ge X (2014) Risk prediction of low temperature in Nanjing city based on grey weighted Markov model. Natural Hazards, 71(2): 1159-1180.

Guo X, Liu S, Wu L, et al. (2014) Application of a Novel Grey Self-Memory Coupling Model to Forecast the Incidence Rates of Two Notifiable Diseases in China: Dysentery and Gonorrhea. Plos One, 9(12):e115664.

He X, Song L (2012) Status and future tasks of coal mining safety in China ☆. Safety Science, 50(4): 894-898.

Lan JY, Zhou Y (2014) Death Rate per Million Ton Prediction of Coal Mine Accidents Based on Improved Gray Markov GM(1,1) Model. Mathematics in Practice & Theory.

Lisnianski A, Elmakias D, Laredo D, et al. (2017) A multi-state Markov model for a short-term reliability analysis of a power generating unit. Reliability Engineering & System Safety, 98(1): 1-6.

Liu Z, Li H, Liu K, et al. (2017) Design of high-performance water-in-glass evacuated tube solar water heaters by a high-throughput screening based on machine learning: A combined modeling and experimental study. Solar Energy, 142: 61-67.

Ruan S, Xie H, Jiang S (2017) Integrated Proactive Control Model for Energy Efficiency Processes in Facilities Management: Applying Dynamic Exponential Smoothing Optimization. Sustainability, 9(9):1597.

Todd AJ, Rufaut CG, Craw D, et al. (2009) Indigenous plant species establishment during rehabilitation of an opencast coal mine, south-east Otago, New Zealand.. New Zealand Journal of Forestry Science, 39(1): 81-98.
Yin W, Fu G, Yang C, et al. (2017) Fatal gas explosion accidents on Chinese coal mines and the characteristics of unsafe behaviors: 2000–2014. Safety Science, 92: 173-179.