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Research on Accident Prediction in Chemical Industry based on Improved Markov Model

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The construction and development of chemical industry park can promote the development of local economy and chemical industry, which also brings new security problems. Because most of the enterprises in chemical industry park are chemical enterprises, the park usually has a large number of major hazards, which frequently causes serious accidents. Generally speaking, most accidents occur mainly in the process of production storage and transportation. So it is very important to analyze and forecast the accidents of chemical enterprise. In the paper, an improved grey Markov model is proposed by combining the classical grey theory and the Markov model. First of all, this paper makes a simple discussion on the grey theory and Markov model. Secondly, we make a Markov prediction on residual random sequence on the basis of grey prediction theory, which realizes the complementary advantages of two traditional models. Finally, the improved prediction model is analyzed by an example, and the results show that the improved Markov prediction model has high prediction accuracy.

1. Introduction

As the pillar industry of the country, the chemical industry greatly promotes the development of economy, and it brings a lot of benefits to the people. At present, the country has already formed a production industry based on pesticide, chemical fertilizer, inorganic chemicals and basic organic raw materials, which involves a wide range of fields (Liang, 2016; Zhao et al., 2016; Wehmeier and Mitropetros, 2016; Cui, 2016; Bessarabov et al., 2016).

The chemical industry is an industry which uses chemical reactions and other measures to change the nature of the substance in order to make new chemicals (Campbell et al., 1983). Chemical accidents not only bring economic losses, as well as casualties, environmental pollution and other issues, which has a great influence on society (Liu, 2015). Accident prediction is a method of predicting the safety state of an object based on explicit information and intelligence. The purpose of the accident prediction research is to provide enough security information for the managers to make the adjustment and eliminate potential risks according to the results of the prediction, which can help us to optimize the security of the whole system (Valerio et al., 2005).

Many scholars at home and abroad have done a variety of research and experiments on prediction models. Von and George (1969) improves the Markov method in the study of the optimal combination of stock price and interest rate. Cao et al., (2013) combines grey theory and neural network algorithm to monitor and predict landslide deformation in mining area. The results show that the proposed method can obtain high precision results when the neuron is trained correctly. Yang and Wang, (2013) proposes a metabolic forecasting model by updating the modeling data constantly. Through a slope deformation monitoring project, he finds that the modified method has high prediction ability. Guo et al., (2014) uses three different grey models to predict the deformation of high speed railway tunnel. The results show that the prediction model can meet the requirements of engineering deformation monitoring of high speed railway tunnel

In the process of modeling, the traditional GM(1, 1) prediction model is vulnerable to random data perturbation, which leads to the system error and poor stability (Li et al., 2016; Li, 2016). In this paper, an improved grey Markov model is proposed by combining the classical grey theory and the Markov model. First of all, this paper makes a simple discussion on the grey theory and Markov chain. Secondly, we make a Markov prediction on residual random sequence on the basis of grey prediction theory, which realizes the

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complementary advantages of two traditional models. Finally, the improved prediction model is analysed by an example, and the results show that the improved Markov prediction model has high prediction accuracy.

2. Combination forecasting model with the square sum of minimum prediction errors

2.1 Gray Forecast Model

Grey forecasting model is a method of establishing mathematical model and forecasting by a small amount of incomplete information.
According to grey system theory, we set a set X_0 as the initial data

$$X_0 = \{X_0^1, X_0^2, X_0^3, \cdots X_0^n\} \tag{1}$$

In order to enhance the regularity of data and predict the future development, we get the set X_1 by accumulating the initial date.

$$X_1 = \{X_1^1, X_1^2, X_1^3, \cdots X_1^n\} \tag{2}$$

Each element in the set above is obtained by the following formula.

$$\begin{cases} X_1^1 = X_0^1 \\ X_1^2 = X_0^1 + X_0^2 \\ \quad \vdots \\ X_1^m = \sum_{i=1}^{m} X_0^i = X_1^{m-1} + X_0^m \end{cases} \tag{3}$$

The linear differential equation of x_1^t can be obtained by following formula.

$$\frac{dx_1^t}{dt} + ax_1^t = u \tag{4}$$

Where, α and μ are the parameters to be identified. At the same time, the grey differential equation model is established.

$$w(t) = \frac{[x_1^t + x_1^{t-1}]}{2} \tag{5}$$

The cumulative matrix is as follows.

$$A = \begin{bmatrix} -w_1^2, 1 \\ -w_1^3, 1 \\ -w_1^4, 1 \\ \vdots \\ -w_1^n, 1 \end{bmatrix} = \begin{bmatrix} t - \frac{[x_1^t + x_1^{t-1}]}{2}, 1 \\ -w_1^3, 1 \\ -w_1^4, 1 \\ \vdots \\ -w_1^n, 1 \\ \end{bmatrix} \tag{6}$$

And the constant vector can be get by the following formula.

$$C = \begin{bmatrix} x_0^2 \\ x_0^3 \\ x_0^4 \\ \vdots \\ x_0^n \end{bmatrix} \tag{7}$$

Then, the two coefficients can be obtained by least square method.

$$\begin{bmatrix} a \\ u \end{bmatrix} = (A^T \cdot A)^{-1} A^T C \tag{8}$$

Finally, we can get the solutions of linear differential equations as follows.

$$\hat{x}_1^{t+1} = \hat{x}_0^1 - \frac{u}{a} e^{-at} + \frac{u}{a} \tag{9}$$

Where, $\hat{x}_0^{t+1} = \hat{x}_1^{t+1} - \hat{x}_1^t$.

2.2 Markov theory model

Markov model prediction is a method named after the Russian mathematician Markov, which is a method of establishing a random time series model by probability.
Assumed a random function M_t, at the moment t the state is k_t.

$$M_t = k_t,\ t \subset T \tag{10}$$

Assume that the function M_t meet the following conditions.

$$P\{M_{t+1} \mid M_0, M_1, M_2 \cdots M_t,\} = P\{M_{t+1} \mid M_t\} \tag{11}$$

The above formula can also be expressed as follows.

$$P\{M_{t+1} = k_{t+1} \mid M_0 = k_0, M_1 = k_1, M_2 = k_2 \cdots M_t = k_t,\} = P\{M_{t+1} = k_{t+1} \mid M_t = k_t\} \tag{12}$$

The process of the above formula is called Markov process.
Define the following formula.

$$\begin{cases} R_0 = R_0 \cdot P_0 \\ R_1 = R_0 \cdot P_1 = R_0 \cdot P \\ R_2 = R_0 \cdot P_2 = R_1 \cdot P \\ R_3 = R_0 \cdot P_3 = R_2 \cdot P \\ \vdots \\ R_n = R_0 \cdot K_n = R_{n-1} \cdot K \end{cases} \tag{13}$$

Where, R_{n-1} is the state vector at the moment t=n-1.
We assume that the possibility of transfer from state R_i to state R_j is p_{ij}. Then, we get the state transition probability by the principle that the frequency is equal to the probability.

$$p_{ij} = \frac{N_{ij}}{N_i} \tag{14}$$

In the above formula, N_i means the number of times the state R_i appears, and N_{ij} is the number of transfer from state R_i to state R_j.
The state transition probability matrix of Markov chain is obtained as follows.

$$R_n = R_0 \cdot K_n = R_{n-1} \cdot \begin{pmatrix} p_{11} & \cdots p_{1i} \cdots & p_{1n} \\ \vdots & & \vdots \\ p_{j1} & \ddots & p_{jn} \\ \vdots & & \vdots \\ p_{n1} & \cdots p_{ni} \cdots & p_{nn} \end{pmatrix} \tag{15}$$

3. Improved grey Markov forecasting model forecasting model

The traditional forecasting model is easily affected by the disturbance of random data, which leads to the existence of systematic errors and poor stability. In this paper, a new prediction model is proposed by

modifying the initial value, background value and residual value based on the state transition matrix of Markov theory model.
(1) Calculate the volatility index series

$$u_i^n = \frac{x_i^n - \widehat{x}_i^n}{\widehat{x}_i^n} \cdot 100\% \tag{16}$$

(2) State classification
We define the total set of states as follows.

$$Q = (Q_1, Q_2, Q_3 \cdots Q_n) \tag{17}$$

Assuming that d_a^k and d_b^k represent the upper and lower bounds of the state Q_k respectively, the volatility index will beat the state k .

$$u_i^n \in [d_a^k, d_b^k] \tag{18}$$

(3) Construct the Primitive state transition matrix
Assuming that Num_i is the total number of states Q_i appears n_{ij}^l is the number of transfer times from state Q_i to state Q_j. Then, the calculation method of element B in transfer matrix is as follows.

$$p_{ij}^l = \frac{n_{ij}^l}{Num_i} \tag{19}$$

(4) Construct the predictive state transition matrix
We select r primitive objects which are closest to the target and sort them according to the order from near to far. By selecting the state of each object as the initial state and getting the corresponding row vector of state transition matrix, we get the predictive state transition matrix.

$$RP_{ij} = \begin{pmatrix} rp_{k1}^1 & \cdots rp_{ki}^1 \cdots & rp_{kr}^1 \\ \vdots & & \vdots \\ rp_{k1}^i & \ddots & rp_{kr}^i \\ \vdots & & \vdots \\ rp_{k1}^r & \cdots rp_{ki}^r \cdots & rp_{kr}^r \end{pmatrix} \tag{20}$$

(5) Get the prediction equation function
According to the following formula, the element rp_{rk}^n in the prediction transfer matrix is accumulated.

$$s_k = \sum_{n=1}^{r} rp_{rk}^n \tag{21}$$

Thus, we can get the vector [S_1, S_2, $S_3 \ldots S_n$].
By setting the corresponding state of the maximum value max{S_1, S_2, $S_3 \ldots S_n$} in the vector as the state of the predicted object, we finally get the prediction equation.

$$\widehat{Z}(k) = X_0^k[1 + \alpha(d_a^k + d_b^k)] \tag{22}$$

Where, α is the weight coefficient.

4. Simulation experiment and result analysis

In this paper, we take the chemical industry related data of a province in china as an example to carry out simulation. The experiment and data analysis are carried out from production accidents and casualties.
The accident and casualty data of chemical enterprises during 2007-2016 is shown in Table 1.

Table 1: Number of accidents and casualties

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Number of accidents	16	18	19	21	23	22	24	26	25	27
Number of casualties	70	78	83	86	91	89	95	99	99	108

In order to show the advantages of the new algorithm more intuitively, the traditional gray level prediction and Markov prediction are also simulated.
We use relative error to represent the accuracy of prediction models. The relative error is calculated by the following formula.

$$ac = \frac{v_x - v}{v} \times 100\% \tag{23}$$

Where, V_x the predicted value, and v is the actual value.

4.1 Accident quantity prediction

According to Table 2 and Figure 1, we know that there are some deviations between the predicted value and the true value. What is more, due to the uncertainty of chemical accident, the deviation of individual years is relatively serious, which leads to the fluctuations of the data.

Table 2: Actual and predicted values of the accidents number

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual Value	16	18	19	21	23	22	24	26	25	27
Gray Prediction	16	20	22	25	26	24	25	29	28	30
Markov Prediction	16	17	18	16	22	23	25	24	25	28
Improved prediction	16	19	20	20	23	23	24	25	26	27

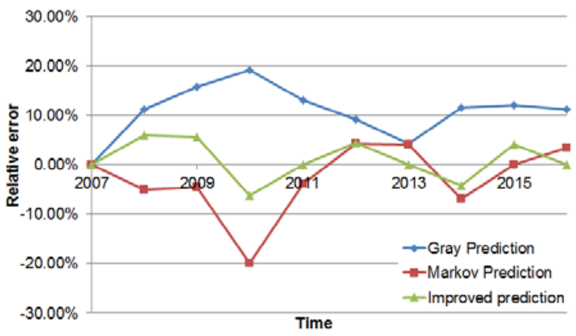

Figure 1: Forecast curve of accident quantity

4.2 Casualty prediction

Figure 2 shows the error information of the three algorithms in Table 3. Through the curve drawing with the data, we can see that the improved prediction model is more stable and the accuracy is higher than other algorithms.
Through example analysis, we find that the error of the improved grey Markov model is much smaller than that of the other two traditional models, which proves the feasibility of the improved grey Markov in the prediction of chemical production accident.

Table 3: Actual and predicted values of the casualty number

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual Value	70	78	83	86	91	89	95	99	99	108
Gray Prediction	72	80	82	88	92	90	94	103	104	111
Markov Prediction	68	75	80	83	88	89	92	95	96	103
Improved prediction	69	77	83	85	90	89	95	97	98	107

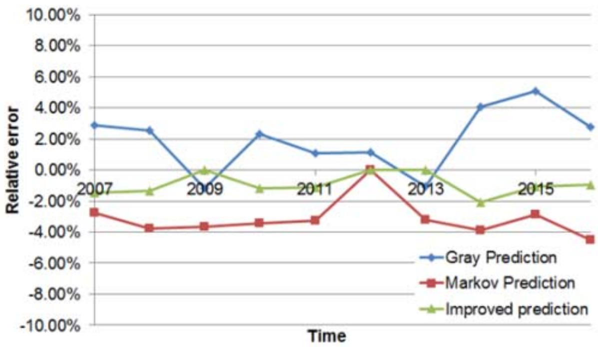

Figure 2: Forecast curve of casualties quantity

5. Conclusion

Although the development of china's chemical industry led to economic development, there is still a long way to go in safety management. In this paper, according to the characteristics of uncertain factors in the occurrence of accidents in chemical industry park, an improved accident prediction method is proposed based on the grey system theory and Markov theory, which can provide data reference for the safety management of chemical production in the future. At last, we do the simulation of accident prediction based on the new model and the simulation results show that the new prediction model has good prediction accuracy.

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