Research on Sultan Grass Repairing Petroleum Contaminated Soil under the Protection of the Ecological Perspective

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Abstract: In order to scientifically and accurately predict petroleum pollutant discharges, according to the random volatility characteristic of petroleum pollutant discharge data, the prediction methods of petroleum pollution based on Grey prediction Hidden Markov Model algorithm (GHMM) has been proposed. Firstly, predict the overall trend of petroleum pollutant discharge on the basis of grey model GM (1, 1), and use Hidden Markov Model as sensor to simulate the random volatility changes of system state, and also correct and improve the model in real time; then, on the basis of petroleum pollutant discharge prediction, plan the repairing of petroleum contaminated soil by sultan grass. Finally, by taking national petroleum pollutant discharge in recent years as example, analyze the prediction accuracy and effectiveness of the model. The result shows that compared with traditional prediction methods, GHMM model has evidently improved prediction accuracy, which is an effective prediction algorithm of petroleum pollutant discharge.

Keywords: petroleum pollutant discharge; hidden markov model; grey model; prediction; sultan grass

1. Introduction

The petroleum is a kind of organic pollutant, which is provided with carcinogenesis, teratogenesis and mutagenicity. With its extensive use in national defense, aerospace, industry and other important fields, vast petroleum and its products entered into soil and water environment through various approaches and has caused severely impair to ecology and human health. Because of the economy and effectiveness, microbial remediation technology becomes a kind of technology for governing petroleum hydrocarbon pollution which has the greatest development potential [1], and it is a controlled or poliothrix conducted process of catalysis degrading organic pollutant by microorganism so as to wipe off or eliminate petroleum organic pollutant in environment. Currently, the biologist finds out that the sultan grass has a good effect on repairing petroleum contaminated soil, and how to accurately predict petroleum pollutant discharge is accompanying. Planning the cultivation of sultan grass reasonably shall have an evident effect on improving repairing effect and reducing cultivating cost. At present, the statistical prediction of petroleum pollutant discharge mainly by linear regression analytical method, time series method, neural network method, grey prediction method, small wave-supported vector machine method and Markov chain method etc[2–5]. However, on account of being influenced by above multiple grey factors, the petroleum pollutant discharge has high randomness and volatility and other characteristics, and the traditional statistical prediction method is for treating pollution problems with nonlinearity characteristic, which has large limitation and cannot accurately identify the random volatility change rule in pollution process, and has relatively low prediction accuracy [6].

Aimed at deficiency of traditional prediction method, this paper firstly use grey prediction to process the uncertainty of system and describe its integral development tendency; then with the help of the sensor of Hidden Markov Model, detect the state change of pollution process and eliminate its volatility [7, 9], and speculate future pollution information data. The innovation point of the model in this paper is based on the combination of grey prediction and Hidden Markov Model to consider the random disturbance factors enter into system over time, and reflecting new features of system by real-time correction. The result of simulation example indicates that the proposed prediction algorithm can complement each other’s advantages and has fine accuracy, which is a kind of prediction algorithm to deal with random volatility problem effectively [10].

2. Modeling mechanism of ghmm

The grey prediction model gives long-term and continuous changing process of system generation sequence by differential equation. This process is gained through transition of generation sequence which refers to the sequence have randomness of its primary sequence weakened, and system tendency effect can be got by restoring the generation sequence [11]. The grey system prediction is mainly applied in prediction problem of short time, little data information and not high volatility, and its prediction image is a smooth curve which is monotonic increasing or monotonic decreasing, and it has relatively low fitness for data sequence of high random volatility and low prediction accuracy [12]. While the object of prediction by Markov chain is randomly changing dynamical system, and its prediction bases on transition probability between states to speculate future development tendency of system, in which the transition probability reflects influences by various random factors and reveals intrinsic regularity of transaction between each state, which is relatively applicable for prediction problem of data with high random volatility. The organic combination of grey theory and Markov chain can give full play to respective merit and avoid respective defect, thus raising the accuracy of prediction by model.

2.1. Theory of GM (1, 1) model

The grey system regards all random variables as grey variables and regards random process as grey process, to ensure a group of original data sequence without regularity or with weak regularity with evident regularity by a series of data generation method. GM (1, 1) Model is one of the most common in grey prediction models, and its modeling process is as follows:

Assume the original time sequence is

\[ X^{(0)} = \{x^{(0)}_t, t = 1, 2, \ldots, n\} \]

Make one accumulative generation and 1-AGO sequence shall be gained

\[ X^{(1)} = \{x^{(1)}_t, t = 1, 2, \ldots, n\}, \quad x^{(1)}_t = \sum_{i=1}^{t} x^{(0)}_i \]

On the basis of generative sequence \( X^{(1)} = \{x^{(1)}_t, t = 1, 2, \ldots, n\} \), establish following linear first-order differential equation:

\[ \frac{dX^{(1)}}{dt} + \alpha X^{(1)} = \beta \quad (1) \]

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Where the model parameter $\alpha, \beta$ are respectively development grey level and internal generation control grey level. The matrix form of differential equation parameter estimation after infinitesimal discretization is

$$
\begin{bmatrix}
\hat{\alpha} \\
\hat{\beta}
\end{bmatrix} = (B^T B)^{-1} B^T Y
$$

(2)

Where

$$
B = \begin{bmatrix}
-(x^{(1)}(x^{(1)}) + x^{(2)}(x^{(2)})/2 & 1 \\
-(x^{(3)}(x^{(3)}) + x^{(4)}(x^{(4)})/2 & 1 \\
\vdots & \vdots \\
-(x^{(n)}(x^{(n)}) + x^{(n+1)}(x^{(n+1)})/2 & 1
\end{bmatrix},
\quad
Y = \begin{bmatrix}
x^{(n)}(x^{(n)}) \\
x^{(n+1)}(x^{(n+1)})
\end{bmatrix}
$$

After solving the differential equation, the time response sequence can be gained

$$
\hat{x}^{(1)}_{t+1} = (x^{(0)}(x^{(0)}) - \frac{\hat{\beta}}{\hat{\alpha}}) \exp(-\hat{\alpha} t) + \frac{\hat{\beta}}{\hat{\alpha}}
$$

(3)

Then conduct inverse accumulated generating operation, so that fitting sequence can be gained

$$
\hat{Y}(t+1) = \hat{x}^{(0)}_{t+1} = \hat{x}^{(1)}_{t+1} - \hat{x}^{(1)}_{t+1} = (1 - \exp(-\hat{\alpha})) (x^{(0)}(x^{(0)}) - \frac{\hat{\beta}}{\hat{\alpha}}) \exp(-\hat{\alpha} t)
$$

(4)

This is the system predicted value.

3. Hard decision-making tree $f_0$ model

3.1. $f_0$ Model in HMM frame

Under normal conditions, fundamental frequency and its derivative and second derivative compose three data flows of multi-space probability distribution (MSD) relying on context from left to right. The model structure generates prediction track from observed value released by hidden state. The output distribution of state is multi-space Gaussian distribution which relies on context, and decision-making tree is used to gather related context into groups so that free parameter number can be reduced, in addition, modeling by visualized context is allowed. To represent simply, the following discussion shall be limited within only HMM of single data flow, which is simpler than multi-data flow condition.

Figure. 1 gives equivalent dynamic state Bayesian network (DBN) which is applied in HMM. In the figure, $q_t, o_t$ and $g_t$ respectively represents the state index, pollution date characteristic vector and time index at time of $t$. When used space defines the output distribution, the observed value of space index is agreed with time label. The factor $c_j$ is also introduced into the figure. Note that the state bound is latent variable, and expectation maximization (EM) must be used to conduct non-supervision training.

It can also be known from Figure. 1 that HMM can be simplified through three basic distribution sets: the first is persistent period probability distribution state $p_{t}(d_{j} \mid c_{j})$; the second is space probability distribution $\alpha_{t}(g_{t} \mid c_{t})$; and the third is given label output probability distribution $b_{t}(o_{t} \mid g_{t}, c_{t})$. By utilizing these basic distributions to think about graph model showed in Figure. 2, the given voice observation likelihood $(o, g, c)$ can be decomposed into:

$$
p(o, g \mid c, \lambda) = \sum_{q_{t}, \ldots, q_{t-j}} \prod_{j=1}^{J} p_{t}(d_{j} \mid c_{j}) = \prod_{j=1}^{J} \alpha_{t}(g_{t} \mid c_{t}) b_{t}(o_{t} \mid g_{t}, c_{t})
$$

In the formula, $J$ and $\lambda$ respectively represents sums of state and model parameter.
Assumed that $g_i$ is two-value parameter: “1” represents voice data frame, and “0” represents non-voice area. Meanwhile, assume $b_j$ and $p_j$ are respectively represented by Gaussian distribution. Hence, the foregoing voice likelihood function can be changed as:

$$p(o,g|c,\lambda) = \sum_{a_{i,j-1}} \prod_{i,j} N \left( d_i; \bar{m}_{ij}, \bar{\sigma}_{ij} \right)$$

$$= \prod_{i,j} \left[ g_i \bar{\sigma}_i N \left( a_i; \bar{m}_i, \bar{\sigma}_i \right) + (1-g_i) \left( 1-\bar{m}_i \right) \right]$$

Where, $N \left( \cdot; \mu, \Sigma \right)$ represents the Gaussian distribution of which the mean vector is $\mu$ and variance matrix is $\Sigma$. In this equation, persistent period and output distribution pass persistent time average $\bar{m}_{ij}$, time variance $\bar{\sigma}_{ij}$, voiced degree $\bar{\sigma}_i$, output mean vector $\bar{m}_i$ and observed covariance matrix $\bar{\sigma}_i$. Just as aforementioned, typical decision-making tree structure can be used to express basic distribution. Assumed that $I^c_j \left( c_j \right)$ and $I^d_j \left( c_j \right)$ are defined as binary system index decision-making tree function of output distribution and persistent period, where $l$ and $c_j$ are leaf index and contextual factor of state $j$, i.e. $I^c_j \left( c_j \right)$ and $I^d_j \left( c_j \right)$ determine whether to allocate state $j$ to the $l$ st persistent period and observation decision-making tree. By using these decision-making tree indicator functions, Markov Model parameter can be expressed:

$$m_j = \sum_{l} I^d_j \left( c_j \right) m_l, \sigma_j^2 = \sum_{l} I^c_j \left( c_j \right) \sigma_l^2$$

$$w_j = \sum_{l} I^d_j \left( c_j \right) w_l, \mu_j = \sum_{l} I^c_j \left( c_j \right) \mu_l$$

$$\zeta_j = \sum_{l} I^d_j \left( c_j \right) \zeta_l,$$

Where, $m_l$ and $\sigma_l^2$ respectively are the mean value and variance yields of persistent period of the $l$ st leaf in time decision-making tree. Similarly, $\omega_j$, $\mu_l$ and $\Sigma_l$ respectively represents probability parameter of voice expression and output, which are used to train the $l$ st leaf of output decision-making tree.

### 3.2. Parameter estimation of hidden markov model

The maximum-likelihood criterion is generally used to estimate the parameter of HMM Model. However, the state bound has hidden; therefore, EM algorithm is required to conduct estimation. If given $N$ independent identical distributions $\{ \left( \omega^i, g^i \right) \}_{i=1}^N$ and accompanied by its relevant factors $\left[ c^i \right]_{i=1}^N$, the following parameter estimation formula can be gained by EM algorithm:

$$\hat{m}_j = \frac{\sum_{n=1}^N \sum_{i=1}^N \sum_{j=1}^{t_j} I^d_j \left( c_j \right) \sum_{i_j=1}^{t_j} x_{i_j} \left( t_j, t_{j-1} \right) \left[ t_j - t_{j-1} \right]}{\sum_{n=1}^N \sum_{i=1}^N \sum_{j=1}^{t_j} I^d_j \left( c_j \right) \sum_{i_j=1}^{t_j} x_{i_j} \left( t_j, t_{j-1} \right)}$$

$$\hat{\sigma}_j^2 = \frac{\sum_{n=1}^N \sum_{i=1}^N \sum_{j=1}^{t_j} I^d_j \left( c_j \right) \sum_{i_j=1}^{t_j} x_{i_j} \left( t_j, t_{j-1} \right) \left[ t_j - t_{j-1} - \hat{m}_j \right]^2}{\sum_{n=1}^N \sum_{i=1}^N \sum_{j=1}^{t_j} I^d_j \left( c_j \right) \sum_{i_j=1}^{t_j} x_{i_j} \left( t_j, t_{j-1} \right)}$$

$$\hat{\mu}_j = \frac{\sum_{n=1}^N \sum_{i=1}^N \sum_{j=1}^{t_j} I^d_j \left( c_j \right) \sum_{i_j=1}^{t_j} y_{i_j} \left( t_j \right) g_i^o \left[ \omega_j \right]}{\sum_{n=1}^N \sum_{i=1}^N \sum_{j=1}^{t_j} I^d_j \left( c_j \right) \sum_{i_j=1}^{t_j} y_{i_j} \left( t_j \right)}$$

$$\hat{\Sigma}_j = \frac{\sum_{n=1}^N \sum_{i=1}^N \sum_{j=1}^{t_j} I^d_j \left( c_j \right) \sum_{i_j=1}^{t_j} y_{i_j} \left( t_j \right) g_i^o \left[ \omega_j \right] \left( \alpha^o_j - \hat{\mu}_j \right) \left( \alpha^o_j - \hat{\mu}_j \right)^T}{\sum_{n=1}^N \sum_{i=1}^N \sum_{j=1}^{t_j} I^d_j \left( c_j \right) \sum_{i_j=1}^{t_j} y_{i_j} \left( t_j \right) g_i^o \left[ \omega_j \right]}$$

$$\hat{\omega}_j = \frac{\sum_{n=1}^N \sum_{i=1}^N \sum_{j=1}^{t_j} I^d_j \left( c_j \right) \sum_{i_j=1}^{t_j} y_{i_j} \left( t_j \right) g_i^o \left[ \omega_j \right]}{\sum_{n=1}^N \sum_{i=1}^N \sum_{j=1}^{t_j} I^d_j \left( c_j \right) \sum_{i_j=1}^{t_j} y_{i_j} \left( t_j \right) g_i^o}$$

Where, in the process of executing EM algorithm, $\hat{m}_j$, $\hat{\sigma}_j^2$, $\hat{\mu}_j$, $\hat{\Sigma}_j$ and $\hat{\omega}_j$ are respectively updated value of $m_l$, $\sigma_l^2$, $\mu_l$, $\Sigma_l$ and $\omega_l$. Meanwhile, $x_{i_j} \left( t_j, t_{j-1} \right)$ is the probability of state $j$ from time $t_{j-1}$ to $t_j$. $y_{i_j} \left( t \right)$ represents the posterior probability of state $j$ at time $t$. These probability subjects shall be calculated by famous forward-backward algorithm.

### 4. GHMM petroleum pollutant prediction

The main targets for discharge reduction of total amount of petroleum pollutant in our country include four leading indicators of sulfur dioxide, nitric oxide, chemical oxygen demand and ammonia nitrogen. The paper selects national total amount (ten thousand tons) of sulfur dioxide discharge from 2007 to 2014 to conduct analog calculation (the actual values are sourced from China Statistical Yearbook on Environment 2015).

#### 4.1. Build GM (1, 1) prediction model
According to the foregoing method of building GM (1, 1) Model, the prediction model of total annual discharge of sulfur dioxide is:

\[
\hat{x}_{111}^{(1)} = 68592.5 - 66337.6e^{-0.04t}
\]

\[
\hat{x}_{111}^{(0)} = 2707.3e^{-0.04t}
\]

The prediction result is as showed in Table 1.

<table>
<thead>
<tr>
<th>Year</th>
<th>Actual value of total discharge</th>
<th>GM(1,1) Model</th>
<th>First analogue value</th>
<th>Residual error</th>
<th>Relative error%</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>2254.9</td>
<td>2254.9</td>
<td>0.0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2008</td>
<td>2549.3</td>
<td>2612.4</td>
<td>-63.1</td>
<td>-2.48</td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>2588.8</td>
<td>2518.1</td>
<td>70.7</td>
<td>2.73</td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td>2468.1</td>
<td>2427.2</td>
<td>40.9</td>
<td>1.66</td>
<td></td>
</tr>
<tr>
<td>2011</td>
<td>2321.2</td>
<td>2339.5</td>
<td>-18.3</td>
<td>0.79</td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td>2214.4</td>
<td>2255.0</td>
<td>-40.6</td>
<td>1.83</td>
<td></td>
</tr>
<tr>
<td>2013</td>
<td>2185.1</td>
<td>2173.6</td>
<td>11.5</td>
<td>0.53</td>
<td></td>
</tr>
<tr>
<td>2014</td>
<td>2095.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.2. Prediction result and analysis

The column vector state of the maximum sum of transition probability is the prediction transition state of random value. Under general conditions, the transition state corresponding to the maximum value of sum of column vectors is sole. If the transition state corresponding to the maximum value of sum of column vectors is not the only, when calculating predicted value, the mean value of several corresponding transition states can be selected.

It can be known from Table 1 that the maximum value of sum of transition probability is 5/6, and the corresponding state is \(E_3\). So the total discharge amount of sulfur dioxide in 2014 is predicted to be in state \(E_3\). The first predicted value of total discharge of sulfur dioxide in 2014 got from GM (1, 1) Model is 20.951 million tons, and from formula (7) the following can be got:

\[
\hat{G}_{\text{year}2011} = \frac{1}{2}(E_{13} + E_{23})\hat{Y}
\]

\[
= \frac{1}{2}(101\% + 103\%) \times 2095.1 = 2141.2 \text{ (ten thousand tons)}
\]

This is the second predicted value of national total discharge of sulfur dioxide in 2014.

According to 2014 China environmental condition bulletin published by national Ministry of Environmental Protection, the national total discharge of sulfur dioxide in 2014 has declined by 2.21% compared with the last year, which is 21.368 million tons. As we can see, the second prediction result got from Grey Hidden Markov Chain Model is relatively ideal, which has greatly improved the prediction accuracy of the model.

In the same way, use Grey Hidden Markov Chain Model to calculate the second predicted value of national total discharge of sulfur dioxide from 2007 to 2014, and the prediction results are showed in Table 2.

<table>
<thead>
<tr>
<th>Year</th>
<th>Actual value of total discharge</th>
<th>Grey Hidden Markov Chain Model</th>
<th>Second analogue value</th>
<th>Residual error</th>
<th>Relative error%</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>2254.9</td>
<td></td>
<td>2254.9</td>
<td>0.0</td>
<td>0.00</td>
</tr>
<tr>
<td>2008</td>
<td>2549.3</td>
<td></td>
<td>2562.8</td>
<td>-13.5</td>
<td>-0.53</td>
</tr>
<tr>
<td>2009</td>
<td>2588.8</td>
<td></td>
<td>2547.1</td>
<td>41.7</td>
<td>1.61</td>
</tr>
<tr>
<td>2010</td>
<td>2468.1</td>
<td></td>
<td>2480.6</td>
<td>-12.5</td>
<td>-0.51</td>
</tr>
<tr>
<td>2011</td>
<td>2321.2</td>
<td></td>
<td>2341.8</td>
<td>-20.6</td>
<td>-0.89</td>
</tr>
<tr>
<td>2012</td>
<td>2214.4</td>
<td></td>
<td>2212.2</td>
<td>2.2</td>
<td>0.10</td>
</tr>
<tr>
<td>2013</td>
<td>2185.1</td>
<td></td>
<td>2175.8</td>
<td>9.3</td>
<td>0.43</td>
</tr>
<tr>
<td>2014</td>
<td>2095.1</td>
<td></td>
<td>2141.2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

By comparing Table 1 with Table 2, it can be known that the average relative error of first prediction result got from GM (1, 1) Model \(\Delta_1 = 1.67\%\), while the average relative error of second prediction result got from Grey Hidden Markov Chain Model \(\Delta_2 = 0.68\%\). Obviously, the second prediction by Grey Hidden Markov Chain Model can notably lower the average relative error of prediction, thus improving prediction accuracy. The fitting condition of prediction result and actual value got from two models is showed in Figure 1. From the figure it can be also observed that the fitting degree of prediction result and actual value got from Grey Hidden Markov Chain Model is apparently higher than that got from GM (1, 1) Model, and can better reflect the actual variation tendency of annual total discharge of sulfur dioxide.
Figure. (2). Comparison of predictive results of two times

4.3. Predictive results and analysis after optimization of model

Next, continue to predict total discharge amount of sulfur dioxide of the whole country in 2014. Except for data of 2007, consider data of 2014 of the 2014 China Environmental Situation Bulletin issued by Ministry of Environment Protection. Establish real-time correction predictive model of gray implicit expression Markov chain. According to GM (1, 1) modeling approach, once value of simulation of total discharge amount of sulfur dioxide can be derived. The result can be shown in Table 3.

Table 3. GM (1, 1) Predictive modeling of total discharge amount of sulfur dioxide of the whole country from 2008 to 2014

<table>
<thead>
<tr>
<th>Years</th>
<th>Actual value</th>
<th>Once value of simulation</th>
<th>Relative value%</th>
<th>State</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>2549.3</td>
<td>2549.3</td>
<td>100.0</td>
<td>$E_2$</td>
</tr>
<tr>
<td>2009</td>
<td>2588.8</td>
<td>2557.4</td>
<td>101.2</td>
<td>$E_1$</td>
</tr>
<tr>
<td>2010</td>
<td>2468.1</td>
<td>2456.8</td>
<td>100.5</td>
<td>$E_2$</td>
</tr>
<tr>
<td>2011</td>
<td>2321.2</td>
<td>2360.1</td>
<td>98.4</td>
<td>$E_1$</td>
</tr>
<tr>
<td>2012</td>
<td>2214.4</td>
<td>2267.3</td>
<td>97.7</td>
<td>$E_1$</td>
</tr>
<tr>
<td>2013</td>
<td>2185.1</td>
<td>2178.1</td>
<td>100.3</td>
<td>$E_2$</td>
</tr>
<tr>
<td>2014</td>
<td>2136.8</td>
<td>2092.4</td>
<td>102.1</td>
<td>$E_2$</td>
</tr>
</tbody>
</table>

It can be seen from predictive result that total discharge amount of sulfur dioxide of the whole country in 2012 deceased by 6.2% compared with 2014 and decreased by 21.3% compared with 2005. Total discharge amount of the rest three-petroleum pollutant index in 2012 can be predicted in the same way. Since the Eleventh Five-Year Plan, because environment protection system of the whole country has reinforced environment supervision, environment emergency operation work and energy conservation and discharge reduction, various environment protection works has made new improvement. Pollution discharge reduction has achieved great achievement. Pollution prevention is propelled gradually. Therefore, total year discharge amount of main petroleum pollutant like sulfur dioxide shows gradually decreasing trend year by year. It is predicted that the objective of total discharge amount of petroleum pollutant of the Eleventh Five-Year Plan will be completed successfully.

Herein, compare real data of somewhere in Dongying Shandong according to corresponding relationship of discharge amount of sulfur dioxide and sudan grass. 1 ton corresponds to one mu. Plant cost of per mu is calculated as 300 RMB. Comparison situation of plant area and plant cost about actual demand amount, GM (1, 1) predictive model and GHMM predictive model is shown in Table 4.

Table 4. Demand amount of sudan grass in 2015

<table>
<thead>
<tr>
<th>Index</th>
<th>Actual demand amount</th>
<th>GM (1, 1) predictive model</th>
<th>GHMM predictive model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plant area(ten thousand mu)</td>
<td>0.82</td>
<td>1.13</td>
<td>1.26</td>
</tr>
<tr>
<td>Plant cost(ten thousand Yuan)</td>
<td>246</td>
<td>239</td>
<td>261</td>
</tr>
</tbody>
</table>

According to data in Table 4, algorithm of this paper is more close to actual data in prediction of plant area and plant cost about sudan grass. On the premise of ensuring soil remediation quality, it will decrease remediation cost and it has great economic prospect.

5. Conclusion

This paper has put forward real-time correcting forecasting model and algorithm of grey implicit Markoff combination aiming at forecasting problem of discharge reduction of petroleum pollutants with the characteristic of stochastic volatility and made full use of characteristic of little information required in building model of grey forecasting and feature of Markoff chain in dealing with data of stochastic volatility. At the same time, this paper also uses real-time correction to optimize the model. The forecasting result of total discharge amount of sulfur dioxide in the whole nation shows that the forecasting precision of real-time correcting and grey implicit Markoff combination is obvious superior to other sole forecasting model. It can effectively deal with the problem of stochastic volatility and reflect the whole law of the development of things and it is suitable for forecast of major oil pollutant discharge reduction in China so that it has practical application and promotion significance and it can provide decision-making basis for national environmental protection department to promote energy conservation and discharge reduction.

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References


