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FORESHADOW PREDICTION OF COAL AND GAS OUTBURSTS BASED ON A WEIGHTED FIRST-ORDER LOCAL-REGION METHOD[**]

1. Introduction

Coal and gas outburst is a very complicated coal and rock dynamic system, and in the system there are a lot factors affecting gas emission, such as geo-stress, gas pressure, gas content, physic-mechanical properties of coal and so on. The relationships between these affecting factors are highly nonlinear, and the gas concentration's variation with time is also uncertainty, which constitutes a typical chaotic movement. As chaos science and nonlinear science developing, the time series analysis is much more promoted. Therefore, the evolution law can be got by using chaotic prediction theory to analyze the historical monitored gas emission data, which will further promote the gas prediction theory.

According to modeling data the chaotic prediction method can be divided into all-region prediction method, local-region prediction method, self-adaptation prediction method and so on. HE J. et al. [1–5] presented some research by using chaotic prediction method to analyze the chaotic properties of gas emission time series and predict the variation tendency of gas emission successfully. On the further, this paper uses a modified weighted first-order local-region method to analyze the gas emission data prior to coal and gas outburst and predict the emission tendency. By comparison to other chaotic prediction methods, these results are more precise and feasible.

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2. Reconstruction of phase space

2.1. Gas emission phase space reconstruction

The influence factors of coal and gas outburst can be seen as state variables $\{x_1, x_2, \ldots, x_n\}$ changing over time, and in this way a n-dimensional space can be erected. That is the system phase space. As every state variable at t moment has a certain value, a point in phase space is confirmed to represent the state of system at this moment. With time passing, the representative points can be linked as a curve. That is phase path which represents the state of system evolution. If these state variables' value in every moment known, the whole system's state evolution process can be mastered, and the coal and gas outburst state can also be well predicted.

So as to recover the system original rule from a variable time series, and draw system phase path in high dimensional space to analyze the system evolution law, the delay coordinates of a certain variable in original system can be used to reconstruct phase space. N. Packard et al. [6] suggested using time delay technique to reconstruct phase space. F. Takens et al. [7] proved that a suitable embedded dimension could be found. That is, if delay coordinates' dimension $m \geq 2d + 1$ (where d is the dimension of system), the system state variation's mapping in phase space will remain unchanged, and in this way the characteristics of system can be reproduced in phase space.

We assume that the coal and gas dynamic system's evolution of discrete time is expressed by the following nonlinear difference equation:

$$Z(t+1) = F(Z(t)) \tag{1}$$

Where $Z(t)$ is the d dimensional state vector at t moment, and $F(Z(t))$ is vector valued function.

Assumed $X(t)$ is the system output vector of observations in gas emission time series, and without regard to the added noise produced by imperfection and inaccuracy of observation means, we can get the next step prediction by embedding the monitored time series into m dimensional phase space:

$$X(t+1) = \mathrm{f}(x(t), x(t+\tau), \cdots, x(x(t+(m-1)\tau)),\ (t = 1, 2, \ldots, M) \tag{2}$$

Where τ is the delay time, m is the dimension of embedded phase space, $M = N - (m-1)\tau$ is the number of points in reconstruction phase space, and N is the length of time series.

2.2. Determining τ and m

The idea was introduced by H.S. Kim et al. [9]. The correlation integral for the embedded time series is defined as follows:

$$C(m.N,r,k)=\frac{2}{M(M-1)}\sum_{1\le i\langle j\le M}\Theta\left(r-\left\|X_i-X_j\right\|\right),\ r>0 \tag{3}$$

Where $\Theta(x)=0$, if $x<0$,$\Theta(x)=1$, if $x\geq 0$, and k is the time delay index, e.g. $k=1$, a single time series $\{x_1, x_2, \ldots, x_N\}$ is generated; $k=2$, two disjoint time series $\{x_1, x_3, \ldots, x_{N-1}\}$ and $\{x_2, x_4, \ldots, x_N\}$ are generated with each of length $N/2$.

By using BDS [11, 12] statistical method, which is based on the correlation integral, the fitting estimated value of N, m and r can be calculated. A function $S(m,N,r,k)$ defined as:

$$S(m,N,r,k)=C(m,N,r,k)-C^m(1,N,r,k) \tag{4}$$

As the gas emission time series is divided into k disjoint time series, then $S(m,N,r,k)$ can be calculated by these series. E.g. if $k=2$,

$$S(m,N,r,2)=\frac{1}{2}\left\{\left[C_1(m,N/2,r,2)-C_1^m(1,N/2,r,2)\right]+\left[C_2(m,N/2,r,2)-C_2^m(1,N/2,r,2)\right]\right\};$$

for general k, it becomes:

$$S(m,N,r,k)=\frac{1}{k}\sum_{s=1}^{k}\left[C_s(m,N/k,r,k)-C_s^m(1,N/k,r,k)\right] \tag{5}$$

As m and k fixed, and we define the quantity measurement of $S(m,r,k)$ variation with r as follows:

$$\Delta S(m,k)=\max\left\{S(m,r_j,k)\right\}-\min\left\{S(m,r_j,k\right\} \tag{6}$$

When m is between 2 and 5, and r is between $\sigma/2$ and 2σ (where σ is variance of the data set), the time parameter can be well approximated. With

$m=2, 3, 4, 5,$

$r_i=0.5i\sigma \quad (i=1, 2, 3, 4),$

$N=3000$

and k is natural number (≤ 200), we calculate the following three averages by using MATLAB programming.

$$\overline{S}(k)=\frac{1}{16}\sum_{m=2}^{5}\sum_{j=1}^{4}S(m,r_j,k) \tag{7}$$

$$\Delta\overline{S}(k) = \frac{1}{4}\sum_{m=2}^{5}\Delta S(m,k) \tag{8}$$

$$S_{cor}(k) = \Delta\overline{S}(k) + \left|\overline{S}(k)\right| \tag{9}$$

The local optimal time can be got from the first zero crossing of $\overline{S}(k)$ or the first local minimum of $\Delta\overline{S}(k)$, and then the delay time $\tau = k_1\tau_s$. Also the delay time window $\tau_w = k_2\tau_s$ can be got when the $S_{cor}(k)$ gets it's minimum. Then we can get the embedded dimension m by $\tau_w = (m-1)\tau$.

3. The weighted first-order local-region method

In the phase space reconstructed based on equation (2), we defined the last point x_m of the phase space path as the central point. The d_{min} is the minimum of distance d_i between central point and near point x_{mi} ($i = 1, 2, ..., q$). Because of defect in the weight of references [8, 10], the weight pi of point x_{mi} is redefined in this paper.

$$p_i = \frac{\ln\left(e + \left|d_i - d_{\min}\right|\right)}{\sum_{i=1}^{k}\ln\left(e + \left|d_i - d_{\min}\right|\right)} \tag{10}$$

If the weight is larger then the point in phase space is much closer to the central point, and it will take a higher proportion in the prediction. As the first-order local-region linear fitting equation is $x_{mi} + 1 = a + bx_{mi}$, the coefficient a and b must meet the following equation by least square method.

$$Q(a,b) = \sum_{i=1}^{q} p_i\left(x_{mi+1} - a - bx_{mi}\right)^2 = \min \tag{11}$$

By the knowledge of how to calculate the extreme value in differential calculus, we get two partial differential equations about a and b.

$$\begin{cases} \dfrac{\partial Q(a,b)}{\partial a} = 0 \\ \dfrac{\partial Q(a,b)}{\partial b} = 0 \end{cases} \tag{12}$$

After simplified, an equation set is got as follows:

$$\begin{cases} a\sum_{i=1}^{q} p_i + b\sum_{i=1}^{q} p_i x_{mi} = \sum_{i=1}^{q} p_i x_{mi+1} \\ a\sum_{i=1}^{q} p_i x_{mi} + b\sum_{i=1}^{q} p_i x_{mi}^{\ 2} = \sum_{i=1}^{q} p_i x_{mi} x_{mi+1} \end{cases} \tag{13}$$

Then a and b are calculated.

$$\begin{cases} b = \dfrac{\sum_{i=1}^{q} p_i \sum_{i=1}^{q} p_i x_{mi} x_{mi+1} - \sum_{i=1}^{q} p_i x_{mi} \sum_{i=1}^{q} p_i x_{mi+1}}{\sum_{i=1}^{q} p_i \sum_{i=1}^{q} p_i x_{mi}^{\ 2} - \left(\sum_{i=1}^{q} p_i x_{mi}\right)^2} \\ a = \dfrac{\sum_{i=1}^{q} p_i x_{mi+1} + b\sum_{i=1}^{q} p_i x_{mi}}{\sum_{i=1}^{q} p_i} \end{cases} \tag{14}$$

After putting a and b into equation $x_{mi} + 1 = a + bx_{mi}$, the tend of phase space path can be got, and then the predicted value of time series can also be separated from the vector.

In short, the weighted first-order local-region prediction method can be summarized in four steps:

— Phase space reconstruction, as the part 2 shows.
— Looking for the near points. Calculating the distance between near points in phase space and the central point x_m to get the reference vector set $\{x_{mi}, i = 1, 2, ..., q\}$.
— Solution of coefficient a and b.
— Prediction by the predictor formula. That is, getting $x_{mi} + 1$ by first order fitting equation, and cycling.

4. Example of foreshadow prediction

The time series of gas emission prior to coal and gas outburst in this paper was used in reference [4], as shown in Figure 1. After the phase space reconstruction of the time series, a nonlinear chaotic model about short term foreshadow prediction was established. As the

method shown in part 2, the embed dimension m and the delay time τ were calculated by using MATLAB program, which m =3 and τ = 2. Then the monitored data were solved by the modified weighted first-order local-region method, because of the space limited we took the last 30 sample points to test. The predicted gas concentration and the error are shown in Figure 2. As it shows, we can get the 75% percent of the foreshadow prediction's error is below 1%, which meets the actual need of production well.

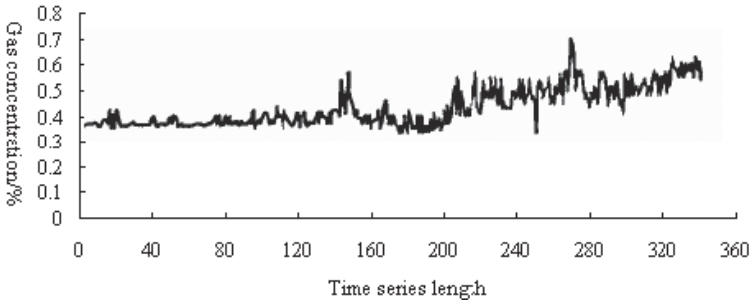

Fig. 1. The curve of gas concentration at working face in danger of coal and gas outburst

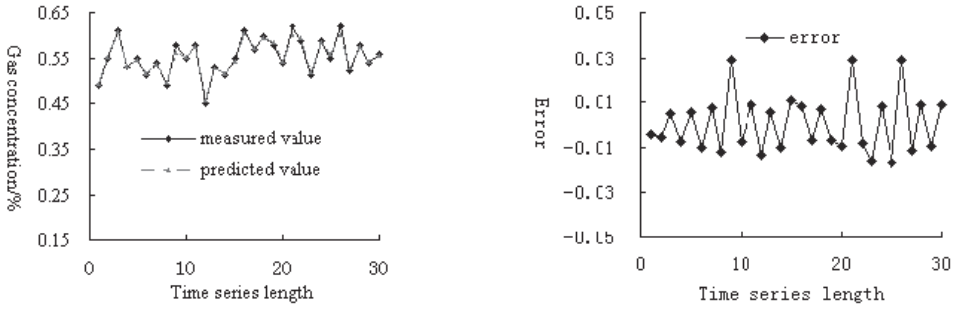

Fig. 2. Prediction results and error of weighted first-order local-region method

5. Discussion and conclusion

This paper represents the weighted first-order local-region prediction method, by which the historical monitored data of gas emission prior to coal and gas outburst was analyzed, and the gas concentration was well predicted for a short-term. The applied results show as follows:

1) The weighted first-order local-region method has a higher prediction precision, and so it is a feasible method for the foreshadow prediction of coal and gas outburst.
2) After the weight pi modified, the prediction model gets more ideal and the predicted results are more suitable to actual need.

3) If the error between the measured value and the predicted value becomes larger, it indicates there are some sudden factors, by which we can find then danger of coal and gas outburst in time. By the way, the longer we predict, the larger the error will be.
4) In order to improve the prediction accuracy, the model can be modified in the future by reconstructing multivariable phase space model, or combining with other prediction methods.

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