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Research on the application of chaos dynamics in coal mine risk prediction

As an extremely complex dynamic phenomenon in coal mine, gas outburst is an urgent problem to be resolved in international mining engineering and engineering mechanics. This paper puts forward the dynamic inversion theory based on the comprehensive hypothesis of coal and gas outburst, which takes the process of coal and gas outburst as a dynamic evolution process. With the aid of chaos dynamics theory, a new prediction method for chaotic time series prediction is creatively proposed and a good fitting effect is obtained.

Keywords: *Coal and gas outburst; dynamic inversion; chaotic time series; prediction.*

Introduction

The frequent coal mine gas explosions in recent years has attracted the attention of a lot of scholars, who have proposed various ways to prevent such accidents (Chen, 2005; Perrone and Amelio, 2016; Qin et al., 2015; Wang et al., 2015; Yassen, 2003; Zhang et al., 2016), It is found in relevant research that the key to preventing coal mine gas explosion is to predict gas outburst. In order to provide information support for the prevention of such accidents, the design plan with smaller frequency of accidents should be selected during the design process to ensure better prevention effects, and the information should be properly extracted during the excavation process for tracking and forecasting (Vallis, 1986; Zhang et al., 2003). According to the research of some scholars, coal mine outburst hazards are distributed regionally, i.e. concentrated in some outburst hazard zones. These areas are not large and generally take up less than 1/5 of the entire mining area (Yassen, 2006; Das, 1988). Targeted prevention against these hazard zones can effectively reduce the significant loss of manpower and material resources. Besides, the high penitence of prevention measures helps reduce the threat on personal safety of miners in these zones, and promote the economic benefits of the coal mine (Uçar, 2003; Huang and Jing, 2011).

At present, there are many modelling methods in the field of risk prediction. One of the major methods is the chaotic time series model, which is mainly founded on the non-linear method. The method can make efficient prediction for some complex systems (Alpigini, 2000; P. Diamond and Pokrovskii, 1994). The principle of chaos dynamics is needed for prediction with this model. As an inherent property of the non-deterministic system, the performance characteristics of chaos are greatly influenced by the initial conditions. One can make high-precision prediction in short term by the corresponding intrinsic determinacy. Under the condition of satisfying chaos, the time series can reconstruct the phase space. On this basis, one can predict the situation for some time to come in the principle of topological isomorphism (Vallis, 1986; Liu et al., 2003). Developed on the basis of the chaos theory, the chaotic time series model rarely produces random errors. The model is very convenient to use. Even the slightest ups and downs are demonstrated when it is used to make a prediction, and only the impact of the model itself needs to be taken into consideration (Dumont and Brumer, 1992; Tusan, 2014). In addition, the predicted results of this model are applicable to the inversion of the coal mine gas outburst, and provide a reference to the determination of the dominant influencing factors on the outburst.

The chaotic dynamics model has many advantages in the prediction of coal mine outburst disasters. Besides, it helps determine the mechanism of coal mine outburst. Its significance goes beyond theoretical innovation. According to the actual prediction effects, the model has positive impact on the work safety of coal mines and brings great economic benefits.

2. Chaotic dynamics inversion model of gas pressure

Before excavation, there is a balance between adsorption and desorption of the gas in the coal. However, if the balance is undermined, gas outbursts will occur. The accidents will also take place when the gas is accumulated to a certain extent (Emadi and Mahzoon, 2012). If the coal rock is damaged much faster than the seepage velocity of gas, there will be a continuous accumulation of gas and increase in gas concentration (Rosenblum, 1993; Dmitriev et al., 2005). When the gas pressure reaches the pressure limit of the coal rock, gas outbursts will happen. To accurately measure how the changing relationship between the factors, a modelling

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analysis is performed as follows.

Set the intensity of pressure of gas on the coal rock as P(t) at time t. As the desorption of gas continues, the pressure intensity will keep rising. Assume there is the following relationship between the pressure intensity and time:

$$\left\{\frac{P(t+\Delta t)-P(t)}{\Delta t}\right\} = aP(t)P(t) \quad \text{...} \quad (1)$$

where *P(t)* is the potential gas pressure, i.e. the pressure intensity at the full desorption of gas; *a* is the increase in pressure intensity within a unit of time.

The pressure intensity can be reduced by the gas seepage and adsorption. The relationship is as follows:

$$\left\{\frac{P(t+\Delta t)-P(t)}{\Delta t}\right\} = bP(t) \quad \text{...} \quad (2)$$

where *b* is the rate of decline in pressure intensity under the action of seepage.

Combine the above two formulas to obtain:

$$\left\{\frac{P(t+\Delta t)-P(t)}{\Delta t}\right\} = aP(t)P(t)-bP(t) \quad \text{...} \quad (3)$$

According to the principle of conservation, the amount of gas is definite at a certain time. Thus, the pressure intensity after all gas is desorbed is also definite, which is denoted with *B(t)*. Substitute *P(t)=B(t)–P(t)* into the above formula.

$$\left\{\frac{P(t+\Delta t)-P(t)}{\Delta t}\right\} = a[B(t)-P(t)]P(t)-bP(t) \quad \text{...} \quad (4)$$

Rewrite the above formula in the form of iteration:

$$P_{n+1} = (aB_n - b + 1)P_n - aP^2{}_n = \mu_n P_n - aP^2{}_n \quad \text{...} \quad (5)$$

where $\mu_n = aB_n - b + 1$.

It can be inferred from analysis that μ_n is a variable. Carry out corresponding variable replacement and let $p_n = ap_n/\mu_n$.

$$p_{n+1} = \frac{\mu^2{}_n}{\mu_{n+1}} p_n(1-p_n) \quad \text{...} \quad (6)$$

Then, make approximate processing.

$$p_{n+1} = \mu_n p_n(1-p_n) \quad \text{...} \quad (7)$$

During actual excavation, if the coal rock is damaged gradually and can be expressed by the formula $\mu_n = aB_n - b + 1$, both B_n and μ_n will decrease continuously under the action of gas seepage. Before the coal rock reaches the pressure limit, if μ_n drops to the interval between 0 and 3, there will be no hazard because the pressure intensity of gas on the coal seam will continue to decrease. However, if the coal seam is suddenly damaged in a short time, the gas pressure will increase exponentially in a brief period due to the weak absorption effect. In this case, *p* will change chaotically if there is no time to cut down μ_n; To a certain extent, gas outbursts will occur when the coal rock reaches the pressure limit. (Gade and Amritkar, 1992; Mukhamedov and Mendes, 2007).

3. Discrimination of chaotic time series

The following examples are given to discriminate the chaotic time series. Targeted at the time series of gas desorption index Δh_2, the author analyzes the chaos of gas. Table 1 lists the measured data on Δh_2 of a coal mine in a certain time. The chaos is analyzed in details as below.

A time series can be determined according to this table, which is denoted as $\{x_1, x_2,..., x_{180}\}$. In order to test the nature of the series, i.e. determine if it is a noise, the constructs the corresponding phase space with the sampling interval of τ, determines the trajectory matrix formed by the time series on this basis, and establishes the principal component diagram of this series by *In(λ/r)* (Fig.1).

The above diagram indicates that the straight lines of the series is not parallel to the x-axis. Thus, the series is not a noise series.

For the purpose of checking the periodicity of Δh_2, the author determines the autocorrelation function first, and then obtains the corresponding power spectrum based on Fourier transform (Fig.2).

There is no obvious peak in the above figure, indicating that the series is a chaotic series.

4. Phase space reconstruction method

4.1 Selection of delay time

In view of the above results, this paper selects the chaotic dynamics tool to determine the corresponding statistics, identifies the delay time in light of the statistics, and uses the mathematical experiment software for simulation analysis. In this way, the author acquires how the variables $\Delta\bar{S}(m,t)$, $\Delta\bar{S}(t)$, $S(t)$, $S_{cor}(t)$ change with the time. (Fig.3)

According to the knowledge of chaotic dynamics, the first null point of the value of $\bar{S}(t)$ corresponds to the delay time τ. Thus, the delay time of this series is determined as τ = 4.

4.2 Selection of multiple dimensions

The classic G-P algorithm is employed to select the number of embedded dimensions. One can use this algorithm to determine the delay time as 4. During the selection of multiple dimensions, the author first sets the number of dimensions at 3, a small value, determines the correlation function, fits the corresponding estimated values, and gets the *Inr* image. After that, the author keeps increasing the number of dimensions and repeats the above operation.

The *Inr* image is shown below as the number of dimensions is increased from 3 to 12. According to this image, the correlation dimension of the attractor remains constant when the number of embedded dimensions is 10. Hence, 10 is chosen as the number of embedded dimensions. In this case, the corresponding correlation dimension is 2.7415.

Therefore, the phase space is constructed with 10

TABLE 1: THE MEASURED DATA ON Δh_2

Time	Δh_2	Time	Δh_2	Time	Δh_2	Time	Δh_2	Time	Δh_2
1	50	11	50	21	40	31	60	41	50
2	50	12	80	22	70	32	60	42	90
3	90	13	80	23	90	33	70	43	80
4	80	14	140	24	120	34	90	44	60
5	110	15	170	25	110	35	100	45	50
6	100	16	20	26	80	36	40	46	70
7	120	17	80	27	80	37	50	47	80
8	30	18	160	28	90	38	90	48	80
9	40	19	190	29	110	39	120	49	110
10	20	20	160	30	130	40	110	50	100
61	70	71	90	81	110	91	50	101	140
62	80	72	90	82	100	92	80	102	120
63	80	73	60	83	90	93	80	103	80
64	90	74	80	84	80	94	120	104	60
65	60	75	80	85	80	95	140	105	110
66	40	76	110	86	70	96	90	106	150
67	50	77	100	87	70	97	80	107	80
68	110	78	80	88	110	98	110	108	60
69	60	79	90	89	100	99	100	109	70
70	70	80	100	90	90	100	120	110	100
111	120	121	120	131	120	141	140	161	100
112	150	122	110	132	140	142	40	162	120
113	110	123	110	133	110	143	90	163	140
114	100	124	90	134	90	144	50	164	110
115	60	125	50	135	90	145	60	165	150
116	80	126	60	136	40	146	40	166	80
117	110	127	70	137	60	147	110	167	110
118	100	128	110	138	110	148	100	168	120
119	140	129	120	139	120	149	40	169	90
120	80	130	110	140	110	160	90	170	90
171	60								
172	60								
173	70								
174	90								
175	110								
176	140								
177	90								
178	120								
179	120								
180	140								

embedded dimensions. Analysis shows there are 144 points in the space. So, the author determines the 145th point in the light of the distribution and trends of these points. The final component corresponding to the point is the value of x_{181}.

4.3 APPLICATION OF CHAOTIC TIME SERIES TO PREDICTION

The points identified through the above operations play an important role in hazard prediction. Moreover, the chaotic time series constructed with these points is applicable to hazard prediction and prevention. x_{181} can also be predicted by mathematical software. During the prediction, there are 10 nodes each on the input layer and the output layer, and 19 in the middle layer. After 200 trainings of the samples, the error is reduced to 0. 0125748 (Fig.5).

$$X_{19}, X_{24}, X_{34}, X_{39}, X_{49}, X_{54}, X_{59}, X_{69}, X_{74}, X_{79}, X_{94}, X_{99}, X_{104}, X_{104}, X_{119}, X_{124}, X_{139}$$

5. Verification by weighted local algorithm

The accuracy of the prediction results can be verified by theoretical calculations. The delay time is still 4 and the

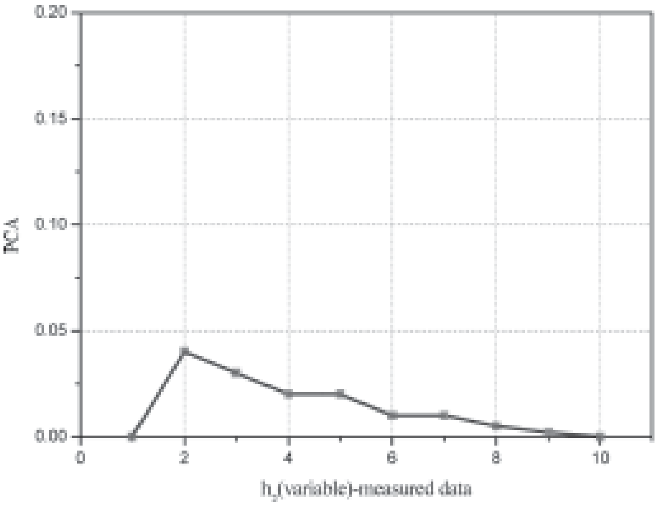

Fig.1 The principal components of the measured data on Δh_2

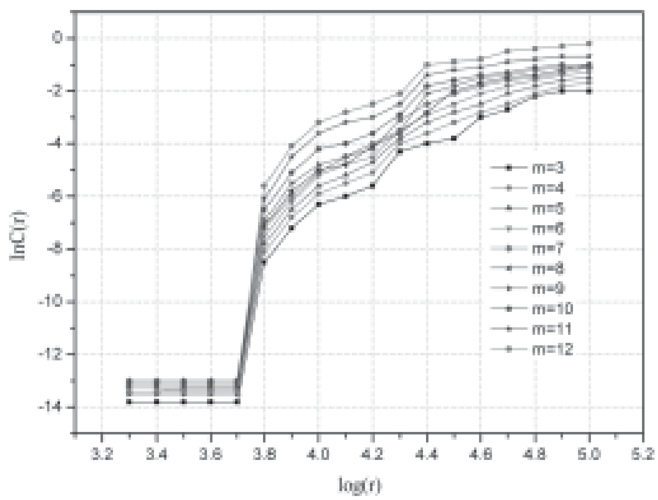

Fig.4 Attractor dimensions and embedded dimensions

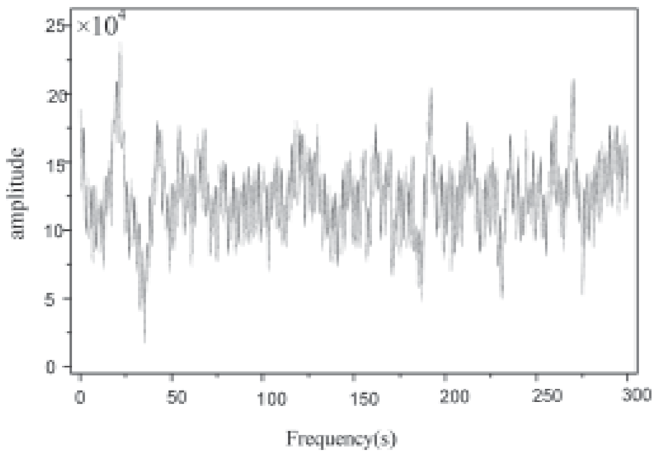

Fig.2 The power spectrum of the measured data on Δh_2

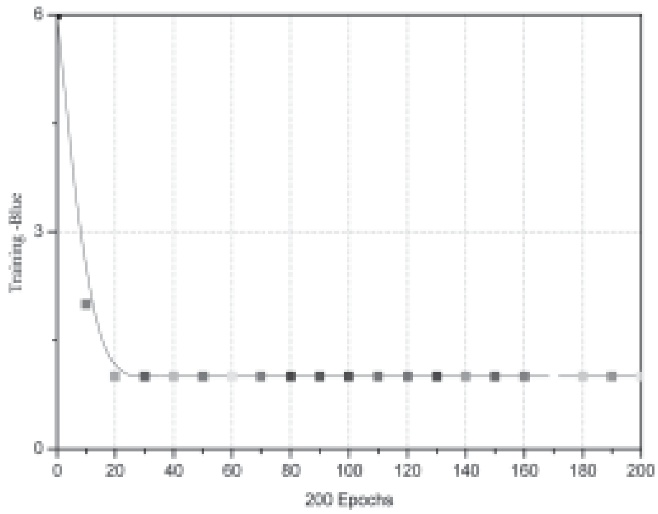

Fig.5 The training error of the time series $\{x_1, x_2,..., x_{180}\}$

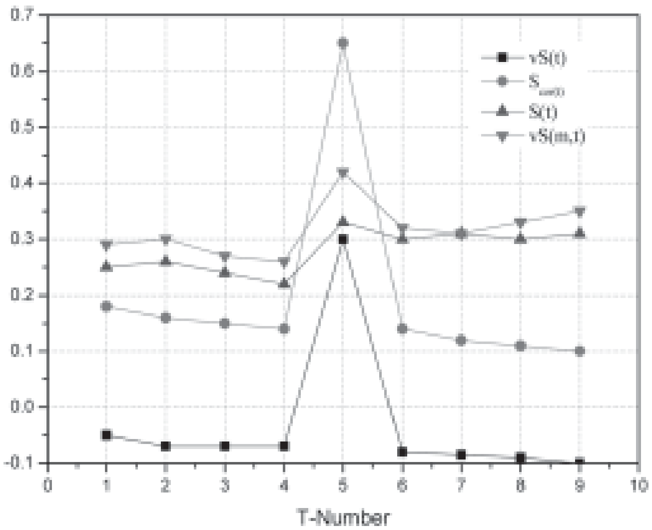

Fig.3 The delay time of the time series $\{x_1, x_2,..., x_{180}\}$

number of embedded dimensions is still 10 during this training. 144 points are identified on the basis of the series, which are denoted by X_1, X_2,..., X_{144} and

i = 1, 2, ..., 144 ... (8)

After that, the author determines the Euclidean distance between these points and the current point X_{144}, and calculates the corresponding average distance. Besides, the author assumes that k is the number of points which are closer to the current point X_N than the average distance, and assigns these points corresponding weights. The nearest point is denoted as X_{N1}, and the next nearest point as X_{N2}…

In view of the above results, it is determined there are 17 points which are closer to the current point X_{144} than d_m, namely

The weight of the points is defined as:

$$P_j = \frac{-l(d_j - d_m)}{\sum_{r=1}^{17} e^{(-l(d_j - dm))}} \quad ... \quad (9)$$

Adopting zero-order weighted local method, the X_{145} is set as:

$$X_{145} = \frac{\sum_{j=1}^{17} X_{Nj} e^{-l(d_j - d_m)}}{\sum_{j=1}^{17} e^{-l(d_j - d_m)}} \quad \text{... (10)}$$

where d_j is the distance between X_{nj} and the current point.

$$X_{145} = \left(x_{145}, x_{149}, ..., x_{181}\right)^T \quad \text{... (11)}$$

Thus, x_{181} can be determined.

Next, the author concludes that x_{181} is 58.9485 by mathematical experiment software.

Comparing the above results, the author finds that the results of chaos dynamics and zero-order weighted local method are in good agreement with each other. Therefore, the predicted value of x_{181} is highly credible, and can be used as a reference for predicting the gas outburst in the future. Since the critical value of Δh_2 is 200, it can be predicted that outburst accident will not occur in the next moment.

It can be seen from the above discussion that the time series analysis based on the proposed method differs greatly from the traditional time series analysis. Whenever the series is determined as chaotic, the proposed method can be used to make the prediction and the results are highly credible.

6. Conclusion

The main conclusions of this paper are as follows:

1. Coal mine gas outburst is a system instability process, which features non-linear characteristics, and complex influencing factors.
2. The corresponding chaotic time series is analyzed by principal component analysis. It is discovered in the analysis that the corresponding signal series is not noise series but chaotic time series. Moreover, this paper calculates the delay time and the number of embedded dimensions m, and obtains the correlation dimension based on the results.
3. The author introduces the zero-order weighted local method in details, and analyzes the application of this model in gas outburst. Numerical calculation by mathematical experiment software proves that the results of the proposed method has high credibility and can provide some reference for the prediction of complex dynamics systems.

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