Study on Prediction Method of CO Overrunning Based on the Inherent Associations of Index Gases Parameters in Renlou Mine

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Abstract

In order to improve the safety of preventing the coal spontaneous combustion fire, the early prediction and initiative prevention for coal spontaneous combustion fire can be achieved by predicting CO overrunning in the process of coal spontaneous combustion. Due to the existing problems of traditional trend prediction method in the process of partitioning data, which include destructing unit integrity isolated prediction data and so on, based on the inherent associations of index gas parameters in Renlou mine, this article established the CO warning level of a working surface, predicted and analyzed the CO overrunning of upper corner airflow at the Ⅱ$8_2$22 face, and proposed segmentation method of feature data, studied the fitting relationship of index gas parameters, and verified the prediction results by combining with related parameters CO/CO_2 and I_{co}, the results showed that data segmentation is reasonable in the process of predicting CO overrunning, effectively extracted feature segments of the CO parameters, which can predict changes of CO concentration in advance and the trend of coal spontaneous combustion, achieved early prediction and initiative prevention for CO overrunning that can result in preventing coal spontaneous combustion fire efficiently. At last, the predicting results proved that the method of predicting CO overrunning is high reliable.

Keywords: COAL SPONTANEOUS COMBUSTION; INDEX GAS PARAMETERS; DATA SEGMENTATION; TREND FITTING; CO OVERRUNNING PREDICTION

0 Introduction

Coal spontaneous combustion not only poses a major threat to the safety production in coal mine, but also may causes serious environmental pollution, casualties and economic losses [1]. In order to effectively prevent and control coal spontaneous combustion, it is necessary to predict the trend of coal seam spontaneous combustion. The change rule of oxygen consumption and generated gas under different temperature usually can be determined by coal samples oxidizing experiment or coal spontaneous combustion simulating experiment, and based on the inherent associations between coal spontaneous combustion temperature and index gases, combined with the actual production conditions predict the coal seam spontaneous combustion trend[2], the CO showed a certain regularity with the temperature changes and can well characterize the process of coal spontaneous combustion oxidation. So if the change trend of index gas CO can be predominated and its deviation state can be estimated before coal seam spontaneous combustion, and it will has important safety sense to prevent coal spontaneous combustion fire.

The method of process parameters trend prediction is that extracting the characteristic fragment from a large number of parameters, and forecasting future trends by certain change rules. The trend of process parameters can reflect the running speed and trend of the important parameters in the operation process [3]. In 1991,Venkatasubramanian and Janusz[4] described the trend of the parameters by defining 7 basic elements; in 2005, Charbonnier, etc. proposed the methods of judging trends by using the combination of three simple elements, which are based on the Janusz's study [5]; In 2010, Song Zhenghui introduced the derivative confidence interval, and improved the robustness and adaptability of the trend identification algorithm [6]; In 2011, Chen Junping proposed an important of trend analysis for step signal [3]. Those methods of process parameters trend prediction is widely used in adaptive control [7], industrial process diagnosis [8-10], mechanical fault diagnosis [11], the stock price trend forecast etc. Due to the continuity of matter state and the effect of parameter deviation each other in the process of coal spontaneous combustion, so the different index gases have certain internal relation in the process of coal low temperature oxidation. Based on the internal correlation of index gases parameters in the process of coal spontaneous combustion, this article forecasted the CO overrunning by studying the fitting relationship of index gases parameters, improving the traditional data segmentation algorithm and posing the characteristics data segmentation method, and the prediction result of the CO overrunning trend were validated through the correlation data, also won the credibility of the results, which will achieve the advanced prediction and prevention of the coal low temperature oxidation spontaneous combustion.

1. Trend prediction

1.1 Characteristics data segmentation

The traditional data segmentation algorithm is to divide specific fixed number of data as the division unit, which destroy the trend unit integrity and affect the accuracy of the trend prediction. The deviation of index gases parameters is mainly divided into step deviation and cumulative deviation in the process of coal low temperature oxidation, and this article posed the data segmentation algorithm by finding the feature points and feature lines, which kept the complete trend features.

Feature points mainly aims at the step parameters that approach the change threshold value, and feature lines mean that the change trend, which caused by the gradually deviation accumulation of index gases parameters.

t is a certain judge time of the parameters, I_t is the parameter value of t. I_{max} is the maximum value for parameters, I_{min} is the minimum value for the parameter, and for $I_h = I_{max}\text{-}I_{min}$, $k_1 = I_2\text{-}I_1$, $k_2 = I_3\text{-}I_2$, $k_{i-1} = I_i\text{-}I_{i-1}$…… . The definition of feature points and feature lines are as follows:

Feature lines: when $\left|\sum_{1}^{i-1} k_{i-1}\right| > 0.2I_h$, the line $I_1 - I_i$ is the feature line.

Feature points: when $|I_i - I_{i-1}| > 0.1I_h$, the point I_i is the feature point.

The corresponding feature points and feature lines can be found through the parameter characteristics, for n=1, data segmentation is performed through the procedure in figure 1:

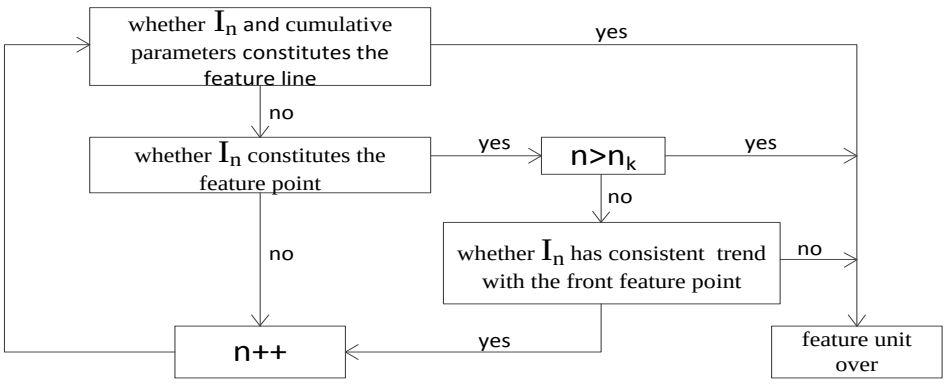


Figure 1. Characteristic data segmentation algorithm

1.2 Trend fitting method

After the feature data segmentation, using a linear fitting function to fit each segmentation part, the coefficient a and b among fitting a linear equation y = ax + b can be calculated by the equation (1) and (2):

$$a = \frac{n\sum_{k=0}^{n-1} x_k y_k - \sum_{k=0}^{n-1} x_k \sum_{k=0}^{n-1} y_k}{n\sum_{k=0}^{n-1} x_k^2 - \sum_{k=0}^{n-1} x_k \sum_{k=0}^{n-1} x_k} \quad (1)$$

$$b = \frac{\sum_{k=0}^{n-1} y_k - a\sum_{k=0}^{n-1} x_k}{n} \quad (2)$$

Compared the function a after fitting with the preset judgment slope a_1 ($a_1 > 0$), simple trend of each division segments can be achieved. If $a > a_1$, belong to rise; If $a_1 > a > -a_1$, belong to stable; If $a < -a_1$, belong to decline.

1.3 Trend prediction method

Based on the law of combination in Table 1, the fitting trend can be combined in turn until the adjacent two trends cannot be combined. The following trends can be achieved through the trend fitting method, which include rise, fall, unchanged, goose-step, negative step, up-under transients, under-up transients and so on. According to the combination results of the last two pieces trend, the future trend of the process parameters can be predicted.

Table 1. Rule of trends combination

	rise	unchanged	fall
rise	rise	rise	under-up
			transients
unchanged	goose-step	unchanged	negative step
fall	up-under transients	fall	fall

1.4 Analysis of CO overrunning trend

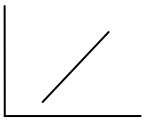
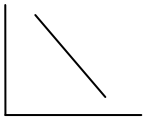
In view of the low alarm threshold value I_{min} and the high alarm threshold I_{max}, for $k = I_{max} - I_{min}$, when the parameter I of a certain time meet the danger parameter scope $I_{max} - 3\%k < I < I_{max}$, I is the danger parameter; when $I_{max} - 3\%k < I < I_{max}$, prediction trend is rise or under-up transients and trigger the high threshold alarm, coal spontaneous combustion trend will further evaluate.

2 Associated validation of index gases parameter

2.1 Association of index gases parameter

In the process of predicting coal low temperature oxidation spontaneous combustion, single index gas (CO) has high associated degree with complex index gases (CO/CO_2, I_{co}, etc.). The coupling of risk factors is strong and has emerged as a whole and so on. In this paper, the related model was established and the fitting relation of parameters was achieved, the prediction results of coal spontaneous combustion trend were mutual verified, the fitting relationship of correlation parameters is shown in Table 2.

Table 2. Fitting relationship of index gas parameters

Serial number	Figure	Concrete relationship	
1		Description	Represent a linear relationship, the reason variable is proportional to the consequence variable.
		Example	The temperature and pressure in ideal gas
		Formula	Y=ax+b(a>0)
2		Description	Represent a linear relationship, The reason variable is inversely proportional to the consequence variable
		Example	The volume and pressure in ideal gas
		Formula	Y=-ax+b(a>0)

The related parameters that correspond the two concrete relationship in Table 2 can be verified by the fitting relationship of index gas parameters in the process of predicting the CO overrunning, for example the relationship between CO/CO_2 or I_{CO} and CO concentration parameter.

2.2 Verification of related parameters

The prediction results of coal spontaneous combustion trend are verified through the process parameters that the consistent correlation, the verification steps are shown in Figure 2. The reliability of the original fault prediction results will be achieved by the verification results of related parameters, and provide judgment basis of coal seam spontaneous combustion state for the field technicians.

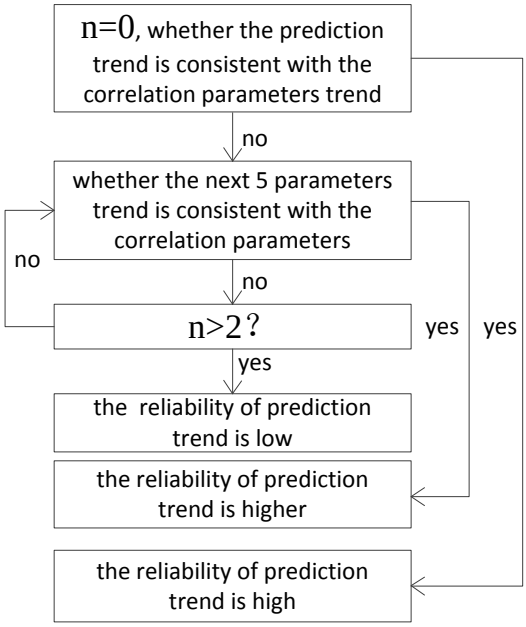


Figure 2. Verification steps of related parameters

3 Case verification of Renlou mine

3.1 CO data verification at the spot

Taking Renlou mine as the study object in this experiment, the temperature programmed experiment revealed the change law of oxygen consumption, carbon monoxide production and other gases in the reaction process of different temperatures and oxygen, and determined the CO as one of the key indicators of coal spontaneous combustion. Combined the temperature programmed experiment and coal spontaneous combustion tendency experiment with actual situation of the scene, the CO warning level of II $8_2$22 working face upper corner at Renlou mine are formulated in Table 3. Beam monitoring index gas CO concentration changes are shown in Figure 3, which are selected from the beam tube observation data that is from July 20th to August 11th , The high alarm threshold of grade I is 10ppm, the high alarm threshold of grade Ⅱ is 15ppm, the high alarm threshold of grade Ⅲ is 20ppm and the high alarm threshold of grade IV is 80ppm.

Table 3. CO warning level of Ⅱ$8_2$22 working face upper corner

Grade	CO concentration of upper corner /ppm	Remark
I	<10	Normal
II	10~15	Hidden danger
III	15-20	May Spontaneous combustion
IV	20-80	Spontaneous combustion
V	>80	May fire

Based on feature data segmentation algorithm, the feature points and feature lines were found, and data segments were determined, the first 9 days CO concentration of beam tube monitoring data were divided into five feature segments: 1-3d, 3-4d, 4-7d, 7-8d, 8-9d. the divided feature segments can be saw in Figure 4, the different colors represent the different segments.

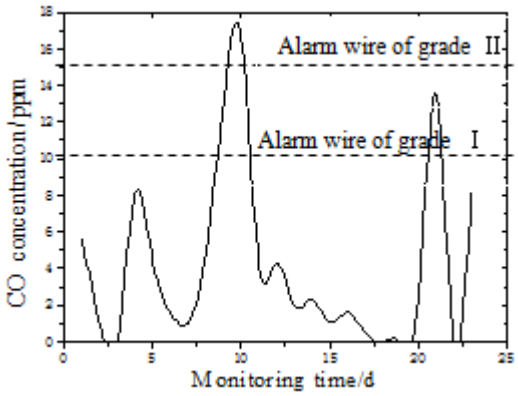


Figure 3. CO concentration within 23 days

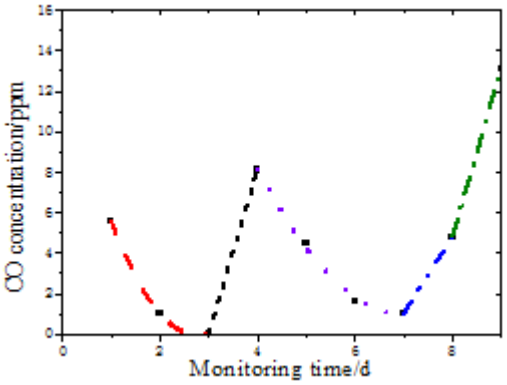


Figure 4. Data segmentation of the first 9 days

Each segment was fitted separately by using a linear fitting function, and the fitting lines of the five segment data are shown in Figure 5, the expression of fitting segments are as follows: *Y1=-2.8x+7.8, Y2=8.1x-24.3, Y3=-2.42x+17.11, Y4=3.8x-25.6, Y5=8.3x-61.6.*

The trend of the five segments that is judged through the fitting line trend is: Y1 is fall, Y2 is rise, Y3 is fall, Y4 is rise, Y5 is rise, and the last two segments trend is rise. The parameter value of the Ninth day is 13.1, which is in the range of danger parameter, so the prediction value of CO concentration will exceed the high alarm line of grade II and its trend is rise.

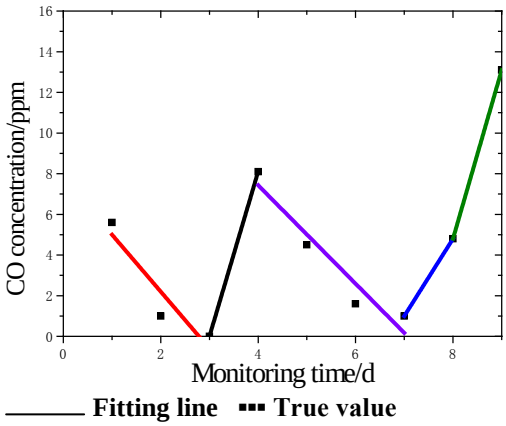


Figure 5. Fitting segment of CO concentration within 10 days

The prediction accuracy of the first 9 days' CO concentration trend was verified by the tenth day's true trend of CO concentration parameters, the Figure 6 and 7 are the feature data segmentation results and its fitting segment of the first 11 days CO concentration parameters. The last feature segment is the 9-10d, the formula of fitting segment is *Y=3.5x-18.4*, the tenth day triggered the alarm wire of grade Ⅱ and the fault trend is rise, which is consistent with the prediction result.

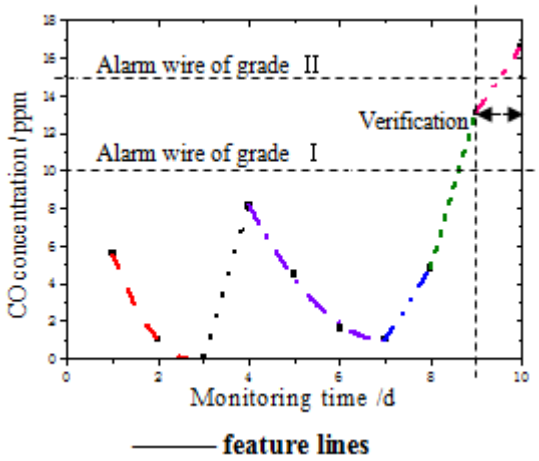


Figure 6. Data segmentation of the first 10 days

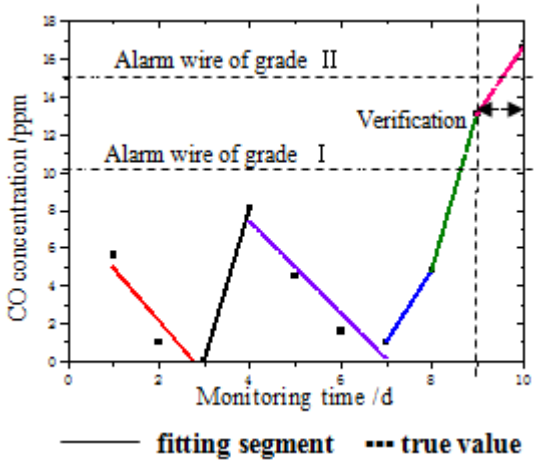


Figure 7. Fitting segment of CO within 10 days

3.2 Verification of related parameters

Based on the judgement procedure in Figure 1, the prediction results of CO

overrunning can be verified by the related parameters that include CO/CO_2 and I_{co}, and the reliability trend prediction results can be judged.

(1) Verification through parameter CO/CO_2

Based on feature data segmentation algorithm, the feature points and feature lines were found, and data segments were determined, the first 9 days' value of CO and CO_2 were handled in the way of CO/CO_2 , and the results were divided into six feature segments: 1-3d, 3-5d, 5-7d, 7-8d, 8-9d, 9-10d.The divided feature segments can be saw in Figure 8, the different colors represent the different segments.

Each segment was fitted separately by using a linear fitting function, and the fitting lines of the five segment data are shown in Figure 9, the expression of the last three fitting segments are as follows:

Y4=0.00199X-0.0131, Y5=0.00169X-0.01073, Y6=0.00102X-0.00463,

The trend of the fitting segments that is judged through the fitting line trend is: Y4 is rise, Y5 is rise, and the last two segments trend is rise, and the last segment trend is rise. Combined with the actual data, the trend of Y6 is rise, which verified the tenth day's trend of CO concentration is rise.

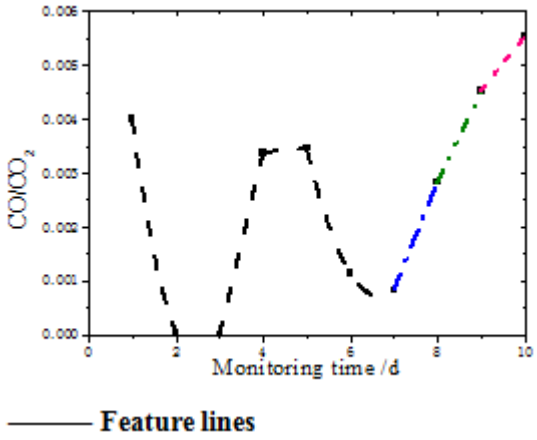


Figure 8. CO/CO_2 data segmentation of the first 10 days

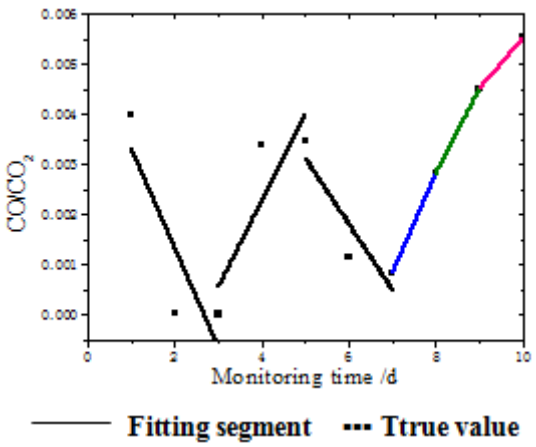


Figure 9. Fitting segment of CO/CO_2 within 10 days

(2) Verification through parameter I_{CO}

Based on feature data segmentation algorithm, the feature points and feature lines were found, and data segments were determined, the first 9 days' value of N_2 and O_2 were handled in the way of I_{CO}, and the results were divided into six feature segments: 1-3d, 3-4d, 5-7d, 7-8d, 8-9d, 9-10d. The divided feature segments can be seen in Figure 10, the different colors represent the different segments.

Each segment was fitted separately by using a linear fitting function, and the fitting lines of the five segment data are shown in Figure 11, the expression of the last three fitting segments are as follows:

Y4=0.00183X-0.01235, Y5=0.00404X-0.02998, Y6=0.00177X-0.00959,

The trend of the fitting segments that is judged through the fitting line trend is: Y4 is rise, Y5 is rise, and the last two segments trend is rise, and the last segment trend is rise. Combined with the actual data, the trend of Y6 is rise, which verified the tenth day's trend of CO concentration is rise.

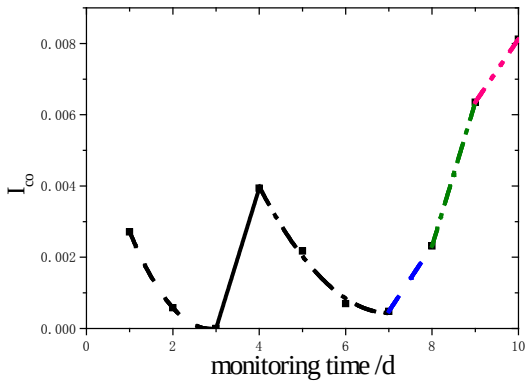


Figure 8. CO/CO_2 data segmentation of the first 10 days

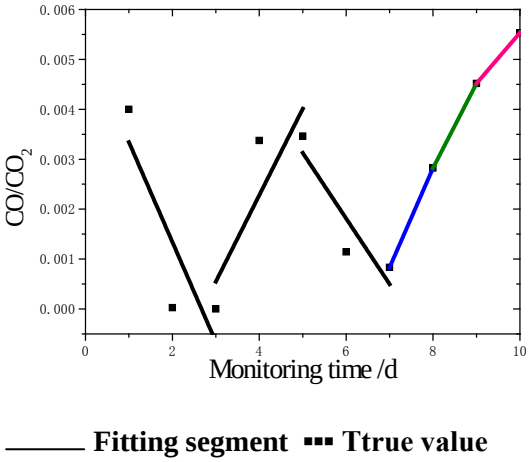


Figure 9. Fitting segment of CO/CO_2 within 10 days

(2) Verification through parameter I_{CO}

Based on feature data segmentation algorithm, the feature points and feature lines were found, and data segments were determined, the first 9 days' value of N_2 and O_2 were handled in the way of I_{CO}, and the results were divided into six feature segments: 1-3d, 3-4d, 5-7d, 7-8d, 8-9d, 9-10d. The divided feature segments can be seen in Figure 10, the different colors represent the different segments.

Each segment was fitted separately by using a linear fitting function, and the fitting lines of the five segment data are shown in Figure 11, the expression of the last three fitting segments are as follows:

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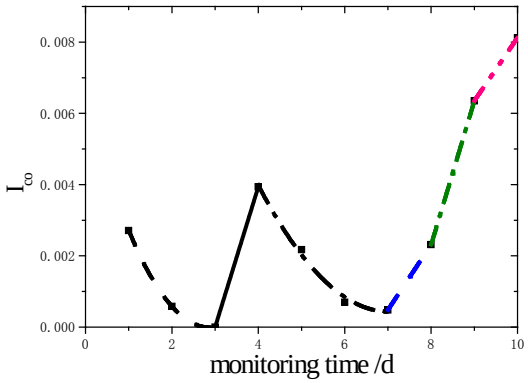

Figure 10. I_{co} data segmentation of the first 10 days

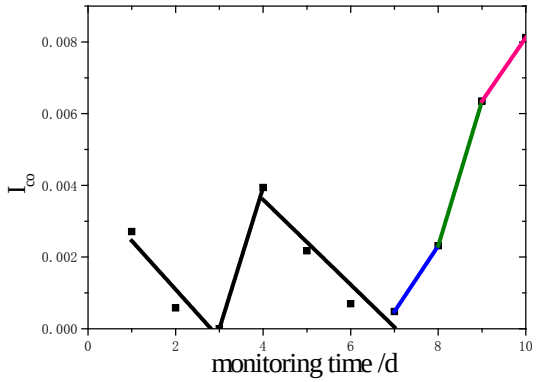

Figure 11. Fitting segment of I_{co} within 10 days

In summary, based on the change trend of the coal spontaneous combustion index gas CO, combined with the judgement procedure, the CO overrunning prediction results were verified by predicting the trend of related parameters that include CO/CO_2 and I_{co} and judged the reliability of trend prediction. According to the fitting results of related parameters, the reliability of the prediction trend of the tenth day's CO overrunning is high, which triggered the alarm wire of grade Ⅱ at the upper corner of Ⅱ$8_2$22 working face.

4. Conclusions

In this paper, the trend prediction method of traditional process parameters is improved, which the data is segmented reasonably and the feature points and feature lines are extracted by using the special data

segmentation method, then the fitting relationship of predicting CO overrunning was achieved. At the same time, based on the alarm information, the trend of coal spontaneous combustion is predicted accurately, and the reliability of predicting CO overrunning by using this trend prediction method is high, which is verified by the related parameters CO/CO_2 and I_{co}. This method can predict CO overrunning trend in advance, and improve the accuracy of predicting CO overrunning trend, which is of great significance for preventing coal spontaneous combustion fire.

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