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Application of Electronic Nose Technology in Coal Mine Risk Prediction

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Coal resources are an important strategic resource in China. The safety situation of coal production is quite serious, and the foundation of coal mine risk prediction is weak. In this paper, the identification and concentration detection of CO and CH_4 released during coal oxidation or oxidative spontaneous combustion are detected by electronic nose (e-nose) gas sensing technology. The influence of temperature and humidity on gas sensors is studied, and the correlation between the degree of coal oxidation and the output frequency of gas sensors is analyzed. The experimental results show that the sensitivity of the five kinds of e-nose gas sensors to CH_4 is almost the same as that of CO, and the sensitivity of 112AJ sensor is the best. The e-nose gas sensors can capture the tiny changes of odor release in the initial stage of coal oxidation, and the artificial neural network analysis method is applied to the gas sensor array, which greatly improves the ability of coal mine risk prediction.

1. Introduction

Coal mine risk refers to the risk that occurs in the production scope of coal mining enterprises and may cause losses in personnel, property, environment or equipment, and the Fire and gas explosion are the causes of major accidents (Chen et al., 2016; Sun et al., 2018; Palei et al., 2009; Yang et al., 2018). There are countless gas explosions in the coal industry around the world. With the increase of mining depth, the increase of mining intensity and the emergence of high-yield and high-efficiency working faces, the danger of underground coal mines is increasing (Ghasemi et al., 2014). Early mine risk prediction and forecasting are important measures to avoid risks, and they are increasingly favored by scholars from all over the world (Mohapatra et al., 2015, Lorenzen et al., 2013; Song, 2018). Anomalous temperature in the coal mine, release of CO gas or special odor can be used as a sign to judge the occurrence of danger. When the temperature reaches a certain point or the gas concentration reaches a certain value, the danger will occur under the interaction of the two (Li et al., 2016).

Currently, the main detection methods for coal mine risks include gas analysis, temperature measurement method, photoelectric method, ionization method, smoke method and magnetic prediction method, etc. (Aghababaei et al., 2015; Christopher et al., 2016; Zuo, 2018). With the development of e-nose sensor technology, e-nose sensor technology can clearly determine the concentration of each gas, combined with the temperature measurement method, we can grasp the actual situation of underground coal mine in real time, so as to realize early detection, early warning and early processing, and avoid the occurrence of coal mine risk accidents (Liang and Wang, 2017). Sensors used in e-nose testing technology include metal oxide sensors, conductive sensors, piezoelectric sensors, field effect sensors, and optical fiber sensors. Among them, metal oxide sensors are the most widely used sensors (Zhang et al., 2016). In view of the situation of frequent coal mine risk occurrence, this paper uses e-nose technology to detect the gas in underground coal mines, and uses the temperature measurement method to predict the underground coal mine risks. The application of e-nose technology is of great significance to coal mine safe production.

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2. Gas product characteristics during calefactive oxidation of coal

2.1 Formation law of gas products during calefactive oxidation of coal

The gas products of spontaneous combustion of coal include coal spontaneous combustion oxidizing gas and coal spontaneous combustion adsorption gas, and the main gas components are methane and carbon dioxide (Jin et al., 2016; Qi et al., 2014). Due to the low concentration of air and oxygen, CO is first generated in the process of oxidation, the formation of CO runs through the whole process of coal oxidation or spontaneous combustion. It has been found that there is a single incremental relationship between the oxidation temperature of coal and the concentration of CO gas, and it satisfies the exponential relationship (Oraee et al., 2016). Figure 1 shows the relationship between the CO incidence rate of typical coal samples and coal temperature. It is obvious that the CO incidence rate is very small before 100 °C, when the temperature exceeds 150 °C, the CO incidence rate increases rapidly. Furthermore, the critical temperature values of CO for lignite and gas coal are lower, followed by long flame coal and fat coal, and the coal with the highest critical temperature value is the lean coal. In addition to CO, the presence of olefins and alkenes can be detected, and olefin gases are produced by the oxidative decomposition process of coal.

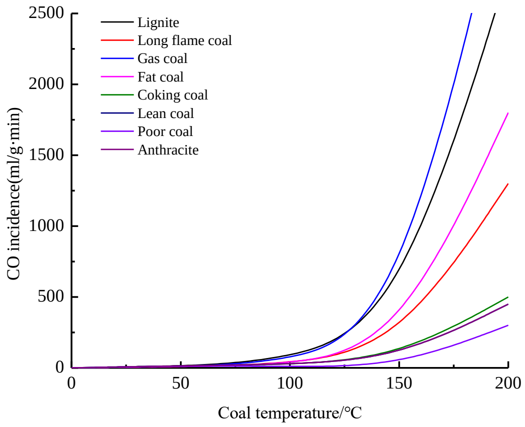


Figure 1: The relationship between the incidence rate of CO in typical coal samples and coal temperature

2.2 E-nose gas sensors and their influencing factors

E-nose gas sensors are various in types and functions. In order to identify the types of gas in coal mines and to determine their concentrations, for the e-nose sensors (Daniels et al., 2016), this study selects five different types of sensors (models including 151AJ, 183AK, 353AN, 453AA, and 112AJ). Humidity has a great influence on the e-nose gas sensors. Figure 2 shows the influence of moisture on the e-nose gas sensors. It can be seen that the e-nose sensors have a linear relationship with humidity. The linear slope of the 112AJ gas sensor is larger, it's more sensitive to humidity, followed by 353AN gas sensor, 453AA gas sensor, 183AK gas sensor and 151AJ gas sensor. Therefore, ensuring humidity environment of underground mine is very important for the e-nose gas sensors.

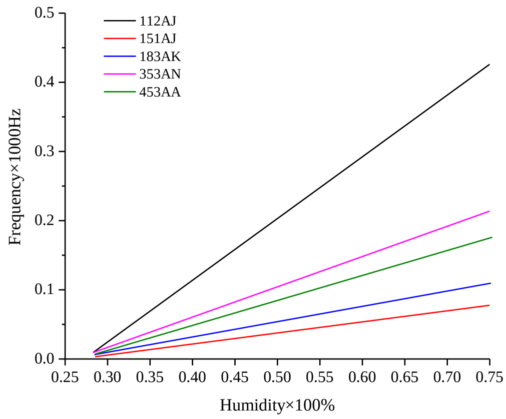


Figure 2: Influence of humidity on e-nose sensors

3. Detection experimental conditions of e-nose gas sensors

3.1 The sensitivity of e-nose sensors to single component of typical fire gas

The oxidation of coal is an important source of gas. The gases produced include CO, CO_2, CH_4, etc., among which CO and methane are colorless and odorless gases. The human sense of smell cannot measure the diffuse air component in space, therefore we must rely on the e-nose gas sensors. Figure 3 shows the sensitivity curve of the e-nose gas sensors for the single component of CO. It can be clearly seen that the sensitivities of the 151AJ, 183AK, 353AN and 453AA gas sensors are roughly equal, and the sensitivity is much smaller than that of the 112AJ sensor. Figure 4 shows the sensitivity curves of the e-nose gas sensor for the single component of CH_4. The sensitivities of each e-nose gas sensor to CH_4 are roughly the same as that of CO. The curve is roughly divided into three segments: steeper curve segment – smooth middle curve segment – steep curve segment.

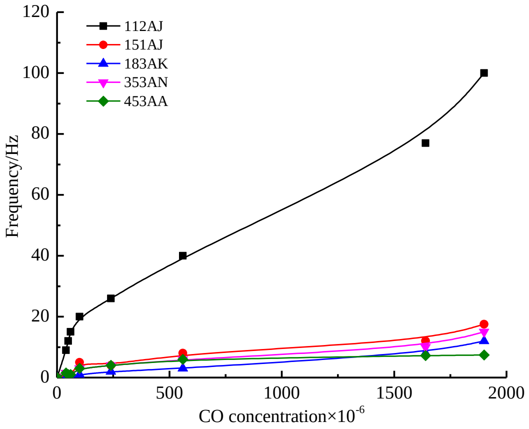


Figure 3: E-nose gas sensor sensitivities to the single component of CO

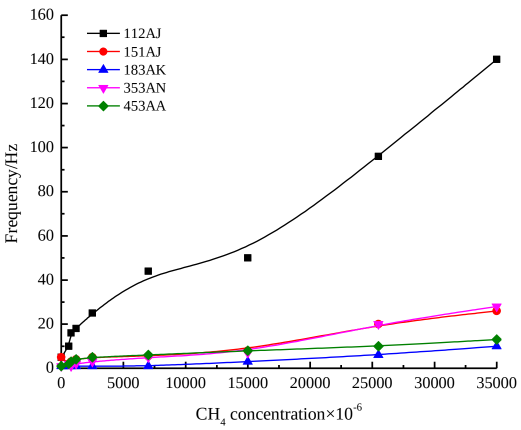


Figure 4: E-nose gas sensor sensitivities to the single component of CH_4

3.2 E-nose detection experimental conditions

The e-nose detecting device of this test includes a flow controller, a program temperature control box, a coal sample chamber, and a gas sensor. During the experiment, the particle size of the coal sample was selected to be 30-60 mesh, the weight of the coal sample was 40 g, and the gas supply amount was 100 ml/min. Pre-drying the coal sample will result in distortion of the experimental results, if the pretreatment is not performed, the water will be dissipated during the heating process, resulting in a large humidity affecting the sensitivity of the gas sensor. Figure 5 is the coal sample program heating curve. The experiment process first raises the room temperature to 30 °C, then stabilizes for 5 min. When the odor component of the gas flowing out of the coal sample chamber is the same as that of the gas-collecting vessel, the temperature rises to 150 °C. In the experiment process, it is necessary to ensure that the coal sample tube connection gas path is sealed. After the experiment is completed, the gas path and the temperature control box power supply should be cut off, the coal sample tube should be taken out, and the equipment should be cleaned with clean water for later use.

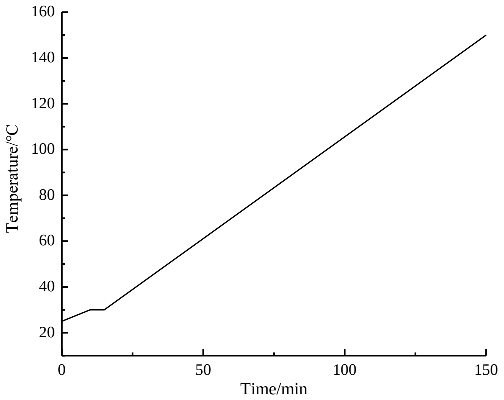


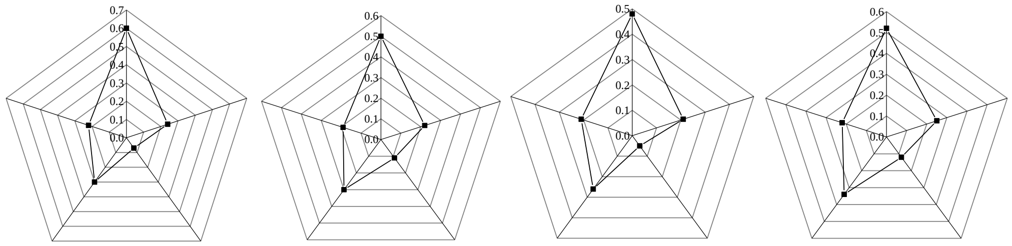
Figure 5: Coal sample program heating curve

4. Gas sensing characteristic parameters during coal heating process

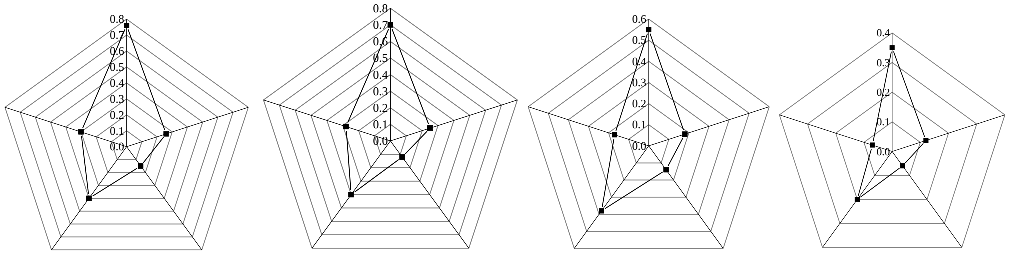
4.1 Radar image characteristics of e-nose sensors

Table 1: Gas sensitivity characteristic parameters of representative coal samples with different coal qualities

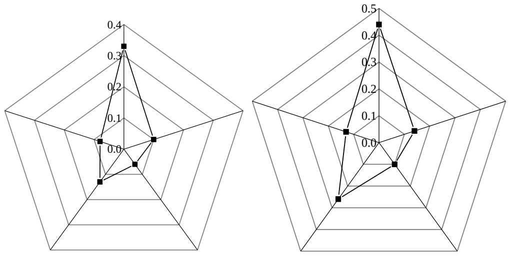
Curve characteristics	Lignite coal					Gas coal		Coking coal	Lean coal	
	1#	2#	3#	4#	5#	6#	7#	8#	9#	10#
Rising starting temperature	36	30	26	33	19	26	30	33	23	41
First inflection point	44	38	38	43	27	27	39	54	60	54
Second inflection point	57	85	79	86	76	73	74	—	—	—



(a) 1# Coal sample (b) 2# Coal sample (c)3# Coal sample (d) 4# Coal sample



(e) 5# Coal sample (f) 6# Coal sample (g) 7# Coal sample (h) 8# Coal sample



(i) 9# Coal sample (k) 10# Coal sample

Figure 6: Radar images of e-nose gas sensor output frequency at 110°C for test coal sample /KHz

In this test, 10 coal samples from different coal mine producing areas in China were selected, of which 1#-5# coal samples were lignite, 6# and 7# coal samples were gas coal, 8# coal sample was coking coal, 9# and 10# coal samples were lean coal. Using the e-nose gas sensors to conduct heating oxidative odor detection and gas analysis experiments on the 10 coal samples, there will be two inflection points in the whole sensor output frequency process. Table 1 shows the gas sensitivity characteristic parameters of representative coal samples with different coal qualities, it can be seen that the initial temperature of the coal sample is not much different from the temperature of the first inflection point. After the first inflection point temperature appears, the frequency of the gas sensor increases rapidly; coking coal and lean coal do not show obvious second inflection point temperature, the curves of lignite and gas coal tend to be gentle after the second inflection point temperature. Figure 6 are radar images of the output frequency of the e-nose gas sensors at 110 °C. It can be seen that the radar images of the output frequency of the five gas sensors are similar, and the 10 experimental coal samples have large differences, their radar images are quite similar, and the shapes of the radar images don't change regularly with the coal samples.

4.2 Artificial neural network identification technology for odor detection of coal mine risk prediction

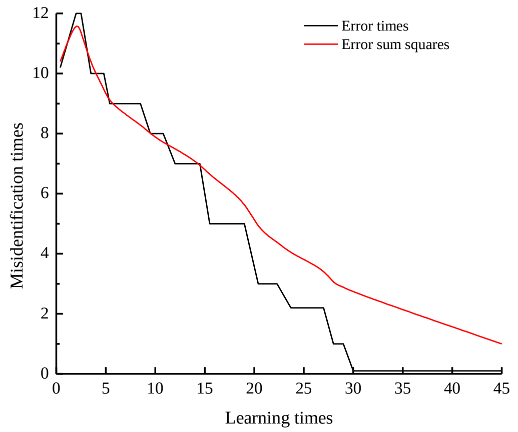


Figure 7: Misidentifications, squared error sums, and learning times

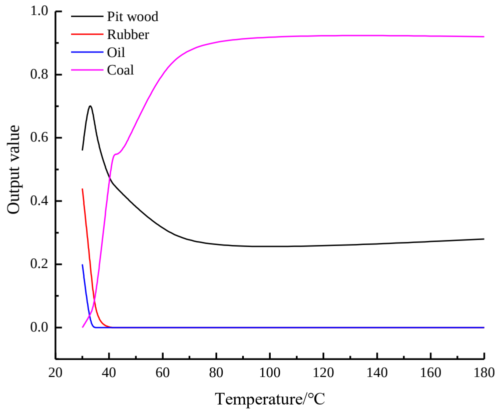


Figure 8: Coal test neural network analysis output value curve

By judging the output frequency of the e-nose gas sensors, the concentration changes of the gas in the coal mine can be judged, and the odor characteristics of different materials can also be analyzed. Applying the artificial neural network analysis method to the gas sensor array can greatly improve the prediction ability of coal mine risks (Kadri O., Mouss, 2017; Ren, 2017). When applying neural network analysis method identification technology, the more the number of learning times, the higher the accuracy of recognition. Figure 7 shows the relationship between the number of misidentifications, the sum of squared errors and the number of learning times. It can be seen that when the number of learning times exceeds 30 times, the number of misidentifications approaches zero. In order to judge the application of artificial neural network identification technology in gas sensor arrays, coal, rubber, wood and engine oil were used as experimental samples, and the gas sample test method was the same as the coal sample test method. Figure 8 shows the output curve of the coal test neural network analysis. It can be seen that when the temperature is higher than 40 °C, the odor of the coal is completely different from that of wood, rubber and engine oil, and the coal can be completely recognized.

5. Conclusion

In this paper, the e-nose technology is used to detect the gas in the underground coal mine, and the temperature measurement method is used to predict the underground coal mine risks. The specific experimental conclusions are as follows:

(1) The sensitivity of the e-nose gas sensors to CH_4 is roughly the same as that of CO. The curve is roughly divided into three segments: steeper curve segment – smooth middle curve segment – steep curve segment.

(2) The radar images of the output frequency of the five kinds of e-nose gas sensors are similar. The 10 experimental coal samples have large differences, and the radar images are quite similar. The shapes of the radar image don't change regularly with the coal samples.

(3) The artificial neural network analysis method is applied to the gas sensor array, which can greatly improve the prediction ability of coal mine risks. When the coal temperature is higher than 40 °C, the odor is completely

different from the smell of wood, rubber and engine oil, and the coal can be fully recognized.

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