Local Economic Cost Sensitivity Analysis in the Application of Gas Emission

Shun Zhou[1], XiaoGuang Yue[2*], ShunLi Zhao[2]
1. School of Economics, Wuhan University of Technology, Wuhan 430070, China;
2. Department of Safety Science and Engineering, Wuhan University of Technology, Wuhan 430070, China
*email: xgyue@live.com

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Abstract. It is difficult to measure the change amount of the factorsIt is difficult to measure the change amount of the factors. In order to solve this problem, local economic cost sensitivity analysis is proposed. The method is a combination of neural network, sensitivity analysis, and economic cost disturbance. First, the nonlinear relationships between input and output variables with neural network for specific engineering are established. Second, same economic cost disturbance to each attribute of input variables is added. Third, the average amount of change of the output variables as the sensitivity coefficient of the input variables attributes is taken. Finally, by application in terms of Gas Emission, result validated that the method is effective.

Introduction

Sensitivity analysis is a method that can be quantitatively used to describe the degree of importance of model input variables to output variables [1]. In practical application, it can give priority to the attribute with large sensitivity coefficient. Currently, the sensitivity analysis has been widely applied to mineral engineering, such as mining rights assessment, slope stability, gas pressure and other fields [2-4].

In the practical engineering, in order to solve the problem that it is difficult to determine the nonlinear relationship between input variables and the output variables, and construct and develop a sensitivity analysis based on neural network [1]. Neural network is widely used in the mineral engineering. In the study of gas, the neural network is applied to the prediction model of gas emission, gas permeability and gas content [5-7]. However, sensitivity analysis based on neural network is seldom used in the mineral engineering.

Sensitivity analysis is divided into local sensitivity analysis and global sensitivity analysis, and the most extensive application is local sensitivity analysis. At present, the widely used sensitivity analysis has the problem that it is difficult to measure the change amount of the factors. For example, in the literature [4], each input variable attribute was changed 10%. The difficulty of each input variables attribute change 10% is not the same, so the calculated sensitivity coefficient will reduce the guiding significance for engineering. Engineering activities are economic activities. In order to allow the disturbance of different input variables attribute comparable, this paper introduced the concept of economic cost and took output variable amount of change under each attribute in the same economic cost disturbance as the attribute's sensitivity coefficient.

Local Economic Cost Sensitivity Analysis

The local sensitivity analysis introduction economic cost is called local economic cost sensitivity analysis. Different from the traditional economic sensitivity analysis, object of local economic cost sensitivity analysis is not an economic system. In order to measure the difficulty of changing the input variables, introduced economic cost into sensitivity analysis.

Assumed that an engineering model output variable is y and input variable is $x_1, x_2 .....x_n$ .Non-linear relationship between the input variable and output variable is $y = f(x_1, x_2 .....x_n)$ .The non-linear relationship could be obtained by neural network training.

For the attribute i, the relationship between the amount of change a_i of x_i and economic cost disturbance b could be expressed by the following equation:

$$a_i = f_i(b) \tag{1}$$

When $b = 0$, a_i =0. When the economic cost disturbance value is small, in order to facilitate data processing, the relationship between the amount of change a_i and economic cost disturbance b could be seen as linear relationship.

First, in order to calculate the sensitivity coefficient, generated a set of small economic cost disturbances $b_1, b_2 .....b_k$, obeyed Gaussian distribution. Also, the researchers used the following equation to produce a $n \times k$ matrix.

$$a_{ij} = f_i(b_j) \tag{2}$$

The $n \times k$ matrix is shown below:

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & \ddots & & \\ \vdots & & \ddots & \\ a_{n1} & & & a_{nk} \end{bmatrix}$$

For the attribute i, the disturbance is $a_{i1}, a_{i2} .....a_{ik}$ .when the value of attribute x_i is change, the values of output become $y_{i1}, y_{i2} .....y_{ik}$. The output values could be obtained by the following equation.

$$y_{ij} = f(x_1, x_2 ...(x_i + a_{ij})..x_n) \tag{3}$$

The local economic cost sensitivity coefficient of attribute i is as follow:

$$S_i = \frac{\sum_{j=1}^{m} |y - y_{ij}|}{m} \tag{4}$$

Local economic cost sensitivity coefficients calculated by the above formula can more accurately describe each attribute of the model's the degree of influence for the model, and can give priority to the attribute with big local economy cost sensitivity coefficient in engineering activities.

Practical Application

Generalized regression neural network training. To further demonstrate the applicability of the local economic cost sensitivity analysis, this paper selected data from the literature [5] concerning the gob gas emission amount. Factors included the seam gas content, coal thickness, recovery coefficient, and mining intensity. The nonlinear relationship between the various factors and gas emission by the generalized regression neural network training and learning is mapped. The specific gas emission data are shown in Table 1.

Table 1 The Specific Gas Emission Data

No.	seam gas content /(m3•t)	coal thickness/(m)	recovery coefficient	mining intensity/(t•d-1)	gas emission/(m^3•min^{-1})
1	1.92	2.0	0.960	1825	0.18
2	2.15	2.0	0.950	1527	0.19
3	2.14	1.8	0.950	1751	0.15
4	2.58	2.3	0.950	2078	0.20
5	2.40	2.2	0.940	2104	0.26
6	3.22	2.8	0.930	2242	0.29
7	2.80	2.5	0.940	1979	0.25
8	3.35	2.9	0.930	2288	0.35
9	3.61	2.9	0.920	2325	0.38
10	3.68	3.0	0.940	2410	0.37
11	4.21	5.9	0.795	3139	1.14
12	4.03	6.2	0.812	3354	1.20
13	4.34	6.1	0.785	3087	1.27
14	4.80	6.5	0.773	3620	1.39
15	4.67	6.3	0.802	3412	1.38
16	2.43	2.2	0.950	1996	0.22
17	3.16	2.7	0.930	2207	0.30
18	4.62	6.4	0.803	3456	1.36

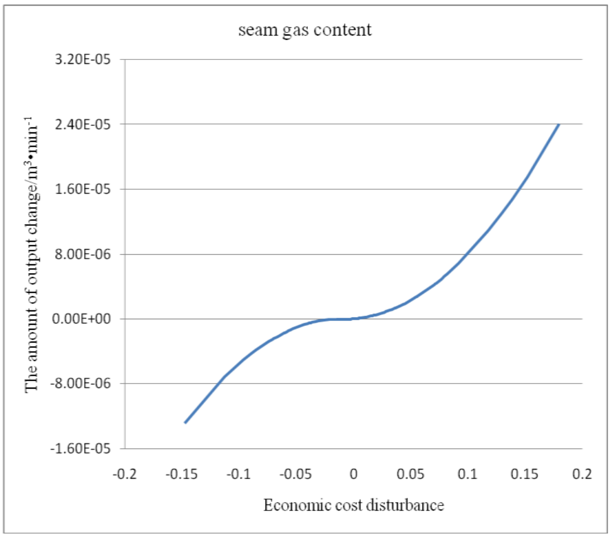
Set the top 15 data in Table 1 as the training data set, and the remaining three groups as training data. This paper uses MATLAB software generalized regression neural network function to write procedures and take smooth factor as 83. The training results are shown in Table 2.

Table 2 Gas Emission Training Result

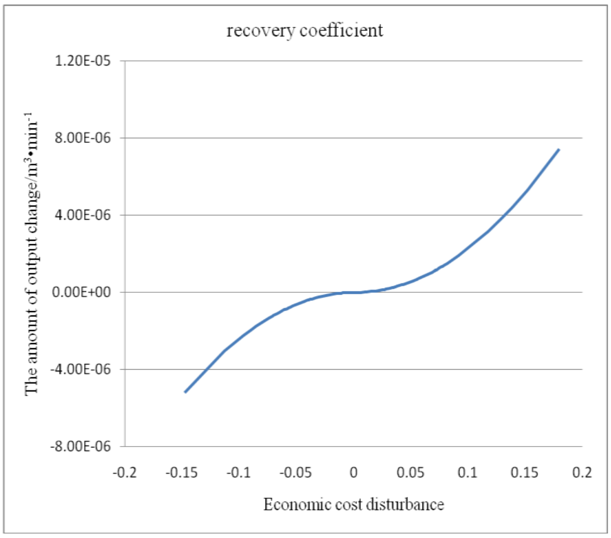
NO.	16	17	18
Actual Gas Emission /（m3•min-1)	0.22	0.30	1.36
Predicted /(m3•min-1)	0.2068	0.2990	1.3589
Absolute Error	0.0132	0.0010	0.0011
Relative Error (%)	6.00	0.33	0.08

As can be seen from Table 2, the prediction error of 16th group is the largest, 6%. In the other two groups, the prediction errors are below 0.5%. The average relative error is 2.14%. The correlation coefficient R is 0.999958. Generalized regression neural network showed higher prediction accuracy.

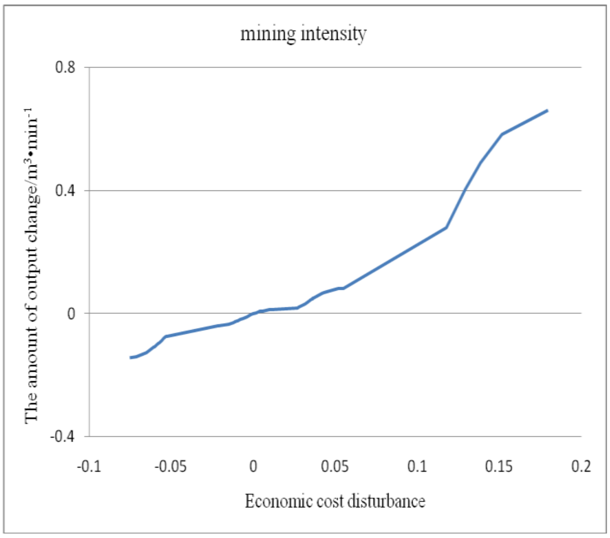
The calculation of local economic cost sensitivity coefficient. Researchers took the 17th group data as the analysis object, produced 100 groups perturbation economic costs date, and the data obeyed Gaussian distribution whose expectation was 0 and the variance was 0.05. Assumed that the relationship between the amount of change a_i and economic cost disturbance b was linear relationship, and was $a_i = cbx_i$ where, c is a constant. The coal thickness was a determined value, and the constant value c was 0. According to the actual situation, this paper proposed the reasonable assumption that the constant value c of seam gas content, recovery coefficient and mining intensity were 3, 2, and 1. Results were shown in Fig. 1(a, b, c) and Table 3.



a



b



c

Fig. 1 Relationships between the Amount of Output Change and Economic Cost Disturbance

Table 3 Local Economic Cost Sensitivity Coefficient

	seam gas content	coal thickness	recovery coefficient	mining intensity
sensitivity coefficient	2.3790e-06	0	7.8855e-07	0.0671

As can be seen from Table 3, Fig. 1, the local economic cost sensitivity coefficient order: mining intensity> seam gas content> recovery rate> seam thickness. If didn't consider the economic costs, there must be a sensitivity coefficient of seam thickness, but there was no guiding significance on actual engineering.

Summary

In the future, researchers can try to use a new method for this research, such as opposite degree algorithm [8]. OD algorithm is a useful way for numerical prediction and classification prediction. Right now, combined with the neural network, sensitivity analysis, the economic cost of disturbance, put forward the concept of local economic cost sensitivity analysis. The specific theoretical derivation is given. This research avoided the problem different attributes the amount of change difficult to measure. Through the application of the gas emission, this paper proved the effectiveness of the method. Through the analysis, the following conclusions could be drawn:

(1) The nonlinear relation between the input variables and output variables could be effectively established with the generalized regression neural network. Through the practical prediction of gas emission, the average relative error is 2.34% and the correlation coefficient is 0.999958. The result shows a high precision.

Local economic cost sensitivity analysis is better in practical engineering significance. It can solve the problem that it is difficult to measure the change amount of the factors.

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