Research On Production Classification Of Coalbed Methane Well Based On MATLAB

Yifang Tang*, Tianxiang Zhang, Zixi Guo, Weiping Zhu, Pengbo He

1PETROCHINA CBM Institute Of Engineering Technology, Xi’an, Shanxi, 710082, China
2School of Sciences, Southwest Petroleum University, Chengdu, Sichuan, 610500, China
3State Key Laboratory of Oil and Gas Reservoir Geology and Exploitation, Southwest Petroleum University, Chengdu, Sichuan, 610500, China

*Corresponding author’s e-mail: tangyifang_swpu@163.com

Abstract. China's coalbed methane resources are very rich, but the coalbed methane mining effect is not good. Fracturing is an important means of coalbed methane mining. It is very important to select coalbed methane wells with mining value before fracturing. For most fracturing wells in China, CBM wells are selected according to the experience of the site and workers. It has blindness and increases the cost of coalbed methane mining. In order to reduce the loss, this paper proposes a prediction model based on support vector machine coal fracturing effect. First, pretreatment studies of fracturing well data are performed to ensure the quality of fracturing well data. Secondly, the gray correlation analysis is carried out on the pre-processed fracturing well data, and eight main controlling factors affecting the coal cracking effect are extracted. Finally, using the support vector machine classifier, the coalbed methane wells are divided into three categories: low-production wells, middle-production wells and high-production wells. At the same time, the support vector machine nonlinear regression model is used to predict the stable production of coalbed methane wells. Using the support vector machine model to predict, predict the stable production value of coalbed methane wells is basically consistent with the field data, which has important guiding significance for on-site coalbed methane mining.

1. Introduction

China's coalbed methane resources are very rich, but the domestic coalbed methane production is not high. It is of great significance to effectively exploit coalbed methane and effectively improve the shortage of other resources in China.

Some researchers at home and abroad have done a lot of research on how to perform fracturing well selection before fracturing, and established different fracturing well selection methods. By processing and analyzing the data, Calabrese found that there is a certain regularity between the properties affecting fracturing well selection and the effects after hydraulic fracturing. By establishing a BP neural network prediction model, it is found that the predicted post-fracture yield is not much different from the actual post-fracturing yield [1]. Robert F. Shelley has done a lot of research on the many influencing factors affecting fracturing well selection, and selected important properties for fracturing well selection, and found that they have different effects on fracturing well selection. Emphasis will be placed on the classification and prediction of fracturing well selection by artificial neural networks [2]. After analyzing
the main controlling factors affecting fracturing well selection, Yanxue Jiang and others used the fuzzy identification model to select the well layer with hydraulic fracturing value. The results show that the predicted oil production after fracturing is compared with the actual one. With a good accuracy rate [3].

This paper analyzes the mathematical analysis method of gray correlation degree, and optimizes the main controlling factors affecting the production of coalbed methane wells. Based on the preferred parameters, combined with the support vector machine model, the coal seam cracking effect prediction is formed. Finally, the classification of coalbed methane wells is completed. Gas wells are divided into three categories: high-yield wells, middle-production wells, and low-yield wells.

2. Related theory and algorithm

2.1 Principle of grey correlation analysis
Grey correlation analysis is a method for gray system to analyze and process random quantities [4], and it is also a data-to-data mapping method. Let the parameters of the primary selection be \( x_i \) after data preprocessing such as data quantification, missing data replenishment, and data normalization. And note that the correlation coefficient of the data \( x_j \) to the target data \( x_i \) to be studied is \( \zeta_{ij}(k) \), where \( k \) represents the sampling point where the data \( x_j \) is related to the data \( x_i \), and the total number of sampling points is \( n \), then the correlation coefficient can be expressed as:

\[
\zeta_{ij}(k) = \frac{a_{ij}(k) + \rho \cdot a_{\text{max}}(k)}{a_{\text{min}}(k) + \rho \cdot a_{\text{max}}(k)} \quad (k = 1, 2, \cdots, n)
\]

In the middle, \( a_{ij}(k) = |x_i(k) - x_j(k)| \); \( a_{\text{min}} = \min_{j} \min_{k} a_{ij}(k) \); \( a_{\text{max}} = \max_{j} \max_{k} a_{ij}(k) \); \( \rho \) is a constant between \([0, 1]\), which is generally 0.5 in the application. Thus, the degree of association \( \gamma_{ij} \) is:

\[
\gamma_{ij} = \frac{1}{n} \sum_{k=1}^{n} \zeta_{ij}(k)
\]

2.2 Support vector machine theory
At first, the support vector machine was used to solve the problem of linear separability [5]. Under normal circumstances, the problem of high-dimensionality could not be solved. However, to solve the nonlinear problem, it is necessary to introduce a kernel function to make the nonlinear problem separable [6]. And only one best classification interface can classify the marked samples. Its classification map is shown in Fig.1.

![Fig 1. Optimal classification map](image)

Consider the training set \( T = \{(x_1, y_1), \cdots, (x_m, y_m)\} \in (x \times y)^m \) where \( x_i \in x = R^n \), \( y_i \in y = \{1, -1\} \) \( i = 1, \cdots, m \), if there is a \( w \in R^n, b \in R \) and a positive number \( \varepsilon \), all of the subscript \( y_i = 1 \) that make \( i \) have \((w \cdot x_i) + b \geq \varepsilon\), and for all \( y_i = -1 \) marked with
\((w \cdot x_i) + b \leq -\varepsilon\), the training set T is linearly separable. Assuming that the data set T can be linearly separable by the hyperplane \((w \cdot x_i) + b = 0\), the basic idea of the optimal classification plane is shown in Fig 1. Even if the optimal classification can make the two types of samples accurately classified, it must also satisfy the classification interval margin. By the classification line equation:

\[
(w \cdot x) + b = 0
\]  

The distance between the upper and lower lines is \(2/\|\omega\|\), and there are optimization equations for variables \(\omega\) and \(b\):

\[
\begin{align*}
\min \frac{\|\omega\|^2}{2} \\
s.t. y_i((\omega \cdot x_i) + b) \geq 1, i = 1, 2, \ldots, N
\end{align*}
\]  

In order to maximize the classification interval, \(\|\omega\|^2\) minimum is required, and the classification surface that satisfies this condition is called the optimal classification surface. Support vector machines can maximize the classification interval.

2.3 Support vector machine regression
Support Vector Machine Linear Regression Model
In the case of support vector machine regression, you need to find a regression plane so that all the data points in the set are closest to the plane. For linear regression, there are the following functions:

\[
f(x) = \omega \cdot x + b
\]  

Data \(f(x) = \sum (a_i - \alpha_i^*) (x_i, x) + b\) is the best estimate. In order to ensure that equation (5) is sufficiently smooth, it is necessary to find the minimum value of \(\omega\). Therefore, assuming that a function \(f\) can estimate all \(\varepsilon\) data within the precision \((x_i, y_i)\), solving the \(\omega\) minimum can become a convex optimization problem:

\[
\begin{align*}
\min_{\omega, b, \xi, \xi^*} & \frac{1}{2} \omega^T \omega + C \sum_{i=1}^{n} \xi_i + \xi_i^* \\
\text{s.t.} & \quad f(x_i) - y_i \leq \varepsilon \\
& \quad \|f(x_i) - y_i\| - \varepsilon, \|f(x_i) - y_i\| \geq \varepsilon
\end{align*}
\]  

Where \(C\) represents the penalty factor, transforming equation (6) into a quadratic programming problem by the dual principle, and establishing the Lagrangian equation:

\[
l(\omega, \xi, \xi^*) = \frac{1}{2} \|\omega\|^2 + C(\sum_{i=1}^{m} \xi_i + \xi_i^*) - \sum_{i=1}^{n} a_i (\varepsilon + \xi_i - y_i + (\omega, x_i) + b)
\]

\[
- \sum_{i=1}^{n} \alpha_i^* (\varepsilon + \xi_i - y_i + (\omega, x_i) + b - \sum_{i=1}^{m} \eta_i^* \xi_i + \eta_i^* \xi_i^*)
\]  

The partial derivative of the parameter \(\omega, b, \xi, \xi^*\) in the formula is equal to 0, namely:

Substitution (6) gives the dual optimization problem:
\[ \min \frac{1}{2} \sum_{i,j=1}^{m} (\alpha_i - \alpha_j^*) (\alpha_j^* - \alpha_i^*) (x_i, x_j) + \sum_{i=1}^{m} \alpha_i (e_i - y_i) + \sum_{i=1}^{m} \alpha_i^* (e_i + y_i) \]

\[ s.t. \begin{cases} \sum_{i=1}^{m} (\alpha_i - \alpha_i^*) \\ \alpha_i, \alpha_i^* \in [0, C] \end{cases} \]

Solving the quadratic plan, you can get:

\[ \omega = \sum_{i=1}^{N} (a_i + a_i^*) x_i \]

(8)

From the (KKT) theorem, the optimal time is:

\[ \begin{cases} a_i (e_i + \xi_i - y_i + ax + b) = 0 \\ a_i^* (e_i + \xi_i^* - y_i + ax + b) = 0 \\ \xi_i (C - a_i) = 0 \\ \xi_i^* (C - a_i^*) = 0 \end{cases} \]

(10)

3. Application and analysis

3.1 Parameter preference

The raw data of 73 wells and 19 parameters that have been fracturing in Linfen block are preprocessed. The pretreatment mainly includes: data screening, missing value processing, outlier processing, data standardization, gray correlation analysis, attribute selection, etc. The results of gray correlation analysis are shown in Table 1.

| parameter       | Pre-liquid volume | Drainage interval | Bottom hole pressure | Nesting pressure |
|------------------|-------------------|-------------------|----------------------|------------------|
| Correlation      | 0.788             | 0.779             | 0.779                | 0.765            |
| Sort parameter   | Natural potential | Natural gamma     | Total liquid volume  | Microsphere Focusing resistivity |
| Correlation      | 0.740             | 0.726             | 0.719                | 0.710            |
| Sort             | 5                 | 6                 | 7                    | 8                |

From the gray correlation degree ranking results in the above table, eight main controlling factors affecting the coal cracking effect are selected.

3.2 Classification of coal fracturing effect based on SVM

According to the data pre-processing results, the stable gas production of 73 wells in Linyi block is divided into three categories, of which [0,300) is a low-yield well and [300,500) is a middle-production well [500,1300]. (Part) is a high-yield well, with 1, 2, and 3 representing the category (1 represents low-yield well, 2 represents middle-production well, and 3 represents high-yield well), of which 23 are low-yield wells, 16 are middle-production wells, and 34 are high-yield wells.

Using the support vector machine classifier for classification, 63 wells were randomly generated as the training set by the random function in MATLAB. The remaining 10 wells were used as test sets. The support vector machine classifier was used to train the training set, and then the training was good. The classifier predicts the test set. The classification results of the support vector machine classifier for the
training set and the test set are shown in Fig. 2.

![Image](image1.png)

Fig 2. Training set and test set classification results

3.3 Prediction of coal fracturing effect based on support vector machine nonlinear regression

In this paper, the support vector machine algorithm is used for training. The kernel function is RBF (radial basis) kernel function, and the meshgrid function in MATLAB is used for cross-validation method to find the best parameters. The support vector machine model training set is used. A comparison between the predicted and actual predicted values of the stable gas produced by the test set is shown in Fig. 3.

![Image](image2.png)

Fig 3. Training set and test set prediction result graph

As can be seen from the above figure, the prediction data of the test set and the prediction set are basically consistent with the field data, which is crucial for the well selection before the on-site coal seam gas pressure cracking.

4. Conclusion

(1) Based on the support vector machine classifier, the coal seam gas cracking effect is classified. The prediction accuracy of the training set and the test set meets the engineering requirements, which has important guiding significance for the on-site coalbed methane mining. The establishment of such a scientific fracturing well selection method avoids the blindness before fracturing well selection and improves the efficiency and accuracy of coalbed methane mining.

(2) The support vector machine classification and prediction results are good. The method is applied to classify and predict the output of 10 coalbed methane wells in Linyi block, and the prediction accuracy
rate reaches 80%.

Acknowledgements
This research was financially supported by the National Science and technology Major Project of China (Grant No. 2016ZX05042-003, Grant No. 2016ZX05065).

References
[1] Calabrese, N., Galgut, P., & Mordan, N. (2007). Identification of actinobacillus actinomycetemcomitans, treponema denticola and porphyromonas gingivalis within human dental calculus: a pilot investigation. Journal of the International Academy of Periodontology., 9(4):118-122.

[2] Mohaghegh, S., Platon, V., & Ameri, S. (0). [society of petroleum engineers spe eastern regional meeting - pittsburgh, pennsylvania (1998-11-09)] spe eastern regional meeting - candidate selection for stimulation of gas storage wells using available data with neural networks and genetic algorithms. Nature.

[3] Yang, E. (2009). Selection of Target Wells and Layers for Fracturing with Fuzzy Mathematics Method. International Conference on Fuzzy Systems & Knowledge Discovery.

[4] Qishan, Z., & Kejia, C. (2007). Measuring grey characteristics of association greyknowledge. IEEE International Conference on Systems. IEEE.

[5] Adankon, M. M., & Cheriet, M. (2002). Support vector machine. Computer Science., 1(4):1-28.

[6] Suykens, J. A. K., & Vandewalle, J. (1999). Least squares support vector machine classifiers. Neural Processing Letters., 9(3):293-300.

[7] Tong, S., & Koller, D. (2002). Support vector machine active learning with applications to text classification. Journal of Machine Learning Research., 2(1):999-1006.