Optimization of Fracturing Construction Parameters of Coalbed Methane Wells

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Abstract. The article analyzes the gas production and construction parameters of the vertical wells in the representative layer of the 15# and 3# layers in the target area due to insufficient construction strength and low gas production in the test well. The influence of the fracturing construction of the test well on its productivity was studied. The fracturing effect prediction model was established by combining the influencing factors such as construction strength, fracturing fluid, sanding strength and sand ratio. The model is used to carry out optimization research on fracturing construction parameters. Based on the analysis of influencing factors, the optimization parameters of construction parameters are proposed. The optimization scheme can obtain better test results through later engineering verification. The results show that the stable gas production of the coalbed methane well in the target block can reach an average of more than 1000 m³/d through the optimization of the fracturing construction parameter system.

1. Introduction
The development test of coalbed methane wells and the results of multi-gas well test and drainage show that it has good gas production potential. However, in most of the implementation projects, most of the wells have unstable gas production and low production wells. It is considered that the construction intensity is not enough, which leads to insufficient improvement of the reservoir.

Many scholars have done a lot of research on fracturing technology and fracturing parameter optimization design. Zhang Y [1] et al used the mathematical models for calculating multiphase flow pressure drops both in horizontal wells and in vertical wells are optimized, and the solution to bottom hole under-pressure value and its calculating flow diagram are also proposed. Song [2] et al used the acid fracturing parameters were optimized using numerical simulation methods. Bozoev, A M [3] used the simulation modelling. The universal equation is derived for this field C, the reservoir J1.

Based on the statistics and analysis of the construction parameters of 29 wells in the coalbed methane well by using hydraulic fracturing stimulation technology, this paper preliminarily reveals the adaptability of the existing fracturing technology and masters the coal seam cracking rules of the block. The application of simple expert decision-making system ideas to achieve the optimization of fracturing parameters is of great significance for the improvement of production capacity in the later stage of the test well.
2. Theoretical Study on Influencing Factors of Coalbed Methane

2.1 Univariate analysis
Univariate analysis is the analysis of a variable at a point in time. The purpose is to describe facts. The single factor experiment or experimental treatment is only one direction, such as the influence of construction strength, fracturing fluid, sand addition strength and sand ratio on the gas production. The construction strength, fracturing fluid, sanding strength and sand ratio in the test are all single experimental treatments.

2.2 BP neural network
The BP network is a neural network with three or more layers of neurons, including an input layer, an intermediate layer (hidden layer), and an output layer. The upper and lower layers are fully connected, while the neurons in the same layer are not. Connected, the input layer neurons between the hidden layer neurons are the weight of the network, that is, the strength of the link between the two neurons. Any neuron in the hidden layer or the output layer integrates the information from all the neurons in the previous layer, and usually adds a threshold to the integrated information. This is mainly because the imitation biology must reach a certain threshold. The principle is triggered, and then the integrated information is input as the layer of neurons. In this process, the "error back propagation algorithm", the BP algorithm, is used. The core of the BP algorithm is the "negative gradient descent" theory in mathematics, that is, the error adjustment direction of the BP network always proceeds along the direction in which the error decreases the fastest. It also involves an excitation function, which is also called an activation function or a transfer function. There are usually three forms:

1. Threshold type (usually used only in MP models of simple classification)
   \[ f(x) = \begin{cases} 
   0, & x < 0 \\ 
   1, & x \geq 0 
   \end{cases} \]  

2. Linear (usually only used in input neurons and output neurons)
   \[ f(x) = x \]  

3. S-type (usually used in hidden layer neurons)
   \[ f(x) = \frac{1}{1+e^x} \]  or  \[ f(x) = \frac{1-e^x}{1+e^x} \]  

Usually a constant is coupled to the variable of the excitation function to excite the output amplitude of the network. For example, the S-type excitation function can be changed to

\[ f(x) = \frac{1}{1+e^x} \Rightarrow f(x) = \frac{1}{1+e^{cx}} \]  

Where c is a constant.

3. Influence of fracturing construction parameters on gas production
The representative well layers of wells 15 and 3 in the target block were randomly selected. The mathematical analysis method [4] was used to reveal the adaptability of the existing fracturing technology, and the coal seam cracking rules of the block were basically grasped. At the same time, the application of simple expert decision-making system ideas to achieve the optimization of fracturing parameters.

| Displacement | Gas production (m³) | Total liquid volume | Gas production (m³) | Pre-liquid percentage | Gas production (m³) |
|--------------|---------------------|---------------------|---------------------|-----------------------|---------------------|
| 5.5~7.5      | 103.91              | 200~500             | 30.93               | 20~32%                | 17.11               |
| 7.5~8        | 34.87               | 500~550             | 100                 | 32~40%                | 34.47               |
| 8~8.5        | 0                   | 550~600             | 50.56               | >40%                  | 241.09              |
According to the above results, for the target block 3# coal seam, the following rules can be obtained:

For construction displacement, the range is 5.5 to 7.5 m³/min. For the total liquid volume, the range is 500 to 800 m³. For the percentage of pre-fluid, the range should be above 20%. For the amount of pre-liquid, the range is 150 to 200 m³. For the amount of sand added, the range is 50 to 55 m³. For sand ratios, the range is 14 to 15%. Summarize the above rules of fracturing parameters, the regular template is shown in Table 2.

Table 2. Target block 3# coal fracture crack parameter rule template.

| Displacement | Total liquid volume | Pre-liquid percentage | Pre-liquid volume | Sand addition | Sand ratio |
|--------------|---------------------|-----------------------|-------------------|---------------|-----------|
| 7.5~8        | 550~800             | 20%~30%               | 150~200           | 50~60         | 14%~15%   |

3.1. Analysis of prediction of fracturing effect in target block

After theoretical research and single factor analysis, the fracturing parameters are optimized and the corresponding software is compiled. The 29 well layers of the target block were randomly selected to verify and analyze the fracturing effect. Therefore, the project draws on the data of a certain block for the training and learning of neural networks, and provides more learning samples for the prediction of fracturing effects in the target block. According to the requirements of the project start-up meeting, the 70 well layers in the Linyi block were added here, plus the 29 well layers of the target block, and a total of 99 well layers data. Here, the 70 well layer data of a certain block and the 18 well layer data of the target block are used as training samples, and the 11 well layers of the target block are used as prediction samples. The overall situation is shown in Table 3. The overall fit and prediction are shown in Table 4.

Table 3. Overall situation of representative well layers.

| Block   | Total number of layers | Number of training samples | Verify the number of samples |
|---------|------------------------|----------------------------|-----------------------------|
| Block 1 | 70                     | 70                         | 0                           |
| Block 2 | 29                     | 18                         | 11                          |

Table 4. Overall situation of fitting and forecasting.

| Total number of layers | Fitting | Forecast situation |
|------------------------|---------|--------------------|
|                        | Number of wells | Accuracy | Number of wells | Accuracy |
| 99                     | 88       | 98.04%             | 11                  | 80.9%    |
3.2. Fitting situation

Using 88 well layers as training samples, using neural network techniques and methods, the three-layer network weights and BP neural network maps are fitted, as shown in Figure 1.

![Figure 1. BP neural network.](image)

Fitted 88 layers. The average relative error of stable gas production is 1.96%, which means the accuracy is 98.04%. The fitting of stable gas production in some wells is shown in Table 5.

| Well | Layer number | Actual stable gas production (m³/d) | Fitting stable gas production (m³/d) | Relative error (%) |
|------|--------------|-------------------------------------|-------------------------------------|--------------------|
| A1   | 3#           | 53.72                               | 54.08                               | 0.67%              |
|      | 15#          | 76.28                               | 76.59                               | 0.41%              |
|      |              | Cumulative steady production         | 30436.96                            | 1.96%              |

4. Coal seam gas pressure cracking example application

The fracturing effect of the remaining 11 layers of data in the target block was predicted and compared with the actual stable gas production. The average relative error was 19.09% and the accuracy was 80.91%. The results are shown in Table 6 and Table 7.

| Well | Fracturing system | Actual steady production | Predicting stable yield | Relative error (%) |
|------|------------------|--------------------------|-------------------------|--------------------|
| B1   | 3#               | 57.3                     | 65.74                   | 14.73%             |
|      | 15#              | 62.7                     | 74.24                   | 18.41%             |
|      |                  | Cumulative steady production | 1323.43              | 19.09%             |

Table 5. Partial fit of layer 88.

Table 6. Prediction of the 11th layer of the target block.
### Table 7. Original and optimized fracturing construction parameters table for C1 well.

| Program category          | Original plan | optimization | Original plan | optimization |
|---------------------------|--------------|--------------|--------------|--------------|
| Fracture Layer            | 3#           | 3#           | 15#          | 15#          |
| Depth                     | 558.6        | 558.6        | 694.5        | 694.5        |
| Thickness                 | 5            | 5            | 4.5          | 4.5          |
| Average displacement      | 6.1          | 8            | 7.7          | 9.1          |
| pre-fluid                 | 160.25       | 380          | 156.78       | 478          |
| Total liquid volume       | 473.89       | 800          | 435.59       | 800          |
| Sand addition             | 40.8         | 52           | 43.14        | 60           |
| Stable gas production     | 489          | 1050         | 350          | 1262         |

### 5. Summary

Aiming at the wells of the 15 and 30 layers of the target block, the single factor analysis was carried out by physical statistics, and the neural network was established on this basis. The adaptability of the existing fracturing technology was preliminarily revealed, and the blocks were basically mastered. Coal fracturing law. For the 3# coal seam, the general rules of fracturing parameters can be known that moderate low displacement, moderate total liquid volume, high pre-liquid percentage, large pre-liquid volume, large sand volume, and moderate sand ratio are favorable for fracturing construction; For the 15# coal seam, the general rules of fracturing parameters show that moderate displacement, high total liquid volume, low pre-liquid percentage, moderate pre-liquid volume, large sand content, and moderate sand ratio are favorable for fracturing construction. The results show that the stable gas production of the coalbed methane well in the target block can reach an average of more than 1000 m$^3$/d through the optimization of the fracturing construction parameter system.

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