The role of Perforation Repair Technology in Extending the Life Cycle of Oil Fields

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Abstract. Perforation repair technology plays an important role in prolonging the life cycle of oil fields. However, the traditional perforation repair method can no longer meet the needs of modern oilfield development. With the continuous growth of artificial intelligence technology, the optimization algorithm based on data analysis and model has achieved remarkable success in many fields. In this paper, an optimization algorithm based on artificial neural network (ANN) is proposed to improve the performance of perforation repair and oil recovery. The algorithm can predict the oil field output under different perforation repair schemes according to the information of geological data, production data and historical data of the oil field, and get the optimal perforation repair scheme through optimization. The results show that this algorithm has obvious advantages compared with the traditional support vector machine (SVM) algorithm, and the error is reduced by 24.58%. By comparing the reservoir state prediction results of SVM algorithm, it is found that the prediction results of ANN are closer to the actual value and can better reflect the actual situation. This method provides new ideas and methods for the optimization and improvement of oil field perforation repair technology, and shows broad prospects for the application of machine learning technology in petroleum engineering.

Key words: Perforation repair; Oil field; Life cycle; ANN.

1. Introduction

As one of the main energy sources, the importance of oil exploitation and utilization is increasingly prominent. However, in the stage of oilfield development, with the continuous increase of oil production, the reservoir pressure gradually decreases, which leads to the decline of oilfield production and brings great challenges to the sustainable growth of petroleum industry [1]. In order to prolong the life cycle of oil field and improve oil recovery, petroleum engineers have been studying and exploring various effective measures to increase production [2]. Perforation repair technology, as an important means of increasing production, is widely used in oilfield development. Perforation repair technology is to increase the effective permeability of oil layer by injecting certain substances into the oil layer, so as to improve the production of oil field [3]. This technology can stimulate the flow of unexploited oil in oil layers, increase the production of oil wells, and extend the life cycle of oil fields. In the past decades, perforation repair technology has been widely used and studied [4]. However, the traditional perforation repair method often lacks pertinence and flexibility and cannot meet the actual needs of different oil fields and different oil layers [5]. Therefore, how to optimize the perforation repair scheme, improve the perforation repair effect and oil recovery has become an important research topic in the field of petroleum engineering.

In recent years, with the continuous growth of artificial intelligence technology, optimization algorithms based on data analysis and models have achieved remarkable success in many fields. These algorithms can extract useful information from a large number of data and predict future trends and behaviors by training and optimizing models [6]. Therefore, this paper proposes an optimization algorithm based on ANN to improve the performance of perforation repair and oil recovery. The algorithm can predict the oil field output under different perforation repair schemes according to the information of geological data, production data and historical data of the oil field, and get the optimal perforation repair scheme through optimization.

In the next chapter, this paper will introduce in detail the principle and application of perforation repair technology, the design and implementation of optimization algorithm based on ANN, experimental verification and result analysis. The research results will help to promote technological innovation and development in the field of petroleum engineering and improve the economic benefits and environmental sustainability of oilfield development. Through in-depth research and experimental verification, it is expected to provide more efficient and sustainable solutions for oilfield development. At the same time, it is also expected to promote the cross-integration and innovative growth of petroleum engineering and other disciplines.

2. Principle and application of perforation repair technology

(1) The principle of perforation repair technology

The principle of pressure repair technology is mainly based on changes in the physical properties of the reservoir. Oil reservoirs are typically composed of pores and throats, these tiny spaces storing oil and natural gas [7]. However, over time, due to geological processes, sediment blockages, or chemical reactions, these pores and throats may be blocked, leading to a decrease in oil mobility and affecting oilfield production.

The purpose of permeability repair technology is to restore or increase the permeability of these pores and throats. To achieve this goal, engineers typically use physical methods (such as hydraulic fracturing) or chemical methods (such as acidification). The physical method mainly involves injecting liquid into rocks under high pressure, thereby opening or expanding pores and throats. Chemical methods dissolve or remove blockages by injecting specific chemical substances.

(2) The application of perforation repair technology

① Hydraulic fracturing: Hydraulic fracturing is a commonly used pressure repair technique that uses a high-pressure water pump to inject fracturing fluid (usually a mixture of water, sand, and chemicals) into the target reservoir. This high-pressure fluid can create new fractures or expand existing fractures in the rock, thereby increasing the permeability of the reservoir. In order to maintain the open state of cracks, proppants (such as sand particles) are usually mixed in to prevent crack closure.

② Acidification: Acidification is another common pressure repair technique mainly used for carbonate reservoirs. This technology dissolves certain components in rocks by injecting acidic liquids (such as hydrochloric acid) into the reservoir, thereby removing blockages in pores and throats [8]. Acidification can be divided into two types: matrix acidification and fracturing acidification. Matrix acidification is the direct injection of acid into the reservoir, while fracturing acidification is the addition of acid during hydraulic fracturing, which can create new fractures and remove blockages.

③ Gas injection: Gas injection is a technology that increases oilfield production by injecting gas (such as carbon dioxide, nitrogen, etc.) into the reservoir. The injected gas can reduce the viscosity of crude oil, increase its fluidity, and make it easier to extract. In addition, gas can also diffuse to further areas of the reservoir, pushing difficult to flow oil towards production wells.

(3) Challenges and limitations of perforation repair technology

① Cost issue: The implementation of performance repair technology usually requires a significant amount of capital and equipment investment. For some small or economically inefficient oil fields, this may be an unbearable burden.

② Environmental impact: During the implementation of forced repair technology, wastewater, exhaust gas, and other pollutants may be generated. If not treated properly, it may cause damage to the environment and ecology. Therefore, when implementing performance repair technology, it is necessary to strictly comply with relevant environmental regulations and operating norms.

③ Technical risk: The implementation of pressure repair technology involves high-pressure, high-temperature, and high-risk working environments. If operated improperly or equipment malfunctions, it may lead to serious accidents and casualties. Therefore, before implementing the performance repair technology, sufficient technical evaluation and security training must be conducted.

3. Monitoring of oilfield performance repair status based on ANN

The implementation of forced repair technology is of great significance for improving oil recovery during oilfield development. The implementation of pressure repair technology involves various factors, such as reservoir properties, pressure repair methods, construction parameters, etc. In order to better understand and optimize the performance repair process, this section proposes an ANN based method for monitoring the status of oilfield performance repair. By monitoring and analyzing various parameters during the performance repair process in real-time, this method can provide engineers with valuable information to help them make wiser decisions. In order to monitor the performance repair status in real-time and make optimization adjustments, it is necessary to construct an ANN model that can handle multivariate and nonlinear relationships. To train the ANN model, it is necessary to prepare a dataset containing multiple performance repair states and corresponding output fluid properties. These data can be obtained through historical data, experimental data, or simulation data. When preparing data, attention should be paid to the integrity and representativeness of the data to ensure that the model can generalize to actual situations. The ANN model for optimizing the effectiveness of oilfield performance repair is shown in Figure 1.

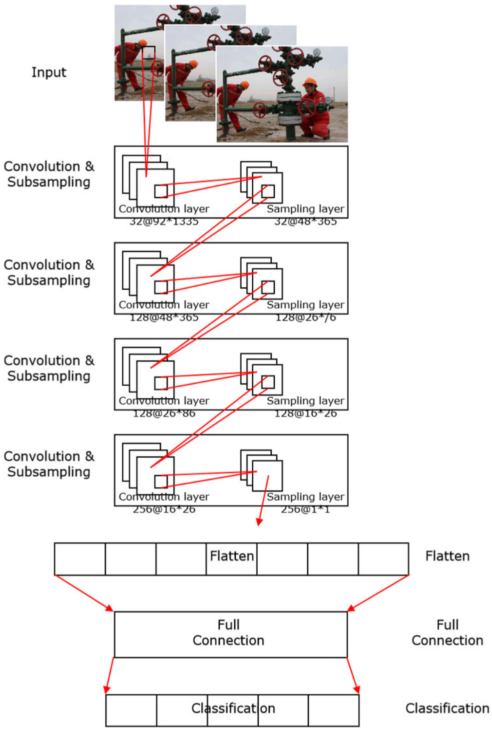

Figure 1 ANN model for optimization of perforation repair effect in oilfield

There are many parameters in the performance repair process that can reflect the effectiveness and status of the performance repair. Choosing appropriate parameters for monitoring is the key to ensuring the success of the performance repair. The monitoring parameters include: injection pressure: reflecting the flow resistance of the liquid in the rock. Injection flow rate: reflects the flow of liquid during the pressure repair process. Crack propagation: It can be monitored through methods such as microseismic monitoring and acoustic logging. The properties and production of the produced fluid: reflect the production situation of the oilfield after the forced repair. The input layer contains multiple neurons, each corresponding to an input variable, such as reservoir properties, performance repair methods, construction parameters, etc. The hidden layer contains one or more neurons for learning and extracting features from input data. The output layer contains a neuron used to predict the performance repair state or output fluid properties. The number of neurons and network depth in the hidden layer need to be adjusted and optimized according to the actual situation. The operating principle of this model is shown in Figure 2.

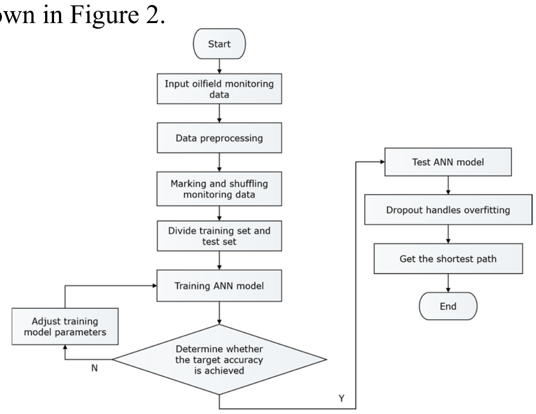

Figure 2 Operation principle of ANN

Once the model training is completed, it can be used to monitor the perforation repair process in real time. By inputting the real-time monitoring parameters into the model, we can get the real-time prediction results about the perforation repair state. These results can provide valuable information for engineers and help them adjust the perforation repair scheme in time. The standardized optimal index set is used as the reference data column, and the standardized index value $(y_{i1}, y_{i2}, y_{i3}, \dots, y_{im})$ $(i = 1,2,3, \dots, n)$ is used as the compared data column. Then use the following formula to calculate the grey correlation coefficient:

$$\delta_i(j) = \frac{\min_i \min_j |s_j - y_{ij}| + \rho \max_i \max_j |s_j - y_{ij}|}{|s_j - y_{ij}| + \rho \max_i \max_j |s_j - y_{ij}|} \quad (1)$$

Where $\delta_i(j)$ is the correlation coefficient between the j index of the i sample and the j optimal index value in the optimal index set; ρ is the resolution coefficient, which is generally taken as 0.5. So the grey assessment matrix is obtained:

$$E = \begin{bmatrix} \delta_1(1) & \delta_1(2) & \dots & \delta_1(m) \\ \delta_2(1) & \delta_2(2) & \dots & \delta_2(m) \\ \dots & \dots & \dots & \dots \\ \delta_n(1) & \delta_n(2) & \dots & \delta_n(m) \end{bmatrix} \quad (2)$$

The relationship between the comparison and reference series is quantified by their correlation degree:

$$\gamma_{0i} = \frac{1}{n} \sum_{k=1}^{n} \gamma_{0i}(k) \quad (3)$$

Where $\gamma_{0i}(k)$ is the correlation degree, that is, the average of the correlation coefficients of the same factor. In order to ensure the safety and effectiveness of the perforation repair process, an early warning system is also designed in this study. Based on the prediction results of ANN model, the system will automatically trigger an early warning signal to inform engineers to intervene when possible abnormal situations or poor perforation repair results are predicted. The early warning system can be customized according to the actual situation, for example, different thresholds can be set to trigger different levels of early warning. In addition, the early warning system can be integrated with other automatic control systems to achieve more advanced automatic monitoring and management. ANN can find its regularity from a large number of oilfield monitoring data of unknown patterns through continuous learning and training. Usually need to meet:

$$m = \sqrt{x + y} + R(10) \quad (4)$$

Where m is the quantity of neurons in the hidden layer, x is the quantity of neurons in the output layer, and y is the quantity of neurons in the input layer. The roughness calculation stage of the set X is:

$$R^{-}(X) = \{U_2, U_3, U_4, U_5, U_7\} \quad (5)$$

$$R\_(X) = \{U_2, U_4, U_5\} \neq \emptyset \quad (6)$$

If $X = \{U_2, U_3\}$, it is not definable because:

$$R^{-}(X) = \{U_2, U_3, U_5, U_7\} \quad (7)$$

$$R\_(X) = \{x \in U | R(x) \cap X \neq \emptyset\} \neq \emptyset \quad (8)$$

4. Result Analysis and Discussion

4.1 Experimental environment and conditions

(1) Experimental environment

① Hardware environment

The experiment is carried out with a high-performance computer, which is equipped with Intel Core i7 processor, 16GB RAM and NVIDIA GeForce GTX 1060 graphics card to ensure the efficient model training and prediction. Use large-capacity hard disk for data storage to ensure the safety and integrity of data during the experiment.

② Software environment

The experiment is carried out under Windows 10 operating system to ensure the stability and compatibility of the software. Python is used as the main programming language, and its rich scientific computing and machine learning library are used for model construction and experiment. Use Excel and SPSS to preprocess some data and analyze the results.

③ Experimental conditions

The experiment uses the historical perforation repair data of an oil field as the training and testing data set. The data set contains a variety of parameters in the stage of perforation repair and the corresponding perforation repair effect information. Pre-processing operations such as cleaning, normalization and labeling are carried out on the collected original data to ensure the quality and consistency of the data. During the experiment, the parameters of ANN and SVM models are adjusted and optimized in detail to obtain the best prediction performance. In order to verify the advantages of the ANN model proposed in this paper, the traditional SVM algorithm is selected as the contrast object for the experiment. Through comparative analysis, the superiority of ANN model in perforation repair state prediction is proved.

4.2 Display and analysis of results

In order to show the superiority of this model, the traditional SVM algorithm is selected for comparison. Figure 3 shows the comparison of prediction error between ANN algorithm and traditional SVM algorithm. From the results, the ANN algorithm performs better than the traditional SVM algorithm in the later operation, and the error is reduced by 24.58%.

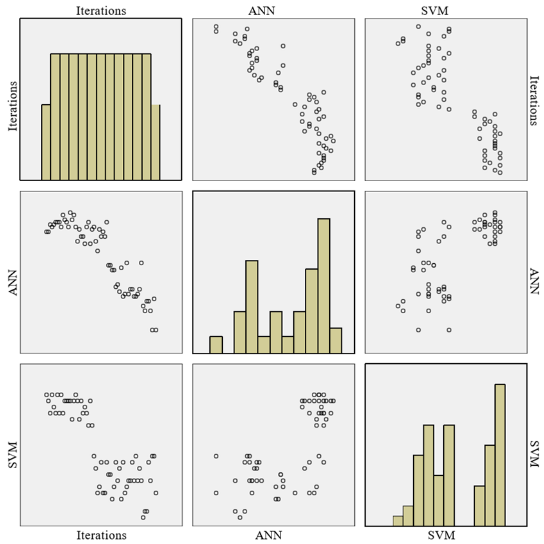

Figure 3 Prediction error of the algorithm

At the initial stage of operation, the prediction errors of the two algorithms are relatively high, which may be due to the fact that the distribution and law of data have not been fully grasped when the model started to run. With the passage of running time, the prediction errors of the two algorithms are gradually reduced, which shows that the model has gradually learned the rules and patterns in the data. Especially in the later stage of operation, the prediction error of the ANN model proposed in this paper is obviously lower than that of the traditional SVM algorithm, which shows the advantages of ANN model in dealing with complex and nonlinear data. ANN model can capture more subtle and complex patterns and relationships in data through the complex connection and calculation of multi-layer neurons, so as to make more accurate predictions. In contrast, the traditional SVM algorithm may need to transform the nonlinear data by kernel function, which not only increases the complexity of the model, but also may introduce additional errors.

Figure 4 shows the reservoir state prediction results of SVM algorithm. It can be seen that with the changes of various factors, there is a certain deviation between the prediction results of SVM algorithm and the actual values. The prediction result of ANN in Figure 5 shows that the points in the figure are obviously closer to the actual straight line. This means that under the same conditions, this AANN can provide a prediction closer to the true value.

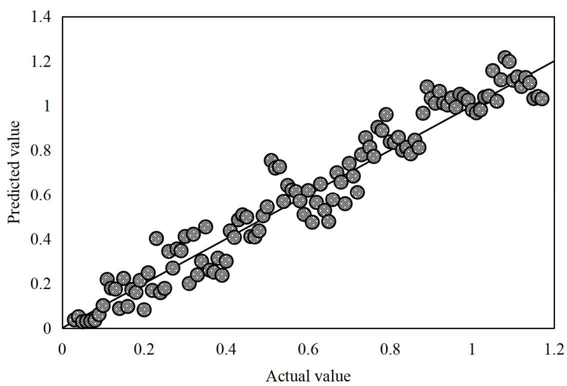

Figure 4 Accuracy test of SVM reservoir state prediction

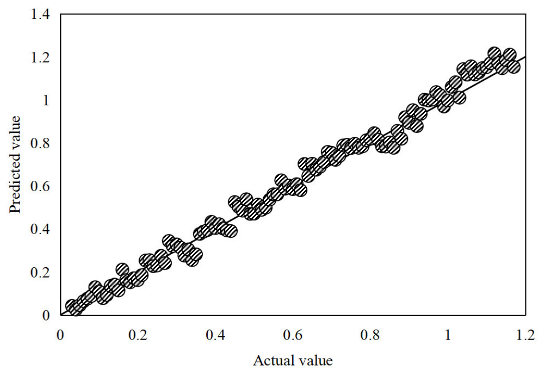

Figure 5 Accuracy test of ANN reservoir state prediction

Figure 4 shows the reservoir state prediction results of SVM algorithm. Although SVM algorithm can predict the state of oil reservoir to a certain extent, there is an obvious deviation between the predicted result and the actual value. This deviation may be caused by many factors, such as data noise, insufficient model complexity or over-fitting. Figure 5 shows the prediction results of ANN. The prediction point of ANN is very close to the actual straight line, which shows that ANN can provide a prediction closer to the real value. This is mainly because ANN has strong representation learning ability, and can capture more subtle and complex patterns and relationships in data through the complex connection and calculation of multi-layer neurons. Therefore, ANN can maintain high prediction accuracy even in the face of changes of various factors. In Figure 5, the prediction points of ANN are not completely concentrated on the actual straight line, but are scattered to some extent. This may be caused by model uncertainty or data noise.

5. Conclusions

In the stage of oilfield development, with the continuous increase of oil production, the reservoir pressure gradually decreases, which leads to the decline of oilfield production and brings great challenges to the sustainable growth of petroleum industry. In this paper, an optimization algorithm based on ANN is proposed to improve the effect of perforation repair and oil recovery. The algorithm can predict the oil field output under different perforation repair schemes according to the information of geological data, production data and historical data of the oil field. By introducing ANN model, this study successfully improves the accuracy of perforation repair state prediction. The results show that the proposed algorithm has obvious advantages compared with the traditional SVM algorithm, and the error is reduced by 24.58%. This improvement proves the superiority of ANN in dealing with complex and nonlinear data, especially in capturing more subtle and complex patterns and relationships in data. By comparing the reservoir state prediction results of SVM algorithm, it is found that the prediction results of ANN are closer to the actual value and can better reflect the actual situation. This means that in the actual oilfield perforation repair operation, engineers can rely on ANN model to provide more accurate and reliable prediction information, so as to make more informed decisions. In order to further improve the performance of ANN model in oilfield perforation repair condition monitoring, it is suggested to collect more historical data, study more advanced ANN structure and integrate other advanced technologies in the future.

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