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Problems and Countermeasures in the Water Injection Development Process of Strong Water Sensitive Sand Conglomerate Reservoir

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Abstract. Due to the unique physicochemical property of strong water sensitive glutenite reservoirs, a series of problems may occur during water injection development, seriously affecting production efficiency and economic benefits. This study analyzed the problems and their causes in the water injection development process, constructed a water injection optimization model based on machine learning algorithms, and rigorously verified and evaluated the performance of the model. The results show that the algorithm proposed in this article has achieved significant advantages in prediction accuracy, reducing prediction error by 28.26%, and maintaining a high recall. In addition, as the sample size increases, the algorithm in this article performs more stably. When facing complex reservoir environments and a large amount of data, this algorithm can provide more accurate and reliable prediction results, providing strong support for the optimization of reservoir water injection development process. The research results can provide an effective decision support tool for the field of petroleum engineering, which helps to improve the efficiency and economy of oil extraction, and promote the sustainable growth of the petroleum industry.

Keywords: Strong water sensitivity; Sandstone; Reservoir; Water injection development.

1. Introduction

With the continuous growth of global energy demand, fossil fuels such as oil and natural gas are still the core energy sources in our daily life and industrial development [1]. However, the traditional oil exploitation methods have encountered many challenges in some complex geological environments. Due to the unique physicochemical property of strong water-sensitive glutenite reservoirs, a series of problems will occur in the stage of water injection development, which will seriously affect the production efficiency and economic benefits [2]. Strong water-sensitive glutenite reservoir refers to the oil accumulation in those glutenite reservoirs that are particularly sensitive to water. Water injection development is a widely used technology in the current petroleum industry [3]. By injecting water into the reservoir, it increases the pressure of the reservoir, thus promoting the flow of oil to the production well. In the stage of water injection development, due to the interaction between water flow and rocks, the physicochemical property of reservoirs may change significantly [4]. These changes may further trigger the structural changes of reservoirs, reduce the fluidity of oil, and even lead to the inability to effectively exploit oil in some areas [5]. Therefore, how to carry out water injection development reasonably and efficiently is the core problem faced by this kind of reservoirs.

Based on the continuous progress of computer technology and data science, machine learning algorithms have been widely used in all walks of life. In the petroleum industry, machine learning algorithm has gradually shown its great potential. From the perspective of data-driven, machine learning algorithm can fully tap and utilize existing data resources and provide decision support for reservoir development and management [6]. In strongly water-sensitive glutenite reservoirs, due to its complex physicochemical property, it is often difficult for traditional mathematical models to accurately describe the reservoir behavior [7]. The machine learning algorithm can build a more accurate and comprehensive model by learning a large number of actual data. These models can not only be used to predict the dynamic behavior of reservoirs, but also provide decision-making basis for optimizing water injection schemes.

In this article, a set of effective solutions are proposed for the problems in the stage of water injection growth of strong water-sensitive gravel reservoirs, combined with machine learning algorithm. In order to achieve this goal, this study first analyzes the problems and their causes in the stage of water injection development, and then introduces the principle and implementation steps of the selected machine learning algorithm. Then, the water injection optimization model based on neural network algorithm is constructed, and the performance of the model is strictly verified and evaluated. Finally, based on these models and results, the optimization strategies and suggestions for water injection growth of strong water-sensitive glutenite reservoirs will be put forward.

2. Characteristics of strong water-sensitive glutenite reservoir and water injection development

Strong water sensitive glutenite reservoirs have unique physical and chemical characteristics that have a significant impact on the water injection development process. Firstly, the rocks of such reservoirs are mainly composed of sandstone and conglomerate, with high porosity and permeability, which is conducive to the storage and flow of oil. However, this type of rock has extremely high sensitivity to water molecules. When in contact with water, the clay minerals in the rock will expand, leading to a decrease in porosity and permeability [8]. In addition, strong water sensitive glutenite reservoirs typically exhibit complex heterogeneity, meaning that reservoir physical properties vary significantly in space. This increases the uncertainty in the development process, making the design and optimization of water injection plans more difficult.

Water injection development is a commonly used method to improve oil recovery in strong water sensitive sandstone and conglomerate reservoirs. However, due to the strong water sensitivity of the reservoir, the water injection process can easily lead to a decrease in reservoir permeability, thereby affecting the production efficiency. When water is injected into the reservoir, it interacts with the clay minerals in the rock, causing the clay minerals to expand, leading to a significant decrease in reservoir permeability [9]. Due to the heterogeneity of strong water sensitive glutenite reservoirs, the response of different parts of the reservoir to water injection varies greatly. Some areas may be prone to water sensitivity, while others may be relatively stable. This brings great complexity to the design of water injection plans, making it difficult to find a suitable water injection strategy for the entire reservoir. Traditional prediction models are often based on simplified assumptions and homogeneous reservoirs, making it difficult to accurately describe the complex behavior in strongly water sensitive glutenite reservoirs. Therefore, in the stage of water injection development, it is difficult to predict changes in the reservoir and the flow of oil, thereby increasing development risks.

3. Optimization algorithm of water injection development based on machine learning

Facing the complex problems in the stage of water injection growth of strong water-sensitive gravel reservoirs, traditional mathematical models and methods are often difficult to provide accurate solutions. Therefore, this article chooses machine learning algorithm as the core tool to optimize water injection development. Machine learning algorithm has powerful data processing ability, and can learn and predict future reservoir performance according to historical data [10]. For the collected data, feature selection and processing are needed to extract the key features closely related to the water injection development process. In this process, feature selection algorithm and correlation analysis tools can be used to ensure that the selected features are of great significance to the prediction ability of the model. The neural network model of water injection development optimization is shown in Figure 1.

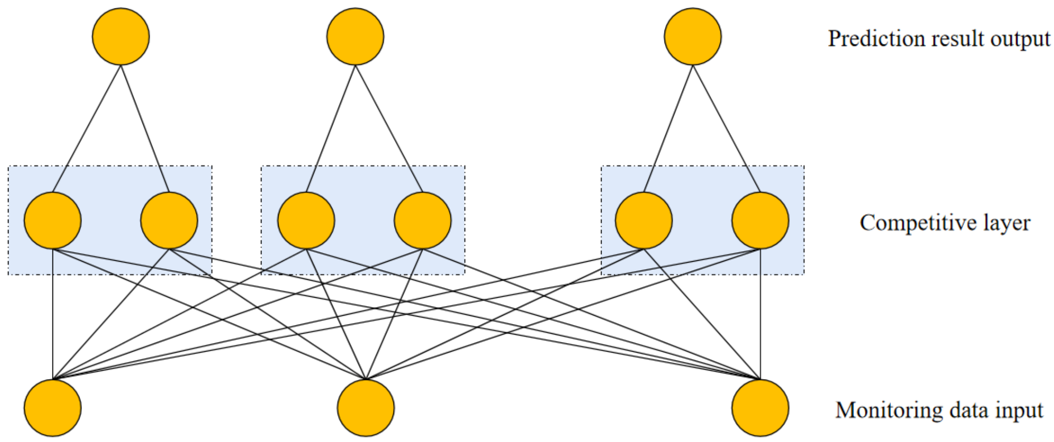

Figure 1 Neural network model for water injection development optimization

Firstly, a large number of data about strong water-sensitive glutenite reservoirs are collected, including but not limited to porosity, permeability, water injection quantity, water injection speed, reservoir pressure and temperature. These raw data are preprocessed, such as normalization, denoising, filling in missing values, etc., so as to make them suitable for the training of neural network models. Analyze and select appropriate features to input into the neural network model. Using the preprocessed data to train the neural network model. See Figure 2 for the operation flow of the water injection development prediction model.

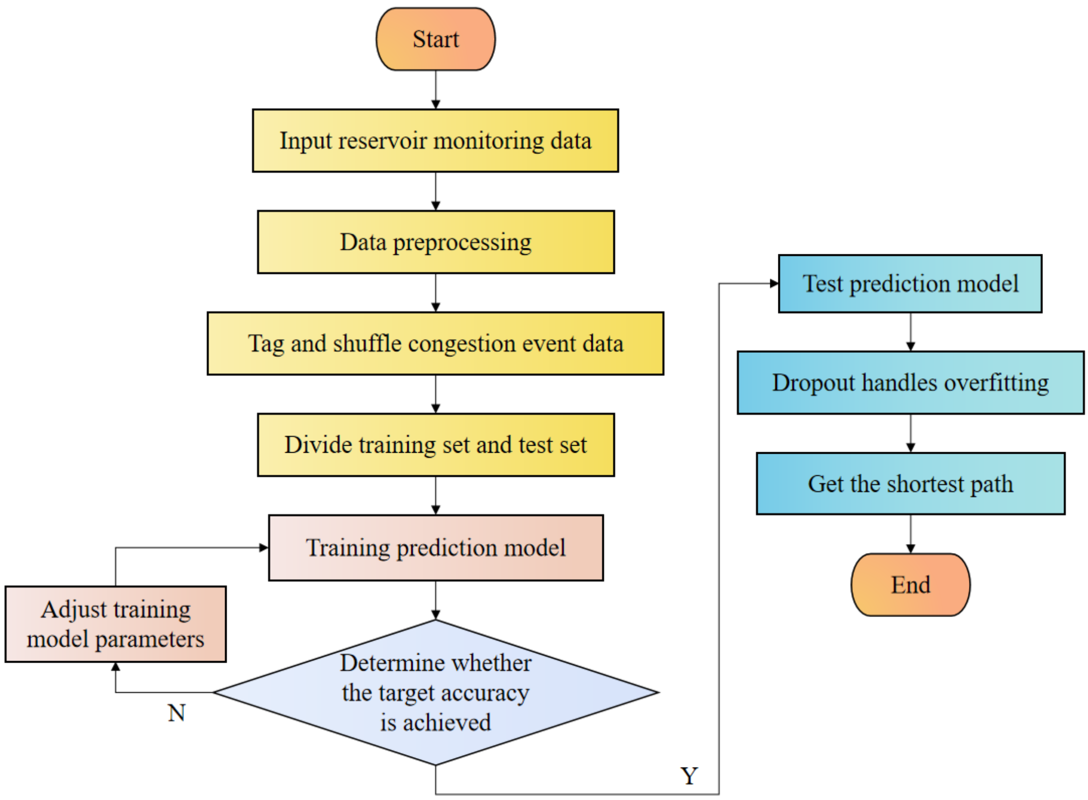

Figure 2 Operation stage of water injection development prediction model

The standardized optimal index set is used as the reference data column, and the standardized index value $(y_{i1}, y_{i2}, y_{i3}, \ldots, y_{im})$ $(i = 1,2,3,\ldots,n)$ is used as the compared data column. Then use the following formula to calculate the grey correlation coefficient:

$$\delta_i(j)=\frac{\min\limits_i \min\limits_j \left|s_j-y_{ij}\right|+\rho \max\limits_i \max\limits_j \left|s_j-y_{ij}\right|}{\left|s_j-y_{ij}\right|+\rho \max\limits_i \max\limits_j \left|s_j-y_{ij}\right|} \tag{1}$$

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:

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

The correlation degree between comparison series and reference series is expressed by correlation degree:

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

Where $\gamma_{0i}(k)$ is the correlation degree, that is, the average of the correlation coefficients of the same factor.

Once the model is trained and optimized, it can be used to predict the state of strong water-sensitive glutenite reservoir. This involves inputting new and unseen reservoir data into the model and obtaining the predicted output of the model [11]. These predicted outputs may include the future pressure distribution, water flow path and oil saturation of the reservoir, which can provide valuable insights for petroleum engineers on how to adjust the water injection development strategy. As time goes on, new data will be produced continuously. In order to maintain the prediction accuracy of the model, it is necessary to update the model regularly to adapt to new data and changes in reservoir conditions. Set factor set U and evaluation grade set V to judge the risk of water injection development in glutenite reservoir;

$$U=\{u_1,u_2,\dots,u_m\} \tag{4}$$

$$V=\{v_1,v_2,\dots,v_m\} \tag{5}$$

Fuzzy evaluation is carried out on each factor in U according to the grade index in the evaluation set, and the evaluation matrix is obtained:

$$R=\left(r_{ij}\right)_{n\times m} \tag{6}$$

In which r_{ij} indicates the degree of u_i's membership in v_i. After determining the importance index of each factor, record it as:

$$A=\{a_1,a_2,\dots,a_m\},\quad \sum_{i=1}^{n}a_i=1 \tag{7}$$

Synthesis:

$$\overline{B}=AR=\left(\overline{b}_1,\overline{b}_2,\dots,\overline{b}_m\right) \tag{8}$$

Therefore, the risk evaluation grade of water injection development in sandy gravel reservoir can be determined.

For the obtained optimization scheme, a comprehensive evaluation is needed. According to the evaluation results, the scheme can be adjusted and improved to ensure its feasibility and effect in practical application [12]. Reservoir water injection development is a dynamic process, and with the change of time and data, the reservoir state will also change. Therefore, it is necessary to update the machine learning model regularly and combine the output results of the new model to continuously optimize the water injection development process.

4. Analysis of experimental results

The purpose of the experiment is to evaluate the performance of the neural network-based model proposed in this article in predicting the state of strong water-sensitive glutenite reservoirs. Firstly, a large amount of data is collected from the actual oil reservoir. These data include various parameters related to the reservoir state, such as porosity, permeability and water injection. As shown in Figure 2, the prediction error between the proposed algorithm and the traditional decision tree algorithm is compared. From the results, it can be seen that in the later stage of operation, this algorithm has obvious advantages compared with the traditional decision tree algorithm, and the error is reduced by 28.26%.

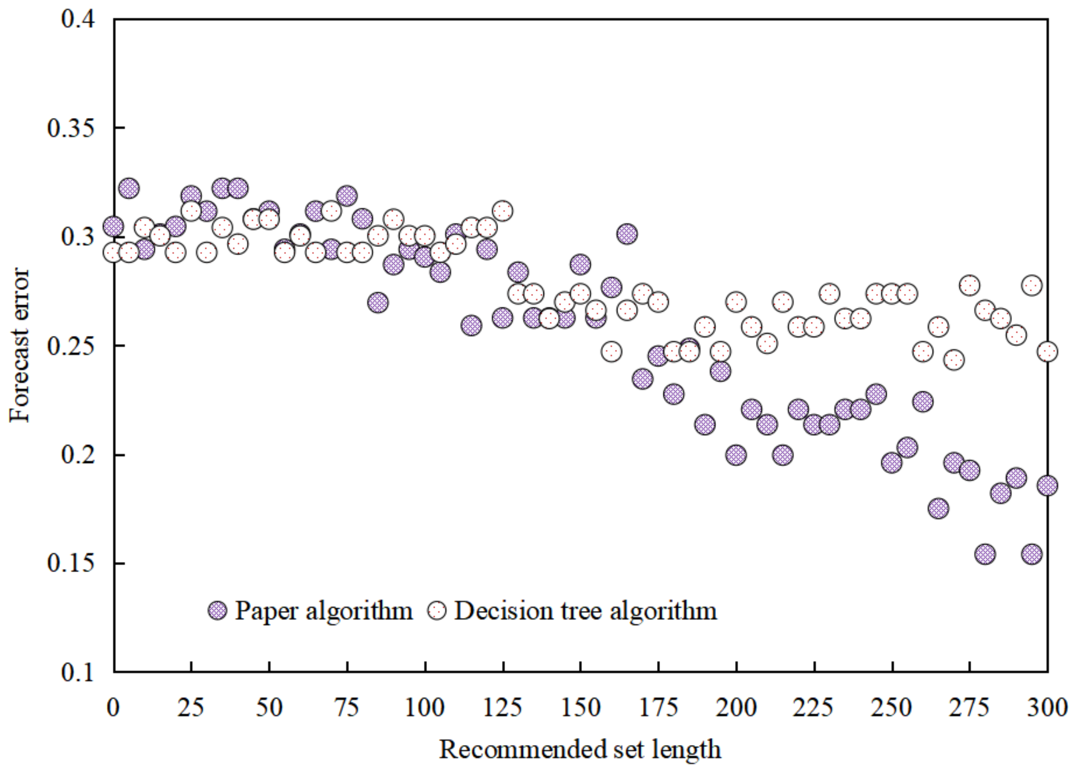

Figure 2 Prediction error of the algorithm

Compared with the traditional decision tree algorithm, the neural network model adopted in this article has stronger expressive ability and higher model complexity. This enables the neural network model to better capture the nonlinear relations and complex patterns in the data, thus predicting the reservoir state more accurately. Neural network model has the ability to learn data features automatically. Through multi-layer nonlinear transformation, neural network can extract high-level feature representation of data, which is especially important for complex data such as strong water-sensitive glutenite reservoir. With the increase of running time, the amount of available data is also increasing. Neural network model can make full use of a large number of data for training, and by learning more samples, the model can further reduce the prediction error. Traditional decision tree algorithm may be limited by computational efficiency and model complexity when dealing with large-scale data.

Tables 1 and 2 present the experimental results of the recall of reservoir state prediction, in which the model proposed in this article is compared with the traditional decision tree algorithm. With the increase of the test sample size, the recall of the two algorithms for reservoir state prediction shows a decreasing trend. However, compared with the traditional decision tree algorithm, the model proposed in this article shows significant advantages under all experimental sample sizes.

Table 1 Recall of reservoir state prediction based on decision tree algorithm

Sample size	Recall of reservoir state prediction (%)
15	98.67
30	97.58
45	96.42
60	95.89
75	92.35
90	89.22
105	85.55

Table 2 Recall of reservoir state prediction based on this algorithm

Sample size	Recall of reservoir state prediction (%)
15	98.25
30	96.36
45	96.01
60	95.89
75	95.26
90	94.59
105	94.37

As the sample size increases, the complexity of the data may also increase, making it more difficult for the model to accurately predict the state of the oil reservoir. In a large number of samples, some categories may have fewer samples, leading to a decrease in the predictive performance of the model for these categories, which in turn affects the recall. When faced with complex reservoir states, traditional decision tree algorithms appear inadequate in the face of a large amount of data. The neural network-based model proposed in this article can not only process a large amount of data, but also maintain a high prediction recall, demonstrating its superiority and potential in reservoir state prediction.

Figure 3 shows the reservoir state prediction results of the traditional decision tree algorithm. It can be seen that with the changes of various factors, there is a certain deviation between the predicted results of the decision tree algorithm and the actual values. In some areas, the predicted points are far from the actual straight line, indicating low accuracy and significant errors in the prediction. In Figure 4, the prediction results of the algorithm proposed in this article show that the points in the figure are significantly closer to the actual straight line. This means that under the same conditions, the algorithm proposed in this article can provide predictions that are closer to the true values and exhibit higher prediction accuracy.

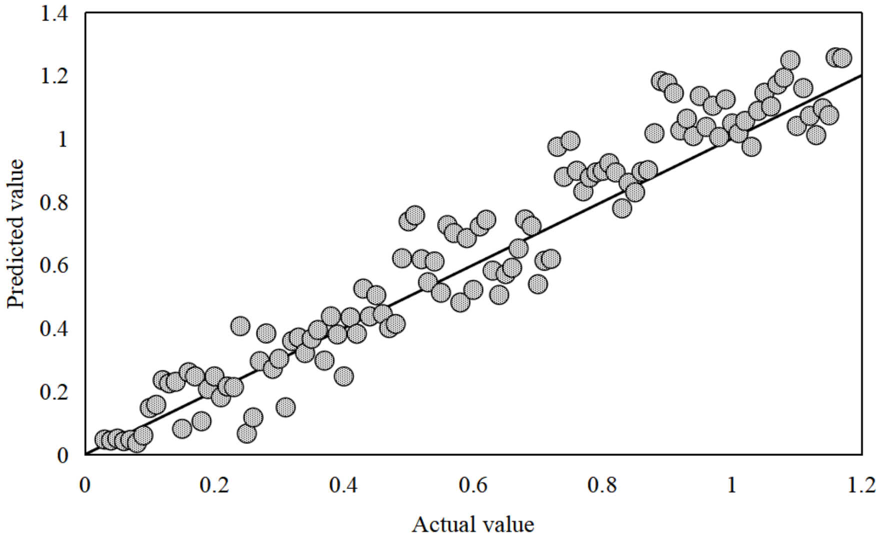

Figure 3 Accuracy test of reservoir state prediction based on decision tree algorithm

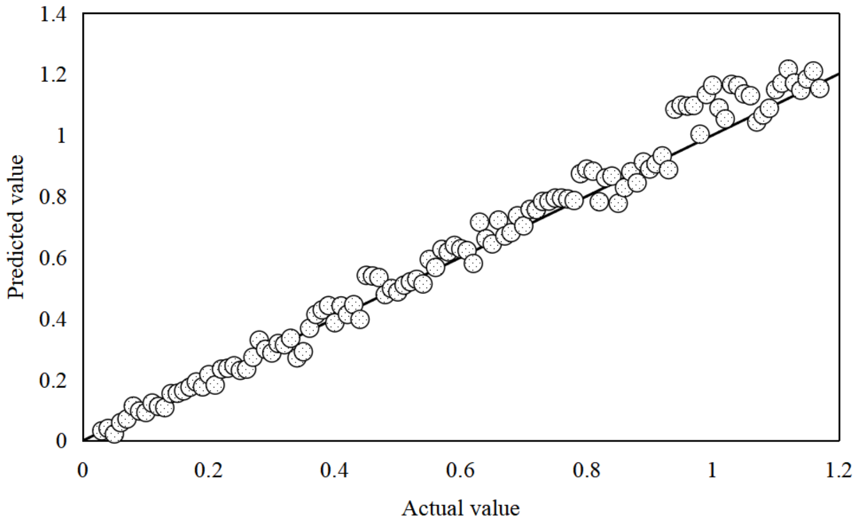

Figure 4 Accuracy test of reservoir state prediction based on this algorithm

Although the decision tree algorithm is simple and intuitive, its ability to model complex nonlinear relationships is weak. In the face of complex reservoir conditions, its prediction performance is limited, resulting in a large deviation between the predicted results and the actual values. The algorithm in this article is based on a large number of data to learn and predict, which can capture more subtle trends and make the prediction more accurate.

Considering the dynamic variability of reservoirs, it is suggested to collect and update reservoir data continuously and in real time. This can not only ensure the prediction accuracy of the model, but also make it adapt to the changes of oil reservoirs and improve the effectiveness of decision-making. In order to better apply the model to actual decision-making, it is suggested to develop a decision support system. This system can integrate forecasting model, optimization algorithm and decision analysis tools, and provide a comprehensive and interactive platform for petroleum engineers to support them in formulating and adjusting water injection development strategies. With the growth of technology and the updating of methods, it is suggested to organize regular technical training and exchange activities to improve the professional level of petroleum engineers and related technicians and ensure that they can effectively use new tools and technologies. By combining machine learning and optimization algorithm, more scientific and accurate decision support can be provided for this process. At the same time, however, it is necessary to continue to pay attention to technological progress and application practice, and constantly improve and optimize methods to ensure the effectiveness and economy of decision-making.

5. Conclusions

During the stage of water injection development, the interaction between water flow and rocks may lead to significant changes in the physicochemical property of the reservoir. From a data-driven perspective, machine learning algorithms can fully explore and utilize existing data resources, providing decision support for reservoir development and management. This article explores the application of machine learning based optimization algorithms for water injection development in strong water sensitive sandstone reservoirs. By comparing the traditional decision tree algorithm with the neural network model proposed in this article, the superiority and effectiveness of the proposed algorithm in reservoir state prediction were verified. From the results, it can be seen that as the experimental sample size increases, although the recalls of both algorithms show a decreasing trend, the algorithm in this article maintains a high recall in all experimental sample sizes, demonstrating better prediction accuracy and stability. This means that in the face of complex reservoir environments and a large amount of data, this algorithm can provide more accurate and reliable prediction results, providing strong support for the optimization of reservoir water injection development process.

The optimization algorithm for water injection development based on machine learning has broad application prospects in strong water sensitive glutenite reservoirs. By continuously collecting and updating data, improving feature selection and processing, regularizing and optimizing models, and integrating other algorithms, strategies and suggestions can further improve the predictive performance and practicality of algorithms, bringing more accurate and efficient decision support tools to the field of petroleum engineering.

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