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Research on displacement efficiency by injecting CO_2 in shale reservoir based on genetic neural network model

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ABSTRACT

Carbon dioxide injection can help solve two issues in shale reservoir production. Firstly, it can reduce carbon emissions while, secondly, improving unconventional reservoir recovery. There are many controlling factors for CO_2 injection to enhance oil recovery in shale reservoirs, and the effect of field implementation varies greatly. The key to popularizing this extraction technology is determining the main controlling factors of CO_2 displacement efficiency. Using CO_2 shale displacement laboratory results from Tovar et al. (2021), the grey correlation analysis method was used to determine the main controlling factors affecting core oil displacement efficiency, such as shale reservoir physical parameters (rock compressibility, porosity, median pore size, matrix permeability, TOC and oil saturation) and engineering parameters (soaking time and injection pressure). The genetic algorithm (GA) was introduced to optimize the backpropagation (BP) neural network to construct the prediction model of the CO_2 indoor displacement experiments in shale core. The results showed that the injection pressure of engineering parameters, the CO_2 soaking time of gas injection parameters, and the porosity of shale physical parameters were the main controlling factors affecting the oil displacement efficiency. The prediction accuracy of the genetic neural network model improved, and the coefficient of determination (R^2) reached 0.983. Compared to the conventional neural network model, the mean absolute error (*MAE*) was reduced by 30%, the root mean square error (*RMSE*) was reduced by 46%, and the R^2 increased by 11%. Optimizing the learning and training of the prediction model significantly reduces the cost of laboratory experiments. The deep learning model completed by training can intuitively show the influence degree of input parameters on output parameters, providing a theoretical basis for studying CO_2 displacement mechanism in shale reservoirs.

Keywords: shale oil; CO_2 fracturing; genetic algorithm; BP neural network; oil displacement efficiency; prediction model

1. INTRODUCTION

In recent years, with the development of shale oil and gas exploration, the world has been committed to realizing the scale and efficient development of shale oil and gas reservoirs to alleviate the increasingly severe energy security situation (Liu et al., 2022). Shale oil and gas are stored in micro and nanopore media, and large-scale volume fracturing using conventional water-based fracturing fluids faces a series of challenges (Wu et al., 2022). CO_2 fracturing-production technology is an effective method to improve shale reservoirs' recovery rate. Compared with water-based fracturing fluid, the advantages of using CO_2 as a fracturing agent are lower fracturing pressure and stronger fracturing ability. It can effectively improve the fracture permeability of shale reservoirs and fully utilize the physical and chemical properties of CO_2 (pressure increase, viscosity reduction, dissolution, diffusion, and replacement, etc.) to improve the recovery of shale reservoirs (Zhang et al., 2017; Zhang et al., 2020). In

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addition, using CO_2 in the extraction of shale oil reservoirs is conducive to carbon capture, utilization, and storage (CCUS), which reduces environmental pollution, helps reduce carbon emissions on a large scale, and mitigates the greenhouse effect. This technology will be critical in long-term emission reduction and deep decarbonization (Sher et al., 2020; Qureshi et al., 2021; Yuan et al., 2022).

Gupta et al. classified more than one thousand rock samples from four regions in North America, including Eagle Ford, to study the heterogeneity of shale reservoirs. The recovery enhancement mechanism and results differed between rock types and fields in the same field (Gupta et al., 2017; Gupta et al., 2018). Tovar et al. conducted experiments on injecting CO_2 in shale reservoirs to enhance recovery and studied the effects of injection pressure, minimum miscible pressure (MMP), and soaking time on recovery. The experimental results showed that CO_2 could significantly improve the recovery of shale reservoirs (Tovar et al., 2021). Yu et al. conducted a study on CO_2 injection in tight oil reservoirs to improve recovery, comparing the effect of CO_2 injection on water-alternating gas (WAG) and active carbonated water alternating gas (ACWAG) technologies. The results showed that ACWAG achieved the highest recovery rate with CO_2 injection (Yu et al., 2021). Wu et al. studied the mechanism of CO_2 fracturing throughput in low-permeability reservoirs. The results showed that CO_2 had a better effect on crude oil in the solubilization and viscosity reduction, and the degree of CO_2 fracture throughput recovery could reach more than 60% (Wu et al., 2022). Zhao et al. conducted a study on the efficiency of CO_2 soaking replacement and replacement of oil and gas in tight reservoirs. Results showed that the replacement efficiency of CO_2 in reservoirs could be effectively improved by increasing the soaking time or improving the reservoir properties (Zhao et al., 2021).

CO_2 fracturing-production technology is still mainly used in indoor experiments and small-scale field trials, such as the Jilin oilfield, Yanchang oilfield, and Jimsar shale oilfield in China (Zhang et al., 2014; Wang et al., 2022; Tang et al., 2022). Due to the small scale of indoor experiments, high experimental cost, generally low CO_2 replacement oil displacement efficiency, and time-consuming and labor-intensive field tests, it is difficult to fully understand and employ the experimental results widely in field tests.

As global oil and gas exploration and development become more complex, the demand for technology tends to be refined and enhanced. With its powerful arithmetic and great potential, artificial intelligence has achieved good application results in the oil and gas field (Min et al., 2022). Jiang et al. studied the development trends of intelligent fracturing technologies. They pointed out that using artificial intelligence for deep mining small data samples and establishing an integrated fracturing intelligent decision-making platform is conducive to promoting a complete and unified intelligent fracturing technology system (Jiang et al., 2022). Yang et al. studied optimizing reasonable soaking time in shale reservoirs based on machine learning and established a prediction model. The results showed that the reasonable soaking time calculated by the new model has high accuracy, and the prediction accuracy can reach up to 94% (Yang et al., 2022). Negash et al. conducted an artificial neural network-based production forecasting for underwater hydrocarbon reservoir injection. The results showed that the proposed fluid production prediction model had a coefficient of determination over 0.9, and the simulation results matched the actual data to a high degree with low computational cost (Negash et al., 2020).

Traditional numerical simulation has limitations such as long modeling time, high computational cost, inaccurate parameter description, and single evaluation effect. Traditional machine learning algorithms are inadequate in terms of computational accuracy, data expansion, and adaptability. As a vital network model for deep learning, BP neural network algorithm has a high degree of nonlinear mapping capability, which can avoid the drawbacks existing in traditional methods.

Based on the CO_2 shale core replacement experiments of Tovar et al. (2021), this paper introduces a BP neural network optimized by a genetic algorithm to construct a prediction model for indoor replacement experiments to study the effects of numerous parameters involved in CO_2 replacement experiments on replacement efficiency. The goal is to create an understanding of indoor experiments that can be employed in field tests.

2. DATA SOURCE AND MECHANISM ANALYSIS

This paper used BP neural network to analyze the factors affecting the displacement efficiency of shale reservoirs. We introduced a genetic algorithm to optimize the prediction model based on the experimental results of CO_2 throughput displacement shale reservoirs conducted by Tovar et al. The experimental results of small samples could replicate and reproduce themselves and established the prediction model of CO_2 indoor displacement experiments in shale cores based on genetic algorithm optimized BP neural network to form better regularity understanding.

Due to technical limitations, the current recovery rate of North American shale reservoirs is generally between 2% and 16% (Delaihdem, 2013). Certain achievements have been made in shale reservoirs in the Wolfcamp Formation in North America using CO_2 fracturing-production technology, providing a new technical idea for exploiting shale reservoirs (Loucks et al., 2009). Accordingly, Tovar et al. (2021) conducted an indoor CO_2 injection displacement experiments in shale reservoirs in the Wolfcamp Formation, which are rich in organic matter, to explore the differences in production mechanisms of traditional oil reservoirs. The material used in the experiments is a Wolfcamp shale reservoir. The core was 2.5cm in diameter and ~ 5cm in length. Thirteen groups of CO_2 injection displacement experiments of shale cores were carried out to study the influences of physical parameters, injection methods, injection pressure, and soaking time of different shale reservoirs on the recovery efficiency of shale reservoirs. Three groups of experiments had no test results due to testing errors, and the test data of the remaining 10 groups of displacement experiments are shown in Table 1.

Table 1 The parameters of displacement experiment by CO_2 injected in shale core.

Serial number	Porosity /%	Compressibility/(1·MPa^{-1}·10^{-3})	Oil saturation/%	MMP/MPa	Crude oil density /(g·cm^{-3})	TOC/wt%	Median pore size/nm	Matrix permeability/nd	Soaking time/h	Injection pressure /MPa	Oil displacement efficiency/%
1#	10.3	1.18	85.91	25.56	0.88	4.4	7	1370	22	24.14	40
2#	8.22	1.43	30.02	25.56	0.88	2.34	6	530	10	17.24	17.8
3#	5.94	0.93	67.45	25.56	0.88	1.87	5	430	0	17.24	9.7
4#	5.94	0.93	67.45	25.56	0.88	1.87	5	430	0	24.14	14.1
5#	6.44	0.65	50.11	13.28	0.83	2.91	5	370	21	8.28	9.5
6#	10.12	1.27	15.23	13.28	0.83	1.55	5	325	0	14.48	7.4
7#	8.1	0.77	32.22	13.28	0.83	4.08	4	170	21	14.48	14.5
8#	8.65	3.1	65.13	13.28	0.83	3.97	6	390	21	21.38	26.2
9#	7.35	1.33	31.83	13.28	0.83	2.97	5	390	0	8.28	1.7
10#	7.17	1.55	62.7	13.28	0.83	2.18	5	440	0	21.38	14.7

Note: The simulated reservoir temperature was 73.9°C.

The experiments were sorted according to the MMP of injected CO_2 and crude oil. The first four sets of experiments corresponded to the MMP of 25.56 MPa for CO_2 and the first fluid sample (crude oil with a density of 0.88 g/cm^3), and the last six sets of experiments corresponded to the MMP of 13.28 MPa for CO_2 and the second fluid sample (crude oil with a density of 0.83 g/cm^3). The experimental results focused on the engineering parameters of gas injection and discussed in detail the influence of gas injection methods, injection pressure, soaking time, and other factors on oil displacement efficiency, which showed that:

(1) Effect of gas injection methods. The five groups of core displacement experiments corresponding to zero soaking time (experimental serial numbers 3#, 4#, 6#, 9#, and 10#) represented continuous CO_2 injection experiments. The remaining five groups were CO_2 injection throughput experiments represented by different soaking times (reflecting on-site soaking time). The experimental results showed that the oil displacement efficiency of cores with continuous gas

injection ranged from 1.7% to 14.7%; the oil displacement efficiency of cores with CO_2 injection throughput ranged from 9.5% to 40%. Overall, it showed that the replacement process with crude oil in the CO_2 injection throughput of shale cores is the main reason for the higher oil displacement efficiency.

(2) Effect of injection pressure. Continuous gas injection (zero soaking time) was used for the first fluid sample. Experiments #3 and #4 increased injection pressure from 17.24 MPa to 24.14 MPa, a pressure increase of 6.9 MPa. The oil displacement efficiency increased from 9.7% to 14.1%, an increase of 4.4 percentage points.

Experiments 6# and 9# with continuous gas injection for the second fluid sample increased injection pressure from 8.28 MPa to 14.48 MPa. The oil displacement efficiency increased by 5.7 percentage points during the continuous gas injection period. Experiments #5, #7, and #8 using gas injection and throughput with 21h soaking time showed that when the injection pressure increased from 8.28 MPa to 14.48 MPa (a pressure increase of 6.2 MPa), the oil displacement efficiency increased by 5 percentage points. When the injection pressure increased from 14.48 MPa to 21.38 MPa (a pressure increase of 6.9 MPa), the oil displacement efficiency increased by 11.7 percentage points. The experimental results showed that the injection pressure significantly impacts the oil displacement efficiency. When the pressure is higher than the MMP, the oil displacement efficiency of oil and CO_2 in a miscible state is better.

(3) Effect of soaking time. For the first fluid sample, experiments 2# and 3# showed that increasing the soaking time from 0 to 10h at a constant pressure of 17.24 MPa increased the oil displacement efficiency by 8.1 percentage points. Experiments 1# and 4# showed that increasing the soaking time from 0 to 22h at a pressure of 24.14 MPa increased the oil displacement efficiency by 26 percentage points.

For the second fluid sample, experiments 5#-10# showed that the oil displacement efficiency of soaking throughput increased significantly over that of continuous gas injection at three pressure levels of 8.28 MPa, 14.48 MPa, and 21.38 MPa, regardless of whether the injection pressure was greater or less than the MMP (13.28 MPa). When the injection pressure was less than the MMP, for example, at an injection pressure of 8.28 MPa, the oil displacement efficiency increased nearly five times. When the injection pressure was greater than the MMP (at an injection pressure of 14.48 MPa or 21.38 MPa), the oil displacement efficiency increased by a factor of one.

Due to the limitation of experimental conditions, indoor experiments can only reflect the oil displacement mechanism under the influence of the experimental factors involved. It is difficult to form a comprehensive understanding of the interrelationship between the experimental factors with a small number of experimental results. They simply cannot be extended to field applications. Additional work is still needed to analyze the relationship between various influencing factors and oil displacement efficiency.

3. DATA PROCESSING AND RESEARCH METHODS

3.1 Data source and processing

The experimental data in Table 1 were obtained from the CO_2 shale core replacement experimental results of Tovar et al. (2021), which contain reservoir geological parameters, crude oil fluid parameters, and injection engineering parameters. To improve the convergence speed of the neural network model and reduce the training error in training, the initial data were normalized before training to normalize the test data to the range of 0~1. The normalization equation is:

$$X_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Where X_i, x_i are normalized data values, original data values; and x_{max}, x_{min} are the maximum and minimum values in the original data.

After integrating the original experimental data and excluding irrelevant data and groups, the cause-free data of the 10 experimental datasets used in this test were obtained, as shown in Table 2.

Table 2 Normalized data.

Serial number	Porosity/%	Compressibility/(1·MPa^{-1}·10^{-3})	Oil saturation/%	TOC/wt%	Median pore size/nm	Matrix permeability/nd	Soaking time/h	Injection pressure/MPa	Oil displacement efficiency

								/%
1	1.000	0.217	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2	0.523	0.319	0.209	0.277	0.667	0.300	0.455	0.000	0.420
3	0.000	0.115	0.739	0.112	0.333	0.217	0.000	0.000	0.209
4	0.000	0.115	0.739	0.112	0.333	0.217	0.000	1.000	0.324
5	0.115	0.000	0.493	0.477	0.333	0.167	0.955	0.000	0.204
6	0.959	0.250	0.000	0.000	0.333	0.129	0.000	0.473	0.149
7	0.495	0.049	0.240	0.888	0.000	0.000	0.955	0.473	0.334
8	0.622	1.000	0.706	0.849	0.667	0.183	0.955	1.000	0.640
9	0.323	0.277	0.235	0.498	0.333	0.183	0.000	0.000	0.000
10	0.282	0.367	0.672	0.221	0.333	0.225	0.000	1.000	0.339

3.2 Establishment of BP neural network model

BP neural network is one of the most widely used neural network models (Zhu et al., 2006). It is a multilayer feedforward neural network trained according to an error back propagation algorithm. The topology of its model consists of an input layer, hidden layers, and an output layer.

Because only 2 groups of fluid samples were selected in this study, corresponding to only 2 groups of crude oil density and MMP, the number of fluid samples would interfere with the ranking of factors. We analyzed the other eight influencing factors using the gray correlation method (Liu et al., 2013). Among them, rock compressibility, porosity, TOC, and oil saturation related to the physical properties of rock reservoirs reflect the original reserves and decaying recovery capacity in matrix reservoirs. The median pore size reflects the ability of CO_2 to enter the reservoir. The influence of matrix permeability is not significant because the reservoir is put into production by fracturing. The soaking time reflects the degree of CO_2 replacement with crude oil in the reservoir, and the injection pressure reflects the degree of CO_2 mixing phase with crude oil in the reservoir.

The results of the gray correlation analysis are shown in Table 3. In order of correlation, the injection pressure and soaking time of engineering parameters were the main control factors affecting the oil displacement efficiency. The geological parameters with the greatest influence to least are porosity, median pore size, TOC, compressibility, oil saturation, and matrix permeability. Finally, the first seven indexes with a correlation higher than 0.95 were selected as the input layer parameters of the BP neural network, and the oil displacement efficiency of indoor experiments was selected as the output layer parameters to establish the prediction model of shale core CO_2 indoor displacement experiments based on BP neural network.

Table 3 The analysis results of correlation degree between various influencing factors and oil displacement efficiency.

Evaluation items	Relevance	Ranking
Injection pressure/MPa	0.991	1
Soaking time/h	0.986	2
Porosity/%	0.986	3
Median pore size/nm	0.984	4
TOC/wt%	0.981	5
Compressibility/($1 \cdot MPa^{-1} \cdot 10^{-3}$)	0.979	6
Oil saturation/%	0.95	7
Matrix permeability/nd	0.615	8

The parameters through the input layer were divided into each hidden layer, and each hidden layer node then performed operations such as encoding of weights and thresholds and error evaluation on each input data. In turn, the output result was obtained: the indoor experimental oil displacement efficiency obtained from this training and prediction. The single-layer structure was chosen for the hidden layer of the BP neural network of this model, and the number of nodes in the hidden layer was obtained by the empirical equation (2), and the error was smaller when the number of nodes in the hidden layer was 10.

$$p = \sqrt{m+n} + q \quad (2)$$

Where p is the number of nodes in the hidden layers; n is the number of nodes in the input layer; m is the number of nodes in the output layer; and q is an integer between 1 and 10.

3.3 Establishment of BP neural network model optimized by genetic algorithm

The traditional BP neural network algorithm has slow convergence problems, poor searching ability, and easily falls into local minima, which are disadvantages in training (Liu et al., 2017). The genetic algorithm (GA) has good optimization ability in the initial weights and thresholds of the BP neural network, and the optimized model quickly convergences and has a low computational cost (Yu, 2015). Considering the small sample of the data set of this research object, we introduced the genetic algorithm to optimize and improve the BP neural network, constructed the prediction model of shale core CO_2 indoor displacement experiment based on GA-BP neural network, and then laid the material foundation for indoor experiments to guide field applications.

The structure of the model mainly includes two parts: BP neural network and genetic algorithm optimization (Huang et al., 2009). First, the BP neural network part determines the parameters and states of the input, hidden and output layers, establishes the topology of the network model, and then initializes the weights and thresholds. The genetic algorithm optimization encodes the weights and thresholds from the BP neural network, performs genetic selection, crossover, and variation operations to obtain the fitness results, and feeds the optimal weights and thresholds back to the neural network. Finally, the BP neural network is continuously trained and evaluated until it meets the target requirements for prediction and output. The GA-BP neural network algorithm flow of the prediction model is shown in Fig. 1.

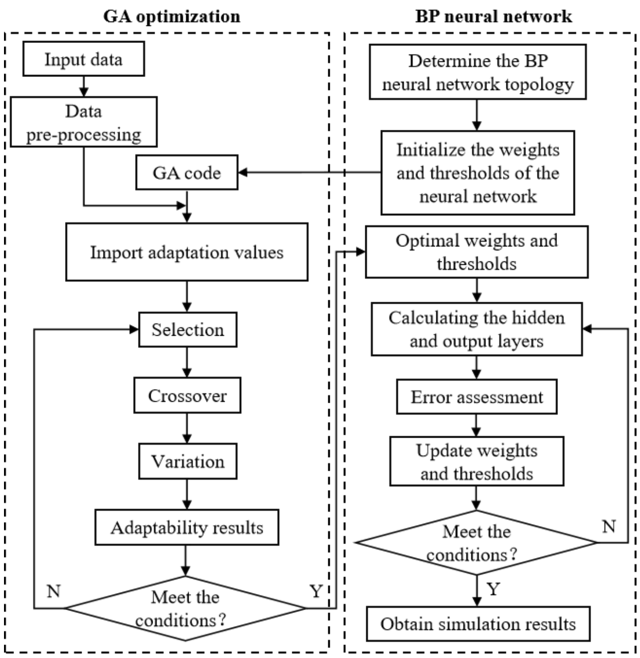


Fig. 1. GA-BP neural network algorithm flow of prediction model.

In this paper, Matlab software was used for programming. Ten sets of data set samples were divided into training and testing sets (the first 6 sets were training samples, and the last 4 sets were testing samples) to train and test the neural network model. In training, the maximum number of iterations for the BP neural network training was set to 1000, the error threshold was 1×10^{-6}, and the learning rate was 0.01. The number of genetic generations for genetic algorithm optimization was set to 50, the population size was 10, the crossover probability was 0.7, and the variation probability was 0.1.

3.4 Evaluation indicators

To comprehensively evaluate the accuracy of the model, the mean absolute error (*MAE*), root mean square error (*RMSE*), and coefficient of determination (R^2) were calculated to evaluate the accuracy of the experimental prediction model of shale core replacement. The smaller the value of *MAE* and *RMSE*, the smaller the model error. The closer the value of the coefficient of determination R^2 is to 1, the better the model fit. The specific formulas for the evaluation indicators are as follows.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i'\right| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i'\right)^2} \tag{4}$$

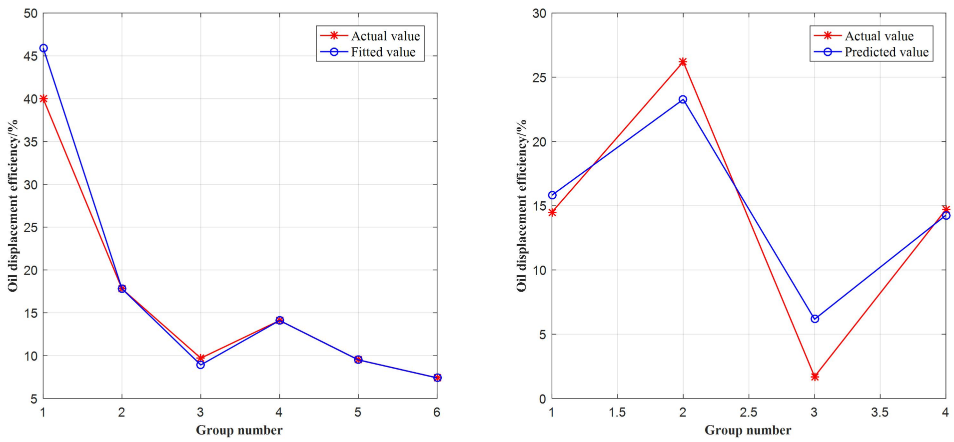
$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y_i'\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{5}$$

Where y_i and y_i' are the actual and predicted values of oil displacement efficiency, % ; $\bar{y}$ is the arithmetic mean of the actual values of oil displacement efficiency; and n is the number of samples.

4. RESULTS AND ANALYSIS

4.1 BP neural network model testing

After data processing, parameter fitting, and error evaluation, the BP neural network prediction model obtained from the training set was used for the prediction of the last 4 sets. The fitting results of oil displacement efficiency are shown in Fig. 2. The comparison shows that the predicted trend of shale core displacement is in good agreement with the actual value. The prediction accuracy of the BP neural network model is shown in Table 4. The mean absolute error of the prediction set is 1.286, the root mean square error is 1.757, and the R^2 is 0.899.



(a) (b)

Fig. 2. Comparison of fitting results of shale core displacement experiments based on BP neural network: (a) Comparison between the fitted value and the actual value, and (b) Comparison between the predicted value and the actual value.

4.2 Model testing and analysis after optimization by genetic algorithm

After the genetic algorithm optimization of the above BP neural network model, the GA-BP neural network prediction model obtained from the training was used again to predict the last four groups of samples. The fitness curve of the optimized prediction model is shown in Fig. 3. It can be seen that the individual adaptation index gradually decreases, and the adaptation ability gradually increases after multiple optimization and calculation of the GA-BP neural network model. When the number of iterations reaches 29, the individual adaptation level gradually stabilizes.

The comparison of the fitting results of oil displacement efficiency obtained after optimization is shown in Fig. 4. The predicted values of the BP neural network prediction model optimized by the genetic algorithm fit better with the actual values. The prediction accuracy of the GA-BP neural network model is shown in Table 4. The results show that the accuracy of the predicted values of the GA-BP neural network model improved, with the mean absolute error of 0.898, root mean square error of 0.946, and R^2 reaching 0.983. After optimization by the genetic algorithm, the mean absolute error is reduced by 30%, the root mean square error is reduced by 46%, and R^2 increased by 11%.

Table 4 Comparison of oil displacement efficiency prediction effect and error analysis based on BP neural network and GA-BP neural network.

Model type	Predicted group number	Actual value/%	Predicted value/%	*MAE*	*RMSE*	R^2
BP model	1	14.50	15.82	1.286	1.757	0.889
	2	26.20	23.28			
	3	1.70	5.86			
	4	14.70	14.26			
GA-BP model	1	14.50	14.64	0.898	0.946	0.983
	2	26.20	26.49			
	3	1.70	2.81			
	4	14.70	15.85			

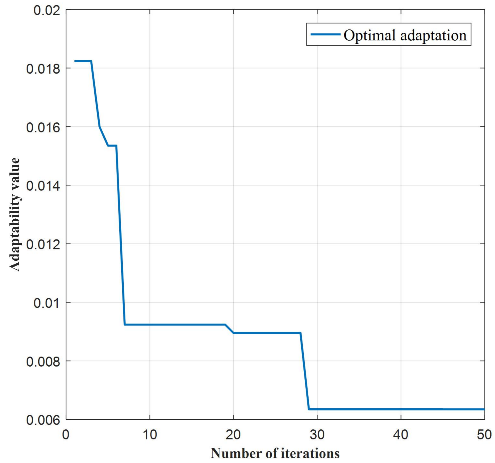
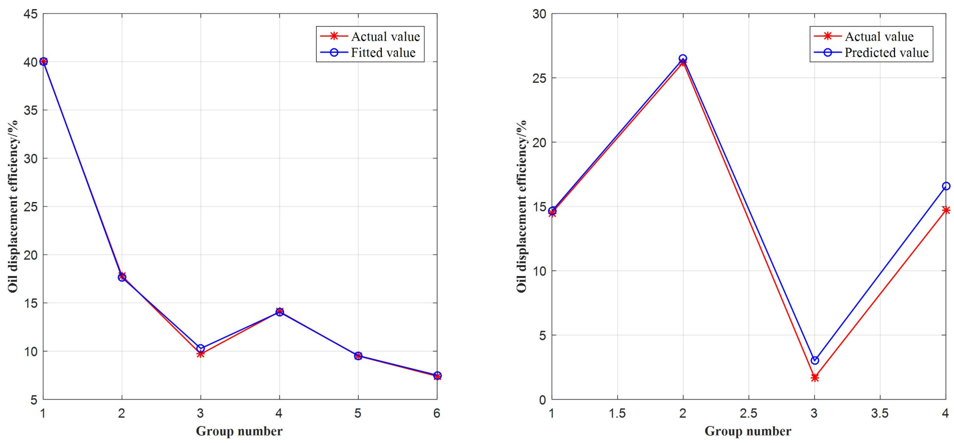


Fig. 3. The fitness curve of GA-BP neural network prediction model.



(a) (b)

Fig. 4. Comparison of fitting results of shale core displacement experiments based on GA-BP neural network: (a) Comparison between the fitted value and the actual value, and (b) Comparison between the predicted value and the actual value.

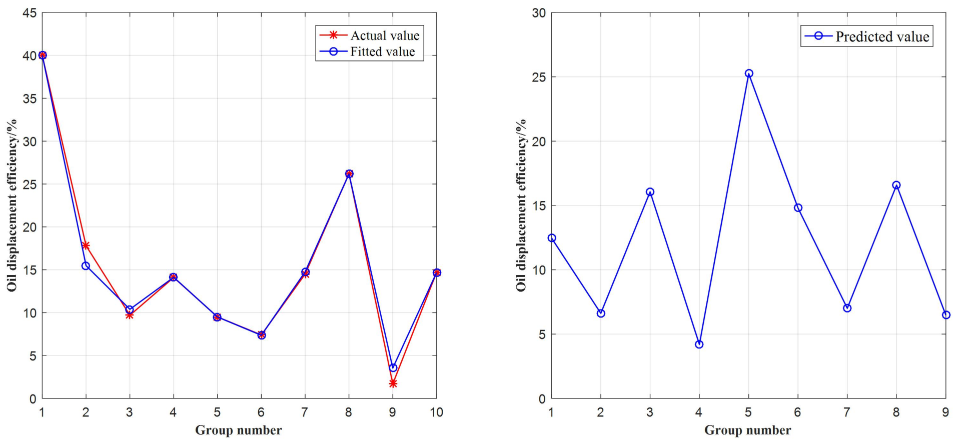
4.3 Application of the method

The prediction model based on GA-BP neural network constructed for shale core CO_2 indoor replacement experiments can be used to examine the effects of various influencing factors on the oil displacement efficiency under different experimental conditions. The experimental fluid sample density was 0.83g/cm^3, the experimental temperature was 73.9°C, the corresponding MMP was 13.28MPa, and multiple sets of prediction experiments were designed. The injection pressure was 7MPa, 15MPa, and 20MPa. The soaking time was 0, 10h, and 25h. The other experimental conditions were set within a reasonable range, and the specific test data are shown in Table 5.

Table 5 The test data of prediction experiment.

Serial number	Porosity/%	Compressibility/(1·MPa^{-1}·10^{-3})	Oil saturation/%	TOC/wt%	Median pore size/nm	Soaking time/h	Injection pressure/MPa
1	7.65	0.98	67.45	3.18	4	25	15
2	5.86	1.43	34.45	1.78	5	0	15
3	7.76	1.67	55.67	2.87	5	10	7
4	6.96	1.24	68.9	1.56	4	0	7
5	10.2	1.52	89.65	2.41	6	25	20
6	8.46	1.14	77.4	3.8	5	10	15
7	8.28	1.2	35.78	2.65	6	25	7
8	7.66	2.3	62.8	2.21	5	10	20
9	9.65	1.16	40.69	2.32	5	0	20

The GA-BP neural network indoor displacement experimental prediction model was subjected to data processing, parameter fitting, and error evaluation. The results of this prediction experiment are obtained as shown in Fig. 5. The mean absolute error, root mean square error, and R^2 of the test set highlight the high accuracy of the model. The predicted oil displacement efficiency results are within a reasonable range. The analysis of the prediction results shows that the experimental pattern of the effect of gas injection methods, injection pressure, and soaking time on oil displacement efficiency is in remarkable agreement with the indoor experiments of core displacement of Tovar et al. (2021). Overall, the prediction results and accuracy of the GA-BP neural network prediction model is high, and the model is suitable for experimental modeling.



(a) (b)

Fig. 5. The prediction experiments results based on GA-BP neural network: (a) Comparison between the fitted value and the actual value, and (b) The predicted value of oil displacement efficiency.

5. CONCLUSIONS

(1) The influencing factors of oil displacement efficiency were ranked using gray correlation analysis based on the shale core CO_2 displacement experiments and parameters. Numerous constraining factors influence oil recovery in the integrated development process of CO_2 soaking-production in shale reservoirs and the significant variation in the field implementation effect. The findings demonstrated that the main control factors affecting the oil displacement efficiency are the injection pressure, CO_2 soaking time, and reservoir porosity.

(2) This paper established a genetic algorithm-optimized BP neural network-based prediction model for CO_2 indoor displacement experiments in shale cores. Compared with the

traditional BP neural network prediction model, the fitting degree and prediction accuracy of the GA-BP neural network prediction model were enhanced. The mean absolute error was reduced by 30%, the root mean square error was reduced by 46%, and the R^2 increased by 11%. This provides a theoretical basis for the indoor experimental study of the CO_2 oil displacement mechanisms.

(3) The model optimized by genetic algorithm overcomes slow convergence problems, poor searching ability, and the tendency to fall into local minima compared to traditional neural networks. In practical production, the model can play an important role in prediction and evaluation by learning various types of dynamic and static influencing factors, overcoming the above issues with previous models, while reducing experimental costs.

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