Method for Potential Evaluation and Parameter Optimization for CO2-WAG in Low Permeability Reservoirs based on Machine Learning

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Abstract. The CO2 water-alternating-gas flooding (CO2-WAG) is a key technology to improve the oil recovery of low permeability reservoirs. The effect of CO2 flooding to enhance the oil recovery is affected by geological conditions and production systems. The effect of CO2 flooding parameters on the enhanced recovery factor should be clarified to optimize the production system. In this paper, the machine learning algorithms are used to carry out the study and establish a set of procedures for optimizing CO2 flooding parameters based on the artificial neural network (ANN) and the particle swarm optimization (PSO) algorithm. Firstly, large amounts of basic data are generated by the Monte Carlo sampling method. Then, the recovery factor by the water flooding and the CO2-WAG and the enhanced recovery factor by CO2-WAG in different models are calculated in the reservoir numerical simulator. Moreover, the machine learning method is used to establish a neural network model, and analysis of the sensitivity of parameters of the enhanced oil recovery (EOR) is carried out by combining with the Sobol method. Finally, the neural network model and the particle swarm algorithm are combined to optimize the parameters of CO2-WAG flooding. The results show that the established model has a good prediction accuracy (97.6%), thus it could be used to predict the enhanced recovery factor by CO2-WAG, and it is applicable in potential evaluation of enhancing the oil recovery and optimization for parameters in the CO2-WAG well group.

Keywords: Artificial neural network; Particle swarm algorithm; Low permeability reservoir; CO2 flooding parameter optimization.

1. Introduction
Low-permeability reservoirs are widespread in China and contribute to most of oil production in China. The development of low-permeability reservoirs is limited by the high water injection starting pressure,
the low water injectivity, the rapid rise in the water injection pressure, the rapid water injection rate decline, the slow pressure build-up in the producer, the rapid production decline, and the low water injection volume, oil production, production rate, and recovery. Generally, the recovery factor of primary and secondary oil recovery is only 10%–15% on average [1]. Currently, due to increasing costs, the development of low-permeability oil reservoirs with the technology of enhancing the oil recovery by water injection is increasingly uneconomic and unsustainable. Especially, in some oil fields with scarce water sources and fragile environments, the water injection development has aggravated conflicts in water use in the industry, society, environment, etc. Therefore, it is inevitable to search alternative technologies for water injection development [2]. The CO2 flooding is a water-saving/water-free way to improve recovery factor. With the rapid progress of CO2 capture technology, a large amount of industrial emissions CO2 that could not be recycled previously has been provided, which drastically reduces the CO2 cost and makes CO2 flooding economically feasible [3,4]. Generally, it is believed that CO2 gas has the superiorities in the strong injectivity, the high expansion coefficient, and the good miscibility with oil. CO2 flooding enhances the oil recovery by about 5–10% on the basis of water injection development and shows the huge technical potential of enhanced oil recovery (EOR). Taking into account of all these factors, the CO2 flooding EOR technology has become an indispensable alternative to the water flooding EOR technology. At the end of 2014, China had cumulative proven oil reserves of 108.5 billion tons, of which low-permeability reservoir reserves were 53.7 billion tons, accounting for 49% of the total resources. Therefore, the CO2 flooding EOR technology is promising in China.

During CO2 flooding, evaluation of influences of various factors on the CO2 flooding effect is a necessity. The factors cover the reservoir properties such as reservoir pressure, temperature, reservoir heterogeneity, permeability, and fractures, and the gas injection parameters such as injected gas composition, injection method, water-alternating-gas (WAG) injection parameters and injection timing. (Fig.1) [5, 6]. The parameter optimization is traditionally performed by obtaining the optimal solution to each parameter through the controlled variable method of well type single factor analysis or through multi-factor analysis by orthogonal design [7].

In recent years, due to the rapid progress in computer, mathematical statistics, probability theory, etc., machine learning has been used to perform prediction in several disciplines and engineering fields, which aims to make up for the deficiency in traditional prediction. In petroleum engineering, machine learning has been applied in remaining oil prediction [8], gas injection parameter optimization [9], minimum miscible pressure prediction [10], well logging [11], relative permeability prediction [12], etc. In this paper, the machine learning algorithms are used to carry out CO2-WAG parameter optimization as follows:

1) Determine the main factors that affect the EOR using the CO2-WAG technology;
2) Establish a CO2-WAG EOR prediction model, which aims to obtain the optimal WAG timing and WAG working system with the known porosity, permeability, fluid properties or relative permeability curves.
2. Method and principle

2.1. Artificial neural network

BP neural network, which was proposed by Rumelhart, McClelland, et al. in 1986, is a multi-layer feed forward neural network trained according to the error back propagation algorithm and is the most widely used among the neural networks [13].

According to the continuous function mapping theory of BP neural network, a tri-layer grid can approximate a continuous function with arbitrary precision under certain conditions. Fig.2 shows a tri-layer multi-neuron structure, which is divided into input layer, hidden layer, and output layer.

![Tri-layer network composed of multiple neurons](image)

2.2. Sobol sensitivity analysis

The core of the Sobol method, which was proposed in 1993, is to decompose the model into the combinations of a function of a single parameter and a function of several parameters [14]. Assuming

![Factors affecting the development effect of CO2 flooding](image)
that the model is \( Y = f(X), (X = x_1, x_2, ..., x_n) \), where \( X \) follows \([0, 1]\) uniform distribution, and \( f^2(X) \) is integrable, the model is decomposed into:

\[
f(X) = f_0 + \sum_{i=1}^{n} f_i(x_i) + \sum_{i<j} f_{ij}(x_i, x_j) + \cdots + f_{12..k}(x_1, x_2, ..., x_k),
\]

(1)

Then, the total variance of the model can be decomposed into the effect of a single parameter and the combined effects of each parameter:

\[
D = \sum_{i=1}^{n} D_i + \sum_{i<j} \sum_{i,j} D_{ij} + \cdots + D_{12..n}
\]

(2)

The equation is normalized. We define:

\[
S_{12..n} = \frac{D_{12..n}}{D},
\]

(3)

The sensitivity \( S \) of a single parameter and the mutual sensitivity of several parameters are obtained, and according to Equation (2), we have

\[
1 = \sum_{i=1}^{n} S_i + \sum_{i=1}^{n} \sum_{i,j} (S_{ij} + \cdots + S_{12..n}),
\]

(4)

where \( S_i \) is the 1st time sensitivity, \( S_{ij} \) is the 2nd time sensitivity, and so forth; \( S_{12..n} \) is the sensitivity of \( n \) times. There are \( 2^n - 1 \) items in total. The total sensitivity \( S_{Tj} \) of the \( i \)th parameter is defined as:

\[
S_{Tj} = \sum S_{(i)},
\]

(5)

Which represents all the sensitivity related to the \( i \)th parameter.

2.3. Particle swarm optimization

The particle swarm optimization (PSO) algorithm is a random search algorithm based on swarm cooperation, inspired by the foraging behavior of birds. It was proposed by American social psychologist Kennedy and electrical engineer Eberhart in 1995 [15, 16].

The PSO algorithm is performed as follows: assume the search space is \( D \) dimensions, and the population number is \( NP \), which represents the particle number, the position of the \( i \)th particle is \( x_i \), the particle velocity \( v_i \), and the fitness value of the particle position \( p_i \). During particle search, the particle speed and position are updated according to Equations (2.6) and (2.7).

\[
v_{i,d}^{k+1} = \omega v_{i,d}^{k} + c_1 \text{rand}(p_{best_{i,d}}^{k} - x_{i,d}^{k}) + c_2 \text{rand}(g_{best_{i,d}}^{k} - x_{i,d}^{k}),
\]

(6)

\[
x_{i,d}^{k+1} = x_{i,d}^{k} + v_{i,d}^{k+1},
\]

(7)

where \( c_1 \) and \( c_2 \) are called as acceleration constants or learning factors, which determine the weight of the influence of the individual optimal position and the population optimal position on the final search direction of the particle; \( \omega \) is the inertia weight factor, which determines the influence on the particle search speed by the previous search speed, and the appropriate \( \omega \) value guarantees a balanced wide-area search ability and a local search ability of the particle, which are called as the particle exploration ability and the particle development ability; \( \text{rand} \) is a random number between 0 and 1; \( v_{i,d}^{k} \) and \( x_{i,d}^{k} \) respectively represent the \( D\)-th dimensional velocity and position of the \( i \)th particle in the \( k \)th iteration; \( p_{best_{i,d}}^{k} \) represents the individual optimal position of the particle; \( g_{best_{i,d}}^{k} \) represents the global optimal position of the population. In the PSO algorithm, a maximum speed \( V_{max} \) needs to be set to control the maximum distance of particle movement.

3. Model training and parameter optimization

In this section, the study is carried out as follows:

1) Establish a typical 1/4 five-point well pattern characteristic model;
2) Determine variable parameters and parameter ranges;
3) Perform multi-parameter sampling using Monte Carlo method to generate 3000 geological models;
4) Use a reservoir numerical simulator to compute the generated model;  
5) Use the Sobol method to analyze the sensitivity of parameters;  
6) Use the artificial neural network (ANN) to establish the relation model (agent model) between parameters and recovery factor;  
7) Use the agent model and the PSO algorithm to optimize the CO2-WAG production system under given geological parameters.

3.1. Building of the basic model

The first step of machine learning is to obtain a large amount of basic data. Thus, a 1/4 five-point well pattern is established, as shown in Fig. 3. The model is transformed to WAG after a period of time of water injection at a rate of 0.1PV/a. Other parameters are listed in Table 4-1.

![Fig. 3 Schematic of the basic numerical model](image)

| Parameters               | Value     | Parameters               | Value     |
|--------------------------|-----------|--------------------------|-----------|
| Grid number              | 21×21×5   | Grid size, m             | 15×15×5   |
| Component                | Field data| Relative permeability    | Field data|
| Injection-production relation | One injector and one producer | Injected gas | CO2 |

3.2. Uncertain parameters and their ranges

Uncertain parameters and their ranges, as shown in Table 2, include: the planar grid size, which indicates the effect of well spacing on the recovery; the vertical grid size, which indicates the effect of the thickness on the recovery; the permeability in the X direction, the ratio of the vertical permeability to the horizontal permeability (Kv/Kh), and the variation coefficient of permeability (VDP), which indicate the effect of permeability, anisotropy, and range on the recovery; other reservoir physical properties and fluid components, including porosity, formation pressure, and initial water saturation; WAG production system, which includes the gas injection rate, the water injection rate, the gas injection timing, the WAG cycle number, and the gas-liquid ratio.

| Parameters               | Value     | Parameters               | Value     |
|--------------------------|-----------|--------------------------|-----------|
| Dx, m                    | 10-25     | Ky, mD                   | 0.01-50   |
| Dy, m                    | 10-25     | VDP                      | 0.45-0.95 |
| Dz, m                    | 1-5       | Initial pressure, MPa    | 10-42     |
| Kx, mD                   | 0.01-50   | Kv/Kh                    | 0.1-0.5   |
| Porosity                 | 0.05-0.20 | WAG cycle number         | 10-100    |
| Gas injection timing     | Water cut | Gas injection timing, d  | 60-150    |
| Gas injection rate, PV/a | 0.05-0.20 | Gas injection time, d    | 60-150    |
| Water injection rate, PV/a | 0.05-0.20 |                       |           |
3.3. Analysis of results
The curves of calculated daily oil production and recovery percentage for all samples are shown in Figs. 4 and 5. As shown in Fig. 6, the recovery in CO$_2$-WAG flooding is mainly 50–80%. The enhanced recovery factor by CO$_2$-WAG flooding is obtained by subtracting the recovery factor of water flooding from that of CO$_2$-WAG flooding. The distribution is shown in Fig. 7. The value of the enhanced recovery factor by CO$_2$-WAG flooding is mainly 0–20%.

![Daily oil production in the CO$_2$-WAG flooding](image)

**Fig. 4** Daily oil production in the CO$_2$-WAG flooding

![Recovery curve in the CO$_2$-WAG flooding](image)

**Fig. 5** Recovery curve in the CO$_2$-WAG flooding

![Recovery distribution in the CO$_2$-WAG flooding](image)

**Fig. 6** Recovery distribution in the CO$_2$-WAG flooding
3.4. Deep learning and sensitivity analysis

Next, the data are fitted using an ANN model.

1) Determine the network structure

According to Kolmogorov theory, the node number in the hidden layer is determined by the equation
\[ n = \sqrt{l + m} + a, \]
where \( l \) and \( m \) are the neuron number in the input layer and the output layer, respectively, and \( a \) is a constant between 0 and 10. Due to 23 neurons in the input layer and 1 neuron in the output layer in the model in this section, the node number \( n \) in the hidden layer is an integer between 5 and 15. In network training, it is found after repeated experiments that the training error is the smallest in case of 11 nodes in the hidden layer, so the value of \( n \) is set as 11. The Gaussian function with probability meaning is selected as the activation function for hidden layer, and the integral function is selected as the aggregate function, which can meet actual needs. The activation function for the output layer is set as a linear function.

2) Network training and prediction

A total of 2100 sets of data, 70% of all the data, are taken as the training data, and the model training results are shown in Fig.8a; a total of 450 sets of data, 15% of all the data, are used for validation, as shown in Fig.8b. The remaining 450 sets of data are used for prediction, and the prediction accuracy is 97.6%, as shown in Fig.8c. The results of the machine learning model and the numerical simulation model are compared in Fig.8d, showing a good agreement.

![Fig. 7 Enhanced oil recovery distribution in the CO2-WAG flooding](image)

![Fig. 8 Evaluation of factors affecting the enhanced recovery factor](image)
The Sobol method is used to analyze the effect of each parameter on the enhanced oil recovery, as shown in Fig.9. It can be seen that the factors affecting the technology of CO2-WAG EOR (from strong to weak) are ranked as the gas injection rate, the oil saturation before gas flooding, the gas injection volume, the water injection rate, the water cut before gas flooding, the cycle time, the gas injection time, the water injection time, the production rate, and the VDP variation coefficient. The cumulative effect of these factors is above 98%.

![Fig. 9 Evaluation of factors affecting the enhanced oil recovery](image)

### 3.5. CO2-WAG parameter optimization

With the known reservoir geological parameters and some production control parameters in a block (Table 3), the production system is optimized by combining with the neural network model and the PSO algorithm, targeting at realizing the highest enhanced recovery factor. The optimization results are listed in Table 4. The main optimized parameters include the WAG gas injection time, the WAG water injection time, the WAG total period, the bottom hole flowing pressure limit, the gas injection rate, and the water injection rate. The predicted overall recovery factor for the optimized plan is 39.44%, which increased by 15.21% compared with the enhanced recovery factor of water flooding.

| Table 3. Input parameters of the artificial neural network model |
|---------------------------------------------------------------|
| **Oil reservoir** |
| Grid size in X direction, m | 20 |
| Grid size in Y direction, m | 20 |
| Grid size in Z direction, m | 3 |
| Average permeability, mD | 5.20 |
| VDP variation coefficient | 0.75 |
| Vertical permeability/planar permeability | 0.1 |
| Porosity | 0.150 |
| **Initial condition** |
| Initial water saturation | 0.400 |
| Initial pressure, MPa | 20 |
| **Production control** |
| Liquid production rate during water injection, m3/day | 30 |
| Water injection speed during water injection, m3/day | 30 |
| CO2-WAG start time, d | 3000 |
| Current water cut, % | 75 |
| Current saturation, % | 60 |
| Reservoir pressure, MPa | 12 |
| Injection pressure, MPa | 30 |
Table 4. Input parameters of the artificial neural network model based on the particle swarm algorithm

| Optimization parameters | Results |
|-------------------------|---------|
| WAG gas injection time, d | 123     |
| WAG water injection time, d | 171     |
| WAG total cycle time, d | 294     |
| Bottom flowing pressure, MPa | 12       |
| Gas injection rate, m³/d | 24500   |
| Water injection rate, m³/d | 30       |
| Water flooding recovery, % | 24.23   |
| Total recovery, % | 39.44   |
| Enhanced recovery factor by WAG, % | 15.21   |

4. Conclusions
In this paper, a machine learning algorithm is used to establish a method for parameter optimization of CO₂ flooding in low-permeability reservoirs, and the sensitivity of the geological conditions and production systems that affect the effect of CO₂ flooding is analyzed. A parameter optimization model for CO₂ flooding is established based on the ANN and the PSO algorithm. The model established in this paper has a good prediction accuracy (97.6%). The factors affecting the technology of CO₂-WAG EOR (from strong to weak) are ranked as the gas injection rate, the oil saturation before gas flooding, the gas injection volume, the water injection rate, the water cut before gas flooding, the initial pressure, the water injection volume, the cycle time, the gas injection time, the water injection time, the production rate, and the VDP variation coefficient.

The results show that the machine learning method can be used to predict the enhanced recovery factor by CO₂-WAG and is applicable in evaluation of the EOR technology and parameter optimization of CO₂-WAG in well groups.

Acknowledgments
The authors are grateful for financial support from the National Science and Technology Major Project (Grant No. 2016ZX05016-005 and 2016ZX05016-001), the Major Project of China National Petroleum Corporation (Grant No. RIPED-2020-JS-50214) and (Grant No. RIPED-2020-JS-50215), the project of Sinopel North China Petroleum Bureau (Grant No. 290018276) and project of Petroleum Engineering Technology Institute of SINOPEC Shengli Oilfield (Grant No. 290018276). We also thank Ennosoft Ltd. for the use of the UNCONG reservoir simulator.

References
[1] Ziming Zhao. A Study on Heterogeneities and Development Characteristics of Chang 4+5 and Chang 6 Reservoirs in Hujianshan Area [D]. Xi’an Shiyou university, 2018.
[2] Li Liu, Mingjing Gao. Study on Effective Development Technology of Low Permeability Reservoir -- a Case Study of Suderte Oilfield [J]. West-China Exploration Engineering, 2018, 30(03): 102-105.
[3] Zhicheng Sui, Junping Ren, Weidong Zhao, Wendong Liu. Analysis on Development Route of Carbon Capture, Utilization and Storage Technology in Xinjiang Oil and Gas Industry [J]. China Energy and Environmental Protection, 2020, 42(02): 75-79+84.
[4] Saqib S. Leverage Energy Optimization to Reduce Carbon Capture Cost[J]. SPE-203377-MS. 2020.
[5] Qi Wei. Study of Gas Channeling Law and Injection Method for CO₂ Flooding in Ultra-low Permeability Reservoirs [D]. China University of Petroleum (Beijing), 2018.
[6] Zhang Kuangsheng, Bai Xiaohu, Liu Shun, et al. Energy enhancement effect and parameters optimization of CO₂ injection in tight oil reservoir[J]. Science Technology and Engineering, 2020, 20(26): 10751-10758.
[7] Yu Peng, Yang Fulin, Oyinkepreye David Orodu, et al. Storage and injection parameter
optimization of CO2 flooding of low permeability reservoir under medium and high water cut period: a case study of S-95 block, Damintun Sag[J]. Science Technology and Engineering, 2020, 20(8): 3029-3034.

[8] Yihan Yuan. Research on the Prediction of Remaining Oil Parameters Based on Neural Net-works [D]. Northeast Petroleum University, 2017.

[9] Hongyang C. Xinwei L.and et al. Applications of Artificial Neural Networks in Gas Injection[J]. SPE-191606-18RPTC-MS. 2018.

[10] Mohammad R.K., Shams K. et al. Comparative Analysis of Intelligent Algorithms to Predict the Mini-num Miscibility Pressure for Hydrocarbon Gas Flooding[J]. SPE-197868-MS.

[11] Zhentao Wang. Research on Lithology Identi-fication Method of Logging Curve for the Reservoir Characterization [D]. Northeast Petroleum University, 2019.

[12] Shams K., Mohammed M., Rizwan A.K., and Sidqi A.A., New Vision into Relative Permeability Estima-tion Using Artificial Neural Networks [J]. SPE-202443-MS. 2020.

[13] Xin Wen, Xinwang Zhang, Yaping Zhu, Xinzhu Li. Intelligent Fault Diagnosis Technology: Applica-tion of MATLAB[M]. Beijing University of Aero-nautics and Astronautics Press, 2015.09.

[14] Sobol I M. Sensitivity Estimates for Nonlinear Mathematical Models [J]. Matematicheskoе model-irovanie, 1990, 2(1).

[15] Kennedy J, Eberhart R. Particle Swarm Optimi-za-tion [C]. IEEE International Conference on Neural Networks, 1995. Proceedings. IEEE, 2002, (4): 1942-1948.

[16] Eberhart R, Kennedy J. A New Optimizer using Particle Swarm Theory [C]. International Symposium on MICRO Machine and Human Science. IEEE, 2002: 39-43.