Proceedings of the 6th International Conference on Materials Chemistry and Environmental Engineering
DOI: 10.54254/2755-2721/2026.31487

Study on Scaling Prediction and Law of Oilfield Gathering and Transportation Pipelines Based on CPO-BP Neural Network and Dynamic Experiments

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Abstract. Aiming at the scaling problem of oilfield gathering and transportation pipelines, this paper conducts a systematic study through experiments and modeling. Orthogonal experiments are used to analyze the effects of temperature, pressure, flow rate and ion concentration on scaling rate, and the formation mechanism of scaling substances is explored. On this basis, a BP neural network prediction model optimized by the Chinese Pangolin Optimization (CPO) algorithm is established to realize nonlinear modeling and trend prediction of scaling rate. The results show that temperature, pressure and flow rate are the main controlling factors of scaling rate. The prediction error of the CPO-BP model is less than 15%, which can effectively predict the scaling trend. This study provides a theoretical basis for pipeline scaling prevention and control as well as operation optimization, and has broad application prospects.

Keywords: Gathering and transportation pipelines, Scaling prediction, CPO-BP neural network, Dynamic experiments

1. Introduction

With the general entry of onshore oilfields in China into the high water cut development stage, the water cut of produced fluid reaches 70%~95% [1,2], and the concentration of scaling ions such as calcium and magnesium in the produced fluid is relatively high. During the gathering and transportation process, affected by the comprehensive effects of temperature and pressure fluctuations and incompatible water quality of individual wells, scaling is prone to occur. Scaling can cause blockage and damage to pipelines, valves and other equipment, seriously affecting the safe and stable operation of the gathering and transportation system, increasing operation and maintenance costs, and restricting the sustainable development of oilfields. The salinity of produced fluid in the high water cut period increases significantly, further exacerbating the scaling risk. Scaling behavior is comprehensively affected by multiple factors such as salinity, temperature, pressure, pH and flow rate [3]. Wang Rui et al. [4] pointed out that scaling is related to salinity, temperature and flow rate; Zou Wei et al. [5] showed that increased temperature, decreased pressure and increased pH promote scaling, while low flow rate aggravates deposition; Zheng Chengyu et al. [6] used ScaleChem to predict scaling risk and proposed ion concentration control measures; Yang et

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al. [7] developed prediction software and found that increasing water injection rate can slow down scaling, while prolonged water injection time and increased ion concentration will aggravate scaling; Zolfagharroshan et al. [8] established a multiphase flow scaling deposition model and revealed the synergistic mechanism of temperature, pH and flow rate.

The produced fluid of the test well group in Niuye No.1 Block of Shengli Oilfield has high salinity and is rich in ions such as Ca^{2+}, Mg^{2+} and HCO_3^-, resulting in significant scaling risk. This paper introduces the CPO optimization algorithm, combines dynamic experimental data to construct a CPO-BP neural network prediction model, and compares it with the traditional BP model to achieve higher precision prediction and provide a new path for scaling prevention and control. Taking the gathering and transportation system of Niuye No.1 Block as the research object, this study aims to provide theoretical and technical references for optimizing prevention and control measures and ensuring efficient operation of the system through systematic analysis of scaling laws.

2. Experiments

2.1. Experimental methods

(1) Water Quality Analysis

On-site water sample analysis is carried out with reference to SY/T 5523—2016 Oilfield Water Analysis Methods and SY/T 5329—2012 Water Injection Quality Indicators and Analysis Methods for Clastic Reservoirs.

(2) Scale Sample Analysis

X-ray diffraction (XRD) and scanning electron microscopy (SEM) are used to analyze the composition of scale samples.

(3) Establishment of Scaling Model

Based on multi-parameter dynamic monitoring data, a scaling rate prediction model is constructed using the BP neural network optimized by CPO. Through feature engineering, the model selects key input factors and establishes a nonlinear mapping between scaling rate and multi-physical field parameters. Compared with the traditional BP model, the CPO-BP model significantly reduces prediction error, improves fitting accuracy and generalization ability, and realizes accurate prediction of scaling trends under complex working conditions.

(4) Dynamic Scaling Experiments

According to the main factors affecting the scaling of the gathering and transportation system and on-site operation conditions, orthogonal experimental design is adopted for 8 factors (temperature, pressure, flow rate, water cut, carbon dioxide content, calcium ion concentration, bicarbonate ion concentration, magnesium ion concentration) with 4 levels each, totaling 32 groups of experiments. The experiments are conducted using a high-temperature and high-pressure reactor.

3. CPO-BP neural network scaling prediction model

3.1. BP neural network algorithm

BP neural network is a machine learning model based on multivariate and nonlinear characteristics. By training a large number of sample data, the model calculates the error between the network output value and the actual target value in the forward propagation process, and dynamically adjusts the connection weights and neuron thresholds between layers using the error back propagation

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mechanism. Through iterative optimization, the predicted output of the model gradually approaches the true value, thereby effectively improving prediction accuracy [9].

3.2. Chinese Pangolin Optimization (CPO) algorithm

To overcome the shortcomings of traditional BP neural network such as being prone to local optimality and slow convergence speed during training, this paper introduces a new intelligent optimization method—Chinese Pangolin Optimization (CPO) algorithm. By simulating the ecological characteristics of Chinese pangolins in nature such as foraging behavior, escape mechanism and cooperative search, the CPO algorithm designs an optimization strategy that balances global exploration and local exploitation, thereby improving the optimization ability and convergence stability [10].

3.3. Construction of scaling prediction model

The factors affecting scaling are taken as the input variables of the CPO-BP neural network prediction model, including 8 indicators: pressure, temperature, flow rate, water cut, carbon dioxide content, calcium ion (Ca^{2+}) concentration, magnesium ion (Mg^{2+}) concentration and bicarbonate ion (HCO_3^-) concentration; the output layer corresponds to the predicted result of scaling rate. The data collected through on-site monitoring are used for model training.

The number of hidden layer nodes is determined using the empirical formula (1):

$$h = 2n + 1 \tag{1}$$

Where: h is the number of hidden layer nodes; n is the number of input layer nodes.

This formula is based on the neural network approximation theory proposed by Hecht-Nielsen, that is, a single hidden layer feedforward network can approximate any continuous function with sufficient hidden layer nodes. Empirically, the network applying this formula can not only ensure sufficient approximation ability but also suppress overfitting to a certain extent.

4. Results and discussion

4.1. CPO-BP neural network scaling prediction model

Based on multi-parameter dynamic data, 275 valid data sets are collected, among which 229 are used for training and 46 for testing. A scaling rate prediction model is constructed using the BP neural network optimized by CPO. The results show that compared with the traditional BP model, the CPO-BP model has significant improvements in prediction error, fitting accuracy and generalization ability, realizing accurate prediction of scaling trends under complex working conditions.

The model shows strong scaling prediction ability overall. As shown in the regression fitting, the correlation coefficient R between the predicted values and the true values of the CPO-BP model reaches 0.85053, which is better than common empirical models, indicating that it can effectively track the true scaling rate trend. The error index comparison shows that the MAE, MSE, RMSE and MAPE of the traditional BP neural network are 0.016215, 0.021404, 0.1463 and 0.13842% respectively. After CPO optimization, the MAE, MSE and RMSE of the CPO-BP model are reduced to 0.014282, 0.016291 and 0.12763 respectively, with a MAPE of 0.14125%. The MAPE values of

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the two models are close, but the CPO-BP is significantly superior to the traditional model in MAE, MSE and RMSE, with an overall improvement in prediction accuracy of about 10%~20%. CPO optimization effectively improves the BP model, enhancing numerical accuracy and stability while maintaining trend prediction ability.

4.2. Analysis of dynamic scaling prediction experiments

The effects of various factors on scaling rate are systematically studied through orthogonal experiments. Within the temperature range of 50–80°C, the scaling rate first increases and then decreases with the increase of temperature, reaching the highest at 60–70°C and slightly decreasing at 80°C, with a range of 0.83, indicating that temperature rise promotes scaling in most cases. In the pressure range of 0.62–11 MPa, the scaling rate shows a downward trend with the increase of pressure, with a range of 0.89. Pressure reduction promotes calcium carbonate precipitation due to CO_2 escape. Within the flow rate range of 0.08–0.32 m/s, the scaling rate decreases with the increase of flow rate, with a range of 0.93. The scouring effect of higher flow rate inhibits deposition. In the CO_2 concentration range of 0–20%, low to medium concentration (10–15%) promotes scaling, while 20% slightly inhibits scaling due to water acidification, with a range of 0.42. Within the water cut range of 80–95%, the scaling rate increases with the increase of water cut, reaching the highest at 95%, with a range of 0.76. The effects of ion concentrations vary significantly: when the Ca^{2+} concentration increases from 3000 to 15000 mg/L, the scaling rate significantly increases from 4.95 to 6.22 g/(cm²·h), with a range of 1.26, making it a key promoting factor; Mg^{2+} has a weak effect within the range of 300–800 mg/L; the scaling rate is the highest when HCO_3^- concentration is 500 mg/L, and then shows a downward trend with the increase of concentration.

In summary, the scaling process is affected by the coupling of multiple factors. Among them, Ca^{2+} concentration is the most critical positive control factor, flow rate is the main inhibitory factor, while temperature, pressure, CO_2 concentration and water cut jointly affect the scaling trend by regulating the chemical equilibrium of the system and hydrodynamic conditions.

4.3. Verification of scaling prediction model

The dynamic experimental data are input into the CPO-BP neural network model for scaling rate prediction. The results show that the predicted values are highly consistent with the experimental values in both trend and numerical value, and the error of each data point is less than 15%. This result verifies that the CPO-BP model has good applicability, reliability and low error in scaling prediction, reflecting the effectiveness and application potential of intelligent algorithms in modeling and prediction in this field.

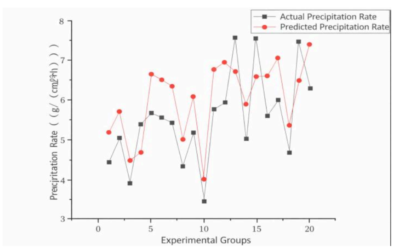

Figure 1. Neural network simulation of experimental data

5. Conclusions

Based on the CPO algorithm-optimized BP neural network and dynamic experimental methods, this paper conducts a systematic study on the scaling law and prediction of shale oil gathering and transportation pipelines. The results show that scaling behavior is significantly affected by the coupling of multiple factors. The constructed CPO-BP prediction model can effectively improve prediction accuracy and stability, providing an important reference for oilfield scaling prevention and control and gathering and transportation system optimization. The main conclusions are as follows:

(1) Temperature, pressure and flow rate all have significant effects on scaling rate. Within a certain range, the increase of temperature increases the scaling rate, but it slightly decreases at high temperature; the increase of pressure leads to the decrease of scaling rate; low flow rate promotes scaling, while turbulence under high flow rate can inhibit the formation of sedimentary layers.

(2) Water quality and scale sample analysis show that the produced water is rich in calcium, magnesium ions and bicarbonate ions, resulting in scaling substances mainly composed of calcite and magnesium-bearing calcite.

(3) The CPO-BP neural network model shows high accuracy in scaling rate prediction, which is highly consistent with experimental data. Compared with the traditional BP model, the CPO-BP model significantly reduces error indicators such as MAE, MSE and RMSE, with an overall improvement in prediction accuracy of about 10%~20%.

(4) Comprehensive analysis shows that temperature, pressure, flow rate and other factors are the main controlling factors affecting scaling behavior. The CPO-BP neural network can accurately characterize the variation law of scaling rate. This method can provide theoretical basis and technical support for the formulation of scaling prevention and control measures and the optimization of operation parameters of oilfield gathering and transportation systems, and has good application prospects.

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