A Prediction Model for Water Absorption Profile Based on IDW-DTW-RNN Method

Xu Zhao¹, Ju Yao Fu², Hong Li Xiong¹, Gao Ming Yu⁴,*

¹Exploration and Development Research Institute Sinopec Jiang Han Oilfield Company Wuhan, China
²School of Petroleum Engineering Yangtze University Wuhan, China
³Exploration and Development Research Institute Sinopec Jiang Han Oilfield Company Wuhan, China
⁴School of Petroleum Engineering Yangtze University Wuhan, China
*Corresponding author: ygm1210@vip.sina.com

Abstract. At present, many low-permeability oil fields are entering the later stages of development, and there will be problems of difficulty in water injection and poor water injection effects. Obtaining water absorption profiles and their changes can more effectively help formulate layered water injection strategies. Generally, the isotope water absorption profile method is often used to obtain the water absorption profile. This method is accurate, but the test cost is higher and the actual oil field measurement data is less. Based on the measured water absorption profile data, this paper selects 8 factors including effective thickness of oil layer, effective permeability, measure coefficient, crude oil viscosity, crude oil volume coefficient, injection-production pressure difference, well spacing, and connection coefficient between oil and water wells as the main influencing factors of the profile prediction model. Taking water injection wells data with 8 factors as input, a water injection profile prediction neural network model based on inverse distance weighting method and dynamic time warping, namely called IDW-DTW-RNN, is trained in this study. This model is applied in oil field, and the accuracy is obviously improved compared with the conventional method, which is in line with the actual development situation. It provides a scientific basis for the adjustment and optimization of the later injection-production structure of the oilfield.

1. Introduction
After the oilfield was put into development, as the production time increased, the formation energy was continuously consumed and the oil production continued to decline. In order to achieve long-term stable production of the oil field and maintain formation pressure, water injection was carried out in the oil field. However, due to the heterogeneity between layers, the water injection volume is often unevenly distributed in the vertical direction, and the development effect is not good. In order to formulate a reasonable allocation of water injection policy, it is necessary to understand the water absorption profile of the water injection profile to determine the water absorption distribution relationship between layers. The conventional methods of obtaining water absorption profile include isotope water absorption profile method and layered water injection calculation method. The principle of the isotope water absorption profile method is to inject isotopes into the well under water injection conditions. As the injected water flows in, the isotopes are filtered on the surface of the water-injected layer. The tracer curve is measured
with a gamma meter, and the difference in radioactivity intensity is shown on the curve. It represents the size of the injection volume. This method can directly reflect the water absorption of the formation, but its logging time is long. There is radioactive contamination during operation, and the test cost is expensive. The principle of the layered quantitative calculation method is to realize the split prediction of water injection based on the calculation of the plane and vertical seepage resistance coefficients based on the balance of injection and production. This method comprehensively considers the influence of geological factors and various dynamic factors, but the establishment and derivation of the formula is more complicated, the model parameters are difficult to determine in practical applications, and the calculation is difficult and cannot be popularized. For this reason, the author combines IDW, DTW and RNN to establish a water absorption profile prediction model that can comprehensively consider reservoir heterogeneity and reservoir dynamic and static parameters. The model establishment process is simple and the calculation efficiency is high. The accuracy and effectiveness of the method are verified by comparing the results with the conventional KH method and water absorption profile.

2. Basic algorithm

2.1. Data Preprocessing-Inverse Distance Weighted Interpolation

The inverse distance weighted (IDW) is an interpolation method based on the principle of similarity, that is, the closer two points are, the more similar their properties are. On the contrary, the farther away, the smaller the similarity. It takes the distance between the interpolation point and the sample point as the weight for weighted average, and the closer the sample point is to the interpolation point, the greater the weight. The general formula of the inverse distance weighted interpolation method is as follows[1]:

$$Z(\mathbf{s}_0) = \sum_{i=1}^{N} \lambda_i Z(\mathbf{s}_i)$$  \hspace{1cm} (1)

Among them, $Z(\mathbf{s}_0)$ is the predicted value at $\mathbf{s}_0$; $N$ is the number of samples around the prediction point to be used in the prediction calculation process; $\lambda_i$ is the weight of each sample point used in the prediction calculation process, and this value decreases as the distance between the sample point and the prediction point increases; $Z(\mathbf{s}_i)$ is the measured value at $\mathbf{s}_i$. The calculation formula for determining the weight is[2]:

$$\lambda_i = \frac{d_{i0}^{-p}}{\sum_{j=1}^{N} d_{j0}^{-p} \sum_{i=1}^{N} \lambda_i} = 1$$  \hspace{1cm} (2)

Among them, $p$ is the index value; $d_{i0}$ is the distance between the predicted point $\mathbf{s}_0$ and each known sample point $\mathbf{s}_i$.

The weight of the sample point in the calculation process of the predicted point value is affected by the parameter $p$; that is, as the distance between the sample point and the predicted value increases, the weight of the influence of the standard sample point on the predicted point is exponentially cut back. In the prediction process, the weight of each sample point value to the predicted point value is proportional, and the sum of these weight values is 1.

2.2. Data Optimization-Dynamic Time Warping

Dynamic Time Warping (DTW) is a typical optimization problem[3]. It uses a time warping function $W(n)$ that satisfies certain conditions to describe the time correspondence between the test template and the reference template, and solves the warping function corresponding to the smallest cumulative distance when the two templates match[4].

Suppose there are two time series P and Q, their lengths are n and m respectively:

$$P = p_1, p_2, \ldots, p_n;$$  \hspace{1cm} (3)
Q = q_1, q_2, …, q_j, …, q_m;

If n=m, just calculate the distance between the two sequences directly[5]. But if n is not equal to m, the two sequences need to be aligned. The simplest alignment method is linear scaling. Linearly enlarge the short sequence to the same length as the long sequence and then compare, or shorten the long linearly to the same length as the short sequence and compare.

In order to align these two sequences, we need to construct an n×m matrix grid. The matrix element (i, j) represents the distance d(P_i, Q_j) between point P and point Q. Each matrix element (i, j) represents the alignment of points P_i and Q_j. The algorithm can be boiled down to finding a path through several grid points in this grid, and the grid points through which the path passes are the aligned points of the two sequences for calculation.

2.3. Data Training - Recurrent Neural Network

RNN (Recurrent Neural Network) is a type of neural network used to process sequence data[6]. First of all, we must clarify what serial data is. Time series data refers to data collected at different points in time. This type of data reflects the state or degree of change of a certain thing or phenomenon over time. The specific form of expression is that the network will memorize the previous information and apply it to the calculation of the current output, that is, the nodes between the hidden layers are no longer unconnected but connected, and the input of the hidden layer not only includes the output of the input layer. It also includes the output of the hidden layer at the previous moment.

3. The establishment of new model

3.1. Model Building Process

Recurrent neural network is a type of recursive neural network that takes sequence data as input, recursively in the evolution direction of the sequence, and all nodes are connected in a chain[11]. It has an adaptive self-learning function, can automatically grasp the environmental characteristics, and realize automatic. It has advantages of good target recognition and fault tolerance, strong anti-interference ability, which is effective mean to establish a water absorption profile prediction model. The author puts the main factors of the water absorption profile prediction model into the recurrent neural network for modeling to form a split model. Through the adaptive simulation of the water absorption ratio of single wells, we can predict the water absorption ratio of each layer in the unknown well. Model technical ideas are shown in Figure 1.

![Figure 1 Model technical ideas](image)

3.2. Data Preprocessing

The preprocessing of the parameters obtained in the oil field requires inverse distance weighted interpolation to improve the simulation accuracy.

3.3. Filter Parameters

DTW is a typical optimization problem. This paper uses the DTW method to screen out the main influencing factors of the water absorption profile, and the results are shown in Table 1.
Table 1 The correlation degree and contribution of the influencing factors of Prediction of Water Absorption Profiles

| Main impact factor                  | Priority | Correlation | Contribution |
|------------------------------------|----------|-------------|--------------|
| Crude oil viscosity               | 1        | 0.7318      | 16.73145     |
| Permeability                       | 2        | 0.6922      | 15.82606     |
| Effective thickness               | 3        | 0.6434      | 14.71032     |
| Crude oil volume coefficient      | 4        | 0.6121      | 13.9947      |
| Injection-production pressure difference | 5    | 0.604       | 13.8095      |
| Well spacing                      | 6        | 0.5088      | 11.63291     |
| Coefficient of measures to increase production | 7 | 0.2843 | 6.500069     |
| Connectivity                      | 8        | 0.2972      | 6.795007     |

According to the actual situation of the oil field, the selected eight dynamic and static parameters that affect the splitting effect are used as the input nodes of the RNN, and a model to predict the water absorption of each layer of the well is established. The established RNN model has 8 input nodes and 1 output node.

4. Specific model example

4.1. Accuracy Verification

The water injection well data of a block in the LX oil field in recent years is selected for analysis, and the water absorption profile prediction model of the block is established. Part of the data is selected as the training data set, and the remaining part is used as the test data, and the water absorption splitting model is trained.

The model built in this paper outputs a diagram to the Average daily water injection volume of the single well X in different years, and obtains the water absorption of each layer. The results are shown in Figures 2-3.

![Figure 2: Fitting results of daily injection in well X](image)

![Figure 3: Results of water absorption ratio of different layers in well X](image)
It can be seen from the figure that the results predicted by the newly established model have a certain degree of fit with the real production data.

4.2. Comparison with KH Method and Real Value of Water Absorption Profile

In order to further verify the rationality of the model, the KH method, the new model method, and the actual water absorption profile of each layer in a single well are statistically analyzed, and the comparison is shown in the Figure 4.

![Figure 4](image)

Figure 4 Comparison of splitting results of different methods for stratified cumulative water absorption

The analysis shows that there is a certain error between the cumulative water absorption predicted by the KH method and the measured value of the water absorption profile, while the calculated value of the new model is closer to the field test data. Through the comparison, it can be seen that the new method has certain advantages, better simulation accuracy, and convenient model building, without considering the formula derivation, which further demonstrates the reliability of the model.

5. Conclusion:

Before establishing the model, first interpolate the parameters through inverse distance weighted interpolation. Then, the main factors of the water absorption profile prediction model are selected through DTW optimization method, and are input into the RNN for training along with some production data, and the model is obtained.

The cumulative water absorption of each layer obtained by the new model is compared with the KH calculated value of the traditional method and the measured suction profile result. The error of the new model is slightly smaller than that of the KH method calculation result, and is closer to the measured profile result, thus demonstrating the accuracy and effectiveness of the model.

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