Neural Network Production Split Model Based on Kriging Interpolation Method and Grey Correlation Analysis Method

Juyao Fu, Gaoming Yu *
School of Petroleum Engineering, Yangtze University, Wuhan, China

*Corresponding author e-mail: ygm1210@vip.sina.com

Abstract. Oil well production split is an important prerequisite for the efficient development of multi-layered reservoir. Conventional split methods do not consider the synergistic influence of dynamic and static factors related to the oil layer with certain errors. Based on the related dynamic and static parameters of production wells and production data, a neural network split model considering Kriging interpolation and grey correlation method was established. Before the model is established, the involved data is first sorted, and Kriging interpolation is used to complete the data at the appropriate time. Then, the grey correlation analysis method is used to calculate the correlation of the dynamic and static parameters related to reservoir production, and the main parameters of it are extracted. The main parameters are treated as input and substituted into the double hidden layer neural network for modelling, and the resulting model is used to split the production of each layer of the oil well. This method is applied to the production well of the N block of the Y Oilfield. Compared with the conventional method, the accuracy is significantly improved, which is in line with the actual reservoir characteristics.

1. Introduction
With the deepening of oilfield development, the heterogeneity of multi-layer reservoirs is becoming more and more serious, and conventional production split methods can no longer meet the need of refined development. At present, there are two normal methods for production split: the formation coefficient method (KH method) and the dynamic equation split method. The KH method is to weight the formation coefficient (KH) to calculate the split coefficient of each production layer. The dynamic equation split method is based on the principle of hydropower similarity, calculating the flow resistance parameter between the injection and production wells and the production of each layer.

The KH method is simple to calculate, but reservoir heterogeneity is not taken into account. KH and production in the actual reservoir do not meet the linear relationship. The dynamic equation split method comprehensively considers the influence of geological factors and various dynamic factors. However, the establishment and derivation process of the formula is relatively complicated, and it’s time-consuming.

To this end, this paper used Kriging interpolation method, grey correlation method and neural network to establish a new production split model that can comprehensively consider reservoir heterogeneity and dynamic and static parameters of the reservoir. The model is easily-built with
calculation efficiency. The accuracy and effectiveness of it are verified by comparing with the conventional KH method and the Production Logging Tool (PLT) method. [1]

2. Kriging interpolation method
Kriging interpolation was invented by South African geologist Krige and named after it. Matheron gave the general formula of Kriging. The formula for Kriging interpolation is:

\[
Z(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i)
\]

(1)

In the formula, \(Z(x_i)\) is the observation value, they are divided into \(x_i\); \(x_0\) is an unsampled point, \(\lambda_i\) is the weight, and its sum is 1.[2]

3. Grey correlation analysis method
Grey correlation analysis method is based on the degree of similarity or dissimilarity of development trends between factors, as a method of measuring the degree of correlation between factors. The specific calculation steps are as follows. [3]

3.1. Clarification of reference and comparison sequences
The reference sequence \(P_0\) is the one that contains multiple samples of dependent variable. Similarly, and the comparison sequence \(P_i\) (i = 1, 2, ..., m) is the one that contains several samples of independent variable.

3.2. Processing of raw data
Since the variable sequence may have different units, in order to be able to compare and get accurate results, it is usually through dimensionless processing to achieve comparative analysis of the data.

The absolute difference matrix between the dimensionless reference sequence and the comparison sequence is generated:

\[
\Delta_{ij}(k) = |x_0(k) - x_i(k)| \quad i = 0, 1, ..., m; k = 1, 2, ...
\]

(3)

In the formula: \(\Delta_{ij}(k)\) represents the absolute value of the subtraction result, which is a dimensionless parameter. The maximum and minimum numbers in the absolute difference matrix are the maximum difference and the minimum difference, respectively.

\[
\lceil M \rceil = \max \Delta_{0i}(k)
\]

(4)

\[
|n| = \min \Delta_{0i}(k)
\]

(5)

3.3. Calculate correlation
The correlation coefficient is between 0 and 1. It reflects the correlation between the i point of the comparison sequence and the k point of the reference sequence. The calculation formula is shown as follows.

\[
\xi_{0i}(k) = \frac{|n|^{1 + \rho} |M|}{\Delta_{0i}(k) + \rho |M|}
\]

(6)

In equation (6): \(\xi_{0i}(k)\) is the dimensionless correlation coefficient; \(\rho\) is the resolution coefficient, and its value ranges from 0 to 1, generally 0.5. The introduction of this value aims to expand the obvious difference between the correlation coefficients.

Because there are many values of correlation coefficients and the information is more scattered and not suitable for holistic comparison, the correlation information is processed centrally and the average value of it is calculated. The correlation degree can be obtained as follows.
In formula (7): \( r_{0i} \) is the degree of relevance, and the value is from 0 to 1.

4. The establishment of neural network split model

4.1. Construction of artificial neural network model
The parameters that affect the split effect are substituted into the double hidden layer neural network for modelling. They are trained to form a split model. The neural network model is used to realize the self-adaptive simulation of the split relationship of small layers, and then accurately predict the oil production, water production and water cut of each small layer. Model technical ideas are shown in Figure 1. [4]

4.2. Data preprocessing
The actual production data monitored by the oil field may have certain deficiencies, and it should be properly preprocessed with Kriging interpolation to improve the accuracy of split.

4.3. Parameter optimization and Modelling training
According to the grey correlation method, the factors affecting the split effect are selected, that is, by calculating the correlation degree of each factor and then sorting, the results are shown in Table 1.

| Main factor                        | Range | Correlation | Contribution (%) |
|------------------------------------|-------|-------------|------------------|
| Well spacing                       | 1     | 0.7126      | 18.31            |
| Permeability                       | 2     | 0.6877      | 17.67            |
| Effective thickness                | 3     | 0.6534      | 16.79            |
| Porosity                           | 4     | 0.6521      | 16.75            |
| Injection-production wells         | 5     | 0.5940      | 15.26            |
| Coefficient of measures to increase production | 6     | 0.3243      | 8.33             |
| Connectivity                       | 7     | 0.2672      | 6.86             |

The seven dynamic and static main parameters affecting split have been selected. The oil production, water production and water cut of each layer of the well are regarded as the target parameters and used as the output terms of the neural network. A neural network model with 7 input nodes and 3 output nodes is established. The calculation process is shown in Figure 2.
5. Analysis and evaluation of model prediction results

5.1. Model verification

The production data of a block in Y Oilfield is selected for analysis, and the model of the research block is established. The running model outputs a set of numerical fitting graphs for the daily oil production, daily water production and water cut of well P, and the production of Layer A, layer B, layer C of well P is obtained. The results are shown in Figures 3-6.

As shown in the figure, the results predicted by the established new model have a high degree of fit with actual production data. Thus, the results of the model demonstrate higher accuracy.
5.2. *Comparison with PLT method and KH method*

In order to demonstrate the accuracy of the new model, the KH method, the Production Logging Tool (PLT) method, and the new model were used to split production in well P. The comparison of three methods is shown in Figure 7.

![Figure 7. Comparison of split results of different methods for stratified cumulative oil production](image)

There is a large error between the calculated value of the KH method and the measured value of the PLT method representing the actual production situation, and the calculated value of the new model is closer to the measurements of PLT and its error is smaller. By comparison, the new model has more advantages than conventional methods like KH method, with high accuracy, easy establishment and strong practicability. It further demonstrates the effectiveness of the new model.

6. *Conclusion*

Before the model is built, all parameters need to be preprocessed like interpolating, and then the parameters are weighted using the grey correlation method, and the important factors are selected. The selected parameters are used as input and substituted into the double hidden layer neural network for modelling to achieve the production split of each layer of the production well.

The new model and the KH method were used to calculate the zone oil production of single well in Y oilfield respectively, and compared with the measurements of PLT. The error of the KH is 71%. The error of the new model is much smaller than that of the KH, showing the accuracy and authenticity of it.

**References**

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