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ABSTRACT

This paper proposes an artificial neural network (ANN) method to calculate reservoir parameters. By improving the algorithm of BP neural network, convergence speed is enhanced and better result can be achieved. Practical applications prove that neural network technique is of significant importance for reservoir description.

INTRODUCTION

Reservoir description is a new practical technique for comprehensively investigating and evaluating the reservoir. It plays an important role in oil and gas exploration and development. The most extraordinary characteristics of reservoir description is that all things are considered, calculation is quantified and full advantage of computer is taken. As the basis of reservoir description and the important gist of making and adjusting exploitation schemes, parameter calculation and reservoir evaluation are always the most concerned problem to the exploration and development operators. In order to analyze a reservoir reasonably, it is essential to predict all items of reservoir parameter accurately. However, it is considerably difficult to calculate all of the reservoir parameters properly and thus analyze the formations precisely by using single well-logging response and simple formula because the reservoir is of serious heterogeneity and well-logging response curves are badly affected by many complicated factors underground. Especially for lithological transitional zone and for regions with complex geology condition, reservoir parameters predicted using theoretical formula or empirical formula has greater errors, which brings a series of troubles to subsequent jobs.[3] [4]

Neural Network method is a jumped-up method for solving complex problems. It is not a simple solution process to theoretical formula, but an advanced technique to obtain the correct output through simulating the function of human's brain to analyze, judge and synthesize the inputs.

Many examples show that Artificial Neural Network (ANN) technique can be used to successfully solve the problems of pattern recognition and parameter estimation widely existed in well-logging interpretation and reservoir description. This technique has a good performance to tolerate faults and resist disturbance and a strong ability of self-adaptation non-linear mapping parallel learning and interpretation. It is capable of recognizing different patterns and predicting reservoir parameters quickly and exactly.

The Artificial Neural Networks currently used include back-propagation neural network, feedback neural network, random neural network and self-organization neural network. Each of them has certain advantages and disadvantages. According to the characters of input and output in reservoir parameter calculation and the geological requirement, we choose the back-propagation neural network as the model for reservoir parameter calculation.

ESTABLISHMENT OF THE BP NEURAL NETWORK

The remarkable quality of back-propagation neural network (BP algorithm) is that it has strong ability of non-liner mapping and its structure is very flexible. Number of hidden layers, number of processing units in each layer and learning coefficient of the network can be determined arbitrarily according to the specific conditions. Different structure presents different performances.

The learning process of BP network consists of forward feeding of input, error back propagation, training and convergence. In theory, the only requirement for the transfer function of BP network nodes is that it has differentiability everywhere. For the reason that practical applications demand the network possesses fairly good ability of nonlinear mapping, so Sigmoid function is used as transfer function, i.e., f(x)=1/(1+exp(-x)).

Forward Propagation Of The Input

The vector of the input pattern is supposed as A.

$$A_K = (a_1, a_2, \cdots, a_n) \qquad k = 1,2,\cdots,m$$

Where, n is the number of the units in input layer and m is the number of learning patterns.

Vector of the desired output pattern is Y.

$$Y_K = (y_1, y_2, \cdots, y_n)$$

Where, q is the number of the processing units in output layer.

The input of each unit in hidden layers, S_j, is calculated firstly.

$$S_j = \sum_{j=1}^{n} W_{ij} a_i - q_j \qquad j = 1,2,3,\cdots,p \tag{1}$$

Where, W_{ij} is connection weight, q_{1j} is the threshold value of the processing unit, p is the number of the units in hidden layer and a_j is the input vector.

The output of each unit in hidden layers is then calculated using S_j as the input of S function.

$$b_j = f(S_j) = \frac{1}{1+e^{-sj}} \tag{2}$$

Where, b_j is the activated value of unit j in hidden layer.

Then, the input and output of each output unit can be computed.

$$L_t = \sum_{j=1}^{n} V_{jt} \cdot b_j - g_t \tag{3}$$

$$C_t = f(L_t) \qquad t = 1,2,\cdots,q$$

Where, V_{jt} is connection weight and g_t is the threshold value of output unit.

Back Propagation Of The Error

The corrected error of output layer can be presented by Equation (4).

$$d_t^k = (y - C_t^k) f'(L_t) \qquad t = 1,2,\cdots,q \quad k = 1,2,\cdots,m \tag{4}$$

Where, $(y_t^k - C_t^k)$ is the absolute error between the desired output and the actual output and $f'(L_t)$ is the deviation coefficient determined according to the actual response of each unit.

The corrected error of each unit in hidden layer can be described as Equation (5).

$$e_j^k = [\sum_{i=1}^{q} d_i^k * V_t^j] f'(s_j) \tag{5}$$

Therefore, connection weight and threshold value of each unit can be adjusted as follows.

$$\Delta V_{jt} = a \cdot d_t^k \cdot b_j^k \; ; \quad j = 1,2,3,\cdots,p \; ; \quad t = 1,2,\cdots,q \tag{6}$$

$$\Delta g_t = a \cdot d_t \; ; \quad k = 1,2,\cdots,m \; ; \quad (0 < a < 1) \tag{7}$$

$$\Delta W_{ij} = b \cdot e_j^k a_j^k \; ; \; i = 1,2,3,\cdots,n \quad j = 1,2,3,\cdots,p \tag{8}$$

$$\Delta q_j = b e_k^j \; ; \quad k = 1,2,\cdots,m \; ; \; (0 < b < 1) \tag{9}$$

Where, a and b are learning rates.

Training

Training is a repeating learning process during which connection weights are modified according to the error between the desired output of teacher’ s signal and the actual output of neural network. With the process of pattern forward propagation and error back propagation being repeated continually, the actual output gradually closes to the corresponding desired value.

Convergence

In this process, the whole error of the network closes to infinitesimal value.

The whole error can be described as Equation (10).

$$E_k = \sum_{j=1}^{q} \left(y_j^k - y_j\right)^2 \Big/ 2 \qquad k = 1,2,\cdots,q \tag{10}$$

IMPROVEMENT OF THE TYPICAL BP ALGORITHM

The typical BP algorithm, which has the following disadvantages, is not a kind of perfect Neural Network.

(1) The learning speed is lower. It requires several hundreds or even thousands of times of learning to achieve convergence even for a very simple problem. [1][2][3]

(2) It can’ t guarantee that the convergence point is the minimal of the whole system, which is the fatal disadvantage of typical BP network. [1][2][3]

(3) There are not a theoretical guidance to choose the number of hidden layer and the number of the units in hidden layer. Experience is always adopted as the accordance. This sometimes lead to a neural network having many redundant units. As a result, a much longer time period will be consumed by the learning course. [[1][2][3]

(4) The learning and memory of the network is not stable enough. The determined connection weights of a trained BP network may be changed when the network receives a new

memory pattern. It may cause the loss of all formerly memorized learning patterns. To avoid this problem, a new training process must be conducted with the new learning patterns together with the former ones. [1][2][3]

The typical BP algorithm is called normalized error back propagation algorithm. It is different from the gradient decline algorithm in the scale of the whole system. Adjustment of the error is implemented through the comparison of the desired output with the actual output, which will inevitably cause the problem of local minimum.
The gradient algorithm in the sense of the whole system is called Accumulated Error Correction Algorithm.

Firstly, the corrected error of the output layer is calculated using Equation (11).

$$d_t^k = (y - C_t^k) f'(L_t) \quad t = 1,2,\cdots,q \quad k = 1,2,\cdots,m \qquad (11)$$

Where, $(y_t^k - C_t^k)$ is the absolute error between the desired output and the actual output and $f'(L_t)$ is the deviation coefficient determined according to the actual response of each unit.
Then the corrected error of each unit in hidden layer can be computed by Equation (12).

$$e_j^k = [\sum_{i=1}^{q} d_i^k * V_t^j] f'(s_j) \qquad (12)$$

For typical BP algorithm, the corrected error can be calculated after every times of the learning of each pattern and, then the corrected error is back propagated. This will inevitably result in the problem of local minimum. For the accumulated error correction algorithm, the errors of m learning patterns can be accumulated after they have been calculated, then the connection weights between output layer and hidden layer or input layer and hidden layer and the threshold value of each unit can be corrected using the accumulated errors. Because all of the connection weights are adjusted in the scale of the whole system, so they can reach to the desired value by repeating iteration. The gradient decline in the sense of whole system error can be achieved by using accumulated error correction algorithm, by this way, it is avoided that BP neural network produces the gradient decline in the sense of local error.

Times of error correction in every learning process needed by the accumulated error correction algorithm is m-1 times less than that needed by the local error correction algorithm. The learning time of the neural network is reduced greatly and the computation efficiency is obviously improved.

RESERVOIR PARAMETER CALCULATION BASED ON ARTIFICIAL NEURAL NETWORK

Selection Of Well-logging Parameters

According to the characteristics of the input and output of reservoir parameter calculation and the requirement of geological condition, through many times of repeat of calculating, testing and analyzing, in order to sufficiently extract the characters of well-logging parameters, we select six parameters as the input of the neural network. They are Spontaneous Potential (SP), Resistivity of Deep Later Log (RLLD), Resistivity of Micro-gradient Log (Rmt), Resistivity of Micro-normal log (Rmd), Interval Transit Time of Acoustic Log (AC) and Resistivity of Shallow Later Log (RLLS).
To assure that the input data represent the real information of a formation, the upper one third and the lower one third of the data of this formation are cut down. Only the intermediate one third of the data is selected and the average of them is input into the neural network for training. Each parameter is normalized to a rational number between 0.0 to 1.0 using the following formula.

$$y = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

The ultimately constructed neural network contains six input units and one output unit.

Normalization Of The Well-logging Curves

Normalization of well-logging data is to make all well-logging data have a common scale in the investigated region by eliminating the influence of well-logging apparatus, personnel, operating time and other environmental factors.
The technique to normalize the well-logging data can be divided approximately into two types, i.e., qualitative method and quantitative method. Qualitative method includes histogram correction technique, superimposed diagram correction technique, mean value correction technique and framework analysis technique. The quantitative method often used is trend analysis correction technique. The common theoretical basis of these two methods is that sediments with the same or similar depositional environment have same or similar lithology and electrical property. That is to say, for all of the wells in the same region, the well-logging response eigen-value of the frequency histogram or frequency cross-plot made from the same kind of well-logging curves of the same standard formation usually appears the similar frequency distribution.

To normalize the well-logging data of Nan-2 and Nan-3 region in DaQing, we take the large interval of mud in the upper SaErTu oil zone as the standard interpretation formation. Due to the absence of complete data of sampled cores in this region, histogram technique to is adopted to determine the acoustic logging and resistivity logging of the standard layers. Resistivity is 3.0 Ω·m and interval transit time is 375 $\mu s/m$. The normalization is completed using histogram correction technique.

During the process of digitized well logging, eight points per meter are usually sampled. According to the requirement of well-logging interpretation, reservoir parameter should be treated continuously in terms of eight points per meter throughout the whole well.

Selection Of The Topological Structure Of The Neural Network

Through iterative calculating, testing and analyzing, the structure of the neural network is finally determined. It is a four layer BP neural network which includes two hidden layers. There are 35 and 40 units in the two hidden layers respectively. When learning rates equal to 0.87 and 0.58, the prediction has the maximal precision.

RESULT OF TRAINING AND RECOGNITION

The standard pattern must be firstly built up for training when the neural network is used to do the job of pattern recognition. The wells used to build up the standard pattern are called key well. The principle to choose key wells is that the well contains core analysis data and has complete microfacies types and the well logging curves show obvious feature at well segments of different microfacies. According to the aforementioned principle, we select N1-J6-37 and N1-6-J448 as the key wells. 205 standard patterns belonging to ten types are determined for six different sedimentation microfacies. The network is trained with these standard patterns on a SUN5000 workstation and convergence is achieved.

Permeability of four wells is calculated. The calculation errors are 18.2373%, 29.4416%, 21.2789%, and 18.8414% respectively. It basically fit for the requests of the prediction of the permeability by well-logging interpretation.

Main factors influencing the recognition result of the network are as follows.

1.The number of training samples. In order to a get higher recognition rate, we must offer abundant samples and adequately gather the features after the training.

2.The distribution of training samples among different types. For neural network, different types should have the same or similar number of training samples. The attractive area of the neural network to one pattern is the aggregation of all possible inputs that lead to the output the neural network may produce. To achieve an efficient recognition result, a neural network must have equivalent attractive area to all of the patterns.

3. Some information is lost from the well logging curves.

CONCLUSIONS

In this study, artificial neural network (ANN) is creatively introduced into the study of reservoir parameter calculation. A BP neural network is established to predict reservoir parameters based on well logging data. By modifying the typical BP algorithm, the constructed BP neural network can give more accurate and reliable results. Developing Practical software using some new theories and methods will improve the actual working efficiency and quality, which will exert more and more important effects on petroleum industry.

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