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# Analysis of Hydrocarbon Loss Based on Neural Network Geochemical Recovery Correction

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**Abstract:** Data obtained by rock pyrolysis analysis is only part of the hydrocarbon content in the stratum, which will affect the credibility of information and evaluation of oil-gas-water layers. Therefore, it is necessary to restore calibration of parameters for pyrolytic chromatography. This paper selects 5 factors to analyze the geochemical analysis of hydrocarbon loss. History data to establish a neural network to analysis the hydrocarbon loss recovery correction model in this paper, the accuracy of the model meets the requirements, get better correction effect, has the value of application.
**Keywords:** neural network; geochemical analysis; Correction

## INTRODUCTION

Data through the rock pyrolysis analysis were just part of the formation of hydrocarbon content. Most of hydrocarbons being lost during drilling, sampling, preservation process, and analysis process. Meanwhile, due to the different sample types, different time it was stored so that the analysis results are very different, all of these factors will affect the credibility of the information and for the evaluation of oil-gas-water layers. Therefore, it is necessary to restore calibration of parameters for pyrolytic chromatography.

There are three main factors that affect the pyrolysis of hydrocarbons losses[1]: the impact of drilling fluid displacement, the gas escaping and volatile hydrocarbons. We only study the impact of the drilling fluid displacement, sealed coring is not affected by displacement of drilling, sidewall coring is affected by the displacement. Establish sidewall coring and sealed coring relationship with the target value of sealed coring and geochemical analysis. Correction can be achieved by displacing hydrocarbon losses.

Geochemical analysis of hydrocarbons loss recovery correction system is a very complex system, and because of the many factors that it is difficult to use an explicit mathematical model to describe its characteristics. Artificial neural networks have a strong nonlinear approximation ability, and many practices have proven that when the neural network for nonlinear, complex, dynamic, multi-variable or difficult to model the system have better results. In this paper, the neural network was chosen to simulate the geochemical analysis of hydrocarbons loss recovery correction system.

## THE BASIC PRINCIPLES OF ARTIFICIAL NEUTRAL NETWORK

Artificial Neutral Network[2,3] is an information processing system by mimicking the biological brain structure and function. Artificial neural network is a complex network system, similar to the large number of people neurons interconnected together, reflecting a number of features of the human brain functions. The best known and most widely used is the Error Back Propagation network, the BP network. BP neural network is a multi-layer networks, including the input layer, an intermediate layer and output layer. The intermediate layer is not visible, called hidden layer. Using the right connection between layers, there is no connection between the same layer of each neuron.

Figure 1 (a), (b) represents the neural network model and a basic unit neuron model.

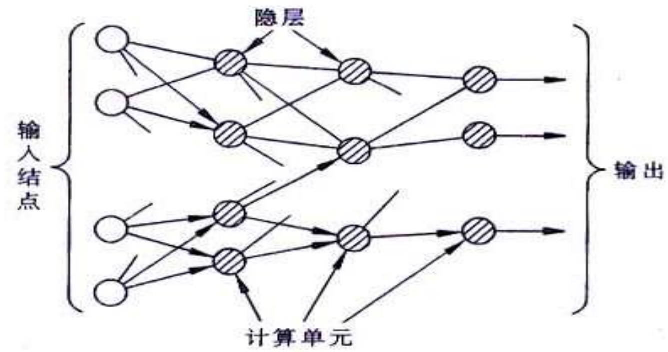


**Fig-1 (a): Neural Network Model**

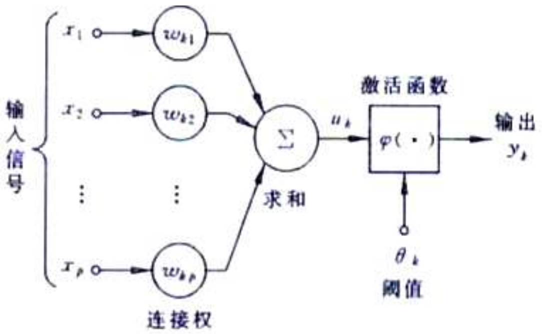


**Fig- 1 (b): Basic Neuron Model**

Set $x_1$ , $x_2 \ldots x_m$ are network input signal, set $y_1$ , $y_2 \ldots y_t$ are network output signal, and set up the entire network is a multi-vector function $F(\cdot)$,that is $(y_1, y_2, \cdots, y_t) = F(x_1, x_2, \cdots, x_m)$ ,Multi-function is a weighted combination of multiple units(Each unit is a function) within the network. For a unit, $w_{k1}, w_{k2} \ldots w_{kp}$ weight value for neuron k, $u_k$ is the result of a linear combination, $\theta_k$ is a threshold value, $\varphi$ is the activation function,$(\cdot)$is output of neuron k. Then

$$u_k = \sum_{j=1}^{p} w_{kj}\ x_j,\ v_k = net_k = u_k - \theta_k,\ y_k = \varphi(v_k),$$

that is

$$y_k = \varphi\left(\sum_{j=1}^{p} w_{kj} x_j - \theta_k\right) \qquad (1)$$

$y_k$ is the output neuron k, which is then used as the input layer neuron, in such a way to continue to put the entire network are connected together, and finally obtained output of network $y_1, y_2, \cdots, y_t$ .Activation function is $\varphi(v) = \dfrac{1}{1+\exp(-v)}$ ,but it belongs to the network weights values $w_{kj}$ and threshold values $\theta_k$ are unknown. We want the output value $y_1, y_2, \cdots, y_t$ of the network consistent with the actual values $d_1, d_2, \cdots, d_t$ , by obtaining network weights values $w_{kj}$ and threshold values $\theta_k$ . The need to solve the network weights values $w_{kj}$ and threshold values $\theta_k$ , such that

$$E_{AV} = \frac{1}{2N} \sum_{j=1}^{t} \sum_{n=1}^{N} (d_j(n) - y_j(n))^2 \qquad (2)$$

minimize. In which, $y_j(n)$ is the output value of the n-th sample, $d_j(n)$ is the actual value of the j-th unit.

Set $e_j(n) = d_j(n) - y_j(n)$ , $E(n) = \frac{1}{2} \sum_{j \in c} e_j^2(n)$ , that is

$$E_{AV} = \frac{1}{N}\sum_{n=1}^{N} E(n),$$

$E_{AV}$ is the objective function of learning, learning is intended to enable $E_{AV}$ minimum. $E_{AV}$ is a function of all weights values、threshold values and input signals on the web.

Steps of Neural Network Algorithm can be summarized as follows:

(1) Initialized, given a reasonable structure of the network, set all adjustable parameters (power and threshold) are the minimum value of a uniform distribution.

(2) The sample for each input is calculated as follows;

We use the forward algorithm to calculate the $j$ units of the $l$ layer

$$v_j^{(l)} = \sum_{i=0}^{T} w_{ji}^{(l)}(n) y_i^{l-1}(n)$$

In which,before the $y_j^{l-1}(n)$ layer ( $l-1$ layer) of unit $i$ sent operation signal (when $i=0$ ,set $y_0^{l-1}(n) = -1$, $w_{j0}^{(l)}(n) = \theta_j^{(l)}(n)$), if the activation function of unit $j$ is sigmoid function, the

$$y_j^{(l)}(n) = \frac{1}{1+\exp(-v_j^{(l)}(n))}$$

and $\varphi'(v_j(n)) = \dfrac{\partial y_j^{(l)}(n)}{\partial v_j(n)} = \dfrac{\exp(-v_j(n))}{(1+\exp(-v_j(n)))^2} = y_j(n)\left[1-y_j(n)\right]$。

If the neuron $j$ belong to the first hidden layer output (ie $l=1$), there

$$y_j^{(0)}(n) = x_j(n)$$

If the neuron $j$ belong to the output layer ( $l=L$ ), there is

$y_J^{(L)}(n) = O_j(n)$ and $e_j(n) = x_j(n) - O_j(n)$

② Back-Calculation $\delta$

For output unit $\delta_j^{(l)}(n) = e_j^{(L)}(n) O_j(n)\left[1-O_j(n)\right]$

For hidden unit $\delta_j^{(l)}(n) = y_j^{(l)}(n)\left[1-y_j^{(l)}(n)\right]\sum_k \delta_k^{(l+1)}(n) w_{kj}^{(l+1)}(n)$

③ According to the following formula correction weights

$$w_{jk}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \eta\delta_j^{(l)}(n) y_i^{l-1}(n)$$

(3) $n=n+1$ enter the new sample (or samples of a new cycle) until $E_{AV}$ reaches predetermined requirements, when training input sequence of each sample was randomly ordered in cycle.

## HYDROCARBON LOSS RECOVERY CORRECTION

Sealed coring is not affected by flooding. The value of $S_0$、$S_1$、$S_2$ and $\sum C_{气相}$, by sealed coring and geochemical analysis of the solution obtained, set to the correction of the target. Sidewall coring is affected by the flooding, select the wellbore pressure, porosity, permeability, oil density and viscosity of crude oil as the five components of loss rate factors. Using historical data to establish the relationship between the components when sealed coring and sidewall coring Geochemical analysis, you can correct the sidewall coring Geochemical analysis values $S_0$、$S_1$、$S_2$、$\sum C_{气相}$.

We selected a total of 67 data ,including Daqing S-1-12-232、G-168-155、N-2-362-P25 and other wells, established $\Delta S_i$ correction of neural network model. BP neural network architecture are: input layer nodes 5,

$x_1, x_2, L\ , x_5$ represent the five factors of porosity, permeability, oil density, oil viscosity and wellbore pressure; The number of hidden nodes is 15, the number of output layer node 1, ie $y$ represents $\Delta S_i = \frac{|XS_i - JS_i|}{XS_i}$. Error in the following table.

**Table-1: Error Statistics**

| $\Delta S_i$ | the average value of the absolute error | the average value of the relative error |
|---|---|---|
| $\Delta S_0$ | 4.116E-03 | 2.78E-03 |
| $\Delta S_1$ | 9.836E-02 | 5.83E-03 |
| $\Delta S_2$ | 2.747E-02 | 1.97E-03 |
| $\Delta S_3$ | 2.754E-01 | 4.004E-03 |

As can be seen from the error statistics, accuracy of the model to meet the requirements. This model can be used to simulate the geochemical analysis of hydrocarbons loss recovery correction system has been quite satisfactory correction results.

## CONCLUSION

Geochemical analysis of influencing factors of hydrocarbon loss is very large, it is difficult to establish a linear model between them, while the artificial neural network has a strong nonlinear approximation ability. This article select five factors, including wellbore pressure, porosity, permeability, oil density and viscosity of crude oil, establish artificial neural network analysis to hydrocarbon loss recovery correction model. Model has high accuracy, can reflect the actual geochemical analysis of hydrocarbons loss recovery correction system features. With this model of rock pyrolysis of hydrocarbons content correction has a certain value, and will enhance the credibility of the gas-water layer and evaluation data.

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