Application of BP Neural Network and 3D Orebody Carving in Estimate of Natural Gas Hydrate Reserves

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Abstract
This paper studies and analyzes the prospect information on the natural gas hydrates in Shenhu area of the South China Sea and predicts the porosity and saturation of the natural gas hydrate by using BP neural network method. This method reduces the manual disturbance and improves the prediction precision. This paper establishes 3D orebody carving model of the natural gas hydrates, which can precisely describe the geology feature inside the orebody, dynamic identify the boundary form of the hydrate orebody, and gives the space distribution trend of the hydrates, next this paper performs volume dissection on the hydrate 3D orebody carving mode, identifies the volume of the basic tetrahedral element of the hydrate orebody, and estimates the hydrate reserves of this sea area by using 3D orebody carving model volume method.
Keywords: BP NEURAL NETWORK, SATURATION, POROSITY, 3D OREBODY CARVING, RESERVE ESTIMATE

1. Introduction

The natural gas hydrate is regarded as a clean energy with huge potential due to extensive distribution scope, large reserve scale, shallow burying, high energy density and small combustion pollution (Wang, X. J. *et al*, 2014). Guangzhou Ocean Geology Survey Bureau drilled and sampled the hydrates in Shenhu area of the South China Sea in Apr-Jun, 2007. Total 8 drilling sites are completed. The hydrate test samples were obtained at 3 sites. A series of important achievements were achieved (Li, G. et al, 2011).

With continuous deepening of research on the natural gas hydrate prospect, it is urgent to identify and study hydrate distribution and accurate estimate. The geophysical log is frequently used to compute the porosity and saturation on the prospect phase of the natural gas hydrates. Two parameters are important for quantitative evaluation of the hydrate reservation layer (Wang, X. J. et al, 2010), the porosity and saturation results computed by different logging methods are different in routine methods. The actual information includes the randomness and complexity problem, so the computing results are very different from the actual conditions. To reduce the disturbance from man-made factors as much as possible and improve the computing precision, the BP neural network method is introduced for prediction.

This paper studies the routine methods based on the hydrate geophysics in Shenhu sea area, predicts the hydrate saturation and porosity by using BP neural network, identifies the hydrate orebody distribution, form and boundary scope by using the 3D orebody carving method, and further estimates the hydrate reserve via the volume method.

2. BP Neural Network

Generally BP neural network includes input layer, hidden layer and output layer and is supervised learning algorithm (James,T. H. L. et al, 2015). The algorithm steps are described as follows:

Step1 Initialize network: assume that the connection strength weight Wij between input node and hidden node and connection strength weight Vjk between hidden node and output node are initialized as a random number within (-1, 1), the sample number is p, the network training time is q, the initial value is 1, and the network training convergence precision Emin is a position fraction.

Step2 The input learning sample is xi and the corresponding expected output ti is known. xi is imposed on the output node via the hidden nodes. After nonlinear transformation, the output vector yk is generated.

Step3 Each sample includes the input vector X and expected output value T, which will be trained via the network to compute the deviation Ep between the network output value Y and expected output value T. Total error is:

$$E(q) = \frac{1}{2}\sum_{q-1}^{p} E^{p}(q) \tag{1}$$

Step4 To make Y and T approach to each other as closely as possible, the weight Wij, Vjk and threshold should be adjusted to make the error descending in the gradient direction.

Step5 After repeated learning and training, if the total inspection error E<Emin, the training will end. Otherwise, E is set as 0. Return to the step2.

The BP neural network learning includes two processes. First, compute from bottom to top in the network, set the network structure and weight, input known learning sample, compute the neutron input at each layer, change the weights and thresholds, compute and change from top to bottom (back), and change from the error of known top layer till the weights of different layers are changed. Two processes will be alternated till convergence.

3. 3D Orebody Carving

One important 3D visualization technology is the carving technology and indicates to select fonts from the data body and change transparency, rotation, zoom and color for representation and description. To effectively identify the hydrate, generally BSR is used as the bottom boundary of the natural gas hydrate of the sediments at the bottom of the sea (Sha, Z. B. et al, 2013). Based on the practices, the wave impedance in the seismic data can significant reflect the hydrates in the natural gas (Sha, Z. B. et al, 2010), so this paper selects 3D wave impedance data obtained via high-precision inversion and drilling data in the research area as the modeling data for orebody carving. From observation to the wave impedance attribute section, the wave impedance value increases much from 2ms time window above the BSR layer of bottom boundary of the hydrate orebody and the anomaly is significant. Based on this position as the center point, the wave impedance data within ±5ms time window can include the distribution scope of the hydrate orebody. Each data point of 3D wave impedance data body is represented as {x, y, z, a}, x indicates the inline number, y indicates the crossline number, z indicates the time of sampling point, an indicates the wave impedance value at the space coordinate on the layer identified by x, y and z.

By combining the features of 3D data body, to better carve the natural gas hydrate orebody, the orebody is divided into N small tetrahedron unit (see, Figure 1). The adjacent up stratum surface and down stratum surface are used as the constraint boundary to dissect the tetrahedron. The scope of the tetrahedron should not exceed two adjacent strata. The external boundary of the up and down stratum and side boundary composed of the external boundary of up and down stratum will be combined to form the enclosed area and the enclosed area is dissected, so the strata realize can be seamlessly integrated. The tetrahedron unit is constructed as follows: interpolate the original data set by using the linear interpolation triangle network to form the regular grid data, then identify the start search point on the up surface of the orebody layer, find the points closest to the start point, form the start edge, establish a triangle by using Delaunay method, identify the ending point of the down surface of the orebody layer, establish the tetrahedron cell according Delaunay rule, and finally exchange the establishment step of the tetrahedron cells on the up and down surface of the orebody till all 3D data sets are spanned.

The tetrahedron texture depends on the wave impedance value of each vertex. The vertex with 0

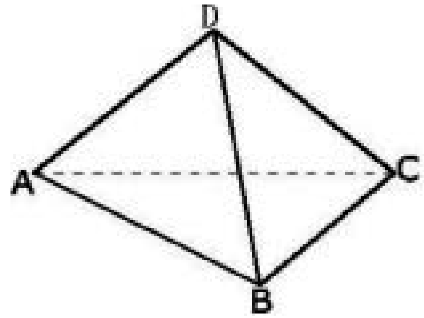

Figure 1. Tetrahedron Unit

wave impedance has no color and is set as transparency (see, Figure 2), so the orebody object on the N tetrahedron will be added with well position data. 8 known wells are added. It is known that SH2, SH3 and SH7 well include the hydrate above the BSR layer. No hydrate is detected at other well positions. At this time, 8 wells will drill through the hydrate orebody object. At this time, the wave impedance minimum is adjusted to only display the tetrahedron which wave impedance is over the minimum. It is observed that the shape of the orebody will gradually approach to the logging position. The minimum of the wave impedance is increased continuously till the P-wave impedance is bigger than 3800g/cm3·m/s. At this time, the SH2, SH3 and SH7 well will drill through the orebody. Other well positions will not drill through the orebody. They are identified as the boundary shape of the natural gas hydrate orebody and provide the prediction reference for selection of the further drilling well position.

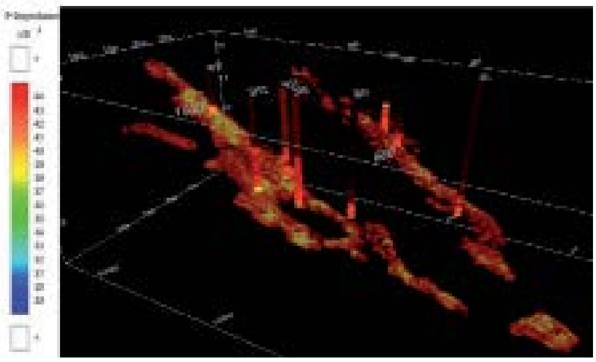

Figure 2. 3D Carving Orebody (The P-Wave Impedance Value is Bigger than 3800g/cm3·m/s)

4. Specific Applications

This paper computes the reserves by using 3D ore body carving volume method. First compute the volume of each ore body unit, multiply the ore body volume with the corresponding porosity, saturation and volume factor, get the reserve of the natural gas hydrate of each orebody unit, compute the sum of the reserve of all small orebody unit, and get the total reserve of the whole hydrate orebody,volume method formula can be defined like this:

$$Q = \sum_{i=1}^{n} Q_i = \sum_{i=1}^{n} V_i \cdot \varphi_i \cdot S_{Wi} \cdot \beta \ ,(i = 1,2,\cdots,n) \qquad (2)$$

Qi is the hydrate reserve of each core body unit, Vi is the volume of ith small ore body unit, φi is porosity of ith small ore body unit, in this equation, Vi is the volume of ith small ore body cell, φi is the porosity of ith small ore body unit, Swi is the saturation of ith small ore body unit and β is the volume factor. β is obtained according to the lab test and field survey data and generally is assigned with the value 160. The fluctuation amplitude of this value is smaller and the range is stable (Jeong, T. et al, 2014). The reserve of the natural gas hydrate computed the volume method mainly depends on the distribution area of the hydrates, stable band thickness of hydrates, porosity and saturation. Generally the hydrates exist in the low-temperature and high-pressure seabed sedimentary basin, is easy to decompose and is unstable, so these parameters cannot be directly measured. The BP neural network and ore body carving method can accurately estimate the reserve of the hydrate.

4.1. Saturation and Porosity of Hydrate Predicted by Using BP Neural Network

The geophysics routine method is used to compute the hydrate saturation and porosity, resistivity logging and sound wave logging, which is regarded as the most effective method to identify the hydrate in the natural gas (Zeng, F.C. et al, 2006), so the samples should be selected according to the representativeness and effectiveness rule. The data are selected from actual 8 drilling wells and the hydrate samples are selected from the SH2 well. Based on these collected sample data, the porosity and saturation of each sample at a depth of a corresponding SH2 well can be obtained. The natural gas hydrates depend on the low visible density, high visible resistivity, high sound wave speed, high neutron porosity and low natural GAMMA value. The selected geophysics logging data include the measured value of 8 logging curves such as natural GAMMA (API), sound wave time difference (AC)(s/m), long and short source distance density (LDEN, SDEN)(g/cm3), well diameter (CAL1, CAL)(mm), deep lateral resistivity (RES1) (Ω·m) and shallow lacteral resistivity (RES2)(Ω·m).

The original logging data includes certain error. When data is processed, the logging curve should be standardized, including logging data normalization, histogram correction and marking layer correction. First the logging data are normalized:

$$Y_i = Y_{\min} + \frac{(y_i - y_{Min})}{(y_{Max} - y_{Min})} \times (y_{\max} - y_{\min}) \qquad (3)$$

In this equation, Ymin and Ymax are the average maximum and minimum of multiple wells, YMin and YMax are minimum maximum of single well and yi is the curve prior to normalization of a well , Yi is the curve after normalization of a well.

Next the logging histogram is corrected and the average is corrected.

$$Y_i = y_i + (Y_{men} - y_{Men}) \qquad (4)$$

In this equation, Ymen is the average of the multiple well averages; ymen is the mean of single well, yi is the curve after normalization of single well and before histogram correction and Yi is the curve after histogram correction after single well.

Finally the marking layer is corrected and the sound wave time difference logging curve of the mud stone in the target section of the standard well is summarized to get the frequency distribution histogram of the sound wave time difference curve. The sound wave time difference standard value of this area is identified according to the maximal ratio of the histogram. The sound wave time difference curve in the mud stone of each well section is separately summarized to draw the frequency distribution histogram of the sound wave time difference curve of each well. The benchmark value of the sound wave time difference curve can be obtained from the histogram. The benchmark value of each well is compared with its standard value to identify the deviation. The sound wave time difference curve is corrected according to the deviation. The target layer section from 1200mm to 2300mm is selected for de-compaction of the sound wave in standardization. After standardization, the sound wave time difference is compacted.

The BP neural network designed in this paper includes input layer, hidden layer and output layer. The selected logging data includes 8 curves, so the input layer should include 8 nodes. The frequent neural network model is single hidden model. It is complicated to select the nodes of the hidden layer. If the hidden layer includes too limited nodes, it may lead to no convergence. if the hidden layer includes too many nodes, it may lead to too long learning time or unstable computing results. Based on the experienced algorithm, the number of the nodes at the hidden layer is about 2 times of the input nodes, so the hidden layer includes 16 nodes and the output layer includes 1 node to represent the output saturation or porosity. Finally the network model structure is 8×16×1.

The network training time is 1096 and the network training error is 0.01. in fact, this learning method is to compute the minimum of the error function. Multiple samples are repeatedly trained to reduce the deviation. The reduction step of the network weight is 0.5, the increment of the weight change is 1.2, the minimal gradient is 10-6, the weight change maximum is 50, and the initial weight change is 0.07. When training reaches the minimum error 0.01, training stops. When training ends, the porosity model and saturation model are respectively established.

After SH2 logging data are trained via the network, the BP neural model is obtained and the corresponding saturation and porosity estimate are computed. Based on it, the SH3 and SH7 logging data are inputted to the network model to compute the saturation and porosity of two wells, shown as the table 1.

The saturation curve results identified by the BP neural network are shown as the Figure 3. The red sound point indicates the saturation computed by the actual core data. The black curve indicates the predicted value processed by the neural network. The saturation curve of SH2, SH3 and SH7 are highly fitted with the actual measured value from the core. The residual 5 wells have no hydrate sample, so the saturation value is low and the curve has no obvious change trend. When the SH2 well model is used to predict other well, besides the trained model, the new training model should be identified according to the prediction well and SH2 well.

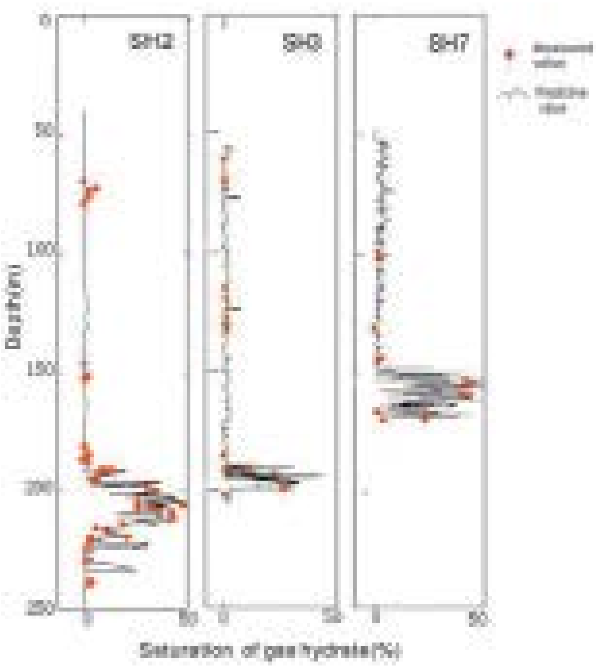

Figure 3. Saturation Prediction Diagram of BP Neural Network

Table 1. Hydrate Saturation and Porosity Predicted by BP Neural Network

Well name	Orebody depth (m)	Saturation minimum (%)	Saturation maximum (%)	Porosity minimum (%)	Porosity maximum (%)
SH2	191-221	21.15	46.12	41.49	49.37
SH3	185-196	11.20	24.80	54.59	63.61
SH7	155-177	13.10	41.94	40.48	54.57

4.2. Volume Dissection of 3D Orebody Carving Model

The hydrate ore body model has irregular features. The hydrate ore body is dissected by using small tetrahedron to easy compute the volume. Based on the P-wave impedance data, the distances of the adjacent points are AB, AC and AD in x, y and z direction (see, Figure 1). The volume of each small tetrahedron is computed as follows:

$$V_{ABCD}=\frac{1}{6}\left|AB(AC\times AD)\right|=\frac{1}{6}\begin{vmatrix} x_A & y_A & z_A & 1 \\ x_B & y_B & z_B & 1 \\ x_C & y_C & z_C & 1 \\ x_D & y_D & z_D & 1 \end{vmatrix} \quad (5)$$

To get the volume of the hydrate ore body, the number of the small tetrahedrons should be summarized under the reasonable and effective identification of the hydrate boundary shape. The number of the small tetrahedrons is multiplied with the volume of each tetrahedron to get the volume of the whole hydrate orebody.

4.3. Reserve Estimate

The ore body is divided into 11 sub-ore body units according to the hydrate saturation and porosity value change. Each ore body includes several small tetrahedrons. First the volume of each sub-ore body is separately computed and the ore body volume of whole hydrate is computed. The hydrate ore body is divided as the Figure 4, it marks the range of the research area line number and road number. The hydrate distribution is fully consistent with it of actual drilling data. Based on the actual prospect data, the hydrate ore body boundary can be identified, the ore body volume is computed, and the hydrate porosity and saturation are predicted. These data are substituted into the equation (2) to effectively estimate the reserve.

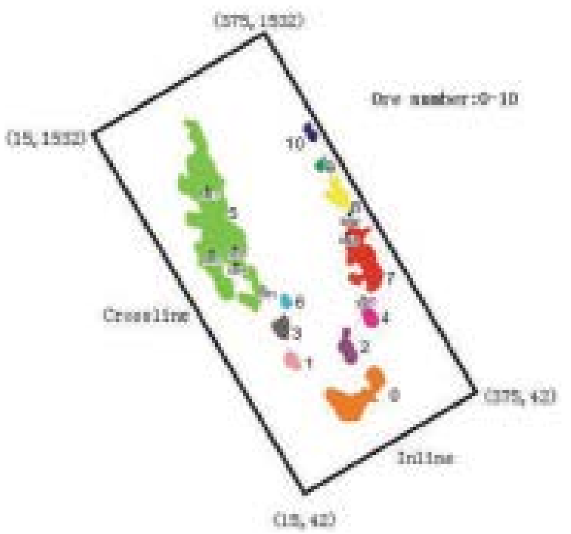

Figure 4. Plane Distribution Diagram of Hydrate Orebody

The following part lists the volume, porosity and saturation of 11 hydrate ore bodies. The reserve of this research area computed by using the Equation (2) is 72.5794×108/m3. The specific computing values are shown as the table 2.

Table 2. Natural gas hydrate reserve in research area

Ore number	Volume (m^3)	Saturation (%)	Porosity (%)	Reserves ($10^8/m^3$)
0	32.79	52.45	27.70	7.6216
1	4.73	51.82	22.29	0.8739
2	8.86	52.50	25.06	1.8648
3	6.99	51.68	21.71	1.2551
4	6.84	52.02	22.11	1.2582
5	190.78	52.37	31.09	49.7061
6	2.10	51.55	18.21	0.3154
7	33.43	52.15	25.36	7.0753
8	8.47	52.29	23.04	1.6328
9	1.88	52.47	22.08	0.3483
10	3.15	52.03	23.93	0.628
Total	300.01			72.5794

5. Conclusion

For big differences in the logging data, all logging data of actual 8 wells in the research area are standardized. With the hydrate bottom boundary of BSR layer as the constraint, the high-quality SH2, SH3 and SH7 are selected to get the logging data of the hydrate samples as the input samples. The BP neural network is sued to predict the hydrate saturation and porosity. From the prediction results, the maximum saturation mean of the wells with hydrates is 37.62% and the maximum porosity mean is 55.85%. The saturation and porosity of the wells without hydrates are smaller. The prediction results are highly accurate. But the network model construction is time-consuming. The algorithm can be further optimized to improve the computing efficiency.

To identify the hydrate ore body and estimate the reserves, the wave impedance data are obtained to construct 3D ore body carving model. The 3D ore body carving method is used to dissect the ore body into the tetrahedrons. The computing of the hydrate distribution and valid thickness of the hydrate with water in 2D model is converted to computing of the ore body unit volume in 3D model. This model precisely carves the geology features inside the ore body, dynamically describes the boundary shape of the hydrate ore body, identifies the space distribution scope of the hydrate mineral resources, provides 3D view for explanation of the hydrate geology, and provides references for deployment of wells in future.

Based on the above processing results, the volume method is used to compute the volume, saturation and porosity of 11 hydrate sub-ore bodies to get the reserve of the sub-ore bodies and finally get the total reserve of this research area.

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Optimization of Rheology Models of Non-dispersed Polymer Drilling Fluid

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Abstract

The accurate calculation of rheological parameters and the optimization of rheology models of drilling fluid are the premise for the optimization design of drilling fluid. The conventional calculation methods and the regression analysis methods of the rheological parameters in common five rheological models are analyzed. We adopt rheo-