Lost Circulation Risk Forewarning Model durning Drilling based on BP neural network

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Abstract

Through the analysis of lost circulation's characterization phenomena and law and changes of Bottom Hole Pressure (BHP) during the normal drilling process, applications of measuring BHP for lost circulation risk warning are established and a forewarning model based on BP neural network is presented. This model uses BP neural network technology to build self-learning algorithm and found a function relationship with the desired output through training multiple features. By means of model validation using field data, the experimental results show that the model can identify and predict the risk of lost circulation correctly.

Keywords

BP neural network; Bottom Hole Pressure (BHP); Lost Circulation Risk; Forewarning Model.

1. Introduction

In recent years, with the development of exploring towards the western regions of high and steep complex structure, accidents of lost circulation have become increasingly. According to statistics[1], lost circulation of different nature and degree nearly appears in every well. Lost circulation is one of the complicated situations in drilling operations, which often brings great difficulites to drilling, and serious lost circulation can even lead to blowout[2]. Therefore, technology of improving the accuracy of risk prediction lost circulation is imminent. Conventional recognition technologies of lost circulation is by monitoring such ground logging parameters as the inlet and these methods exist certain lag in time, which leads to the inability to accurately determine the underground real-time situation. Li E. Y. et al studied a forewarning model of lost circulation using the fusion method of Rough Sets and Rules, and this method can predict the occurrence of lost circulation during well drilling effectively, which to a certain extent can reduce the false alarm rate. However Rough Sets cannot handle continuous attributes, which can only deal with discrete attributes[3].

For these situations above, this paper analyzed lost circulation's characterization phenomena and law and changes of BHP during the normal drilling process to establish an application program of BHP measurement for lost circulation forewarning, and proposed a lost circulation risk forewarning algorithm based on BP neural network, and a lost circulation risk forewarning model depending on the application program.

2. Scheme of Well Leakage Risk Forewarning

2.1 well leakage's characterization phenomena and law and changes of bottom hole pressure

Lost circulation's characterization phenomena and anomaly rule of risk factors durning normal drilling operations are expressed as follows:

when the lost circulation happens durning normal drilling, if the drilling annulus level doesn't change because of the annulus fluid flow is reduced above leakage zone which leads to the upper leakage zone annulus fricyion's decrease, the BHP and Stand Pipe Pressure (SPP) are reduced significantly.

The lost circulation caused by Downhole Pressure imbalance and the BHP decreases. Meanwhile, the total volume of mud sump declines, and the outlet flow of drilling fluid is reduced, and the annulus level falls off.

The lost circulation caused by the well borehole collapse or hourglass bridge blockage and the pumping pressure presents a trend of rise first then fall, and the total volume of mud sump and the outlet flow are reduced. At the same time, there will be resistance when moving drilling, and the greater amount the loss, the greater value the resistance.

The lost circulation happens during the normal process of drilling wells, due to the leakage effects of drilling fluids, the inlet and outlet mud's temperature will face abnormal changes. And in combination with the three pressure annulus profile, in this case BHP is greater than formation pore pressure, loss pressure and fracture pressure.

To sum up, the most direct characterized phenomenon of lost circulation is changing of BHP, and simultaneously the total volume of mud sump, the inlet and outlet flow and twmperature also change accordingly. Therefore there lists a table of parameters' change of well leakage risk during normal well drilling shown in Table 1-1.

Table 1-1 Risk identification parameters' characterization of phenomenon and law durning drilling

<table>
<tr><td colspan="7">Pressure measurement parameters（P_{bh} reduced）</td></tr>
<tr><td colspan="3">$P_{bh} > P_p$</td><td colspan="2">$P_{bh} > P_f$</td><td colspan="2">$P_{bh} > P_l$</td></tr>
<tr><td colspan="5">Comprehensive logging parameters measurement</td><td colspan="2">Geological measurement parameters</td></tr>
<tr><td>Stand pipe pressure</td><td>Drilling time</td><td>Mud pit volume</td><td>Flow</td><td>Temperature</td><td>Rock Stratum</td><td>Rock Debris</td></tr>
<tr><td>Reducing</td><td>Change</td><td>Reducing</td><td>Output reduce</td><td>Input and Output anomalous change</td><td>high ermeability fracture and cavern</td><td>Porous seam</td></tr>
</table>

In this table, P_{bh} is Bottom Hole Pressure, P_{bh} is Pore Pressure, P_f is Fracture Pressure, and P_l is Loss Pressure.

2.2 Forewarning Scheme

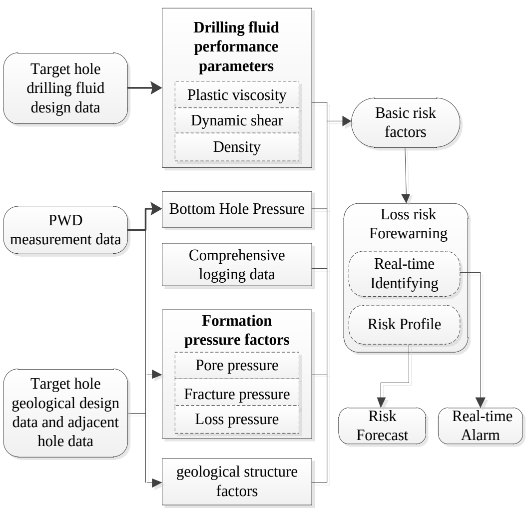

Figure 1-1 Lost Circulation Risk Forewarning Scheme

Due to the BHP, formation pore pressure, leakage pressure and fracture pressure are the direct factors affecting the risk of lost circulation; the performance of drilling fluid is the key risk factors of lost circulation, which can directly affect the size of the BHP; abnormal low pressure zone, natural fracture and cave geological structure can also cause the risk of lost circulation; and at the same time, the ground logging data reflect the change of BHP in a certain extent, is an effective parameter for characterization of lost circulation too. Therefore, on the basis of the factors above, combining with the regulation characterization phenomenon and law of the lost circulation, in this paper we established a Lost Circulation Risk Forewarning Scheme, as shown in Figure 1-1.

This scheme using the drilling fluid design data and comprehensive logging measurement information to provide reference data of BHP, using the data of adjacent Wells to provide geological reference data, and using Pressure While Drilling (PWD) tools to provide real-time data of BHP.

3. Establish a Lost Circulation Risk Forewarning Model durning Normal Drilling

When doing lost risk forewarning analysis, the original data obtained are diversity and complexity, and are also acattered and disorderly, have no clear correlation. Using conventional analysis method which based on single feature data extraction can't ensure real-time and accuracy of forewarning results, and it’s difficult to effectively realize the recognition of lost circulation risk. On account of this, in this paper we use BP neural network algorithm to establish a los risk warning model durning normal drilling. And the algorithm has highly nonlinear, that can do multifarious logical operation and non-linear processing.

3.1 BP neural network

BP neural network is a multilayer feedforward network algorithm, it’s signal is spread forward propagating and error back propagation. It has good nonlinear mapping ability, by constantly adjusting the weights and threshold between each layer nodes of network to achieve better approximation ability[4-6]. The basic structure of it as shown in Figure 2-1.

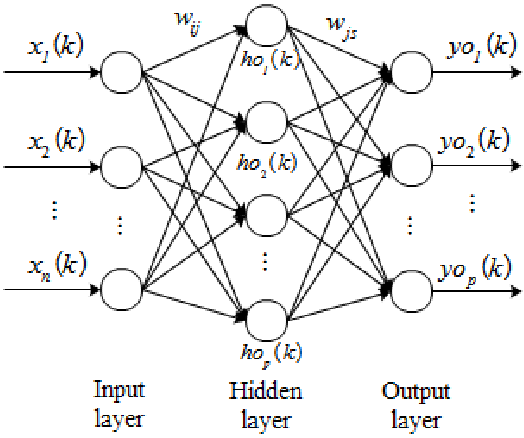

Figure 2-1 Three layer BP neural network model

As shown in Figure 2-1, the input function $hi_j(k)$ and output function $ho_j(k)$ of hidden layer neurons are respectively as formula (2-1) and formula (2-2).

$$hi_j(k) = \sum_{i=1}^{n} w_{ij} x_i(k) - a_j \tag{2-1}$$

$$ho_j(k) = f(hi_j(k)) \tag{2-2}$$

In above formulas, i is the neural nodes of input layer, j is the neural node of hidden layer, and $j \in [1, p]$, w_{ij} is the weight between input layer nodes i and hidden layer neural node j; $x_i(k)$ is the number i input value in the number k sample; and a_j is the corresponding threshold.

The input function $yi_s(k)$ and output function $yo_s(k)$ of output layer neurons are respectively as formula (2-3) and formula (2-4).

$$yi_s(k) = \sum_{i=1}^{p} w_{js} ho_j(k) - b_s \tag{2-3}$$

$$yo_s(k) = f(yi_s(k)) \tag{2-4}$$

In above formulas, s is the neural nodes of output layer, and $s \in [1, q]$, w_{js} is the weight between output layer nodes s and hidden layer neural node j; and b_s is the corresponding threshold.

The partial derivative $\delta_s(k)$ of calculation error function for output layer node is as formula (2-5).

$$\delta_s(k) = (\varepsilon_s(k) - yo_s(k)) \cdot f^{'}(yo_s(k)) \tag{2-5}$$

In this formula, $\varepsilon_s(k)$ is a desired output of neural network.

Using w_{js}, $\delta_s(k)$, and $ho_j(k)$ to calculate the partial derivative $\delta_j(k)$ of calculation error function for hidden layer nodes.

$$\delta_j(k) = \left(\sum \delta_s(k) w_{js}\right) \cdot f^{'}(ho_j(k)) \tag{2-6}$$

Using $\delta_s(k)$ and $ho_j(k)$ to revise the weights w_{js} and threshold values b_s between hidden layer and output layer. Respectively as shown in formula (2-7) and (2-8).

$$w_{js}^{N+1} = w_{js}^{N} + \eta \delta_s(k) ho_j(k) \tag{2-7}$$

$$b_s^{N+1} = b_s^{N} + \eta \delta_s(k) \tag{2-8}$$

Using $\delta_j(k)$ and $x(k)$ to revise the weights w_{ij} and threshold values a_j between hidden layer and output layer. Respectively as shown in formula (2-9) and (2-10).

$$w_{ij}^{N+1} = w_{ij}^{N} + \eta \delta_j(k) x_i(k) \tag{2-9}$$

$$b_j^{N+1} = b_j^{N} + \eta \delta_j(k) \tag{2-10}$$

Calculate the global error E as formula (2-11).

$$E = \frac{1}{2m}\sum_{j=1}^{m}\sum_{s=1}^{q}(\varepsilon_s(k) - yo_s(k))^2 \quad (2\text{-}11)$$

Constantly amended each weights and threshold of neural network with error back propagation, until the error E is meetting the precision of its rules, end training.

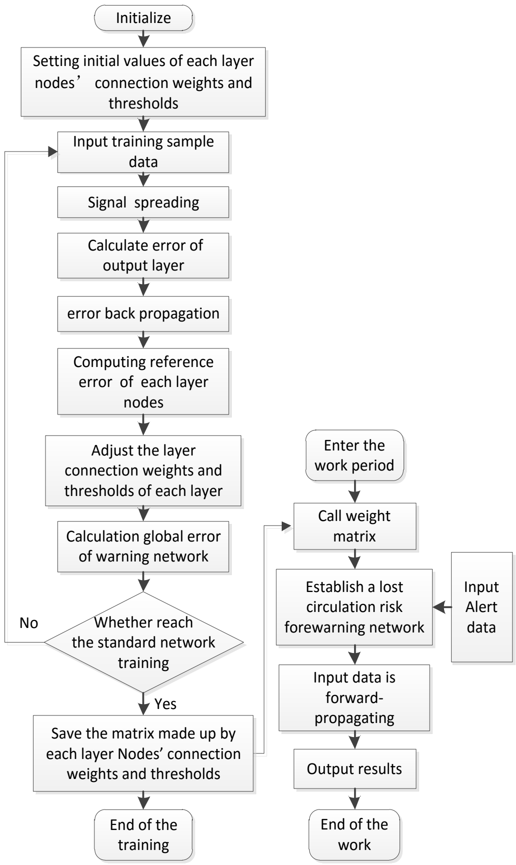

Figure 2-2 Realizable flow of BP neural network Lost Risk Forewarning Model

3.2 Establish the Lost Circulation Risk Forewarning Model

According to the design of above risk forewarning scheme, the inputs of BP neural network maybe nearly nineteen factors, they are PWD meassurement data, formation pore pressure, fracture pressure, leakage pressure, drilling fluid density, dynamic shear, plastic viscosity, inlet flow rate, outlet flow, casing pressure, stand pipe pressure, pump speed, drilling time, drilling fluid inlet temperature , outlet temperature, total pool volume, whether the fault fracture zone, whether fracture water-eroded cave sensitivity formation, whether it is abnormal low pressure zone and so on. Due to the actual data collection situation is different, its inputs can be targeted to choose according to the actual situation.

Because the enter items of a network entries have different physical meaning and dimension, this paper useing scale transformation and linear normalization method for data processing[7], convert it value to [0,1].

$$\overline{x_i} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (2\text{-}12)$$

In this type, x_i , $\overline{x_i}$, $x_{\min}$, $x_{\max}$ respectively representing the initial sample data, unitary data and the minimum and maximum values in the initial sample data in each sample information.

If the value of output single y about output layer nodes approaches to 1, the more prone to risk; on the contrary, the more prone to no risk.

In view of the selection of hidden layer nodes wether reasonable directly affects the ability of risk forewarning model to deal with complicated hole condition, and in order to ensure the reasonableness of training time, we choose empirical formula to determine the hidden layer nodes.

$$l = \sqrt{m+n} + c \tag{2-13}$$

In the type, l is the hidden layer nodes, m is the input layer nodes, n is the output layer nodes, and c is a constant between one and ten. Figure 2-2 shown the realizable flow of BP neural network lost risk forewarning model.

Using collected data to train the designed model above, the training error close to 0.005 after training, and error convergence curve as shown in Figure 2-3.

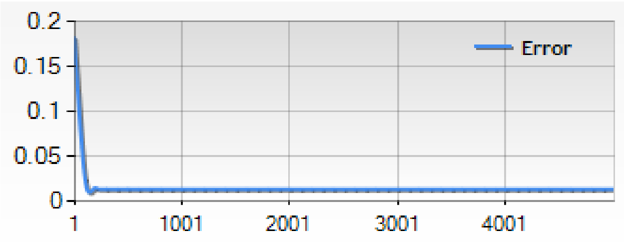

Figure 2-3 Error convergence curve

4. Application analysis

Based on the aboved theory and model, in this paper we select adjacent well data of X well in XX oilfield to establish the lost circulation risk forewarning model of X well at A horizon. Adjacent well sample data of X well is shown in table 3-1, choose the data of 2660-2665 M depth of X well for real-time analysis in this model. Interval data is shown in table 3-2, and the results of lost circulation risk forewarning analysis are shown in Table 3-3 and Figure 3-1. We can seen from Figure 3-1 that the results of this model are consistent with actual situation of X well.

5. Conclusion

1) Based on the characterizations and bottom hole perssure changing rules when lost circulation occured, we established the lost circulation risk forewarning program durning normal drilling;

2) Combined the designed lost circulation warning scheme with BP neural network, we maked a lost circulation risk forewarning model. And through the field data validation shows that the model established in this paper is effective in early warning of loss. Compared with the warning system which using the measurement data on the ground, the model we eatablished increasing the real-time and accuracy of risk early warning of lost circulation.

Table 3-3 Lost Circulation Risk Forewarning Model analysis results output table of X well

Hole depth（m）	Value-at-risk	Warning result
2660	0.009765	No risk
2661	0.142658	No risk
2662	0.837498	Risk of lost circulation
2663	0.743662	Risk of lost circulation
2664	0.936256	Risk of lost circulation
2665	0.908654	Risk of lost circulation

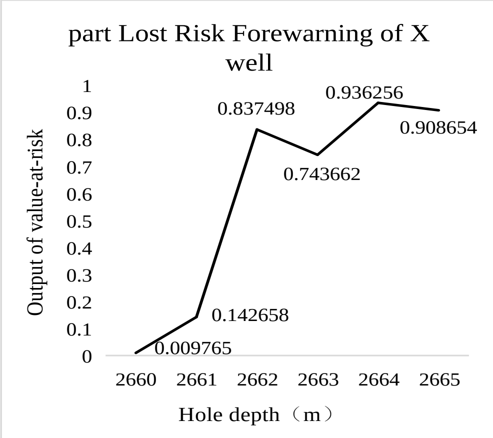

Figure 3-1 part Lost Risk Forewarning of X well

Table 3-1 Adiacent well data of X well in XX oilfield

No.	Hole depth（m）	Bottom hole pressure（MPa）	Pore pressure（MPa）	Fracture pressur（MPa）	Leakage pressure（MPa）	…	Drilling fluid density（g/cm^3）	Inlet flow rate（L/s）	Outlet flow rate（L/s）
1	2612	32.970	32.040	34.117	33.091	…	1.164	32.071	32.071
2	2613	32.035	32.054	34.131	33.105	…	1.166	32.069	32.015
3	2614	32.843	32.068	34.145	33.119	…	1.167	32.072	32.127
4	2615	32.291	32.082	34.159	33.134	…	1.168	32.179	29.813
5	2616	32.277	32.096	34.173	33.148	…	1.169	32.181	31.768
…	…	…	…	…	…	…	…	…	…
85	2696	31.803	28.680	35.316	29.192	…	1.125	32.000	31.970
86	2697	31.787	28.389	35.980	29.734	…	1.126	32.005	31.865
87	2698	32.745	27.742	35.994	28.683	…	1.126	32.005	31.783
88	2699	32.783	28.109	35.380	29.490	…	1.125	32.014	31.695

Table 3-2 Application data of X well

No.	Hole depth（m）	Bottom hole pressure（MPa）	Pore pressure（MPa）	Fracture pressur（MPa）	Leakage pressure（MPa）	…	Drilling fluid density（g/cm^3）	Inlet flow rate（L/s）	Outlet flow rate（L/s）
1	2660	32.080	31.258	34.175	33.149	…	1.170	32.365	32.562
2	2661	32.102	30.842	34.406	32.119	…	1.175	32.364	32.183
3	2662	31.575	29.835	33.844	30.001	…	1.173	32.564	31.371
4	2663	31.003	28.776	33.752	29.968	…	1.177	32.840	30.864
5	2664	30.680	28.083	33.522	29.040	…	1.168	32.865	30.855
6	2665	31.430	27.587	33.670	28.990	…	1.162	32.015	30.245

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